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WOCAT
World Overview of Conservation Approaches and Technologies

ADVANCED UNEDITED VERSION

GOOD PRACTICE GUIDANCE ADDENDUM

SDG Indicator 15.3.1

Proportion of land that is degraded over total land area

This is an Advanced Unedited Version

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EXECUTIVE SUMMARY

This Addendum to Good Practice Guidance for SDG Indicator 15.3.1 (GPG) provides updated methodological guidance for countries reporting on SDG Indicator 15.3.1: the proportion of land that is degraded over total land area. Developed by the United Nations Convention to Combat Desertification (UNCCD) and the World Overview of Conservation Approached and Technologies (WOCAT) of the University of Bern, Center for Development and Environment, in collaboration with technical partners, the addendum builds on Version 2 of the GPG and responds to lessons learned during the 2022 reporting cycle. As such, this document should be read in conjunction with Version 2 of the GPG and it is advisable that readers understand the theoretical and methodological basis for SDG Indicator 15.3.1, as described in Version 2, before reading the Addendum.

The Addendum is targeted at national reporting officers, researchers and software developers who require an in-depth understanding of SDG Indicator 15.3.1 in order to carry out national-level monitoring, reporting, tool development and research related to SDG Indicator 15.3.1 and land degradation neutrality (LDN).

The Addendum is structured around three main sections. The first section introduces refined guidance on combining data across multiple reporting periods, enabling consistent tracking of land degradation and improvement. The updated approach allows for the generation of "status" maps that reflect land condition at the end of each period, integrating changes since the baseline. The second section clarifies the distinction between monitoring SDG Indicator 15.3.1 and assessing progress toward land degradation neutrality (LDN). It presents a retrospective approach to operationalizing the counterbalancing concept introduced in the Scientific Conceptual Framework for Land Degradation Neutrality, evaluating whether degradation observed since the baseline has been offset by actual improvements within the same land type. This method assesses neutrality based on actual past changes, rather than projecting future gains and losses. Step-by-step guidance is provided for applying this spatially explicit framework at national and subnational levels. Finally, the third section focuses on the enhancement of datasets and methodologies, providing countries with guidance to select, verify, and use the most appropriate data and methods for assessing trends in land cover, land productivity, and soil organic carbon (SOC). It introduces tools and workflows for dataset comparison and verification, promotes the integration of national expertise, and highlights the use of cloud-based platforms such as Trends.Earth to support efficient and scalable analysis.

Together, the enhancements presented in this addendum aim to improve the reliability, transparency, and relevance of national reporting on land degradation. They also reinforce the broader objective of achieving Land Degradation Neutrality by 2030, supporting evidence-based decision-making, and enhancing national ownership of data and reporting processes.

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GLOSSARY of new/updated Terms

Counterbalancing: A process in LDN monitoring used to measure and offset, within each land type, losses of natural capital with gains in other areas. Counterbalancing quantifies the net balance between degraded and improved land after the baseline, ensuring that any land degradation is balanced by improvements elsewhere.

Period: A specific span of time over which land condition is assessed. When used without any qualifiers (e.g. "reporting period"), it simply denotes a defined timeframe.

Period Assessment: The result of evaluating land condition for a specific period, derived from combining the three sub-indicators (Trends in Land Cover, Trends in Land Productivity, and Trends in Carbon Stocks) using the "one-out, all-out" principle. This assessment reflects changes in land condition that have occurred during the period.

Reporting Period (Tn): The designated time frame over which the three sub-indicators of SDG indicator 15.3.1 are measured and quantified to assess land condition. Each successive reporting period increases in duration by four years, aligning with the four-year UNCCD reporting cycle.

Reporting process: Periodic submission of reports by Parties in accordance with the 4-year reporting frequency established by Decision 15/COP.13. Each reporting process is named after the year in which reporting occurs (e.g., 2022 reporting process, 2026 reporting process) and encompasses the assessment and submission of data relevant to the Convention's objectives during that cycle.

Status (St): Refers to the condition of land (categorized as degraded, stable, or improved) at the end of a period compared to a baseline. This is determined by integrating the baseline and the period assessment using the Status Matrix.

Status Matrix: A 3x3 matrix illustrating possible combinations of land condition changes between the baseline and period assessments. It systematically compares the period assessment with the baseline to determine the land's final status at a pixel level. An expanded version of the Status Matrix helps in understanding when the observed changes in status have taken place.

Status Map: A spatial representation of the status of land condition, illustrating areas categorized as degraded, stable, or improved compared to the baseline. It can be derived by integrating period assessment results with baseline data and serves as the basis for SDG Indicator 15.3.1 reporting and land degradation neutrality (LDN) monitoring. An expanded version of the Status Map shows where persistent and recent improvements and persistent and recent degradation occurs at a pixel level.

INTRODUCTION

INTRODUCTION

The United Nations Convention to Combat Desertification (UNCCD), as the custodian agency for SDG Indicator 15.3.1, “proportion of land that is degraded over total land area”, is responsible for offering methodological guidance to countries, collecting and analyzing country data, and estimating regional and global aggregates for inclusion in SDG progress reports. The Good Practice Guidance for SDG Indicator 15.3.1, originally published by the UNCCD in 2017 and subsequently revised and updated in 2021[1], provides guidance on how to calculate the extent of land degradation. The approach to estimate this indicator and monitor land degradation globally has been inter-governmentally agreed both as part of the UNCCD monitoring framework (specifically for Strategic Objective 1[2]), and of the global SDG indicator framework[3]. This approach is based on the combination of three spatially explicit sub-indicators:

- Trends in land cover
- Trends in land productivity and
- Trends in carbon stocks above and below ground, which is currently represented by a temporary metric - soil organic carbon (SOC) stocks.

Box 1: SUSTAINABLE DEVELOPMENT GOAL 15 (‘LIFE ON LAND’)

Protect, restore and promote sustainable use of terrestrial ecosystems, sustainably manage forests, combat desertification, and halt and reverse land degradation and halt biodiversity loss

Box 2: TARGET 15.3

“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”

Since 2018, and every four years thereafter, countries officially submit their estimations of SDG Indicator 15.3.1 to the UNCCD as part of the national reporting process. These submissions are made through the UNCCD's reporting platform, the Performance Review and Assessment of Implementation System (PRAIS). Once the country data are collected, the UNCCD secretariat compiles these estimates, along with sub-regional, regional, and global aggregates, and submits them to the United Nations Statistics Division (UNSD). This information is then published in the SDG Report and the Global Database. For the reporting process in 2022, the PRAIS system was upgraded to align with modern systems architecture and to address the specific requests made by UNCCD country Parties. In its fourth iteration, PRAIS offered several key improvements to facilitate national reporting, including a rich information base comprised of over seventy spatial data layers from free and open global datasets.

However, the Earth Observation products and guidelines used for reporting on SDG Indicator 15.3.1 adopt a global perspective, and they have known limitations under certain conditions. Based on

[1] https://www.unccd.int/sites/default/files/documents/2021-09/UNCCD_GPG_SDG-Indicator-15.3.1_version2_2021.pdf
[2] “Improving the condition of affected ecosystems, combating desertification/land degradation, promoting sustainable land management (SLM) and contributing to Land Degradation Neutrality”.
[3] https://unstats.un.org/sdgs/metadata/files/Metadata-15-03-01.pdf

feedback from country Parties and technical partners, the UNCCD has identified the need to expand and refine Version 2.0 of the Good Practice Guidance for SDG Indicator 15.3.1. To address critical aspects that were highlighted as problematic or unresolved during the 2022 reporting process, the UNCCD has led the development of this Addendum to the Good Practice Guidance. In addition to the experience gained from past reporting processes, new datasets and methodological advancements have been developed that can enhance estimations, particularly in specific areas like Small Island Developing States (SIDS), where the spatial resolution of current default datasets is often too coarse to detect the necessary variability for meaningful results.

This addendum intends to provide clarifications and additional methodological guidance aimed at improving national estimations of SDG Indicator 15.3.1 and enhancing the ability to track changes over successive reporting periods up until 2030. The addendum also builds on current implementations in software such as Trends.Earth to ensure consistency and alignment with widely-used approaches while enhancing guidance for countries to monitor and report progress effectively.

Key aspects revised in the Addendum

The addendum introduces several updates and expansions to the guidance provided in GPG Version 2, enhancing clarity and usability for countries reporting on SDG Indicator 15.3.1. These include:

- **Further Elaboration on Reporting Periods.** The addendum provides detailed explanations of the timeframes for each reporting period. Reporting periods are now explicitly defined, with durations increasing by four years per period.
- **Enhanced Methodology for Period Assessment.** While the rationale for estimating the indicator remains the same, the methodology to compare the period assessment with the baseline has been further detailed. A **status matrix** is introduced to operationalize the concepts presented in GPG Version 2 for estimating SDG Indicator 15.3.1.
- **Characterizing Changes in Land Condition** The addendum presents a method to further characterize changes from baseline to current conditions. This approach helps identify areas of degradation or improvement since the baseline, providing valuable insights in the context of achieving Land Degradation Neutrality (LDN).
- **Operationalization of the Counterbalancing Mechanism.** A mechanism to operationalize counterbalancing is introduced, offering further guidance on how to estimate net balance of gains and losses of natural capital to monitor progress towards LDN.
- **Guidance on Selecting Representative Datasets.** Additional guidance is provided to help identify the most representative datasets for each sub-indicator. A verification workflow is presented, incorporating cloud computing and expert knowledge—a process already adopted by many countries.
- **Updated References to Key Datasets.** References to datasets relevant to each sub-indicator have been reviewed and updated, ensuring alignment with the latest available data sources.

These updates aim to clarify processes, enhance operationalization, and support countries in effectively reporting on and addressing land degradation in alignment with the SDG 15.3.1 framework. Mapping land degradation, especially at global and national scales, still presents significant challenges. By addressing key challenges and incorporating the latest advancements, this addendum represents one more step towards accurately assessing and reporting land degradation, thereby contributing to more effective monitoring of progress towards SDG target 15.3 and the achievement of Land Degradation Neutrality (LDN).

This addendum is structured into three sections:

Section 1: **Integrating land condition assessments over time**

This section develops methods for integrating information across multiple reporting periods. As countries prepare for the 2026 reporting process, there is a need for clear guidance on how to combine data from the baseline period and subsequent reporting periods. This section focusses on the timeframe of the data used to assess land condition in each reporting period, on how to integrate the period assessment with the baseline, as well as providing additional guidelines on how to interpret and visualize changes over multiple reporting processes.

Section 2: Tracking progress towards Land Degradation Neutrality

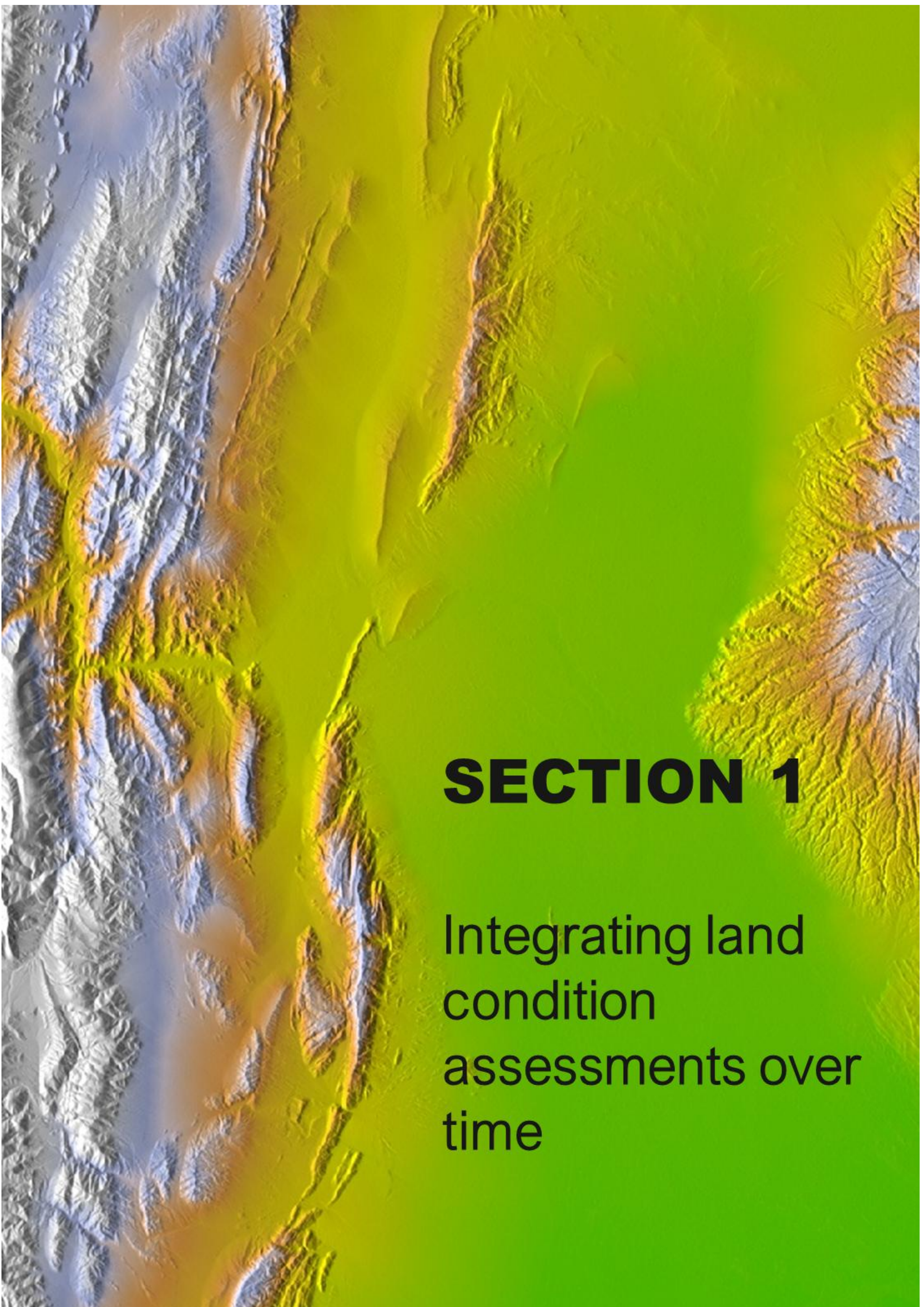
While Version 2.0 of the Good Practice Guidance focuses on the methodology for monitoring degraded land (degraded or not degraded) as per SDG Indicator 15.3.1, this section expands on the data-driven approaches required for monitoring not only land degradation, but also land improvement, to effectively track progress toward SDG Target 15.3 and LDN. This involves balancing losses (declines in land-based natural capital) and gains (increases in land-based natural capital) across land types. This section responds to the need for guidance on incorporating the improved land component and the neutrality mechanism into target setting, LDN intervention planning, prioritizing areas for investment, and tracking progress towards LDN.

Section 3: Enhancement of datasets and methodologies

The final section addresses the enhancement of datasets and methodologies to support the selection of the most appropriate data products for different contexts. It introduces new datasets related to land cover, land productivity, and soil organic carbon (SOC), and discusses various methods and experiences in comparing and selecting the most representative datasets for different contexts. This section highlights workflows implemented by national experts that have contributed to verifying results and selecting the most accurate datasets.

This addendum aims to provide further guidance on these critical issues. It recognizes that the methodology for mapping land degradation at global and national levels in a standardized manner will continue to evolve, improving with advances in scientific research, data collection, and practical implementation by countries.

This document was co-produced by the UNCCD secretariat and the World Overview of Conservation Approached and Technologies (WOCAT) of the University of Bern, Center for Development and Environment, through a consultative process with experts and UNCCD technical partners, including the Commonwealth Scientific and Industrial Research Organization (CSIRO), Conservation International (CI), European Space Agency (ESA), Group on Earth Observation-Land Degradation Neutrality Flagship (GEO-LDN), Joint Research Centre of the European Commission (EC-JRC), Open Geospatial Consortium (OGC) and OpenGeoHub foundation (OGH).



SECTION 1

Integrating land condition assessments over time

SECTION 1: Integrating land condition assessments over time

This section further develops the methods for integrating land condition information over time. In view of the upcoming 2026 and subsequent reporting processes[4], additional guidance is provided to clarify the timeframe of each reporting period, how to integrate each reporting period assessment with the baseline, and how to assess the status of land condition at the end of each reporting period. This section also includes additional guidelines on how to interpret and visualize changes over multiple reporting periods.

The section addresses these three key aspects:

1.1 **Assessing changes in land condition in a reporting period (PERIOD ASSESSMENT):** The *period assessment* involves determining the changes in land condition within each reporting period[5]. This sub-section intends to clarify the timeframes of each reporting period, and the timeframes of the datasets used to assess the three sub-indicators in each.

1.2 **Assessing CURRENT STATUS:** This sub-section provides further guidance on how to integrate the baseline and the period assessment to assess *current status*, i.e. land condition at the end of a reporting period. The goal is to consistently map the current status of land condition (degraded, stable or improved) at each reporting process, ensuring that the final results are relative to the baseline assessment and account for previously existing degradation and improvement.

1.3 **Tracking CHANGES in SDG indicator 15.3.1 over time (across more than two periods):** This aspect focuses on how to visualize changes in land condition over multiple reporting periods. It provides a framework for a deeper understanding of changes over time.

Together, these additional guidelines offer a simple and clear approach for integrating and interpreting land condition data across multiple periods.

1.1 Assessing changes in land condition during each reporting period (PERIOD ASSESSMENT)

In decision 15/COP. 13, the UNCCD has approved a four-year frequency for submission of national reports to provide information on the strategic objectives of the UNCCD 2018–2030 Strategic Framework. The frequency of SDG indicator 15.3.1 reporting was aligned with the 4-year frequency of UNCCD reporting processes. The first reporting process, initiated under the UNCCD 2018–2030 Strategic Framework in 2018, focused on establishing the baseline, to which all future changes will be compared. The baseline period (t_0) is defined as the 16-year period from January 1st, 2000, to December 31st, 2015. After this initial reporting process, Parties continue to report the status of land condition and the SDG indicator 15.3.1 every four years, thereby increasing the reporting periods in four-year increments.

[4] See Figure 1.1 for a description of the UNCCD reporting processes and reporting periods

[5] A reporting period is the specified time interval (i.e increments of 4 years) from the last year of the baseline period over which land degradation is assessed

After the 2018 reporting process, when the baseline period assessment was conducted, the following UNCCD reporting process was finalized in 2022, when countries reported land condition status and SDG indicator 15.3.1 for the first reporting period (Period 1), covering the timeframe from January 1st, 2016, to December 31st, 2019. The results of the Period 1 assessment included the estimation of the proportion of degraded land (SDG indicator 15.3.1) for 2019 (t_1). Subsequent reports will reflect the land condition at the end of 2023 (t_2), 2027 (t_3) and 2031 (t_4), integrating changes that have occurred since the end of the baseline period (from January 1st, 2016) (Figure 1.1).

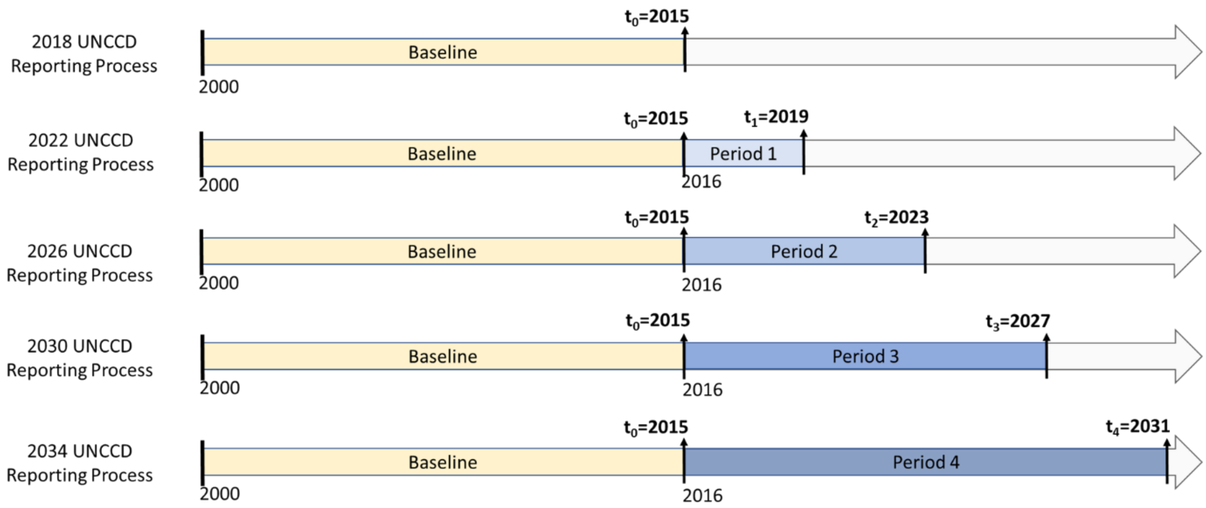


Figure 1.1: Timeline illustrating the four-year UNCCD reporting frequency for SDG 15.3.1. After the baseline period (2000–2015), the first reporting period (Period 1) covers January 1, 2016, to December 31, 2019. Subsequent reporting processes follow every four years, with periods increasing their duration by four years: Period 2 spanning 2016–2023, Period 3 covering 2016–2027, and Period 4 assessing changes from 2016 to 2031. Each reporting period evaluates changes in land condition through the three sub-indicators.

The period assessments evaluate changes in land condition since the end of the baseline period. This assessment involves estimating the three sub-indicators as defined in the Good Practice Guidance (GPG):

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

The results of the degradation analysis for each of these sub-indicators are then integrated using the "one-out, all-out" (1OAO) method. In this method, if any one of the sub-indicators shows a significant reduction or negative change, the area is classified as degraded. This ensures that the occurrence of land degradation is captured even if only one aspect of land condition deteriorates.

Assessment of trends in land cover in each period

For the baseline period, changes in land cover are assessed by assessing the differences between the land cover maps from the beginning and the end of the baseline period (2000 and 2015). For the subsequent periods, changes in land cover are assessed by comparing the land cover map used at the end of the baseline period (2015) with land cover maps of the end year of the subsequent reporting periods (Table 1.1).

The land cover map from the end of the baseline period (t_0= 2015) is always used as the initial reference for all subsequent reporting periods. This approach ensures that changes in land cover are assessed consistently across different periods and allows for an integration of the changes since the baseline, regardless of any intermediate transitions that may occur within the reporting period.

Using the 2015 land cover map as the starting point allows assessment of the overall trajectory of land cover changes since the baseline, offering a clearer and more stable picture of whether land degradation or improvement due to land cover change has occurred over time. This method avoids complications that might arise from assessing short-term fluctuations, which can introduce noise.

While it is always possible to analyze land cover changes over shorter intervals, such as every four years, this level of detail is not necessary for tracking progress toward SDG target 15.3, as explained in the GPG Version 2. The focus of LDN is on long-term, sustained improvement or degradation, making the baseline-to-end-of-period assessment more suitable for understanding meaningful changes in land condition over time. This ensures a consistent comparison of progress across reporting periods, providing a clear basis for assessing a country's efforts to achieve LDN goals. However, since Parties will report every four years, it is still possible to visualize the land condition status every four years (see section 1.3), which can provide further insights for decision making.

Period	**Trends in Land cover**	
	Initial Land Cover Year	*Final Land Cover Year*
Baseline: 2000-2015	2000	2015
Period 1: 2016-2019	2015	2019
Period 2: 2016-2023	2015	2023
Period 3: 2016-2027	2015	2027
Period 4: 2016-2031	2015	2031

Table 1.1: Initial and final years for the land cover maps used to assess changes in land cover for each reporting period.

In cases where countries have access to more representative or accurate land cover datasets that provide a better estimation of land cover changes than the default global datasets, it is possible to use land cover maps that do not necessarily match the initial and final years indicated in Table 1.1. These alternative datasets may offer finer spatial resolution or might be the official datasets that have undergone national validation processes, which can enhance the accuracy of the results. Provided these datasets allow for a reliable and improved assessment of land cover changes during the reporting period, countries are encouraged to utilize them in their national reporting.

Assessment of trends in land productivity in each period

In the second version of the GPG, significant change was introduced regarding how trends in land productivity should be assessed. Previously, in Version 1, Land Productivity Dynamics (LPD) were evaluated using a period of 16 years for the baseline and 8 years for the reporting periods. However, to ensure a more robust and consistent evaluation across time, Version 2 of the GPG (GPG v2) recommends assessing land productivity changes using a moving window of 16 years for both the baseline and reporting periods.

This extended assessment period provides greater consistency by maintaining the same methodology applied during the baseline evaluation for subsequent reporting periods. The rationale behind this is that using a shorter window (e.g., 8 years) would reduce the ability to capture longer-term trends and could lead to inaccurate assessments of land productivity changes. Therefore, the recommendation is to calculate the trend for each reporting period using a 16-year timeframe that ends in the last year of the reporting period.

As the reporting period advances (every 4 years), the 16-year window also shifts forward to reflect more recent data. While this approach is beneficial, it is not ideal, as there is overlap in the datasets of land productivity used for each period, which may affect the independence of the assessments. However, by 2031, this methodology will allow for two independent datasets, both spanning a 16-year timeframe, providing a more reliable basis for evaluating changes in land productivity over time. The timeframes of land productivity data used for each reporting period are shown in Table 1.2 and Figure 1.2, illustrating how the 16-year moving window is applied for each period assessment.

Period	**Trends in Land Productivity**	
	Initial Year	*Final Year*
Baseline: 2000-2015	2000	2015
Period 1: 2016-2019	2004	2019
Period 2: 2016-2023	2008	2023
Period 3: 2016-2027	2012	2027
Period 4: 2016-2031	2016	2031

Table 1.2: Initial and final years of the 16-year moving window used to assess changes in land productivity for each reporting period. The initial year is defined as starting from January 1 of that year, while the final year extends to December 31 of that year. This approach ensures that both the initial and final years are fully included in the assessment of land productivity changes across the reporting periods.

As explained in GPG v2, to assess trends in land productivity, three complementary metrics are used to estimate a Land Productivity Dynamics (LPD) dataset:

1. **Trend**: Measures the long-term trajectory of productivity change over a 16-year time series.
2. **State**: Compares current productivity levels in a given area to historical productivity observations, assessing recent productivity relative to a longer baseline period.
3. **Performance**: Evaluates local productivity in relation to similar productivity potential areas regionally, providing a benchmark of productivity levels within a comparable context.

In Table 1.2 the initial and final years of the 16-year moving window for each period are described. However, each metric in the LPD analysis uses data from distinct periods. The recommended timeframes for each LPD metric are described below and in Table 1.3.

The **Trend (or Trajectory) metric uses the full time series of 16 years for analysis, as described in Table 1.2 of this document.** This approach remains unchanged from GPG v2, capturing long-term trends in productivity and allowing a comprehensive view of productivity changes over time.

In the **State** metric, the productivity degradation is evaluated by comparing the mean annual Net Primary Productivity (NPP) of the three most recent years to the historical distribution of NPP values observed over the preceding 13 years. In practice, different users have adjusted these two periods to suit specific conditions, with varying lengths for both the historical reference and the recent comparison periods. Altering the length of these periods can produce different results in the productivity state assessment. Therefore, it is important that Parties are aware of this variability and use their expert knowledge to select the appropriate period lengths for their specific context. In the Trends.Earth software, the length of the two periods in the State metric can be parameterized. The general recommendation is to maintain a 13-year historical period and a 3-year recent comparison period within the 16-year time frame for consistency and comparability, however, users can and are encouraged to adjust the periods as needed.

The **Performance** metric should be calculated as the mean of the annual productivity assessments over the 16 year period to ensure robust estimations. In the GPG v2 it is proposed to estimate performance over the years since the baseline. However, using a longer timeframe (16 year moving window) minimizes the influence of outliers or exceptional conditions, such as extreme climatic events, which could otherwise distort the estimates. By assessing the maximum and observed productivity over a more extended period, the analysis accounts for natural variability and provides a more stable basis for comparison. This is also the approach implemented in Trends.Earth.

	Trends in Land Productivity			
Period	**Trend / Trajectory (16 years)**	**State (16 years)**		**Performance (16 years)**
		Baseline (13 years)	*Comparison Period (3 years)*	
Baseline: 2000-2015	2000 -2015	2000-2012	2013-2015	2000 -2015
Period 1: 2016-2019	2004 -2019	2004-2016	2017-2019	2004 -2019
Period 2: 2016-2023	2008 -2023	2008-2020	2021-2023	2008 -2023
Period 3: 2016-2027	2012 -2027	2012-2024	2025-2027	2012 -2027
Period 4: 2016-2031	2016 -2031	2016-2028	2029-2031	2016 -2031

Table 1.3: Specific timeframes recommended to estimate each Land Productivity metric (Trend, State and Performance) for multiple reporting periods.

Assessment of trends in carbon stocks in each period

The third sub-indicator for monitoring SDG Indicator 15.3.1 focuses on quantifying changes in carbon stocks (above and below ground) over the reporting periods. As outlined in the UNCCD decision 22/COP.11, soil organic carbon (SOC) stock is the metric currently used to assess carbon stocks and will be replaced by total terrestrial system carbon stock once operational. Assessing changes in SOC presents several challenges due to the high spatial variability of soil properties, the time and cost-intensive nature of conducting representative soil surveys, and the general lack of time series data on SOC for most regions worldwide.

To address these limitations, version 2 of the GPG presents a range of datasets and processing options, consistent with the IPCC guidelines, supplements and refinements (IPCC 2006; 2013; 2019), 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). The Tier 1 and 2 methods leverage information on land cover change, along with climate and land cover default conversion coefficients[6], to estimate changes in SOC stocks. Ideally, annual land cover maps are preferred for this analysis, but at a minimum, land cover maps for the starting and end years of the reporting period are required.

To estimate changes in SOC stocks for the different reporting periods, conversion coefficients for changes in land use, management, and inputs, as recommended by the IPCC and the UNCCD, are employed. These coefficients represent the proportional change in carbon stocks after 20 years of land cover change.

Only land cover changes that occurred after the baseline should be considered in this analysis and therefore the same periods used for assessing land cover change should also be applied for SOC changes (Table 1.4), ensuring a consistent measurement of changes since the baseline. Referring to 2015 as the baseline year for assessing SOC changes offers significant advantages, as it provides a longer timeframe essential for capturing meaningful shifts in SOC dynamics as subsequent reporting periods increase. Given the time it typically takes for changes in SOC to manifest, using 2015 as a reference point enables more robust analyses and helps to identify trends that may not be evident in shorter timeframes.

Period	**Trends in SOC Stocks**	
	Initial Year	*Final Year*
Baseline: 2000-2015	2000	2015
Period 1: 2016-2019	2015	2019
Period 2: 2016-2023	2015	2023
Period 3: 2016-2027	2015	2027
Period 4: 2016-2031	2015	2031

Table 1.4: Initial and final years for the assessment of trends in Soil Organic Carbon stocks for each reporting period.

If Tier 3 methods for estimating SOC changes are available, they should be employed to enhance the assessment of SOC during the reporting periods as indicated in Table 1.4. These innovative approaches could provide more accurate and reliable estimations, addressing the limitations associated with the Tier 1 and 2 land cover/SOC methods.

Figure 1.2 graphically illustrates the timeframes used for estimating each sub-indicator during the baseline and subsequent reporting processes under the UNCCD framework. It highlights that, for land cover, the initial year for each reporting period is the end of the baseline. Similarly, for SOC trends, the periods increase by four years, aligning with the approach for land cover and starting at the end of 2015. For productivity, the 16-year moving window remains consistent across periods. This visualization demonstrates that by the reporting process of 2034, the timeframes of the baseline and

[6] https://docs.trends.earth/en/latest/for_users/features/landdegradation.html#soil-organic-carbon

the last reporting period will no longer overlap and will have equal durations. This ensures a fair and consistent comparison between the reporting period and the baseline.

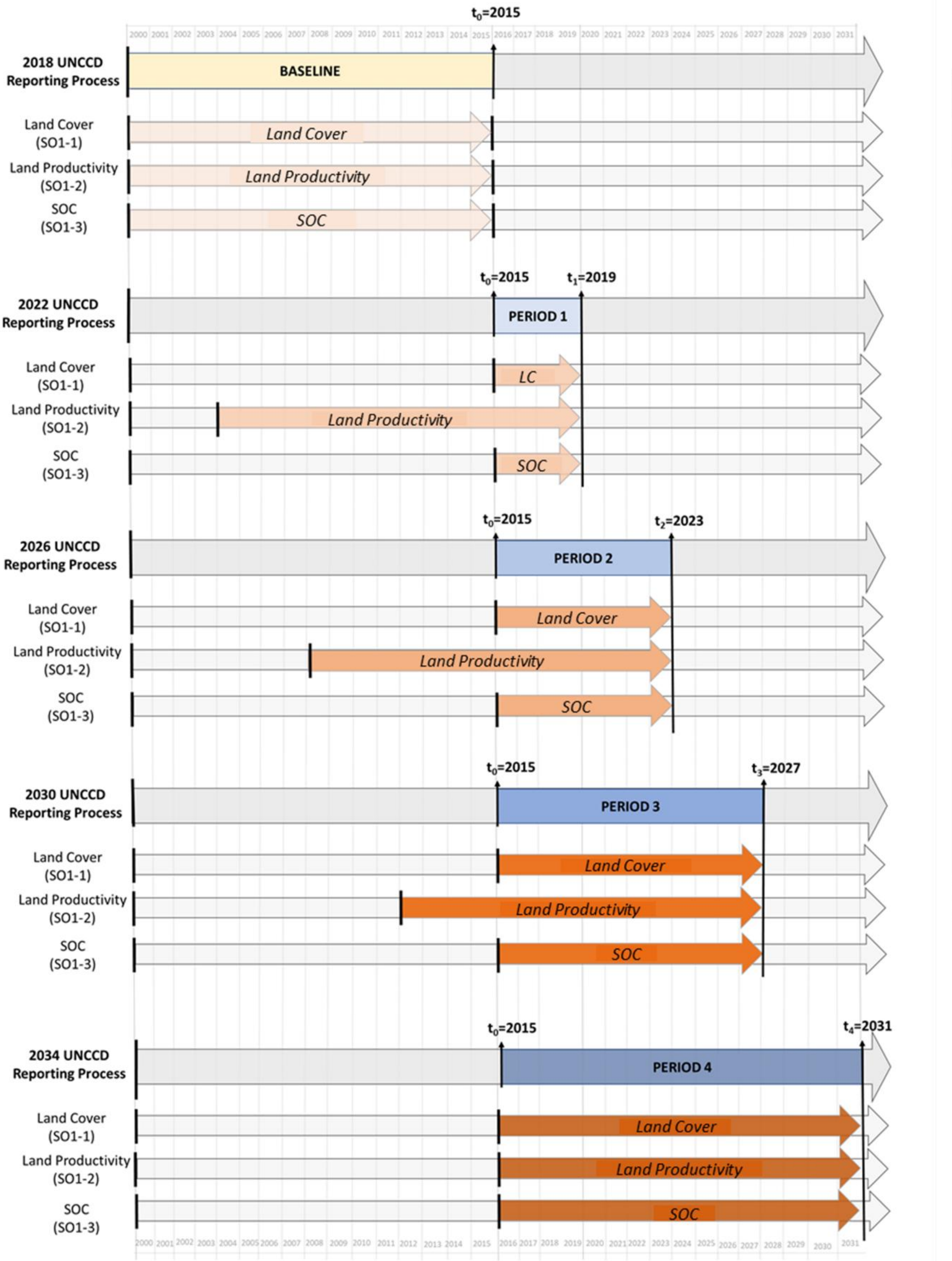


Figure 1.2: Timeframes used for the estimation of each sub-indicator in the baseline and subsequent reporting processes under the UNCCD framework. The figure illustrates the number of years considered for calculating land cover trend, land productivity trend (16-year moving window), and carbon stock changes. By the last reporting period, the two time series do not overlap, enabling a fair comparison of land degradation assessment with the baseline.

Combination of sub-indicators for each period

The results of the degradation analysis for each of the sub-indicators for each period should be combined using the one-out, all-out (1OAO) method in which a considerable reduction or negative change in any one of the three sub-indicators is considered to comprise land degradation (Figure 1.3).

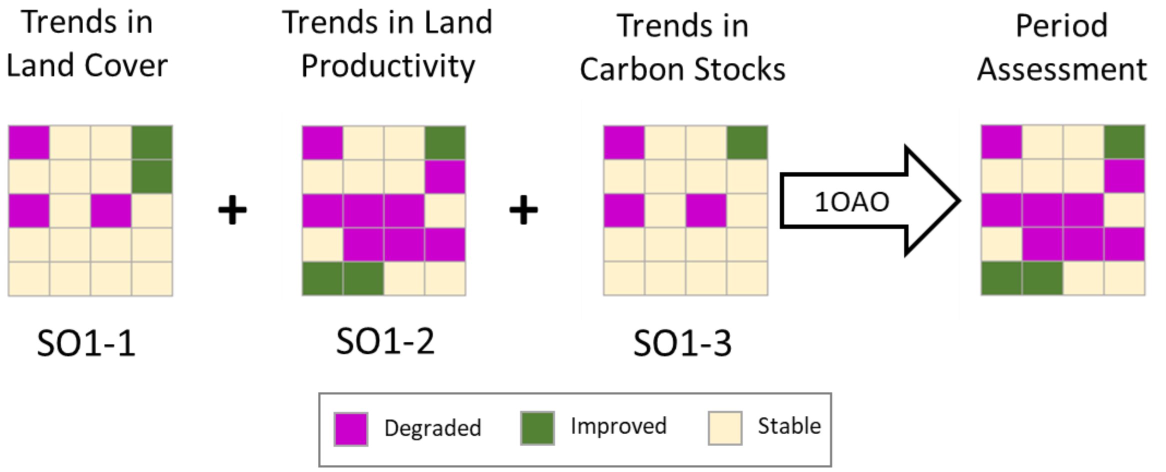


Figure 1.3: Application of the 'One Out, All Out' (1OAO) principle to combine the three sub-indicators for assessing land condition status for each period. Each square represents a pixel and their colors represent the result of assessment, where purple corresponds to degradation, yellow to stable and green to improved.

For each reporting period a final map that shows the results of the *period assessment* is obtained. **The "*Period Assessment*" is the result of the evaluation of land condition for a specific reporting period, based on the combination of the three sub-indicators (Trends in Land Cover, Trends in Land Productivity, and Trends in Carbon Stocks) by applying the one-out, all-out principle.** The period assessment does not capture the degradation or improvement that occurred during the baseline period and therefore it cannot be used to estimate SDG indicator 15.3.1 on its own. The next sub-section (sub-section 1.2) further clarifies how to integrate the baseline period assessment to also consider the areas that were degraded during the baseline and did not improve.

In the first and second versions of the Good Practice Guidance (GPG), the baseline assessment was focused exclusively on identifying the occurrence of degraded lands. The resulting baseline maps generated were binary in nature, categorizing areas as either degraded or not degraded. This approach aligns with the reporting requirements for SDG Indicator 15.3.1, which quantifies the extent of degraded land and expresses it as a proportion (percentage) of the total land area.

However, in this addendum, the baseline assessment has been expanded to include not only degraded areas but also land areas that have shown improvement, creating a third category in the original binary baseline map. This expanded baseline assessment simplifies the approach to simultaneously estimate SDG Indicator 15.3.1 and monitor progress towards LDN. By incorporating areas of improvement into the baseline, the addendum supports a more comprehensive understanding of land condition, essential for accurate monitoring over time and evidence-based decision-making. Section 2 elaborates on the methodology for estimating the balance between gains and losses in natural capital, enabling assessment of whether neutrality has been achieved by tracking both degradation and improvement.

1.2 Assessing STATUS for each reporting process

“Status” refers to the final condition (considering the baseline) of land at the end of each reporting period, classified as either degraded, stable, or improved. The Status is determined by combining the results of the current period assessment (as described in section 1.1) with the baseline assessment. This integrated approach ensures that the status reflects not only changes observed during the reporting period but also the baseline degradation or improvement, capturing a complete picture of the land’s condition over time. The resulting status map enables the estimation of SDG Indicator 15.3.1 by providing a spatially explicit view of areas that are either stable, improved, or degraded, considering also their initial condition.

It is important to distinguish between the two key concepts: the "period assessment" and the "Status". As explained in section 1.1, the *period assessment* involves evaluating the land condition based solely on the period's data (i.e. combination of the three sub-indicators for the period using the 1OAO principle), without considering the previous status. In contrast, the *Status* is obtained by comparing the reporting period assessment with the baseline.

Since the *Status* reflects the integration of the period assessment with the baseline, for the baseline period, the *Status* is identical to the period assessment (baseline assessment = Status 2015). In subsequent reporting periods, it is necessary to not only estimate the three sub-indicators (as indicated in section 1.1) but also to compare the period assessment with the baseline to obtain a new Status map and estimate SDG indicator 15.3.1. This comparison is essential to account for areas identified as degraded in the baseline that have since remained unchanged in land condition. For example, if an area was classified as degraded during the baseline period but was stable afterwards, it will be assessed as stable during the period assessment. However, the land's condition is still degraded as there has been no improvement since the baseline. As outlined in the Good Practice Guidance, these are areas that were previously identified as degraded and have not improved to a non-degraded state after the baseline assessment. This is why to estimate SDG 15.3.1 it is necessary to not only consider the current period assessment but also the baseline assessment to effectively capture the status of the land condition.

A straightforward method to perform this comparison is by using a 3 x 3 matrix showing the different possible combinations of the changes in land condition between the baseline period and the reporting period. The “Status Matrix” (Table 1.5), allows a systematic comparison of the period assessment with the baseline to determine the status of land condition at pixel level. The resulting map, called the *Status Map*, integrates the assessment of changes that occurred during the reporting period with the previous status of land condition (baseline). This approach ensures that the map reflects both past and recent changes, offering a more accurate overall assessment of land degradation and improvement over time.

As such, the map resulting from this comparison should be the primary tool for decision-making, providing a clear picture of current land condition. It is also the map that should be used to estimate SDG Indicator 15.3.1, ensuring consistency and accuracy in reporting over the periods.

It is important to highlight that both the stable and improving classes in the status map can be merged into a single "non-degraded" class if a binary map is required for specific applications. Additionally, careful reflection on the interpretation of the classes in the status map is crucial. First, while the status map integrates baseline data, it does not provide an assessment of how conditions have progressed relative to the baseline. Instead, it represents the current condition of the land, informed by the initial status (baseline). For further characterization of changes relative to the baseline, please refer to Section 2. Second, it is essential to consider that an area classified as "stable" in the status map could represent either healthy or degraded conditions, depending on what occurred before the baseline period (year 2000). For instance, if degradation occurred prior to the baseline and then conditions stabilized, the area would not be classified as degraded, even though it may still reflect the impacts of past degradation. This phenomenon is sometimes referred to as "legacy degradation". This limitation is inherent to the framework, that aims at monitoring land condition since 2000. However, countries can identify and further characterize these areas through complementary analyses, which can be valuable in efforts to combat land degradation. Understanding legacy degradation and its implications allows for more nuanced strategies and targeted interventions, contributing to the broader goal of achieving Land Degradation Neutrality (LDN).

		PERIOD ASSESSMENT		
		DEGRADED	**STABLE***	**IMPROVED***
BASELINE	**DEGRADED**	Degraded	Degraded	Improved
	STABLE*	Degraded	Stable	Improved
	IMPROVED*	Degraded	Improved	Improved

* Not Degraded areas.

Table 1.5: The "Status Matrix" is a 3 x 3 matrix to assess Status (in italics) by comparing the reporting period assessment (columns) and the baseline (rows). The categories Stable and Improved correspond to Not Degraded areas.

As previously stated, for the baseline period (t_0), which corresponds to the 16-year period from 2000 to 2015, the *period assessment* is equal to the *status*, since there is no comparison with a previous period and it is estimated by the integration of the three sub-indicators through the 1OAO principle. For the following reporting period (t_1), which corresponds to the 4-year period from 2016 to 2019, the status (Status 2019) is estimated by comparing the reporting period assessment with the baseline using the 3 x 3 status matrix. Subsequently, in the next reporting period (t_2), which corresponds to 2015-2023, Status 2023 is calculated by comparing the 2015-2023 period assessment with the baseline using the 3 x 3 status matrix. Figure 1.4 shows this process.

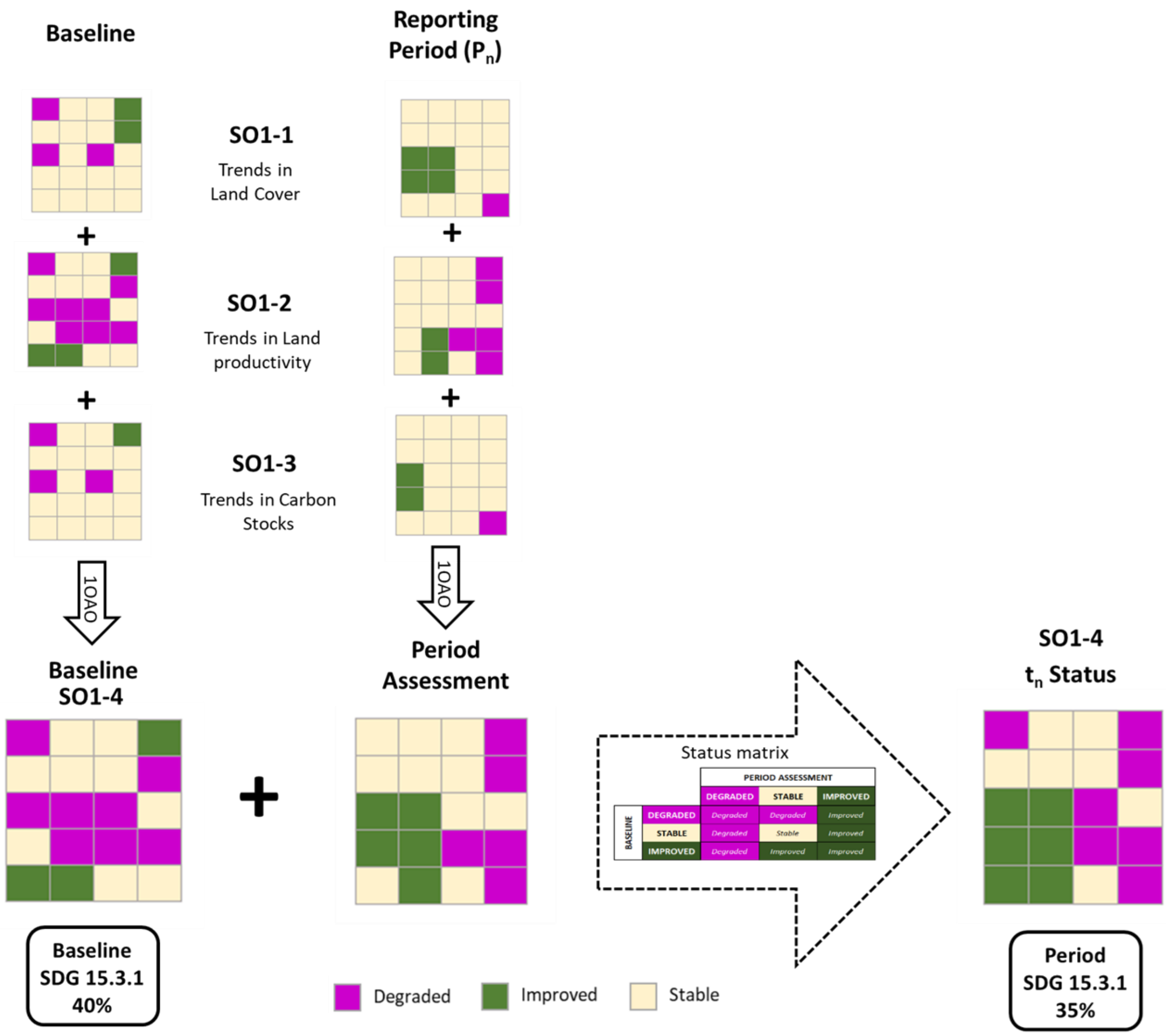


Figure 1.4: Process of estimating land status for the baseline (2000-2015) and subsequent periods by comparing period assessments of the three Strategic Objective 1 (SO1) indicators with the baseline using the 3 x 3 Status matrix.

For subsequent reporting periods, the same process is applied to determine the land status. In Table 1.6, the datasets used for each period to obtain the *period assessment* and *status* are indicated. The status of each period is labeled with the last year of that period, as it reflects the land condition at the end of the period by integrating data from the baseline.

UNCCD Reporting Process	Reporting Period	Period assessment: 1OAO applied on 3 sub-indicators			Status (St)
		Land Cover maps	*Land Productivity*	*Change in carbon stocks*	
2018	**Baseline: 2000-2015**	2000-2015	2000-2015	2000-2015	**St 2015** = Baseline Assessment
2022	**Period 1: 2016-2019**	2015-2019	2004-2019	2015-2019	**St 2019** = St 2015 + 2016-2019 assessment
2026	**Period 2: 2016-2023**	2015-2023	2008-2023	2015-2023	**St 2023** = St 2015 + 2016-2023 assessment
2030	**Period 3: 2016-2027**	2015-2027	2012-2027	2015-2027	**St 2027** = St 2015 + 2016-2027 assessment
2034	**Period 4: 2016-2031**	2015-2031	2016-2031	2015-2031	**St 2031** = St 2015 + 2016-2031 assessment

Table 1.6: Years used for the estimation of each sub-indicator across reporting periods. The combination of these using the 10AO principle generates the period assessments. The final column indicates how the resulting assessments are then compared with the previous period status using the 3 x 3 status matrix to determine the status (St) for each period.

1.3 Tracking CHANGE over multiple reporting processes

The reporting process for SDG Indicator 15.3.1 requires tracking changes in land degradation every four years. At the time of publication of this addendum, countries have submitted their estimates for SDG indicator 15.3.1 twice: once for the baseline period ($t_{0;}$ 2000-2015) in 2018, and once for the first reporting period (t_1; 2016-2019) in 2022. These submissions provide initial insights into the extent of land degradation and the estimated change since the baseline year. However, as countries move forward in their reporting cycles, they will continue to provide new estimates for subsequent periods (t_2, t_3 and so on).

In each UNCCD reporting process, the reporting period duration grows by an additional four years. Although the period assessment accounts for cumulative changes since the baseline, visualizing the intermediate steps remains valuable, especially for tracking changes in SDG Indicator 15.3.1. These intermediate assessments are also essential for reporting to the UNSD for inclusion in the SDG Report and Global Database. Given ongoing advances in methodologies and data availability, it is recommended that countries recalculate previously submitted national estimates with each reporting cycle. While recalculations add to the parties' workload, they are key to ensuring the time series consistency of SDG Indicator 15.3.1 and maintaining comparability between the baseline and future monitoring data.

For example, with the updated calculation methods outlined in this addendum to GPG, it is recommended that countries recalculate and resubmit all baseline and period 1 estimates for SO-1 indicators, including SDG Indicator 15.3.1, in their 2026 national report. Updated default national estimates will be recalculated and provided through the PRAIS forms for country Parties, incorporating the new methods to improve alignment and accuracy. In this context, it becomes increasingly important to have a standardized approach to compare these estimates across different periods. The growing dataset will offer richer insights, but a simple and clear approach to analyze and present these changes over time and interpret them is still needed. This section provides the necessary additional guidance for summarizing the SDG Indicator 15.3.1 results of each reporting period and their integration over more than two periods, offering a robust approach to track, compare, and report these changes effectively.

As explained in section 1.2, for each reporting period, countries generate a Status Map that categorizes land into three distinct categories: degraded, stable, and improved. From the Status Map, countries can estimate the extent of degraded, stable, and improved land. These estimates provide a quantitative assessment of the land condition for each period. These can be calculated as absolute area estimates (in km², hectares, etc.) or relative to total land area (percentage or proportion). In Figure 1.5 the Status maps for the baseline and the two subsequent periods are presented together with the estimations of percentage of degraded area over total land area. The results can be presented in a table format, as illustrated by the example provided in Figure 1.4 and Table 1.7. This table summarizes the extent of degraded land for each period, expressed both in absolute terms (area) and relative terms (percentage of total land area).

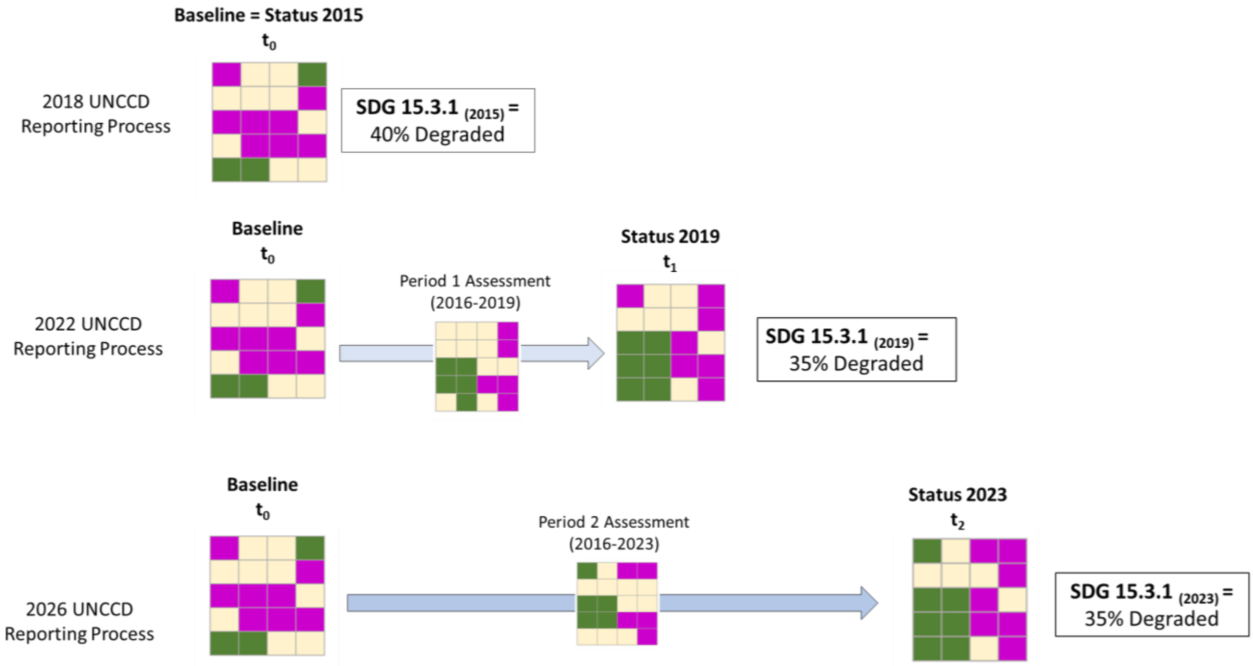


Figure 1.5: Status maps showing land condition over three reporting periods: Baseline period (t_0), 2016-2019 period (t_1), and 2016-2023 period (t_2). Each map categorizes land as degraded (purple), stable (yellow), or improved (green). The proportion of degraded land over total land area (SDG indicator 15.3.1) is indicated next to each map, illustrating changes across the different periods.

Period	Degraded Area (SDG 15.3.1)	
	(km^2)	(%)
t_0	8	40
t_1	7	35
t_2	7	35
t_n	…	…

Table 1.7: Extent of degraded land for each reporting period (t_0, t_1, t_2, …, t_n), expressed both in absolute terms (area in km²) and relative terms (percentage of total land area, which is 20 km²), following the example of Figure 1.4.

Once these statistics are obtained for each period, the change of the extent of degradation can be estimated relative to the baseline period. The SDG framework, including target 15.3, emphasizes the importance of tracking changes against a baseline. This aligns national reporting with global standards, ensuring consistency across countries and facilitating global assessments of progress towards SDG target 15.3. Baseline comparisons provide a transparent way to track progress, allowing stakeholders, including policymakers, civil society, and the international community, to monitor land degradation.

Equation 1 shows how the estimation of change in the extent of degraded land is calculated as the difference between the total area of degraded land in the baseline (t_0) to the most recent reporting period. This estimation gives an overarching view of the change made since the baseline and can be expressed as either the change in terms of absolute area or as the change in terms of the proportion of degraded area over the total land area (percentage points).

$$\Delta D_n = D_{t_n} - D_{t_0} \qquad \text{(Eq. 1)}$$

Where,

- $\Delta \mathrm{D_n}$ is the overall change in the area of degraded land from the baseline period t_0 to the most recent reporting period t_n
- D_{t_n} is the area (or percentage points) of degraded land in the most recent reporting period.
- D_{t_0} is the area (or percentage points) of degraded land in the baseline period

The results from the calculations using Equation 1 can be either positive, null or negative, depending on whether the area of degraded land has increased, remained the same or decreased with respect to the baseline period. Negative values for $\Delta \mathrm{D_n}$ (change in degraded extent) indicate a decrease in the extent of degraded land compared to the baseline period. This is a positive outcome, as it reflects a reduction in land degradation. Conversely, a positive value for $\Delta \mathrm{D_n}$ indicates an increase in the extent of degraded land compared to the baseline period, which is undesirable as it shows an increased degradation. In all these calculations the land area being assessed is assumed to remain constant, e.g. if the area compared between t_n and t_0 varies, the results from this equation will not be valid. Following the example presented in Figure 1.4 and Table 1.7, Table 1.8 indicates the changes in degraded land relative to the baseline for the two subsequent periods (t_1, t_2), expressed in both km² and percentage points.

Period	ΔD	
	(km^2)	(%)
t_1	-1	-5
t_2	-1	-5
t_n	…	…

Table 1.8: Changes in the extent of degraded land relative to the baseline (t_0) for the two subsequent periods (t_1, t_2), expressed in both km^2 and percentage points, following the estimations presented in Table 1.7.

Additionally, a chart plotting the extent of degraded land over time (from t_0 to the most recent period) can help identify patterns such as consistent improvement, or growing degradation (Figure 1.6).

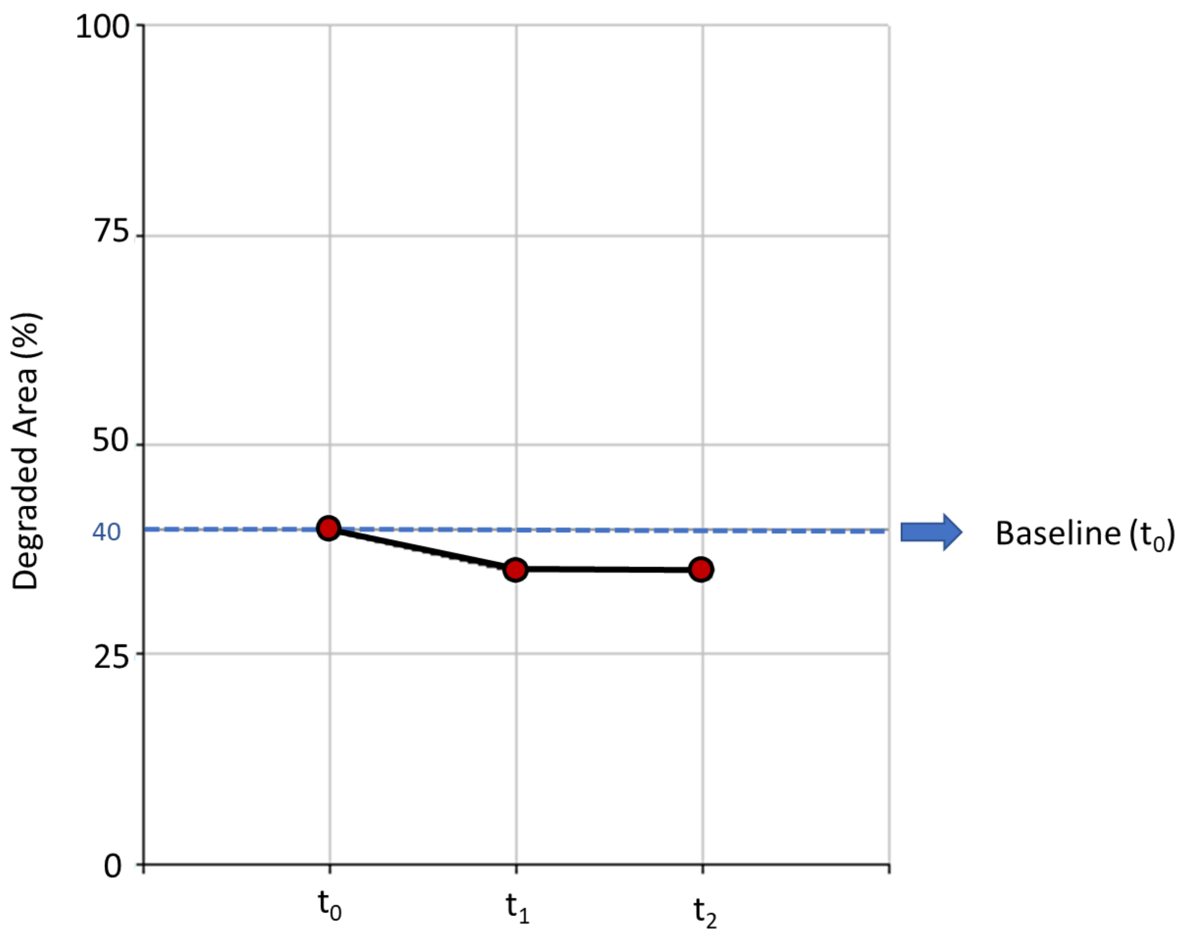


Figure 1.6: Plot of the percentage of degraded area over total land area across three periods (t_0, t_1, t_2). The visual representation highlights change in the extent of degraded land over time.

It is important to note that the comparison approach discussed here is not spatially explicit. This means that while the methodology focuses on the percentage of land degradation relative to the total land area, it does not account for the specific locations where degradation occurs. For example, a country might report the same percentage of degraded land across two periods, but the areas that are degraded in each period could be entirely different. A spatially explicit analysis, tracking the trajectories of each pixel, would provide deeper insights. This more detailed approach is covered in the next section, where methodologies for spatially explicit analysis are discussed.

Monitoring changes in SDG Indicator 15.3.1 does not equate to monitoring progress towards LDN. The SDG Indicator 15.3.1 offers a simplified framework for assessing changes in the proportion of land degradation, focusing on the three sub-indicators. While this provides a useful snapshot of land condition over time, it does not capture the full complexity of the LDN framework.

In contrast, the LDN framework is more detailed and requires that "no net loss" is achieved for each land type, meaning that any degradation in one area must be counterbalanced by improvements elsewhere. Neutrality is calculated based on changes in land condition since the baseline, considering a much broader range of factors and spatial dynamics. As a result, the assessment of SDG Indicator 15.3.1 is a valuable tool for monitoring degradation extent, and it should be considered only one component of the more comprehensive LDN approach. The next section introduces LDN principles, including the concept of counterbalancing, which allows countries to track their progress towards achieving neutrality more effectively.

SECTION 2

Tracking progress towards Land Degradation Neutrality

SECTION 2: Tracking progress towards Land Degradation Neutrality

In the context of global efforts to achieve the Sustainable Development Goals, particularly Target 15.3 aimed at achieving Land Degradation Neutrality, over 130 countries have committed to setting LDN targets, and more than 100 have formally established their national voluntary LDN targets[7]. As countries work towards meeting these voluntary national goals, there is a critical need for practical guidance to help them monitor progress in a data-driven way. While the initial versions of the Good Practice Guidance primarily addressed how to calculate and report the extent of degraded land under SDG Indicator 15.3.1, there is an increasing recognition of the need to go beyond tracking degradation alone. By also monitoring improvements in land condition, countries can gain deeper insights into their progress towards LDN. This section provides essential information to assist countries in tracking the balance between degradation and improvements in land condition spatially over time to monitor progress towards their national LDN commitments.

In this context it is essential to differentiate between SDG Indicator 15.3.1, which measures the "Proportion of land that is degraded over total land area," and the broader monitoring framework of LDN[8]. The estimation of SDG Indicator 15.3.1 focuses on the extent of degraded land while LDN is about achieving a balance where the gains of natural capital (improved land condition) offset the losses of natural capital (degraded land condition) for each land type since the baseline. Therefore, while SDG Indicator 15.3.1 is a critical component, it is only one aspect of the larger goal of LDN.

To accurately track progress towards LDN and plan for interventions that contribute to counterbalancing losses of natural capital with gains, it is imperative to measure changes in land condition in a spatially explicit manner. This requires assessing land degradation and improvement across specific geographic areas rather than relying solely on aggregate statistics. A spatially-explicit approach allows for a more detailed understanding of where degradation is occurring, where improvements are being made, and how these changes are distributed across different land types. This level of detail is crucial for designing targeted interventions and for assessing the effectiveness of LDN strategies at both national and subnational levels.

Tracking the proportion of degraded land is equally important to monitor the proportion of areas that have shown improvement since the baseline. This involves distinguishing between areas where improvement and degradation occurred after the baseline (recent) and areas that are degraded or improved but where no gains or losses of natural capital occurred since the baseline (stable after the baseline). The use of the 3 x 3 Status matrix to compare the period assessment with the baseline (see section 1.2), is an effective tool for this purpose. As formerly indicated, this matrix categorizes areas based on their status in the baseline and their current period assessment, allowing for a further interpretation of land condition changes.

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[7] Global Mechanism of the UNCCD. 2019. Land Degradation Neutrality Target Setting: Initial findings and lessons learned. Bonn, Germany

[8] 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.

To achieve LDN, it is essential to consider the specific land types being monitored. The neutrality mechanism, which involves counterbalancing areas of degradation with areas of improvement, should be explicitly considered in LDN monitoring. This mechanism ensures that any degradation is offset by equivalent improvements, maintaining the overall natural capital stock for each land type. This is why degradation in one land type cannot be neutralized with improvement in a different land type. Additionally, by tracking progress within specific land types and applying the neutrality mechanism, countries can better demonstrate their commitment to achieving LDN. The ability to demonstrate impact is crucial for securing continued support and resources for LDN initiatives. By incorporating the guidance provided in this section, countries can better illustrate the results of their land restoration and degradation prevention efforts.

2.1 Further characterization of land degradation and improvement

Even though the status maps categorize land condition into three broad categories (Degraded, Stable, and Improved), the underlying dynamics that lead to this final status can be more complex. Specifically, there are nine different types of changes of land condition when baseline and period assessment are compared using the Status matrix (Table 1.5). Understanding these different pathways enables a deeper interpretation of the land condition changes, allowing for the identification of gains and losses of natural capital that have occurred relative to a baseline state (recent improvement and recent degradation). This can contribute to understanding how different change patterns contribute to the final status map and what they reveal about gains and losses of natural capital since the baseline (Table 2.1). For example, degradation and improvement can correspond to recent changes, or former trends in areas that have remained stable afterwards (baseline improvement/degradation).

		PERIOD ASSESSMENT		
		DEGRADED	**STABLE**	**IMPROVED**
BASELINE	**DEGRADED**	*1- Persistent Degradation*	*3 - Baseline Degradation*	*6 - Recent Improvement*
	STABLE	*2 - Recent Degradation*	*4 - Stability*	*6- Recent Improvement*
	IMPROVED	*2- Recent Degradation*	*5- Baseline Improvement*	*7 - Persistent Improvement*

Table 2.1: Expanded version of the "Status Matrix" showing land condition that results from the comparison of the baseline (rows) and the period assessment (columns): degraded (purple), stable (yellow), and improved (green).

Each type of change represented in the expanded version of the status matrix (Table 2.1) is detailed below. The table captures the nine possible combinations in the 3 x 3 matrix, reflecting transitions from the baseline assessment to the current period assessment. For each combination, a brief interpretation of the change is provided, along with its classification as either a recent or baseline improvement or degradation. This classification helps in understanding whether the observed changes represent new developments that have occurred during the current reporting period or whether no changes in status have taken place.

Degraded to Degraded = Persistent Degradation (PD)

- **Change Description**: Areas that were already degraded in the baseline and continued to experience degradation or intensified degradation after the baseline.
- **Interpretation**: long term degradation processes are occurring and there is loss of natural capital since baseline; no improvement is observed, and the land condition worsens over time. Unless interventions take place, these areas will continue losing natural capital and investments need to be planned to counterbalance these anticipated losses with commensurate gains in natural capital.

Stable to Degraded = Recent Degradation (RD)

- **Change Description**: Areas that were stable in the baseline period but experienced degradation after the baseline.
- **Interpretation**: Although the land condition remained stable in the baseline period, recent conditions have led to a decline in land condition, indicating new degradation and recent loss of natural capital. These areas can be prioritized to implement actions to reduce and avoid further land degradation.

Improved to Degraded = Recent Degradation (RD)

- **Change Description**: Areas that improved during the baseline but experienced degradation in the period.
- **Interpretation**: The land condition was improving, but recent intense events or processes have led to a decline, indicating changes and loss of natural capital. These areas should be further characterized to better understand the causes of these dynamics and plan actions to reverse land degradation if possible.

Degraded to Stable = Baseline Degradation (BD)

- **Change Description**: Areas that were degraded at baseline, but the rate of degradation has stopped or slowed down. However, there has been no improvement in land condition.
- **Interpretation**: There has been neither gain nor loss of natural capital in these areas since baseline. Degradation processes have been halted or reduced or the system has reached its maximum degradation level. The area remains in a degraded state due to former degradation processes (Baseline degradation). If these areas coincide with target or implementation areas where interventions are taking place, more time might be needed to detect improvement on the indicators.

Stable to Stable = Stability (S)

- **Change Description**: Areas that have consistently remained stable since the year 2000 (during the baseline period and afterwards).
- **Interpretation**: The land condition has not changed; some of these areas may be in good condition and interventions to conserve and avoid land degradation should be prioritized. However, another possibility is that some of these areas may have been degraded prior to the baseline assessment but no significant changes have occurred since 2000.

Improved to Stable = Baseline Improvement (BI)

- **Change Description**: Areas that were improving during the baseline period but have stabilized without further change.

- **Interpretation**: There have not been gains or losses of natural capital in these areas since baseline. However, their condition is good and efforts to avoid land degradation in these areas should be planned.

Degraded to Improved = Recent Improvement (RI)

- **Change Description**: Areas that were degraded in the baseline period but have experienced a reversal in condition, resulting in an improved land condition.
- **Interpretation**: Natural Capital was gained in these areas. This could be the result of implementation of sustainable land management practices to reverse previous degradation (i.e. active restoration) or the result of a quick recovery after avoiding degradation (i.e. passive restoration).

Stable to Improved = Recent Improvement (RI)

- **Change Description**: Areas that were stable during the baseline assessment but have recently shown improvement in land condition.
- **Interpretation**: There has been a positive change and natural capital has been gained. This could be the result of the successful implementation of Sustainable Land Management Practices and restoration initiatives.

Improved to Improved = Persistent Improvement (PI)

- **Change Description**: Areas that have shown continuous improvement both during the baseline assessment and afterwards.
- **Interpretation**: There has been persistent improvement in land condition and gains of natural capital after the baseline, indicating ongoing positive change and successful management.

Below is an example of an area represented by 20 pixels, with data from both the baseline and the current period assessment (Figure 2.1). Using the expanded status matrix (Table 2.1), the area's land condition has been analyzed to produce a new status map, allowing for a more detailed characterization of land degradation and improvement. As indicated before, this further analysis helps to distinguish between recent degradation (RD) and legacy degradation (LD), as well as recent improvement (RI) and legacy improvement (LI).

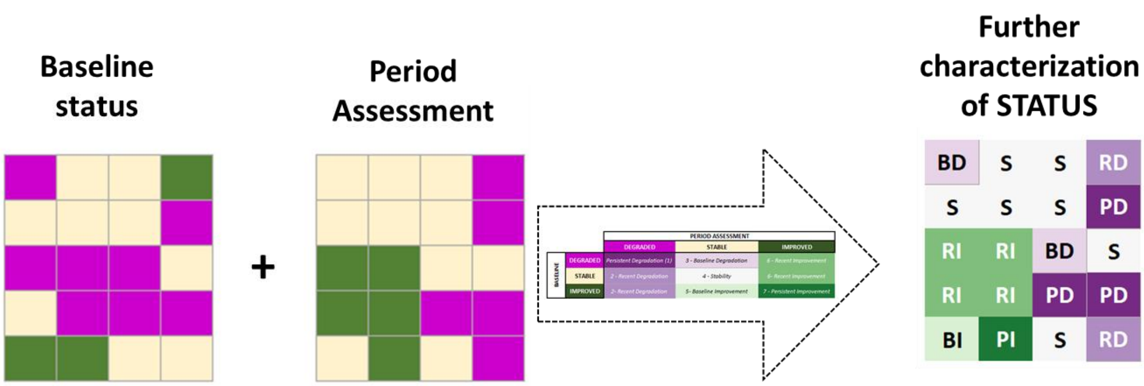

Figure 2.1: Example of further characterization of land degradation and land improvement, which allows detection of areas with persistent degradation (PD), recent degradation (RD) and baseline degradation (BD) and areas with persistent improvement (PI), recent improvement (RI) and baseline improvement (BI).

As Figure 2.1 shows, at the baseline, 8 out of the 20 pixels were classified as degraded, and 3 pixels were marked as improved, therefore SDG indicator 15.3.1 at the baseline is 40%. During the reporting period, 5 pixels experienced degradation processes, while 5 pixels showed improvement. By analyzing each pixel and tracing its change from the baseline to the current period using the Status matrix, we obtain the new status map, from which SDG indicator 15.3.1 for the reporting period can be estimated. As a result, 7 pixels in total are classified as degraded in the new status map. Out of these, 5 correspond to areas that underwent degradation during the reporting period, reflecting a loss of natural capital since the baseline. These are categorized as recent degradation (RD). The remaining 2 degraded pixels were already degraded at the baseline and remained stable during the reporting period, so they are classified as baseline degradation (BD), indicating that even though these are degraded areas and are considered in the estimation of SDG indicator 15.3.1, there was no recent loss of natural capital in these areas. This is why the final SDG 15.3.1 indicator value for the area is 35%. This analysis shows that though some areas have improved, recent degradation has affected a significant proportion of the land.

BOX 3:

FURTHER CHARACTERIZATION OF DEGRADED AND IMPROVED AREAS BASED ON CHANGE FROM BASELINE

Persistent Degradation (PD): Corresponding to areas identified as Degraded in the baseline and also as Degraded during the period, these changes help pinpoint areas where degradation processes are persistent in time and natural capital was lost since baseline.

Recent Degradation (RD): Identified by changes from Stable or Improved in the baseline to Degraded, these changes help pinpoint areas where recent degradation has occurred, and natural capital was lost since baseline.

Baseline Degradation (BD): Corresponding to changes from Degraded to Stable, where degradation processes occurred previously, during the baseline assessment but afterwards there was no gain nor loss of natural capital.

Recent Improvement (RI): Identified by transitions from Stable or Degraded (baseline) to Improved, these changes help identify areas where recent improvement and gains of natural capital occurred since baseline.

Baseline Improvement (BI): Corresponding to changes from an Improved status to Stable assessment, where improvement occurred during the baseline but the land condition did not change during the reporting period.

Persistent Improvement (PI): Corresponding to areas where improvement was identified during the baseline and the period, indicating areas where processes that improve land condition are persistent in time and natural capital was gained since baseline.

2.2 Counterbalancing: monitoring neutrality

Land Degradation Neutrality monitoring is focused on the monitoring of neutrality, that is, ensuring that net area of significant new negative changes (losses of natural capital) are counterbalanced with new significant positive changes (gains of natural capital) in the same land type. This section outlines a step-by-step methodology to estimate and monitor this balance over time, leading to a comprehensive report on LDN status.

SDG 15.3.1 and the Role of Counterbalancing

It is important to note that while SDG indicator 15.3.1 is the official indicator for tracking progress toward SDG target 15.3, it alone is not sufficient to monitor the achievement of LDN. A state of "no net change" in SDG 15.3.1 does not automatically equate to LDN because the SDG indicator captures only degradation, including degradation that occurred during the baseline assessment (see Figure 2.2). However, in counterbalancing, only the degradation and improvements that have occurred since the baseline should be taken into account to assess whether neutrality has been achieved.

Counterbalancing as a Mechanism for Neutrality within Land types

Counterbalancing is a core mechanism that satisfies the principle of neutrality within the same land type. Land types are defined as distinct classes based on their land potential, influenced by factors such as soil (edaphic), geomorphology, topography, hydrology, biological components, and climatic features. These characteristics determine the natural or historical vegetation structure and species composition of the land[9]. For counterbalancing to be effective, any degradation in a specific land type must be offset by equivalent improvement in the same type, adhering to the principle of "like for like".

Land types may change over time, for example, due to land cover changes. However, for LDN monitoring, the land types should be mapped and identified at the end of the baseline (2015), and these categories should remain fixed for the purpose of calculating gains and losses in natural capital. This approach ensures that the balance of degradation and improvement is consistently evaluated within the same land type as it existed at the baseline, regardless of any subsequent changes.

LDN is achieved when neutrality is reached across all land types. This means that the total area of degraded land must be fully balanced by an equivalent area of improved land within the same land type and across all land types.

At present, no global map delineates these land types, which poses a challenge for implementing LDN counterbalancing on a global scale. However, for simplicity and practicality, the land cover map can be used as the best available proxy at a global level[10]. This serves as an interim measure to support counterbalancing calculations. Alternatives are ecosystem type maps[11]. Countries can utilize their own national data to define land types more accurately across different scales.

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[9] Orr et al., 2017

[10] Cowie, A. 2020. Guidelines for Land Degradation Neutrality: A report prepared for the Scientific and Technical Advisory Panel of the Global Environment Facility, Washington D.C

[11] GEO is currently developing the Global Ecosystems Atlas, which will integrate high-quality global, regional, and national ecosystem maps into a single, accessible online resource.

This is why Integrated Land Use Planning (ILUP) is regarded as the mechanism to achieve LDN[12]. Planning allows for anticipation of future natural capital losses and the implementation of targeted actions to balance these losses with planned gains.

Accounting for Recent degradation and improvement

As outlined in section 2.1, if an area was already degraded at the baseline and undergoes further degradation during the reporting period, it is classified as persistent degradation. This is because additional loss of natural capital has occurred since the baseline, which must be factored into counterbalancing calculations. Similarly, areas that were improved at the baseline but show further improvements during the period assessment (persistent improvement) should count as gains of natural capital. When both degradation and improvement occurred during the period assessment, there is a loss or gain in natural capital since the baseline, consistent with the scientific framework of LDN.

Table 2.2 provides a detailed overview of how the different types of changes in land condition from the baseline to the period assessment are considered for the estimation of SDG indicator 15.3.1 and if they are used in the counterbalancing mechanism. The first column presents the seven categories that describe the possible changes in land condition, offering a nuanced framework to understand how land conditions have evolved over time. The second column explains how each category is accounted for in the estimation of SDG Indicator 15.3.1, specifically indicating whether the land is classified as degraded or not. The third column highlights the role of each category in the counterbalancing mechanism, specifying whether the change represents a gain or loss in natural capital since the baseline. For instance, areas categorized as baseline degradation are included in the estimation of SDG Indicator 15.3.1 as degraded land. However, these areas are not considered within the counterbalancing mechanism because they reflect pre-existing conditions rather than a change in natural capital relative after the baseline. This table provides clarity on the relationship between the status of land conditions, their contribution to SDG Indicator 15.3.1, and their implications for the counterbalancing mechanism.

Category	Reported in SDG Indicator 15.3.1 as	Used in LDN counterbalancing mechanism
PERSISTENT DEGRADATION	Degraded	✓ (LOSS)
RECENT DEGRADATION	Degraded	✓ (LOSS)
BASELINE DEGRADATION	Degraded	×
PERSISTENT IMPROVEMENT	Not-degraded	✓ (GAIN)
RECENT IMPROVEMENT	Not-degraded	✓ (GAIN)
BASELINE IMPROVEMENT	Not-degraded	×
STABILITY	Not-degraded	×

Table 2.2: Categories of land condition according to the expanded status characterization and their usage for

[12] P.H. Verburg, G. Metternicht, E. Aynekulu, X. Deng, S. Herrmann, K. Schulze, F. Akinyemi, N. Barger, V. Boerger, F. Dosdogru, H. Gichenje, M. Kapović-Solomun, Z. Karim, R. Lal, A. Luise, B.S. Masuku, E. Nairesiae, N. Oettlé, A. Pilon, O. Raja, N.H. Ravindranath, R. Ristić and G. von Maltitz. 2022. The Contribution of Integrated Land Use Planning and Integrated Landscape Management to Implementing Land Degradation Neutrality: Entry Points and Support Tools. A Report of the Science-Policy Interface. United Nations Convention to Combat Desertification (UNCCD), Bonn, Germany

estimation of SDG indicator 15.3.1 (binary classification) and for counterbalancing (gains and losses of natural capital).

Step-by-Step Procedure to Assess Counterbalancing for LDN

A step-by-step approach is outlined below to assess counterbalancing for LDN. The method ensures that losses in natural capital (recent degradation) are offset by equivalent gains (recent improvements) within the same land type, as required by the "like for like" principle.

STEP 1: Baseline Assessment

The baseline assessment sets the foundation for LDN monitoring by identifying the initial condition of the land using the three LDN sub-indicators. According to the one-out-all-out (1OAO) principle, if any of these three sub-indicators shows degradation, the land is considered degraded at baseline.

STEP 2. Assessment of the Reporting Period (as explained in GPG and Section 1 of this addendum)

After defining the baseline, subsequent assessments are conducted at each reporting period. Again, the three LDN sub-indicators are used to detect changes in land condition during these periods. The 1OAO principle is applied again: if any of the three sub-indicators indicates degradation during the reporting period, the area is classified as degraded.

STEP 3. Expanded Status Matrix to Calculate New Status

Using the expanded status matrix (Table 2.1) to compare the baseline and period assessment, the new status of the land after the reporting period is obtained. This matrix should only be used to compare the baseline condition with the period assessment. The results identify persistent and recent improvements (gains in natural capital) and persistent and recent degradation (losses of natural capital) since the baseline.

STEP 4. Calculate the Difference Between Recent Improvements and Degradation for Each Land Type

For each land type, the balance between recent improvements and recent degradation is calculated by subtracting the area of land degraded since the baseline from the area of land that has improved:

$$\Delta_{LDN}^{i} = \mathrm{A}_{gains}^{i} - A_{losses}^{i} \qquad \text{(Eq. 2)}$$

Where:

- A_{gains}^{i} is the area of persistent and recent improvement (gains of natural capital) in a given land type (i).
- A_{losses}^{i} is the area of persisten and recent degradation (loss of natural capital) in the same land type (i).
- Δ_{LDN}^{i} is the net balance of natural capital (positive, negative, or neutral) for the given land type (i).

STEP 5. Assess LDN Achievement for Each Land Type

For each land type, the result of the above calculation determines whether LDN has been achieved:

- If $\Delta^{i}_{LDN} = 0$, there is no net loss, meaning LDN has been achieved for that land type.
- If $\Delta^{i}_{LDN} > 0$, there has been a net gain of natural capital, and LDN has not only been achieved but exceeded for that land type.
- If $\Delta^{i}_{LDN} < 0$ there has been a net loss of natural capital, meaning that LDN was not achieved for that land type.

STEP 6. Assess Overall LDN Achievement

LDN is achieved overall when neutrality is reached in all land types. This means:

$$\forall_i, \Delta^{type}_{LDN} \geq 0 \qquad \text{(Eq. 3)}$$

If LDN is achieved in every land type, then LDN is considered to be met. If LDN is not achieved in any land type, further efforts are needed to restore balance.

Example: assessing LDN

In Figure 2.2 an example is shown of the counterbalancing of a land unit under two scenarios. The land unit is represented by 20 pixels, or 20 km², where each pixel represents 1 km². For simplicity, we assume all the pixels belong to the same land type. In both scenarios, the baseline condition is the same, but the outcomes during the reporting period differ, leading to different results in terms of achieving LDN.

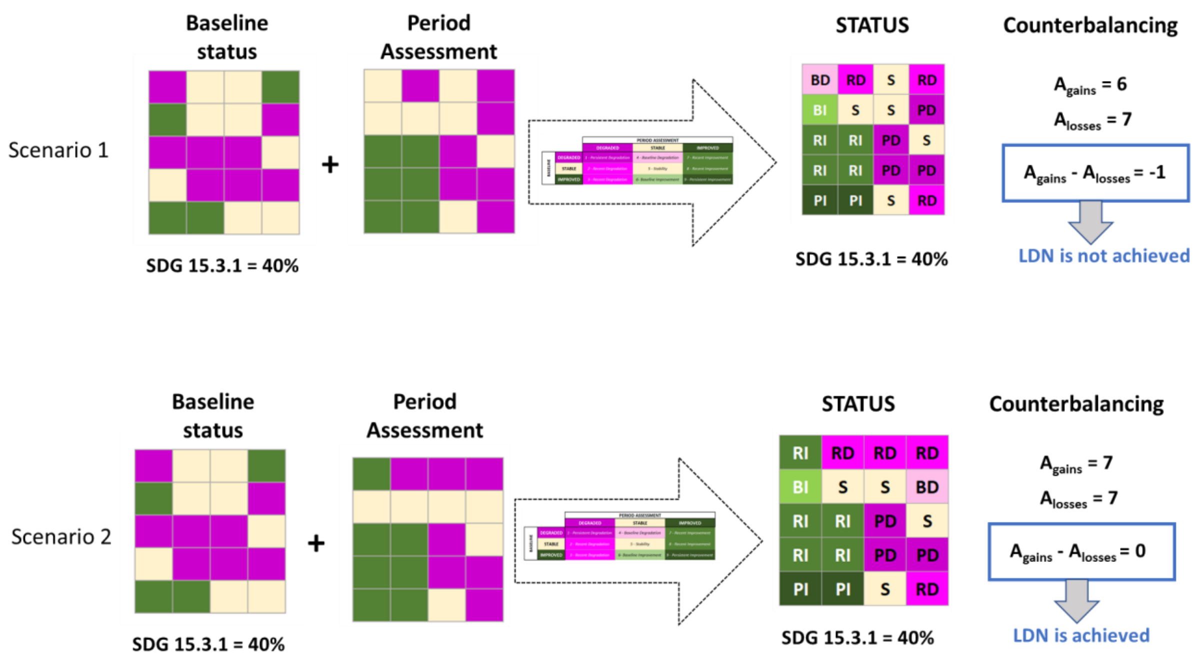

Figure 2.2: Comparison of two scenarios for achieving LDN in a 20 km² area with a constant 40% degraded of land (8 km²). In Scenario 1, LDN is not achieved whereas in Scenario 2, LDN is achieved. This comparison underscores the importance of assessing net gains and losses in natural capital for accurate LDN evaluation beyond SDG Indicator 15.3.1.

In the baseline assessment, 8 pixels (8 km²) are degraded, while 4 pixels (4 km²) are improved. The remaining 8 pixels are stable. Therefore, the total degraded area is 8 km² and SDG indicator 15.3.1 is 40%, since 40% of the total land area is degraded at baseline.

In the first scenario, during the reporting period, degradation occurs in 7 pixels (7 km²), while improvement occurs in 6 pixels (6 km²). After applying the expanded status matrix to assess the current status, we find that the total degraded area remains at 8 km² (8 pixels), which means the SDG Indicator 15.3.1 still reports 40% degradation. However, 7 of these degraded pixels correspond to recent degradation, while only 1 pixel corresponds to legacy degradation, meaning it was already degraded at baseline and was stable during the period assessment. As a result, the total area representing losses of natural capital (recent degradation) is 7 km². On the other hand, the total improved area is 7 pixels (7 km²), but only 6 of these pixels correspond to recent improvement, while 1 pixel represents legacy improvement from the baseline that has remained stable. This means the area showing gains of natural capital (recent improvement) is 6 km².

When we calculate the difference between gains and losses for this scenario, it is 6 km² of gains minus 7 km² of losses, resulting in a net difference of minus 1 km². This negative value indicates that LDN was not achieved. Although the SDG Indicator 15.3.1 remained constant at 40% degraded area, the land type experienced a net loss of natural capital, meaning neutrality was not reached.

In the second scenario, the baseline condition is exactly the same, but during the reporting period, there are gains in 7 pixels (7 km²) and losses in 7 pixels (7 km²). After applying the expanded status matrix to compare the baseline with the current status, the percentage of degraded land remains at 40%, just as it was in the first scenario. However, 7 pixels correspond to recent degradation, and 1 pixel remains as legacy degradation, resulting in 7 km² of losses of natural capital.

Similarly, 7 pixels correspond to recent improvement, meaning the area showing gains of natural capital is also 7 km². When we calculate the difference between gains and losses, we get 7 km² of gains minus 7 km² of losses, resulting in a net difference of zero. In this case, LDN was achieved because the gains in natural capital exactly balanced the losses. This balance means the land type in this land unit is neutral in terms of natural capital.

In both scenarios, the percentage of degraded land (SDG Indicator 15.3.1) remained the same at 40%. However, only in the second scenario was LDN achieved, demonstrating that just tracking the SDG Indicator 15.3.1 is not enough to determine whether LDN has been reached. To properly evaluate neutrality, it is essential to compare the gains and losses of natural capital, which represent recent improvements and recent degradation, respectively. By following these steps, countries can systematically assess whether LDN has been achieved for each land type, and for different land units, which are the finest resolution spatial unit used in LDN planning and monitoring.

SECTION 3

Enhancement of datasets and methodologies

SECTION 3: Enhancement of datasets and methodologies

This section addresses the enhancement of datasets and methodologies to support the selection of the most appropriate data products for different contexts. It introduces new globally available datasets related to land cover, land productivity, and soil organic carbon (SOC), as well as methods and country experiences in comparing and selecting the most representative datasets. Additionally, it highlights workflows implemented by national experts that have contributed to verifying results and improving data accuracy, including the use of cloud computing, interactive web apps for dataset comparison, and subnational approaches for estimating subindicators.
This section expands on the general methodology for estimating the three subindicators that remains outlined in the Good Practice Guidance Version 2 (GPG v2) by providing new insights derived from practical applications during the 2022 reporting process, including innovative datasets and tools developed since the publication of GPG v2.

The section is divided into three subsections:

- **3.1- Enhancements for assessing trends in land cover:** This subsection presents advances in high-resolution datasets and digital analytical tools and workflows that support countries and experts in making informed decisions for estimating degradation due to land cover changes.
- **3.2- Enhancements for assessing trends in land productivity:** This subsection describes alternative methodologies for estimating land productivity dynamics (LPD), such as those developed by Joint Research Center (JRC), Conservation International (CI) and FAO-WOCAT[13], including the introduction of high-resolution global LPD datasets co-developed by different institutions. It also presents approaches and workflows that countries have applied from previous reporting processes to identify the most representative datasets and to parametrize the LPD algorithms to their national context.
- **3.3- Enhancements for assessing trends in SOC:** This subsection introduces new datasets and innovative approaches that countries have undertaken from previous reporting processes, such as the estimation of nationally determined conversion factors.

By incorporating lessons learned from the 2022 reporting process and leveraging emerging datasets and methodologies, this section aims to support countries in refining their approaches to land degradation assessment and estimation of SDG indicator 15.3.1.

[13] Food and Agriculture Organization of United Nations (FAO) and World Overview of Conservation Approaches and Technologies (WOCAT)

3.1 Enhancements for Assessing Trends in Land Cover

To assess changes in land cover under the LDN framework[14], it is necessary to use land cover maps representing the initial and final years of each period, including the baseline and reporting periods. Section 1 of this addendum specifies the initial and final years of these periods, with Table 1.1 specifying the years of the land cover maps used for each reporting period. Section 3 of the GPG v2 (Land Cover and Land Cover Change) presents the general methodology for assessing this sub-indicator, which remains valid, including the good practice principles. This section of the GPG addendum introduces newly available datasets, updates the list provided in the GPG Version 2 appendix, and highlights innovative approaches and tools applied by countries in the 2022 reporting process. It also further explores three critical steps in estimating changes in land cover: (1) the identification of the best available land cover dataset, (2) the selection of the land cover legend and (3) the definition of the land cover transition matrix.

3.1.1 Identification of the best available land cover dataset

Selecting an appropriate land cover dataset is a crucial first step in assessing land cover change to estimate SDG indicator 15.3.1. The default dataset used for UNCCD reporting since 2018 has been the Land Cover data set provided by the European Space Agency Climate Change Initiative (ESA CCI), at 300 m resolution. However, countries are strongly encouraged to examine the quality of the default data and further explore and utilize alternative datasets that better reflect national realities. The ideal scenario is to use national land cover datasets, preferably those that are officially adopted, as they can, with an appropriate legend, capture land degradation processes more accurately than standardized global datasets, thereby increasing confidence in the results.

A key challenge when using national datasets is ensuring comparability between initial and final land cover maps. Harmonizing land cover legends across different years is crucial, as discrepancies can prevent direct comparisons. Tools such as the FAO's Land Cover Classification System and Land Cover Legend Registry (LCLR)[15] may support this process. Another challenge when not using global default dataset is the availability of maps that align precisely with the start and end years required for the baseline and reporting periods. For example, in the 2022 UNCCD reporting process, Colombia used national land cover maps for 2000, 2010, and 2018, mapping changes for 2000–2010 instead of 2000–2015 (baseline) and 2010–2018 instead of 2015–2019 (reporting period). Similarly, Panama used national land cover maps for 2000, 2012 and 2021 (Figure 3.1), as detailed in a recent publication showcasing country experiences with reporting on land degradation and drought[16]. However, despite temporal mismatches, using national datasets often provides a more representative picture of national degradation processes due to land cover change, as they are typically based on locally validated classifications, reflect country-specific land cover typologies, and are better aligned with national definitions, policy priorities, and monitoring frameworks.

[14] 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

[15] Mushtaq, F., Di Gregorio, A., Tchana, E., Ghosh, A., Jalal, R., O'Brien, D., Mosca, N., Tefera, M. & Henry, M. 2023. Land Cover Legend Registry (LCLR) – Functionalities and legend preparation. User guide. Rome, FAO.

[16] United Nations Convention to Combat Desertification (UNCCD) and World Overview of Conservation Approaches and Technologies (WOCAT), 2024. The Land Story. Country experiences with reporting on land degradation and drought. UNCCD, Bonn, Germany; WOCAT and Centre for Development and Environment (CDE), University of Bern, Switzerland.

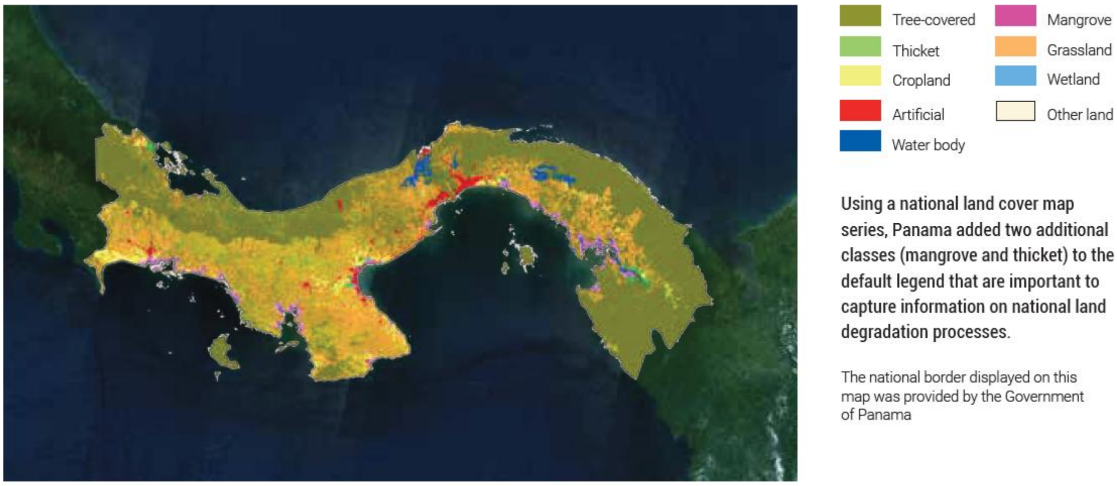

Figure 3.1: Panama Land Cover Map used for the 2022 Reporting Cycle with a 9 classes legend. Source: Panama 2022 National Report to the UNCCD, licenced under CC BY-NC 2.0.

In cases where national datasets are unavailable, regional datasets can be more representative than global datasets. For instance, CORINE Land Cover maps, which are freely accessible with 100 m spatial resolution, cover many European countries for 1990, 2000, 2006, 2012, and 2018, with a 2024 version expected. For the 2022 reporting process, Türkiye organized a participatory workshop with national experts, where it was determined that CORINE Land Cover maps would yield more accurate results than ESA CCI. Given the available years, Türkiye used the 2000 and 2012 maps for the baseline period (2000–2015) and the 2012 and 2018 maps for the reporting period (2015–2019).

Where national and regional datasets are unavailable, countries can use global datasets. While the default ESA CCI dataset is suitable in many cases, alternative global land cover datasets may provide better representation of national land degradation processes. Even when using global datasets, reclassification may be necessary to enhance relevance (see section 3.1.2). One of the primary challenges in assessing land degradation due to land cover change has been the coarse resolution of global datasets, which is particularly problematic for Small Island Developing States (SIDS) where the landscape heterogeneity is often minimally captured because the pixels often represent a mixture of two or more land cover types. Two new high-resolution datasets now offer improved spatial resolution alternatives: the Global Land Analysis and Discovery (GLAD) Land Cover[17] (available for years 2000, 2005, 2010, 2015, 2020) and the GLC_FCS30D[18] product (available every five years from 1985 to 2000, then annually up to 2022). Both products have a 30m spatial resolution. All global datasets exhibit differences in classification of land cover, and therefore a rigorous comparison should be conducted to identify the most appropriate land cover product for each country. For instance, different products like GLAD and GLC_FCS30D differ in the way that different land cover classes are classified (Fig. 3.2). These classification discrepancies can significantly impact degradation assessments. Thus, careful selection and interpretation of datasets are crucial to ensure consistency and accuracy in land cover transition trends[19].

[17] Potapov, P., Hansen, M.C., Kommareddy, I., Kommareddy, A., Turubanova, S., Pickens, A., Adusei, B., Tyukavina A., and Ying, Q., 2020. Landsat analysis ready data for global land cover and land cover change mapping. Remote Sens. 2020, 12, 426; doi:10.3390/rs12030426

[18] Zhang, X., Zhao, T., Xu, H., Liu, W., Wang, J., Chen, X., and Liu, L.: GLC_FCS30D: the first global 30 m land-cover dynamics monitoring product with a fine classification system for the period from 1985 to 2022 generated using dense-time-series Landsat imagery and the continuous change-detection method, Earth Syst. Sci. Data, 16, 1353–1381, https://doi.org/10.5194/essd-16-1353-2024, 2024.

[19] García, C. L., Pozzi Tay, E. F., Raviolo, E., Paredes-Trejo, F., Francis, R., & James, C. (2025). Land Cover Trends in SIDS: Supporting UNCCD 2026 reporting process and SDG indicator 15.3.1 monitoring. Zenodo. https://doi.org/10.5281/zenodo.15276250

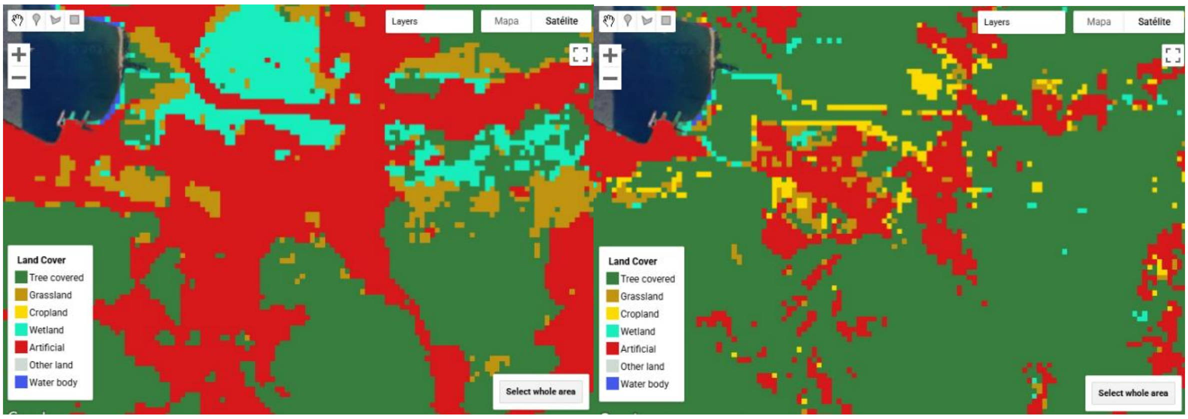

Figure 3.2: Screenshot of GLAD (left) and GLC_FCS30D (right) at the same area (South of Castries, Saint Lucia) showing considerable differences, especially in urban-peri urban areas. Source: the Land Cover Comparison Tool for SIDS[20] (Apacheta & PISLM 2025). Licenced under CC BY 4.0 by Apacheta and PISLM.

Given the range of available datasets, selecting the most appropriate one can be a complex task. A good practice recommendation is to undertake a participatory approach involving national experts to compare and identify the best available dataset. Innovative tools, such as FAO-WOCAT Apps for Land Cover Comparison[21], can facilitate this process by enabling users to compare datasets, analyze reclassifications, generate transition matrices, and obtain statistics and maps at various spatial scales. For the 2022 UNCCD reporting process, Bhutan used this tool to compare reclassifications of ESA CCI and national datasets, while Colombia used it to refine classifications of its national land cover maps. For the 2026 reporting process a new tool, the Land Cover Comparison Tool for Small Island Developing States[22], was developed (Apacheta & PISLM 2025) to make comparisons of high-resolution datasets at the regional and national levels. This tool provides overlay maps, agreement-disagreement masks, transition matrices, and degradation trend analyses.

Table 3.1 shows characteristics of global geospatial land cover datasets, covering those suitable for SDG 15.3.1 reporting. Other publicly available datasets exist but were excluded since they cover only limited areas, focus on specific land cover types, or lack the required temporal scope for UNCCD reporting.

Product	Source	Measurement method	Extent	Spatial resolution	Thematic resolution	Temporal coverage
ESA-CCI	ESA CCI	Based on AVHRR, SPOT, PROBA-V, and Sentinel-3 satellite imagery	Global	300 m	36 classes	Every year from 1992 to 2022
MODIS Land Cover (MCD12Q1 v061)	NASA	MODIS sensor onboard the Terra and Aqua satellites	Global	500m	17 classes	Every year from 2001 to 2021
Global Land Analysis and Discovery	University of Maryland	Landsat 5, 7, and 8 scenes	Global	30 m	11 classes	2000, 2005, 2010, 2015 and 2020

20 https://apacheta.projects.earthengine.app/view/compare-lct-sids
21 wocat.net/en/ldn/wocatapps
22 García, C. L., Pozzi Tay, E. F., Raviolo, E., Paredes-Trejo, F., Francis, R., & James, C. (2025). Land Cover Trends in SIDS: Supporting UNCCD 2026 reporting process and SDG indicator 15.3.1 monitoring. Zenodo. https://doi.org/10.5281/zenodo.15276250

(GLAD) Land Cover						
GLC_FCS30D	Aerospace Information Research Institute, Chinese Academy of Sciences	Landsat 5, 7, 8, 9 scenes	Global	30 m	35 classes	1985, 1990, 1995, 2000 and annually up to 2022

Table 3.1: Characteristics of global land cover datasets available to monitor land cover change

3.1.2 Selecting a land cover legend for monitoring key degradation processes

Another essential step in monitoring land degradation through land cover change is developing an appropriate land cover legend. Guidance of this step is comprehensively covered in the GPG v2. However, new insights have emerged from the 2022 reporting process, particularly regarding successful country-specific adaptations to their national context and the implementation of subnational approaches. In addition, further training materials were developed to guide users on the use of land cover data to monitor SDG 15 (BOX 3.1).

UNCCD seven default land cover classes correspond to: tree covered areas, grasslands, croplands, artificial areas, other lands wetlands and water bodies. This is a modified version of the IPCC land use categories, where 'water bodies' are separated from 'wetlands' and grouped in a seventh class including: lakes, rivers and streams (natural/artificial, standing/flowing, inland/sea), artificial reservoirs, coastal lagoons, and estuaries. However, many countries, and particularly countries with highly diverse environments and contrasting land degradation processes, often require a more detailed land cover classification. In these cases, increasing the number of land cover classes or subdividing the country into regions for tailored analysis is essential. These adjustments ensure that key land degradation processes are accurately captured, ultimately improving the reliability of SDG indicator 15.3.1 estimation and supporting informed decision-making on land management and Integrated Land Use Planning. This approach has been taken by different countries during the UNCCD 2022 reporting process[23]. For example, during Colombia's 2022 reporting process, experts highlighted glacier retreat and snow cover reduction as a key degradation process. Although these areas are relatively small in proportion, and only affect a specific area of the country, they represent critical climate change-related phenomena with significant environmental and socio-economic impacts. To monitor such changes effectively, the standard seven UNCCD land cover classes were insufficient. After careful analysis of national land cover maps, experts determined that a minimum of 12 land cover classes was necessary, including the addition of Permanent Snow and Glaciers category. Additionally, this category is particularly important for monitoring SDG sub-indicator 15.4.2b, proportion of degraded mountain area which helps building synergies among SDGs and custodian agencies. In these cases, to enhance the international comparability of land cover statistics, it is necessary to translate national land cover legends into the reference 7 classes legend, so that national land cover statistics can be compared directly and regional and global aggregates can be calculated.

Even in the absence of national land cover datasets, countries can modify the default land cover legend from the default land cover datasets provided by the UNCCD to better align with national dynamics. The standardized global land cover maps are derived from the ESA-CCI dataset, which originally includes 36 classes but is reclassified into the seven UNCCD default categories for aggregate reporting. However, these 36 land cover classes can be re-classified differently to capture key land degradation processes at the national level. This approach was also taken by some countries during

[23] United Nations Convention to Combat Desertification (UNCCD) and World Overview of Conservation Approaches and Technologies (WOCAT), 2024. The Land Story. Country experiences with reporting on land degradation and drought. UNCCD, Bonn, Germany; WOCAT and Centre for Development and Environment (CDE), University of Bern, Switzerland.

the UNCCD 2022 reporting process. For example, Bhutan and Bosnia and Herzegovina[24] utilized the default land cover dataset but applied their own reclassification approaches to ensure that shrublands were explicitly represented. In Bhutan, woody encroachment was identified as a significant degradation process, necessitating the differentiation of shrublands from forests. After evaluating various reclassification options, experts adopted a seven-class legend that incorporated shrublands while merging wetlands with water bodies, as Bhutan wetlands were not well mapped in ESA-CCI dataset (Table 3.2). Similarly, in Bosnia and Herzegovina, national experts recognized that maquis, a Mediterranean shrubland ecosystems found mainly in the southern part of the country, were classified as grasslands under the default legend. Given the ecological and legal significance of these protected areas, stakeholders decided to add a specific shrubland category to the default classification (Table 3.3).

ID Original	Original	Color	ID Default	Default Category	ID BTN	BTN Category	ID Workshop	BTN Workshop
0	No Data		0					
10	Cropland, rainfed		3	Cropland	4	Cropland	4	Cropland
11	Herbaceous cover		3	Cropland	4	Cropland	4	Cropland
12	Tree or shrub cover		3	Cropland	2	Shrubland	2	Shrubland
20	Cropland, irrigated or post-flooding		3	Cropland	4	Cropland	4	Cropland
30	Mosaic cropland (>50%) / natural vegetation (tree, shrub, herbaceous cover) (<50%)		3	Cropland	4	Cropland	4	Cropland
40	Mosaic natural vegetation (tree, shrub, herbaceous cover) (>50%) / cropland (<50%)		3	Cropland	2	Shrubland	2	Shrubland
50	Tree cover, broadleaved, evergreen, closed to open (>15%)		1	Forest	1	Forest	1	Forest
60	Tree cover, broadleaved, deciduous, closed to open (>15%)		1	Forest	1	Forest	1	Forest
61	Tree cover, broadleaved, deciduous, closed (>40%)		1	Forest	1	Forest	1	Forest
62	Tree cover, broadleaved, deciduous, open (15-40%)		1	Forest	1	Forest	1	Forest
70	Tree cover, needleleaved, evergreen, closed to open (>15%)		1	Forest	1	Forest	1	Forest
71	Tree cover, needleleaved, evergreen, closed (>40%)		1	Forest	1	Forest	1	Forest
72	Tree cover, needleleaved, evergreen, open (15-40%)		1	Forest	1	Forest	1	Forest
80	Tree cover, needleleaved, deciduous, closed to open (>15%)		1	Forest	1	Forest	1	Forest
81	Tree cover, needleleaved, deciduous, closed (>40%)		1	Forest	1	Forest	1	Forest
82	Tree cover, needleleaved, deciduous, open (15-40%)		1	Forest	1	Forest	1	Forest
90	Tree cover, mixed leaf type (broadleaved and needleleaved)		1	Forest	1	Forest	1	Forest
100	Mosaic tree and shrub (>50%) / herbaceous cover (<50%)		1	Forest	2	Shrubland	2	Shrubland
110	Mosaic herbaceous cover (>50%) / tree and shrub (<50%)		2	Grassland	3	Grassland	3	Grassland
120	Shrubland		2	Grassland	2	Shrubland	2	Shrubland
121	Evergreen shrubland		2	Grassland	2	Shrubland	2	Shrubland
122	Deciduous shrubland		2	Grassland	2	Shrubland	2	Shrubland
130	Grassland		2	Grassland	3	Grassland	3	Grassland
140	Lichens and mosses		2	Grassland	3	Grassland	3	Grassland
150	Sparse vegetation (tree, shrub, herbaceous cover) (<15%)		2	Grassland	3	Grassland	3	Grassland
152	Sparse shrub (<15%)		2	Grassland	3	Grassland	3	Grassland
153	Sparse herbaceous cover (<15%)		2	Grassland	3	Grassland	3	Grassland
160	Tree cover, flooded, fresh or brakish water		4	Wetland	5	Wetland	7	WaterBody
170	Tree cover, flooded, saline water		4	Wetland	5	Wetland	7	WaterBody
180	Shrub or herbaceous cover, flooded, fresh/saline/brakish water		4	Wetland	5	Wetland	7	WaterBody
190	Urban areas		5	Artificial	6	Artificial	5	Artificial
200	Bare areas		6	BareLand	7	BareLand	6	BareLand
201	Consolidated bare areas		6	BareLand	7	BareLand	6	BareLand
202	Unconsolidated bare areas		6	BareLand	7	BareLand	6	BareLand
210	Water bodies		7	WaterBody	8	WaterBody	7	WaterBody
220	Permanent snow and ice		6	BareLand	7	BareLand	6	BareLand

Table 3.2: Bhutan´s reclassifications of ESA CCI Land Cover classes. 3 alternative re-classifications are shown: (1) Default reclassification into 7 UNCCD classes, (2) are classification into 8 classes, differentiating shrublands, and (3) a 7-classes re-classification including shrublands but merging wetlands with water bodies, which was regarded as the best during the participatory workshop. Source: FAO E-learning course: Using land cover information to monitor progress on SDG 15 (UNCCD and FAO, 2024).

[24] United Nations Convention to Combat Desertification (UNCCD) and World Overview of Conservation Approaches and Technologies (WOCAT), 2024. The Land Story. Country experiences with reporting on land degradation and drought. UNCCD, Bonn, Germany; WOCAT and Centre for Development and Environment (CDE), LCUniversity of Bern, Switzerland.

ESA CCI Color	ESA CCI Classes	UNCCD Classes	Bosnia and Herzegovina Classes
	No Data		
	Cropland, rainfed	Cropland	Cropland
	Herbaceous cover		Cropland
	Tree or shrub cover		Shrubland
	Cropland, irrigated or postflooding		Cropland
	Mosaic cropland (>50%) / natural vegetation (tree, shrub, herbaceous cover) (<50%)		Cropland
	Mosaic natural vegetation (tree, shrub, herbaceous cover) (>50%) / cropland (<50%)		Shrubland
	Tree cover, broadleaved, evergreen, closed to open (>15%)	Tree-Covered areas	Forest
	Tree cover, broadleaved, deciduous, closed to open (>15%)		Forest
	Tree cover, broadleaved, deciduous, closed (>40%)		Forest
	Tree cover, broadleaved, deciduous, open (1540%)		Forest
	Tree cover, needleleaved, evergreen, closed to open (>15%)		Forest
	Tree cover, needleleaved, evergreen, closed (>40%)		Forest
	Tree cover, needleleaved, evergreen, open (1540%)		Forest
	Tree cover, needleleaved, deciduous, closed to open (>15%)		Forest
	Tree cover, needleleaved, deciduous, closed (>40%)		Forest
	Tree cover, needleleaved, deciduous, open (1540%)		Forest
	Tree cover, mixed leaf type (broadleaved and needleleaved)		Forest
	Mosaic tree and shrub (>50%) / herbaceous cover (<50%)		Shrubland
	Mosaic herbaceous cover (>50%) / tree and shrub (<50%)	Grassland	Grassland
	Shrubland		Shrubland
	Evergreen shrubland		Shrubland
	Deciduous shrubland		Shrubland
	Grassland		Grassland
	Lichens and mosses		Grassland
	Sparse vegetation (tree, shrub, herbaceous cover) (<15%)		Grassland
	Sparse shrub (<15%)		Grassland
	Sparse herbaceous cover (<15%)		Grassland
	Tree cover, flooded, fresh or brakish water	Wetland	Wetland
	Tree cover, flooded, saline water		Wetland
	Shrub or herbaceous cover, flooded, fresh/saline/brakish water		Wetland
	Urban areas	Artificial surfaces	Artificial
	Bare areas	Other land	Bare land
	Consolidated bare areas		Bare land
	Unconsolidated bare areas		Bare land
	Water bodies	Waterbodies	Waterbody
	Permanent snow and ice		

Table 3.3: Bosnia and Herzegovina's reclassifications of ESA CCI Land Cover classes to differentiate maquis (shrublands) and its correspondence to UNCCD 7 default classes. Source: The Land Story. Country experiences with reporting on land degradation and drought (UNCCD and WOCAT, 2024).

The reclassification of ESA-CCI land cover data can be effectively performed using different tools, including Trends.Earth, which allows for flexible adaptation of the original 36 land cover categories to national and subnational conditions. When the legend is adapted to the local context, efforts should be made to ensure that the definition of the land cover classes is clear and unambiguous. It is advisable to minimize the number of classes as much as possible, because the more land cover classes in the legend, the larger and more complex the land cover transition matrix will be. Thus, only those classes that are important for monitoring land degradation and improvement should be included in the legend.

BOX 3.1

E-learning course : Using land cover information to monitor progress on SDG 15

In 2024 an e-learning course was developed by UNCCD, GEO LDN, GIZ and FAO to provide a basic understanding of land-cover data and its use for monitoring progress towards the achievement of Sustainable Development Goal (SDG) 15, with a practical focus on its Indicators 15.3.1 (proportion of land that is degraded over total land area) and 15.4.2 (including its subindicators: Mountain Green Cover Index and Proportion of degraded mountain land).
It is open and free and can be accessed here[25].

3.1.3 Defining the land cover transition matrix

Once the best available land cover datasets are identified and the most appropriate legend is defined, the next step in assessing degradation due to land cover change is the generation of a transition matrix, which specifies whether observed land cover changes constitute degradation, improvement, or neutral transitions. This classification is not always straightforward and requires careful consideration of local ecological, socio-economic, and policy contexts. To ensure transparency and fairness, the development of an appropriate transition matrix should be conducted in a participatory manner, bringing together stakeholders from different regions, sectors, organizations, and disciplines. Facilitating these discussions is critical, as different groups may have contrasting perspectives on land cover change.

For example, the transition from grasslands to forests is often regarded as an improvement due to increased carbon sequestration and potential biodiversity benefits. However, this is not always the case, and extensive research exists on the negative impacts of afforestation in non-forested ecoregions[26], as exemplified by the paramo ecosystem in Colombia. National land cover maps used to

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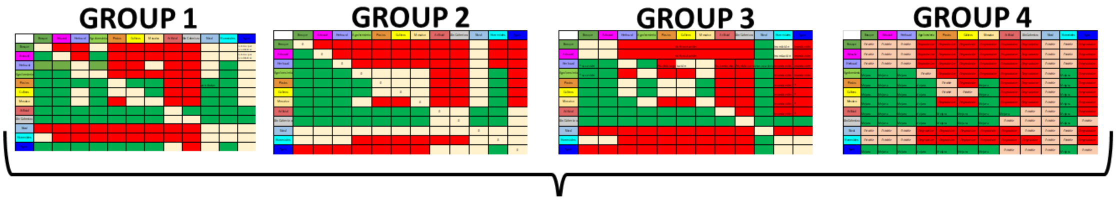
[25] https://elearning.fao.org/course/view.php?id=1098

[26] Jobbágy, E.G. and Jackson, R.B. (2004), Groundwater use and salinization with grassland afforestation. Global Change Biology, 10: 1299-1312. https://doi.org/10.1111/j.1365-2486.2004.00806.x

distinguish between natural grasslands and pastures revealed cases where afforestation efforts unintentionally degraded biodiverse natural grasslands in the páramo ecosystem. These high-altitude ecosystems provide essential services, including water regulation, and afforestation in these areas can be detrimental, as it alters hydrological cycles, reduces native biodiversity, and undermines ecosystem resilience to climate change[27]. On the other hand, in humid lowland regions, experts generally viewed the conversion of grasslands to forests as a positive trend (Figure 3.3).



	Forests	Shrublands	Grasslands	Agroforestry	Pastures	Cropland	Productive Mosaics	Artificial	Bareland	Snow and glaciers	Wetlands	Water
Forests	4n	2-2n	2n2-	3-1n	4-	4-	4-	4-	4-	3n1+	3n1-	3-1n
Shrublands	1+3n	4n	2-2n	3-1+	4-	4-	4-	4-	4-	3n1+	3n1-	3-1n
Grasslands	2+2n	2n2+	4n	1+3-	4-	3-1n	2n2-	4-	4-	3n1+	2-1n1+	3-1n
Agroforestry	4+	4+	2+1n1-	4n	3-1n	3-1n	2n2-	4-	4-	4n	3+1-	3-1n
Pastures	4+	4+	3+1n	4+	4n	1+1-2n	3+1n	4-	4-	4n	3+1-	3-1n
Cropland	4+	4+	2+2n	4+	4n	4n	3+1n	4-	4-	4n	3+1-	3-1n
Productive Mosaics	4+	4+	3+1n	2+2n	4-	3-1n	4n	4-	4-	4n	3+1-	3-1n
Artificial	4+	4+	4+	4+	4+	4+	4+	4n	2n1-1+	4n	3+1-	3-1n
Bareland	4+	4+	4+	4+	4+	4+	4+	3n1+	4n	4n	4+	2-2n
Snow and glaciers	2n2-	2n2-	2n2-	3-1n	3-1n	3-1n	3-1n	3-1n	3-1n	4n	3n1-	2-2n
Wetlands	4+	3n1-	2n2-	4-	4-	4-	4-	4-	4-	4n	4n	4n
Water	4+	2-2+	2-2+	2-2+	2-2+	2-2+	2-2+	3n1-	3n1-	4n	3+1-	4n

n NEUTRAL + POSITIVE - NEGATIVE

Figure 3.3: Colombia's land cover transition matrix: the results of each group are shown above, while the final matrix is shown below. The number of neutral (n), positive (+) and negative (-) votes is shown in the final matrix. Colors indicate the final decision made after discussions. Source: FAO E-learning course: Using land cover information to monitor progress on SDG 15 (UNCCD and FAO, 2024).

In many cases, differences in the interpretation of the same type of land cover transition arise from varying local contexts. A transition that signifies improvement in one area may represent degradation in another, depending on environmental, social, or economic conditions. Some countries are addressing this challenge by adopting a subnational approach to LDN monitoring and SDG Indicator 15.3.1 estimation. This approach acknowledges that a one-size-fits-all transition matrix is not always appropriate, particularly in countries with diverse bioclimatic conditions.

To implement a subnational assessment of land degradation, it is necessary to first define specific zones based on a combination of biophysical, climatic, and socio-economic factors. The goal is to ensure that assessments remain relevant and context-specific while maintaining a structure that facilitates comparability and national integration. For example, in Ecuador, experts developed a land cover assessment methodology that divided the country into homogeneous zones, each with distinct environmental characteristics (Figure 3.4). The proposed zoning included:

- Litoral Seco: Areas with ustic or aridic moisture regimes.
- Litoral Húmedo: Evergreen forests from the Andean Montane West to the Pacific coast.
- Altoandino: Glaciers, páramos, and high-altitude ecosystems (nival and subnival bioclimatic zones).
- Valles Interandinos: Inter-Andean valley ecosystems, excluding Altoandino and Litoral Seco.
- Amazonía: Evergreen forests from the Andean Montane East to the Amazon basin.

[27] Murad, C.A., Pearse, J. & Huguet, C. Multitemporal monitoring of paramos as critical water sources in Central Colombia. Sci Rep 14, 16706 (2024). https://doi.org/10.1038/s41598-024-67563-z

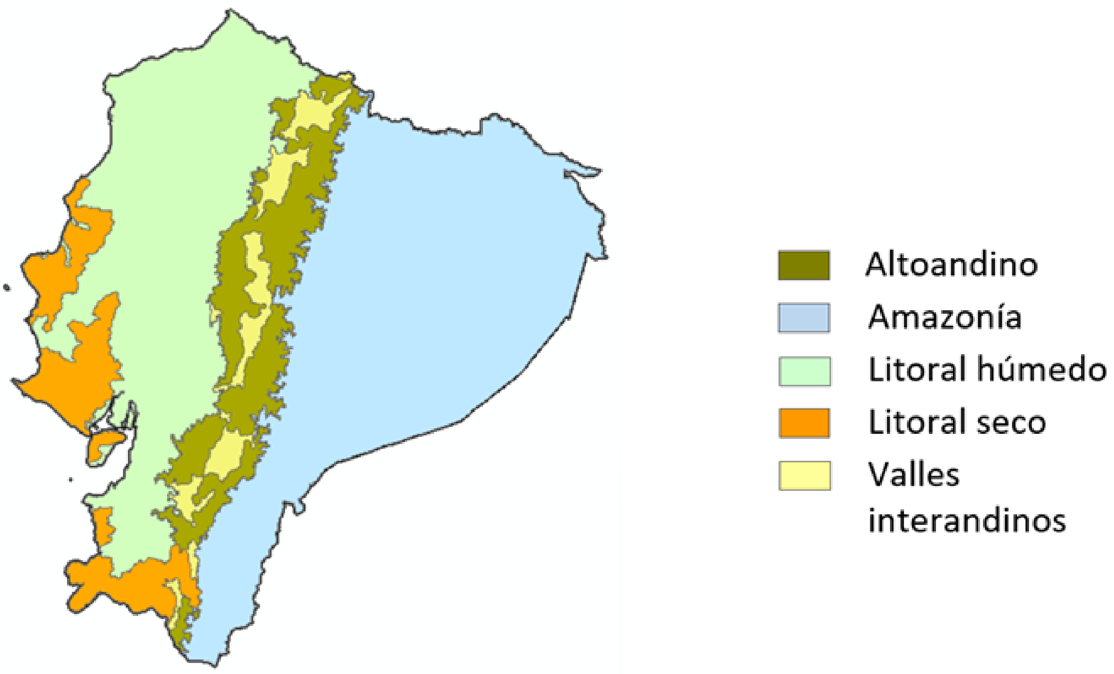


Figure 3.4: Ecuador’s subnational stratification for the estimation of SDG indicator 15.3.1. Source: CONDESAN and WOCAT, 2025.

Once the subnational zones are defined, a specific transition matrix for each zone can be established, incorporating local expertise and stakeholder input. These zone-specific transition matrices ensure that land cover changes are assessed within their ecological and socio-economic context, rather than applying a uniform classification across the entire country. Finally, the results from each region should be integrated to provide a national-level assessment that reflects local realities while maintaining coherence in LDN and SDG indicator 15.3.1 monitoring. By adopting a participatory and subnational approach, countries can enhance the accuracy and credibility of land cover trends assessments, ensuring that land degradation monitoring aligns with both global standards and national priorities.

3.2 Enhancements for Assessing Trends in Land Productivity

This subsection builds on the key processing steps introduced in Section 4 of the GPG v2 and further elaborates on a workflow to obtain a representative map of trends in land productivity. As in the GPG v2, land productivity refers to the biological productive capacity of the land: the principal source of the food, fiber and fuel that sustains humans. The UNCCD methodology for estimating the proportion of land that is degraded over total land area (i.e. SDG indicator 15.3.1) uses changes in land productivity as an indicator of long-term variations in the health and productive capacity of the land. Trends in Land productivity is a fundamental sub-indicator for assessing land degradation as it reflects the net effects of changes in ecosystem functioning on plant and biomass growth. This sub-indicator is monitored by tracking spatial and temporal changes in Land Productivity Dynamics (LPD). In most countries, the percentage of degraded land reported under SDG Indicator 15.3.1 has been largely driven by the trends in land productivity[28]. This makes the accurate assessment of Land Productivity Dynamics (LPD) crucial for mapping land degradation, estimating of SDG indicator 15.3.1 and tracking progress towards Land Degradation Neutrality (LDN).

In this context, the concept of land productivity should not be confused with agricultural productivity. Agricultural productivity refers to the output of agricultural products, such as crops, per unit of input (such as land, labor, or fertilizer). In contrast, trends in land productivity aims to identify long-term changes in the health and productive capacity of the land in terms of net primary productivity (NPP), i.e. the net carbon assimilation by vegetation[29]. Expressed in units such as kg/ha/year, NPP is a key ecological variable that provides valuable insights into the state of vegetated land, ecological functions, ecosystem services, and human well-being. However, within the framework of SDG Indicator 15.3.1, land productivity trends are rarely expressed in kg/ha/year. Instead, LPD maps are typically presented as categorical classifications with five distinct categories of land productivity dynamics (Increasing, Stable, Stable but Stressed, Moderate decline and Declining), without explicitly indicating the change in absolute NPP terms. LPD maps primarily serve to identify areas experiencing increasing productivity, stable productivity, or declining productivity, regardless of the absolute levels of productivity. Further reflections on ecological thresholds and better characterization of the magnitude of change of this indicator can be found in Section 7 of GPG v2.

For the 2018 and the 2022 reporting processes and to support countries in reporting trends in land productivity, the UNCCD provided a default LPD dataset[30] produced by the Joint Research Centre (JRC) of the European Commission. As with the default land cover dataset, many countries found that the default LPD dataset did not adequately represent national realities and explored alternative datasets[31]. While countries are encouraged to develop their own national LPD datasets, in many cases they improve the estimation of the LPD by exploring and re-parametrizing alternative global LPD datasets that better reflect national realities (see section 3.2.3). For the 2022 reporting process, three main global LPD datasets were available, all of which were integrated into the Trends.Earth software: the JRC default dataset, the Trends.Earth LPD dataset, and the FAO–WOCAT LPD dataset[32]. To facilitate

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[28] unccd.int/sites/default/files/2024-12/2315444E.pdf

[29] Clark, D.A., Brown, S., Kicklighter, D.W., Chambers, J.Q., Thomlinson, J.R., Ni, J., Holland, E.A., 2001. Net primary production in tropical forests: an evaluation and synthesis of existing field data. Ecol. Appl. 11, 371–384. DOI: https://doi.org/10.1890/1051-0761(2001)011[0371:NPPITF]2.0.CO;2

[30] Rotllan-Puig, X., Ivits, E. and Cherlet, M., 2021. LPDynR: A new tool to calculate the land productivity dynamics indicator. Ecological Indicators, 133, p.108386. https://doi.org/10.1016/j.ecolind.2021.108386

[31] The land story: Country experiences with reporting on land degradation and drought | UNCCD. https://www.unccd.int/sites/default/files/2024-12/2315444E.pdf,

[32] https://docs.trends.earth/en/latest/for_users/downloads/index.html

the comparison of these datasets and the selection by countries of the most suitable for reporting SDG Indicator 15.3.1, an interactive application[33] was developed by Conservation International, FAO, and WOCAT under the global GEF funded Tools4LDN project (Figure 3.5). This tool enabled countries to assess how different datasets influenced their SDG indicator 15.3.1 estimations and select the one that aligned most closely with the known situation in the country, based on expert knowledge. For the 2026 reporting process the default LPD dataset will correspond to the default parametrization of the Trends.Earth LPD dataset.

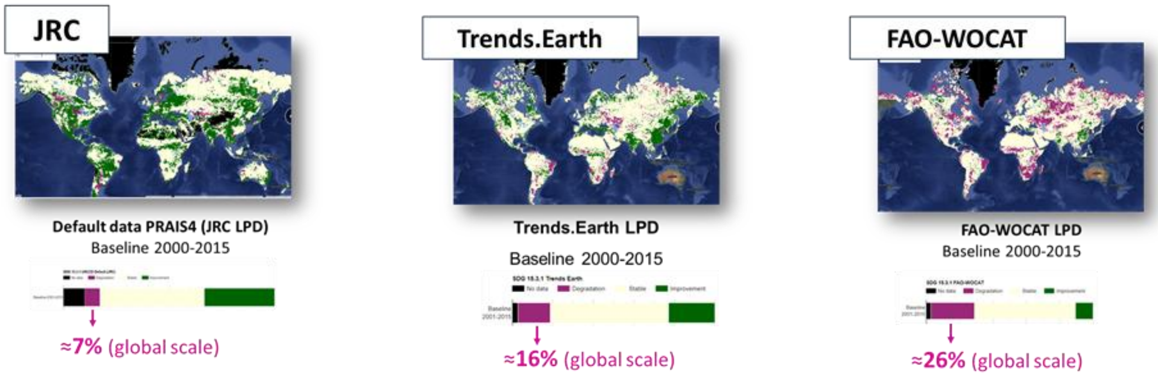

Figure 3.5: Alternative estimations of SGD indicator 15.3.1 and extent of land degradation for the baseline period using different Land Productivity Dynamics Maps. *Source: Tools4LDN LPD Product comparison - https://maps.tools4ldn.org/ (CI, WOCAT & FAO, 2022).* Licenced under *CC BY 4.0.*

Building on lessons from the 2022 reporting process and recent advances in data and methodologies, this Addendum clarifies the distinction between the **LPD input dataset** (a time series of annual vegetation indices) and the **LPD algorithm** (the methodology used to analyze this time series and generate the LPD map). For example, the FAO-WOCAT LPD algorithm can be applied on either a Landsat-derived NDVI or a MODIS-derived NDVI, with each option offering different spatial resolutions and data characteristics. Likewise, applying different LPD algorithms to the same LPD input dataset can yield significantly different results, as exemplified in Figure 3.5, which illustrates how the same MODIS NDVI dataset yields varying outcomes when used with different LPD algorithm (Trends.Earth and FAO-WOCAT LPD).

By treating the LPD algorithm and LPD input dataset as independent components, this approach enhances transparency, facilitates methodological comparisons, and helps explain discrepancies in results. For the 2026 reporting cycle, additional LPD datasets will be available including 30 m resolution NDVI time series and LPD maps for SIDS, such as the ones developed by CBAS[34] and PISLM-CI-Apacheta[35]. Given the increased number of options and the relevance of this sub-indicator, countries are encouraged to make an informed decision through participatory processes when selecting the most appropriate combination of both the LPD algorithm and the LPD input dataset.

This subsection is organized into three parts. The first outlines the key decisions involved in producing the LPD input dataset, including the selection of a vegetation productivity index, the choice of satellite imagery source, and the calculation of annual productivity estimates. The second part introduces the three main LPD algorithms, JRC, FAO-WOCAT, and Trends.Earth, summarizing their

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[33] Tools4LDN LPD Product comparison - https://maps.tools4ldn.org/ (CI, WOCAT & FAO, 2022).

[34] Xiaosong Li & Tong Shen. Land Productivity Dynamics Product of Small Island Developing States (30 meters Resolution), International Research Center of Big Data for Sustainable Development Goals (CBAS). Big Earth Data Center, CAS, 2025. DOI: https://doi.org/10.12237/casearth.686dc91f24e15709b381ae4e

[35] García, C. L., Raviolo, E., Francis, R., Maharaj, T., Zvoleff, A., Antunes Daldegan, G.,Pozzi Tay, E. F., Paredes-Trejo, F., Noon, M. & James, C. (2025). A 30m Land Productivity Dynamic Dataset for SIDS computed from Mixed Landsat Time Series and FWv2 model [Data set]. Zenodo. https://doi.org/10.5281/zenodo.15276519

methodologies and explaining how users can adjust their parameters. Finally, the third part provides guidance on the tools and workflows available for identifying and selecting the most representative LPD map.

3.2.1- The LPD input dataset

To estimate trends in land productivity it is first necessary to have a time series of annual vegetation productivity estimates. In section 1 of this Addendum, particularly in Table 1.3, the initial and final years to assess changes in land productivity for each reporting period are described. These periods are defined to be 16 years, in concordance with the moving window described in GPG v2. However, this sub-indicator can be used to assess land degradation for other purposes instead of reporting to UNCCD and other time periods can be used. For example, it might be of interest to assess the trends in land productivity for a longer period, i.e. from 2000 till present. In any case, three key decisions need to be made to obtain this time series:

- which vegetation index will be used as proxy for productivity
- which satellite imagery dataset will be used for the input data
- how annual estimates will be calculated

Satellite spectral data can be processed to generate various vegetation indices (VIs) that serve as proxies for vegetation productivity, including the Normalized Difference Vegetation Index (NDVI), Enhanced Vegetation Index (EVI), and Soil-Adjusted Vegetation Index (SAVI). VIs are widely employed to assess different vegetation characteristics, such as fractional vegetation cover, photosynthetic capacity, leaf area index, biomass and vegetation structure, among others. Each of these indices can be derived from different satellite sensors, which offer varying spatial and temporal resolutions and, in some cases, small radiometric differences since not all sensors have the same wavelength width for the bands used in the computation of a VI. For instance, NDVI is a widely used Red/Near Infra-Red normalized difference band math that can be obtained from most optical sensors like MODIS data at a 250 m spatial resolution or from Landsat data at a 30 m resolution. Selecting a vegetation index and identifying an appropriate satellite imagery source are two distinct tasks, however they are intrinsically related, as the decision usually depends on available datasets for the target region and time period needed. The choice of VI and satellite data source has significant implications, and selecting the most appropriate dataset depends on national circumstances and monitoring priorities.

Although the NDVI remains the most widely used vegetation index due to its simple computation, ease of interpretation, broad applicability, and the availability of ready-to-use time series datasets, it has certain limitations, particularly in environments with very high biomass, where it tends to saturate, and in areas with very low biomass, where it may be sensitive to soil background noise.

In a review of publicly available geospatial datasets and indicators in support of land degradation monitoring, recommendations for using alternative VIs to assess land degradation were provided[36]. For example, for regions with dense plant canopies and high biomass, EVI and EVI2 provide improved responses compared to NDVI. EVI was specifically developed to enhance sensitivity in densely vegetated tropical forests, correcting noise from atmospheric additive path effects and canopy background reflectance. However, despite these improvements, EVI has been found to be less effective for global-scale vegetation assessment.

[36] Antunes Daldegan, G., Noon, M., Zvoleff, A., & Gonzalez-Roglich, M. (2020). Tools4LDN Project Roadmap for Trends.Earth Data Enhancements - A Review of Publicly Available Geospatial Datasets and Indicators in Support of Land Degradation Monitoring. Zenodo. https://doi.org/10.5281/zenodo.4162290

In areas where vegetation cover is sparse, such as hyper arid areas (see Box 3.2), traditional vegetation indices such as NDVI or EVI will vary as a function of the spectral signals of soil relative to vegetation. This limits the applicability of standard global methodologies that perform well for other climatic zones. In such environments, Soil-adjusted Vegetation Index (SAVI) or the Soil-Adjusted Total Vegetation Index (SATVI) can offer more suitable alternatives. SAVI was developed to account for soil brightness by incorporating a soil adjustment factor (L), which minimizes background soil influence due to variations in soil color and moisture. However, this adjustment also makes SAVI less sensitive to variations in vegetation coverage and more susceptible to atmospheric artifacts. Beyond NDVI, EVI, and SAVI, other vegetation indices such as the Plant Phenology Index (PPI) may also be relevant, depending on the specific context. A detailed overview of these indices can be found in Table 3.4.

Vegetation Index	Spectral Bands Required to Calculate VI	Parameters Required	Pros	Cons
NDVI	Red (~680 nm) and Near-InfraRed (NIR: ~860 nm)	None	Simple equation; easy to calculate; most used VI; works relatively well in most areas; very widely used.	Saturates at high biomass areas; sensitivity to background influence (soils, non-photosynthetic vegetation structure); viewing geometry dependent.
EVI	Blue (~465 nm), Red (~680 nm), and Near-InfraRed (NIR: ~860 nm)	Gain factor (G), variable to adjust for background influence (L); coefficients to adjust for aerosol scattering (C1 & C2)	Improved response to high biomass areas; accounts for influences from atmosphere and background.	Coefficients to adjust for aerosol scattering (C1 & C2) are region specific; high sensitivity of the blue band (~465 nm) to Raleigh scattering.
EVI2	Red (~680 nm) and Near-InfraRed (NIR: ~860 nm)	None	Improved response to areas with dense plant canopies; simple equation; does not use the blue band (~465 nm).	Sensitivity to snow cover at mid to high latitudes.
SAVI	Red (~680 nm) and Near-InfraRed (NIR: ~860 nm)	Variable to adjust for background influence (L Factor)	Improved response to areas with sparse vegetation.	Decreased response to vegetation coverage and variability; sensitivity to atmospheric artifacts; L Factor is empirically determined.
MSAVI	Red (~680 nm) and Near-InfraRed (NIR: ~860 nm)	None	Low sensitivity to soil background; improved response to areas with sparse vegetation; high correlation to field measurements over varying canopy structures, LAI, and soil conditions.	Relatively complex equation.
SATVI	Red (~680 nm), Shortwave InfraRed (SWIR: ~1,660 nm), and Shortwave InfraRed #2 (SWIR2 ~2,250 nm)	Constant to account for the slope of the soil-line in a feature-space plot (L)	Improved response to areas with sparse vegetation; high correlation to field measurements over varying canopy structures, LAI, and soil conditions.	Sensitivity to rock outcrops; not thoroughly tested for areas featuring a mixture of grasses, shrubs, and woodlands.
PPI	Red (~680 nm) and Near-InfraRed (NIR: ~860 nm)	Gain factor (K) derived from 1/k (k being the light extinction coefficient per unit of LAI); site-specific canopy maximum Difference Vegetation Index (DVI)	Improved response over boreal forests; decreased sensitivity to snow; strong correlation to leaf area index (LAI).	Complex equation; high parameterization level.

Table 3.4: Summary of main Vegetation Indices (VIs) used to assess Land productivity trends. Source: Review by the Tools4LDN Project https://doi.org/10.5281/zenodo.4162290, licenced under CC BY 4.0 by Conservation International.

BOX 3.2: Global efforts to enhance the assessment of Land Productivity Trends in HyperArid Areas

Hyper-arid regions cover nearly 10% of the global land area (Figure B3), with approximately 30 UNCCD member countries having land classified as hyper-arid. Many of these countries have expressed concerns that the current globally adopted methodology for assessing land degradation is ineffective in such environments and requires improvements. This challenge is particularly evident for the Trends in Land Productivity sub-indicator, as low vegetation cover in hyper-arid zones leads to satellite sensors detecting more of the soil signal than the vegetation signal, limiting the applicability of standard methodologies used in other climatic zones. Additionally, global LPD datasets often lack data in these regions or classify them as "Stable" or "No Data," significantly impacting national reporting on land degradation to the UNCCD and global SDG Indicator 15.3.1 assessments. The inability to accurately assess land productivity trends in hyper-arid zones hampers efforts to identify degradation hotspots, prioritize land-based interventions, mobilize resources, and monitor the impact of restoration efforts.

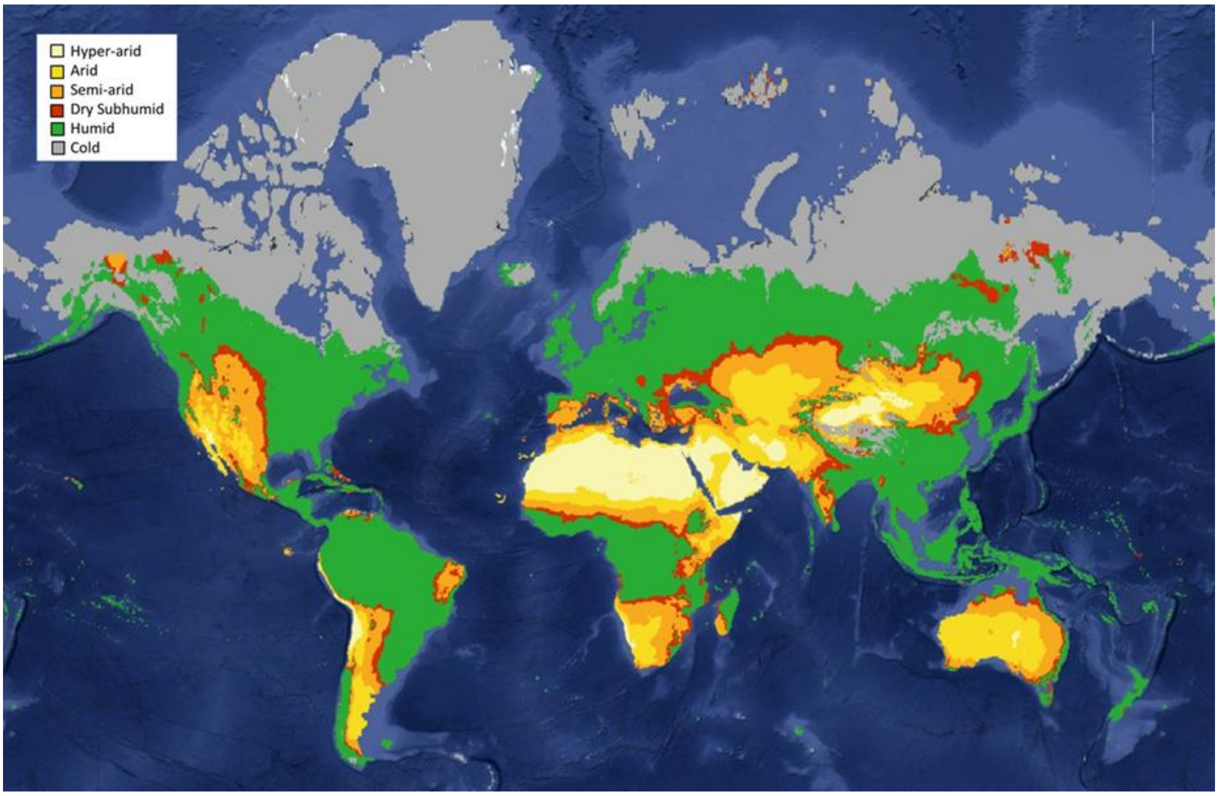

Fig B3. Global aridity index (AI) map for 2000-2024. The areas considered to be hyperarid account for about 9% of the global land area. Source: produced by C.L. Garcia (Apacheta 2025)[37] using Terraclimate dataset[38]. Licensed under CC BY 4.0.

To address this issue, the Ministry of Environment, Water, and Agriculture (MEWA) of Saudi Arabia and the National Center for Vegetation Cover Development (NCVC) convened an international workshop on 26–28

[37] https://code.earthengine.google.com/2db1f27ab2df447f4b4466f9ea46729e

[38] Abatzoglou, J.T., S.Z. Dobrowski, S.A. Parks, K.C. Hegewisch, 2018, Terraclimate, a high-resolution global dataset of monthly climate and climatic water balance from 1958-2015, Scientific Data 5:170191, doi:10.1038/sdata.2017.191
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August 2024, bringing together leading experts to discuss key challenges in monitoring LPD in hyper-arid environments and to identify practical steps toward improving methodologies. As a result of these discussions four key pathways to address this challenge were identified:

1. Stocktaking of Alternative and Innovative Solutions for Hyper-Arid Zones. Experts explored options to improve accuracy, including the use of better datasets and refinements in satellite-based modeling. A key recommendation was to move beyond representing LPD in hyper-arid zones as "No Data" or "Stable" and to investigate the underlying causes of inaccuracies in current methods while exploring promising alternatives, which can include the use of alternative VIs, such as SAVI or SATVI and the use of higher resolution datasets.

2. Systematic Integration of Remote Sensing and Ground-Based Monitoring. Given that satellite-based techniques dominate global land degradation monitoring, the workshop emphasized the need for alignment between remote sensing and ground-based methods. Bridging the massive data gaps in hyper-arid zones through improved ground-based data collection is essential for validating satellite-derived results.

3. Promoting a User-Centered Design Approach. Effective monitoring systems must engage a broad range of end users from the outset. Saudi Arabia was highlighted as a potential pilot for integrating scientific research with monitoring networks across government agencies, offering a framework for a national-scale land degradation monitoring system involving multiple stakeholders.

4. Building Institutional Partnerships and a Community of Practice. Addressing LPD challenges in hyper-arid regions requires sustained collaboration. The workshop facilitated discussions among international organizations and universities on leveraging expertise and developing structured institutional partnerships at both national and global levels.

Source: Workshop report "International Workshop. Land Degradation Monitoring in Hyper-arid Zones: Monitoring Land Productivity dynamics and trends in Soil Organic Carbon stocks in Hyper-arid Environments". NCVC, 2025

Once the vegetation index (VI) and the source data are defined, measurements are typically aggregated to obtain annual values that represent annual productivity. This step simplifies the LPD analysis and removes intra-annual variability. Within a year, vegetation productivity fluctuates due to seasonal changes in temperature, sunlight, and precipitation. In most areas, productivity tends to increase during the growing season, when plants are green and photosynthetically active, and decline during senescence. Additional factors, such as atmospheric conditions and sensor noise, can introduce variability, making it harder to detect long-term trends. By removing these short-term fluctuations, it becomes easier to analyze actual long-term changes in land productivity dynamics. Various approaches exist for aggregating productivity data, but this addendum focuses specifically on methods that produce annual estimates as they are the ones used by the different algorithms described below.

In Figure 3.6 an example of the process to obtain an LPD input dataset (for one area/pixel) by estimating annual averages is represented. In this example NDVI was selected as VI and the satellite data source is MOD13Q1 Terra Vegetation Indices[39], which provides 16-day global images at 250m resolution. The figure shows how the original time series is simplified by estimating annual averages. The MOD13Q1 product provides NDVI values every 16 days, resulting in 23 observations per calendar year and capturing the typical seasonal vegetation patterns. Once annual averages are calculated, intra-annual variations are no longer visible. The result is a time series dataset with a single NDVI value per year, representing the annual mean, used as annual productivity proxy and LPD input dataset.

[39] Didan, K. (2021). MODIS/Terra Vegetation Indices 16-Day L3 Global 250m SIN Grid V061 [Data set]. NASA EOSDIS Land Processes Distributed Active Archive Center. Accessed 2024-07-23 from https://doi.org/10.5067/MODIS/MOD13Q1.061

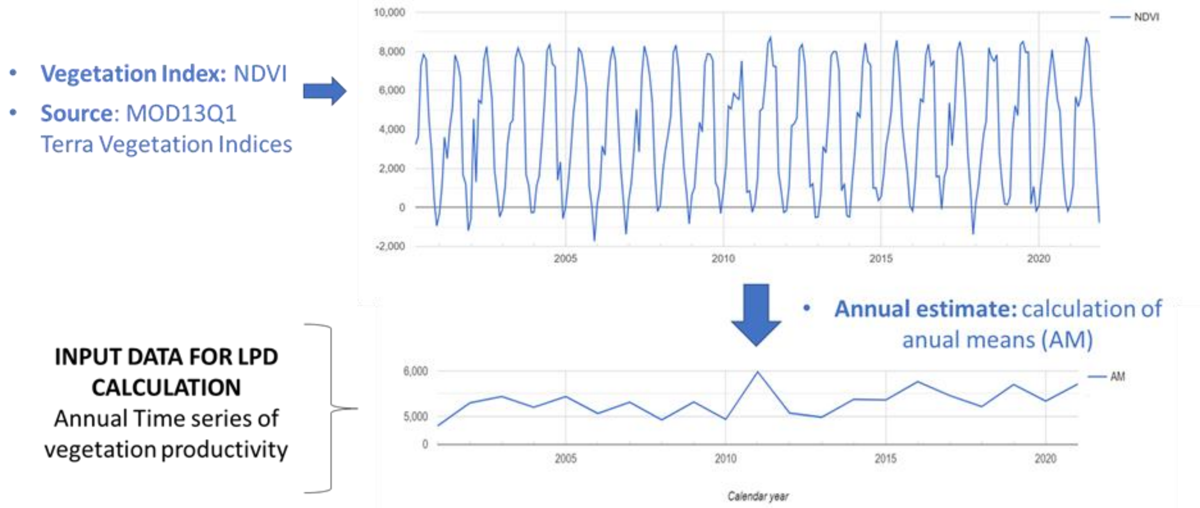

Fig. 3.6: Example of the process to obtain an LPD input dataset (for one area/pixel) from a NDVI time series derived from MODIS for the period 2001-2021.

Different statistics can be used to derive annual values from the same dataset. In the previous example, annual statistics are calculated using the most commonly used metric: the annual mean (AM), which provides an overall average of productivity for the year. However, as an average, the AM can be influenced by extreme values. For example, in regions with frequent cloud cover, low NDVI values may distort the annual mean. To address this, the median can serve as a more robust statistic, as it is less affected by outliers. Other alternatives include the annual maximum, or the 90th percentile, which capture peak vegetation activity but may not always be as stable as the median. Additionally, the coefficient of variation (CV), which measures intra-annual variability, can provide insights into seasonal dynamics. Long-term changes in seasonality can also be assessed through time series of this metric. These annual metrics can be used individually to analyze trends or combined to create new indices. For example, the Ecosystem Services Productivity Index (ESPI)[40] integrates both the annual mean NDVI (AM) and the intra-annual coefficient of variation (CV)[41]. While ESPI does not directly measure ecosystem services, it helps differentiate land cover types with similar annual NDVI values, such as croplands and pastures[42]. Croplands typically exhibit higher intra-annual variability than pastures, resulting in lower ESPI values.

While NDVI remains the most widely used vegetation index due to its advantages, alternative indices may offer better sensitivity in specific environments. This is particularly relevant for ecologically diverse countries, where subnational stratification may be necessary to account for extreme biomass variation. In such cases, using different vegetation indices (e.g., EVI or SAVI) for different sub-regions can improve the accuracy of land productivity assessments and provide a more detailed understanding of land productivity dynamics. Similarly, selecting appropriate annual integration metrics (e.g., median instead of mean) can enhance the reliability of LPD assessments. These decisions should be made through participatory processes and a careful evaluation of alternative datasets, as real-world conditions may differ from theoretical expectations. Following the example presented in Section 3.1

[40] Paruelo, J.M.; Texeira, M.; Staiano, L.; Mastrángelo, M.; Amdan, L.; Gallego, F. An integrative index of Ecosystem Services provision based on remotely sensed data. Ecol. Indic. 2016, 71, 145–154. https://doi.org/10.1016/j.ecolind.2016.06.054

[41] ESPI is calculated as the product between the annual mean and the difference between 1 and the coefficient of variation: ESPI = AM * (1 - CV).

[42] Teich, I.; Gonzalez Roglich, M.; Corso, M.L.; García, C.L. 2019. Combining Earth Observations, Cloud Computing, and Expert Knowledge to Inform National Level Degradation Assessments in Support of the 2030 Development Agenda. Remote Sensing. 2019, 11, 2918. https://doi.org/10.3390/rs11242918

on Ecuador, Figure 3.7 presents three LPD maps generated from time series of annual means of NDVI, EVI, and ESPI, respectively. In all cases, the same LPD algorithm, FAO-WOCAT, was applied. However, because each map was based on a different input dataset, the resulting outputs varied significantly in some areas. These maps were evaluated through a participatory process at the subnational level to identify the most appropriate approach for each region. Experts assessed the different LPD alternatives using the workflow described in Part 3 of this subsection. Their evaluation revealed that performance varied across regions[43]. For instance, in the Humid Litoral zone, the EVI and ESPI-based maps more accurately reflected known areas of degradation and restoration.

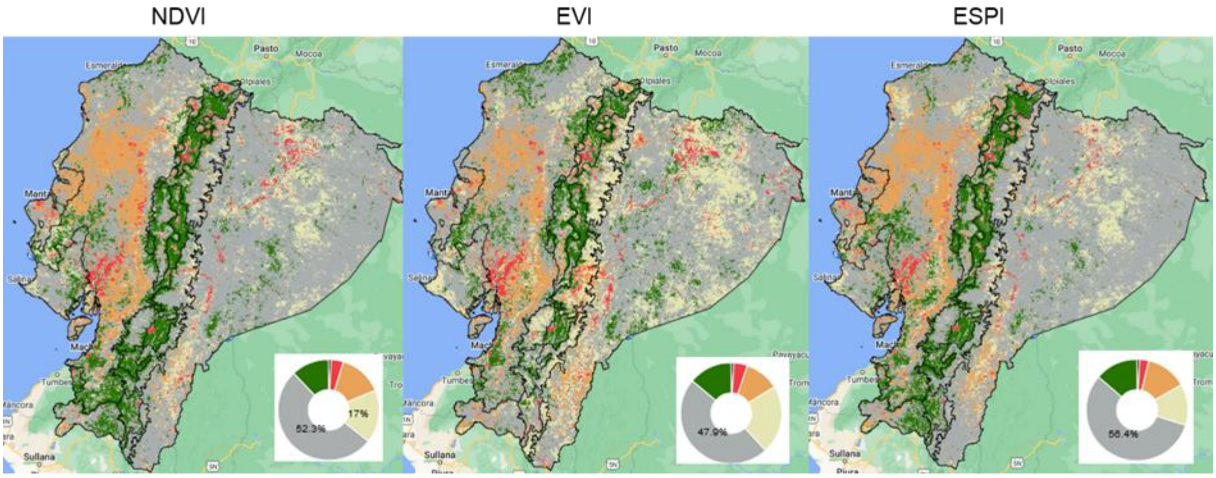

Figure 3.7: LPD Maps for the period 2000-2024 using different input LPD datasets (NDVI Annual Means, EVI, and ESPI). Source: WOCAT and CONDESAN 2025, licensed CC by 4.0 by WOCAT and CONDESAN.

An overview of key ready-to-use vegetation index (VI) datasets available from various satellite missions, including Landsat, MODIS, VIIRS, AVHRR, and Copernicus is provided in Table 3.4. It summarizes their spatial and temporal resolutions, coverage periods, and available vegetation indices (NDVI, EVI, etc.), offering a reference for selecting appropriate datasets for vegetation monitoring and land degradation assessments. Additionally, these same missions, as many others, offer raw satellite images from which the same or others VI can be calculated at different time steps.

Name	Source	VI	Spatial Resolution	Temporal Coverage	Temporal Frequency
Landsat 32-Day EVI Composite	NASA-USGS-GEE	EVI	30 m	Jan 1, 1984–Present	32-day Composite
Landsat 8-Day EVI Composite	NASA-USGS-GEE	EVI	30 m	Jan 1, 1984–Present	8-day Composite
Landsat Annual EVI Composite	NASA-USGS-GEE	EVI	30 m	Jan 1, 1984–Present	Annually
Landsat 32-Day NDVI Composite	NASA-USGS-GEE	NDVI	30 m	Jan 1, 1984–Present	32-day Composite
Landsat 8-Day NDVI Composite	NASA-USGS-GEE	NDVI	30 m	Jan 1, 1984–Present	8-day Composite
Landsat Annual NDVI Composite	NASA-USGS-GEE	NDVI	30 m	Jan 1, 1984–Present	Annually
MODIS Terra MOD13Q1 v006	NASA-USGS	NDVI & EVI	250 m	Feb 18, 2000 - Present	16-Day Composite

[43] Informe Técnico Final. Neutralidad de Degradación de la Tierra en Ecuador. WOCAT y CONDESAN, 2025.

MODIS Terra MOD13A1 v006	NASA-USGS	NDVI & EVI	500 m	Feb 18, 2000 - Present	16-Day Composite
MODIS Terra MOD13A2 v061	NASA-USGS	NDVI & EVI	1 km	Feb 18, 2000 – Present	16-Day Composite
MODIS Aqua MYD13Q1 v061	NASA-USGS	NDVI & EVI	250 m	July 4, 2002 – Present	16-Day Composite
MODIS Aqua MYD13A1 v061	NASA-USGS	NDVI & EVI	500 m	July 4, 2002 - Present	16-Day Composite
MODIS Aqua MYD13A2 v061	NASA-USGS	NDVI & EVI	1 km	July 4, 2002 - Present	16-Day Composite
VIIRS Vegetation Indices (VNP13A1 v002)	NASA-USGS	NDVI, EVI & EVI2	500 m	Jan 19, 2012 - Present	16-Day Composite
VIIRS Vegetation Indices (VJ113A1 v002)	NASA-USGS	NDVI, EVI & EVI2	500 m	Jan 1, 2018 - Present	16-Day Composite
Copernicus Global Land Monitoring Service (NDVI 300m v1)	Copernicus	NDVI	300 m	2014-2020	10-day
Copernicus Global Land Monitoring Service (NDVI 300m v2)	Copernicus	NDVI	300 m	2020-Present	10-day
Copernicus Global Land Monitoring Service (NDVI 1 km v2)	Copernicus	NDVI	1 km	1998-2020	10-day
Copernicus Global Land Monitoring Service (NDVI 1 km v3)	Copernicus	NDVI	1 km	1999-2020	10-day
Landsat/MODIS Fusion HiLPD	CBAS	NDVI	30m	2000-2023	Annually
Annual 30m NDVI Time Series from Mixed Landsat Images	Apacheta-CI-PISLM[44]	NDVI	30m	2000-2023	Annually

Table 3.4: Global Vegetation Index Datasets

As the MODIS instruments aboard NASA's Terra and Aqua satellites approach the end of their operational life after more than two decades of service, ensuring continuity for Earth observation datasets, particularly those based on vegetation indices, is critical. MODIS has served as the default source for Land Productivity Dynamics (LPD) calculations in Trends.Earth and FAO-WOCAT, providing consistent, moderate-resolution data on vegetation health and productivity. With the upcoming phase-out of MODIS, attention is shifting to the Visible Infrared Imaging Radiometer Suite (VIIRS), onboard the JPSS (Joint Polar Satellite System) platforms operated by NASA and NOAA. VIIRS offers similar observational capabilities and will continue the legacy of MODIS with compatible spatial and temporal resolutions. While VIIRS does not provide the Enhanced Vegetation Index (EVI), a key MODIS-based metric, it supports alternative vegetation indices that can be used to sustain long-term LPD assessments. VIIRS instruments aboard Suomi NPP, NOAA-20, and NOAA-21 will extend the Earth observation record, and platforms such as NASA's Global Imagery Browse Services (GIBS) and Worldview are working to ensure continuity and accessibility of comparable visualization products. Although the loss of MODIS's morning overpass (Terra) introduces a temporal observation gap, the

[44] García, C. L., Pozzi Tay, E. F., Raviolo, E., Maharaj, T., Francis, R., Zvoleff, A., Antunes Daldegan, G., Paredes-Trejo, F., Noon, M. & James, C (2025). Annual 30m NDVI Time Series from Mixed Landsat Images. Zenodo. https://doi.org/10.5281/zenodo.15276535

afternoon acquisitions by VIIRS maintain daily global coverage. Moving forward, adapting the LPD framework to incorporate VIIRS-derived indices will be essential to uphold consistency in monitoring land productivity and support countries in tracking land degradation trends.

BOX 3.3

Looking ahead: New Land Surface Phenology Datasets

The release of the new Global Land Surface Phenology (LSP) 2023 dataset by the Copernicus Land Monitoring Service represents a significant advancement in Earth observation, offering global, high-resolution information on the timing and intensity of vegetation growth cycles derived from Sentinel-3/OLCI imagery. While this dataset currently cannot be used directly for monitoring SDG Indicator 15.3.1—due to its recent introduction and the requirement for long-term, consistent time series—it exemplifies the accelerating pace of innovation in remote sensing. LSP captures key phenological metrics such as the onset, peak, and end of the growing season, making it a powerful tool for understanding vegetation dynamics, terrestrial productivity, and climate-driven ecosystem changes. With up to two growing seasons per year and detailed phenological parameters supported by quality indicators, this product sets a new standard for global vegetation monitoring.

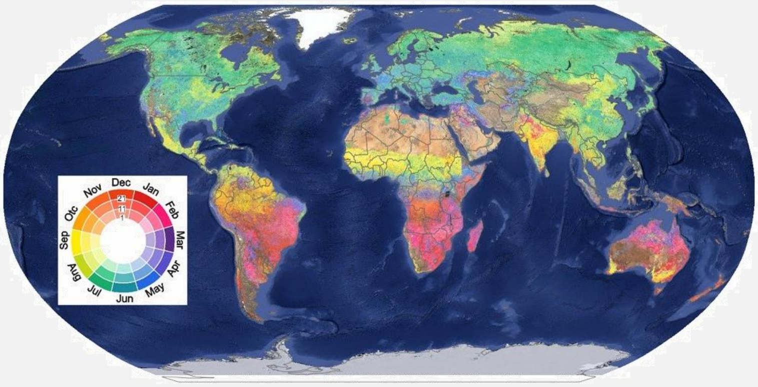

Fig B2: Global map of the date of the peak of growing season (season maximum date). Source: Global Land Surface Phenology 2023 — Copernicus Land Monitoring Service

Looking ahead, the rapid emergence of such advanced datasets reflects a broader transformation in how we observe and understand the Earth system. As we approach 2030, the target year for the current SDG framework, it is increasingly important to consider how new Earth observation capabilities can inform not only existing indicators but also future environmental monitoring architectures. These innovations will be critical for shaping post-2030 sustainability frameworks.

3.2.2- The LPD algorithm: Parametrizing and estimating LPD models

As previously noted, once the LPD input dataset is prepared, it must be analyzed using statistical methods to determine whether productivity is increasing, decreasing, or stable over time. This analysis is carried out using an LPD algorithm. Section 4 of the GPG introduced a general methodology for assessing LPD, which has been implemented in Trend.Earth. The methodology is based on the approach proposed for the World Atlas of Desertification[45] (WAD), developed by the Joint Research Centre (JRC) to monitor land degradation trends at a global scale. While the GPG adopts the core of the WAD method, it also proposes a different methodological approach that allows more flexible analysis, as reflected in its integration into Trend.Earth. In addition, FAO and WOCAT developed an alternative approach that leverages strengths from both the JRC and Trend.Earth algorithms. For the 2022 reporting cycle, these three main LPD algorithms, JRC, Trend.Earth, and FAO-WOCAT, were used globally to assess land productivity dynamics.

With the growing availability of datasets and tools, it has become increasingly important to decouple the LPD input dataset from the LPD algorithm used to assess land productivity trends. This

[45] Cherlet, M., Hutchinson, C., Reynolds, J., Hill, J., Sommer, S. and Von Maltitz, G., World Atlas of Desertification, Publications Office of the European Union, Luxembourg, 2018, ISBN 978-92-79-75349-7, doi:10.2760/06292, JRC111155]

shift is evident in recent practices, where users are applying the same LPD algorithm across a variety of LPD input datasets. For instance, the FAO-WOCAT LPD algorithm has been used not only with MODIS-derived indices such as NDVI and EVI[46], but also with higher-resolution 30-meter Landsat data[47]. Likewise, the JRC algorithm, originally designed for the Copernicus Global Land Service NDVI time series based on SPOT/VEGETATION and PROBA-V, has been successfully used with Landsat and MODIS NDVI data[48]. It is also important to highlight that even when the same input dataset is used, applying different algorithms can lead to varying results due to differences in methodology. Furthermore, each algorithm includes user-defined parameters that can be fine-tuned, meaning that even the same LPD algorithm applied to the same input dataset can produce different outputs depending on how it is parametrized. This flexibility is both a strength, as it enables countries to tailor the analysis to better reflect national circumstances, biophysical conditions, and policy needs, but is also a challenge in ensuring consistent and meaningful monitoring of land productivity trends. Countries are encouraged to explore these parameters in consultation with experts and stakeholders to ensure that the final results align with national knowledge and objectives.

A brief overview of the three main global LPD algorithms is provided below, outlining their general characteristics, methodological approaches, default parameters, and possibilities for customization. Annex 1 complements this overview by detailing the input datasets and parameter settings used in the default versions of each algorithm, along with their respective results for the baseline, first reporting period, and second reporting period.

The JRC (Joint Research Centre) LPD algorithm

The JRC LPD algorithm[49] has been used as the default product during the 2018 and 2022 UNCCD reporting processes. While the 2018 reporting only included the baseline period (2000–2015), for the 2022 reporting process both the baseline and the first reporting period (2004–2019) were estimated. In preparation for the 2026 UNCCD reporting cycle, the JRC LPD product has been further refined, delivering three harmonized datasets, each covering a 16-year time window:

- Baseline period: 2000–2015
- First reporting period: 2004–2019
- Second reporting period: 2008–2023

The methodology for generating the JRC LPD was originally developed and implemented in R as part of the LPDynR package, which is available on GitHub[50]. Recently, JRC translated this methodology into Python to align with broader data science practices and support increased accessibility and scalability of the toolset.

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[46] Paredes-Trejo, F.; Barbosa, H.A.; Daldegan, G.A.; **Teich, I.**; García, C.L.; Kumar, T.V.L.; Buriti, C.d.O. Impact of Drought on Land Productivity and Degradation in the Brazilian Semiarid Region. **Land** **(2023)**, *12*, 954. https://doi.org/10.3390/land12050954

[47] Li, X., Shen, T., Garcia, C.L., **Teich, I.** , Chen, Y., Chen, J., Kabo-Bah, A.T., Yang, Z., Jia, X., Lu, Q., Nyamtseren, M. *A 30-meter resolution global land productivity dynamics dataset from 2013 to 2022.* **Sci Data 12, 555 (2025).** https://doi.org/10.1038/s41597-025-04883-3

[48] Shen, T., Li, X., Chen, Y., Cui, Y., Lu, Q., Jia, X., & Chen, J. (2023). HiLPD-GEE: high spatial resolution land productivity dynamics calculation tool using Landsat and MODIS data. *International Journal of Digital Earth*, *16*(1), 671–690. https://doi.org/10.1080/17538947.2023.2179675

[49] https://doi.org/10.1016/j.ecolind.2021.108386

[50] https://github.com/xavi-rp/LPDynR

The JRC LPD indicator is constructed by integrating two main components: the Long-Term Change Map and the Current Status (Figure 3.7). The Long-Term Change Map integrates three types of information: the Steadiness index (tendency of change), the Baseline productivity level (starting condition) and the Change in productivity state (shift in condition over time). While the Long-Term Change Map captures past dynamics, the Current Status Map focuses on present-day relative productivity, using the Local Net Scaling method. This compares each pixel's productivity to that of neighboring pixels with similar ecosystem functions, grouped into homogeneous land units (HLUs). This helps identify areas that may show positive trends but are still underperforming relative to their ecological potential.

Figure 3.7: JRC LPD Processing workflow.

The **Steadiness Index** measures the direction and strength of productivity trends, based on the slope of a linear trend (positive or negative) and the net change in productivity (from start to end of the period). Both are simplified into binary classes (positive/negative), and their combination yields four "steadiness" classes:

- Strong negative (– slope & – net change)
- Moderate negative (– slope & + net change)
- Moderate positive (+ slope & – net change)
- Strong positive (+ slope & + net change)

For the **Baseline Productivity Level** each pixel's productivity at the start of the time series (e.g., 2000–2002) is classified into Low, Medium or High. To determine these classes, a three-year average is calculated, and pixels are first ranked into ten quantiles. Then, based on global dryland distributions:

- 40% (first 4 quantiles) = Low
- 50% (middle 5 quantiles) = Medium
- 10% (top quantile) = High

The **Change in Productivity State** assesses whether a pixel's productivity class has shifted from the baseline to the final period (e.g., from medium to low). For this, the last three years are averaged and then classified into 10 quantiles. Finally the baseline state is compared to the final state to classify the pixel into:

- No change
- Moderate change (±1 class)
- Significant change (more than 1 class)

To obtain the Long-Term Change Map the Steadiness Index (4 classes), the Baseline Level (3 classes), and the State Change (3 classes) are combined. This results in 22 unique categories that describe combinations of condition and change (e.g., strong positive trend starting from low productivity, with a shift to higher productivity).
Each of these classes represents a specific scenario of long-term productivity dynamics, reflecting the interplay of past conditions, trend behavior, and recent change.

In addition to these temporal analyses, the tool allows for the optional removal of multicollinearity from auxiliary variables such as other NDVI metrics or phenological indicators. It does this by averaging each raster variable over a selected period and computing pairwise Pearson correlation coefficients. Variables that are highly correlated (beyond a specified threshold, typically 0.7) are excluded, resulting in a reduced set of independent inputs for subsequent modeling or clustering.

The ecological context of productivity is then addressed through the derivation of Ecosystem Functional Types (EFTs). Using clustering algorithms the tool groups pixels with similar NDVI-derived characteristics into functional clusters. This can be done globally across the whole raster or within individual land cover types to better reflect ecological heterogeneity. The resulting EFTs map provides a functional landscape classification based on vegetation dynamics.

These EFTs are fundamental for the next step, which is the calculation of Local Net Productivity Scaling. For each EFT, the tool identifies the upper 90th percentile of productivity values, representing the local potential. It then calculates, for each pixel, the percentage of the potential that the pixel currently achieves. This results in a map where values close to 100% indicate optimal or near-optimal performance, while lower values reveal areas underperforming relative to their potential ecological productivity.

In the final step of the processing chain, the tool combines the Long-Term Change Map with the Local Net Scaling layer to generate the definitive five-class LPD map. This stage, known as the Combined Assessment, integrates long-term productivity dynamics with the current productivity status to produce a spatially explicit and policy-relevant evaluation of land condition. Each pixel is classified according to established rules into one of five categories:

- Declining
- Moderate decline
- Stable but stressed
- Stable
- Increasing

Classification is based on whether the pixel shows a declining trend and underperformance, moderate or temporary fluctuations, signs of recovery, or sustained improvement combined with performance near or above its local ecological potential. When the Current Status layer (LNScaling) is not available, the tool automatically reverts to a classification based solely on the Long-Term Change Map, using predefined groupings of its 22 classes.

This five-class map provides a compact and interpretable representation of land productivity condition, supporting evidence-based decision-making, spatial prioritization for restoration or conservation efforts, and standardized reporting under international sustainability frameworks such as UNCCD's Land Degradation Neutrality (LDN) and SDG indicator 15.3.1.

Parametrization of JRC LPD Tool

The JRC LPD tool is designed to be flexible and adaptable to a wide range of ecological conditions and data contexts. To support customization, the tool includes several configurable parameters that allow users to fine-tune each processing step according to the characteristics of their study area or reporting needs. This is particularly important when working in ecologically specific environments such as drylands, where default thresholds may not reflect local dynamics.

During the *Steadiness Index* computation, users can define custom time intervals by adjusting the *year_ranges* parameter. This allows for the processing of multiple periods (e.g., 2000–2015, 2004–2019, 2008–2023) and supports alignment with national reporting cycles or alternative historical baselines.

For the *Baseline Productivity Level*, two key parameters allow users to tailor the classification to regional productivity distributions. The *drylandProp* parameter sets the proportion of pixels to be classified as low productivity (typically 40% in drylands at global level), while *highprodProp* defines the threshold for high productivity (commonly set at 10%). These values are used to allocate productivity classes (Low, Medium, High) based on quantile thresholds, and can be entered either as decimals (e.g., 0.4) or percentages (e.g., 40). This flexibility ensures that the classification reflects the productivity structure of the landscape being assessed.

In the *State Change* step, users can configure how many years are used to calculate average productivity at the beginning and end of the time series through the yearsBaseline parameter. The changeNclass parameter controls the sensitivity of the classification when comparing baseline and final productivity, allowing users to specify how much deviation qualifies as a moderate or significant change.

To reduce variable redundancy in the preprocessing phase, the multicollinearity filter allows users to provide a list of candidate raster layers and specify:

- *yrs2use:* the bands (years) to be averaged for each variable,
- *multicol_cutoff*: the Pearson correlation threshold above which variables are considered too strongly correlated and are excluded from the final dataset (e.g., 0.7).

This ensures that only independent, non-redundant variables are included in later modeling steps such as clustering or regression.

The tool also provides configuration options in the generation of Ecosystem Functional Types (EFTs) through clustering. Users can choose the clustering mode (CLUSTER_MODE)—whether global, stratified by land cover, or a hybrid approach—and define the maximum number of clusters

(NUM_CLUSTERS). The clustering module also allows integration with a land cover raster to perform ecologically constrained classification.

For the Local Net Scaling (LNScaling) process, which evaluates current productivity relative to local ecological potential, users can define the time range for calculating the recent productivity average (start_year, end_year) and select the percentile used to represent the ecological potential (default: 90th percentile). This step ensures that productivity assessments are locally contextualized and not biased by absolute NDVI values alone.

In the computation of the final five-class LPD map, users can adjust the *local_prod_threshold* parameter to define the cutoff (in percentage) for distinguishing between "adequate" and "underperforming" productivity when comparing actual performance with potential. This threshold is essential in distinguishing areas that may show positive trends but are still functioning below their ecological capacity.

To further streamline the configuration process and facilitate reproducibility, a centralized JSON configuration file is currently under development. This file will allow users to manage all input paths, parameter values, time ranges, and output settings in a single place. Once implemented, it will simplify the execution of the entire LPD workflow, ensure transparency in processing decisions, and support automation in large-scale assessments and reporting pipelines.

Trends.Earth LPD algorithm

Trends.Earth LPD algorithm closely aligns with the methodology outlined in the Good Practice Guidance version 2 (GPG v2). It integrates three key metrics: Trend, State, and Performance, which are combined to produce the five-class LPD classification.
Trend: This metric identifies statistically significant changes in productivity over time using pixel-level linear regression and a Mann-Kendall significance test. Trends with $p \leq 0.05$ are considered significant, which if positive are considered potential improvement and if negative are considered potential degradation. In some cases, it may be relevant to apply a correction in the trajectory assessment to account for climatic variability, particularly rainfall, which has a strong influence on vegetation growth. Several methods can be used for this purpose, including Residual Trend Analysis (RESTREND), Rain Use Efficiency (RUE), and Water Use Efficiency (WUE), each offering a different approach to factoring in the role of precipitation. In addition, a range of rainfall datasets are available, each with its own spatial and temporal characteristics. The choice of both the correction method and the rainfall dataset can significantly influence the LPD results. Therefore, it is important that countries carefully assess and justify the methodology and data they adopt to ensure the robustness and accuracy of their LPD estimates (BOX 3.4).

BOX 3.4

Applying Climate Correction to Land Productivity Dynamics (LPD) using Trends.Earth

For the 2022 reporting process Ecuador applied a climate correction to the Land Productivity Dynamics indicator to account for the influence of climate variability, particularly due to the impacts of the El Niño-Southern Oscillation, on vegetation growth and productivity. Recognizing that land productivity can fluctuate due to both land use practices and climatic factors like rainfall, Ecuador opted not to use the standardized global LPD data provided via the UNCCD platform.

Instead, through a participatory process with national and international experts, the country used the Trends.Earth tool to apply a climate correction. This involved using satellite-derived rainfall data (PERSIANN-CDR) and the Residual Trend Analysis method.

The results of this method are very sensitive to the specific precipitation data set adopted and also the model used to apply the climate correction. In the light of this, Ecuador is continuing to research ways to improve the models used to apply the climate corrections to support more accurate estimates of its LPD in the future.

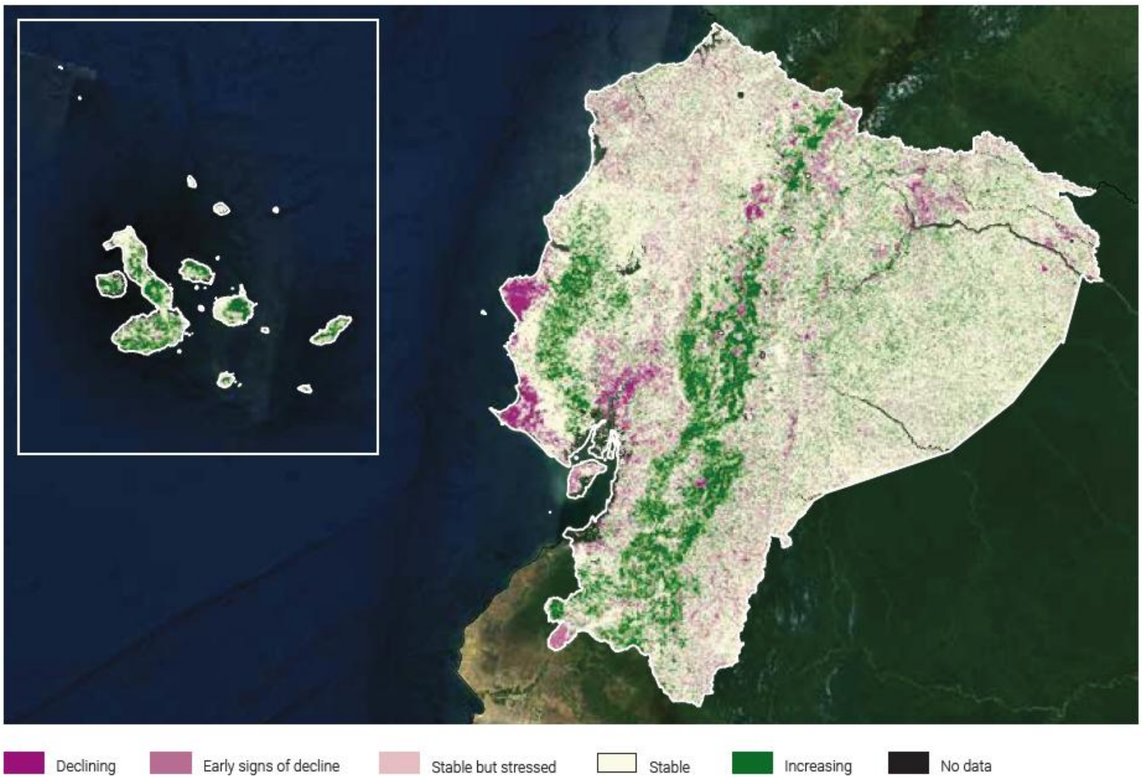


Figure XX : Ecuador land productivity dynamics map for the period 2001 – 2015. The national border displayed on this map was provided by the Government of Ecuador. Source : Ecuador 2022 National Report to the UNCCD, licenced under CC BY-NC 2.0.

To estimate **State**, recent changes are compared to a baseline. For this, mean values for a recent target period (typically 3 years) are compared to a historical baseline (see section 1, Table 1.3). The vegetation index values are grouped into percentile classes to detect shifts in productivity:

- A drop of ≥2 classes suggests potential degradation.
- A rise of ≥2 classes indicates potential improvement.
- Small changes reflect stability.

However, the timeframes chosen for the baseline and comparison target periods can be adjusted, and these choices can lead to different results. As such, they should be selected carefully and with consideration of their potential impact on the outcomes.

The **Performance** metric assesses the productivity of a given pixel by comparing it to ecologically similar areas, defined by shared soil type and land cover classes. Within each ecological unit, productivity values are ranked, and areas falling below 50% of their unit's 90th percentile are flagged as potentially degraded. One limitation of this metric is its sensitivity to the input datasets used for soil and land cover classification. By default, Trends.Earth uses ESA CCI land cover data at 300-meter resolution and soil taxonomy units provided by SoilGrids at 250-meter resolution using the USDA system to define ecologically similar units. However, countries can improve the accuracy of their performance estimates by incorporating national land cover and soil datasets, though this customization must be implemented outside the Trends.Earth environment.

Finally, the three metrics, Trend, State, and Performance, are integrated to produce the 5 LPD classes. The GPG v2 introduced the possibility of combining these metrics in different ways (Table 4.5). However, it is important to note that the Trend metric is generally the most robust, as it directly reflects long-term trends in vegetation productivity. For this reason, the combination method illustrated in Figure 3.8 is the recommended approach. Any deviation from this method should be carefully justified. It is particularly advisable not to base the integration primarily on the Performance metric, as it is the least reliable metric. This metric depends on additional datasets, such as land cover and soil classifications, which can introduce considerable uncertainties. Therefore, unless the Performance metric is calibrated using high-quality, national land cover and soil datasets, it should be given limited weight in the overall assessment.

Aggregating Land Productivity metrics

Trend	State	Performance	5 Classes	3 Classes
Improving	Improving	Stable	Improving	Improving
Improving	Improving	Degrading	Improving	Improving
Improving	Stable	Stable	Improving	Improving
Improving	Stable	Degrading	Improving	Improving
Improving	Degrading	Stable	Improving	Improving
Improving	Degrading	Degrading	Moderate decline	Degrading
Stable	Improving	Stable	Stable	Stable
Stable	Improving	Degrading	Stable	Stable
Stable	Stable	Stable	Stable	Stable
Stable	Stable	Degrading	Stressed	Stable
Stable	Degrading	Stable	Moderate decline	Degrading
Stable	Degrading	Degrading	Degrading	Degrading
Degrading	Improving	Stable	Degrading	Degrading
Degrading	Improving	Degrading	Degrading	Degrading
Degrading	Stable	Stable	Degrading	Degrading
Degrading	Stable	Degrading	Degrading	Degrading
Degrading	Degrading	Stable	Degrading	Degrading
Degrading	Degrading	Degrading	Degrading	Degrading

Fig 3.8: recommended aggregation of productivity metrics into 5 LPD classes, and 3 classes of land productivity degradation. Source: Trends.Earth User Guide,[51] licenced under CC BY 4.0 by Conservation International.

FAO WOCAT LPD algorithm

Both FAO and WOCAT-CDE have played a fundamental role in supporting numerous countries in their efforts to implement the UNCCD, particularly through the execution of GEF projects related to

[51] https://docs.trends.earth/en/latest/for_users/index.html

Sustainable Land Management (SLM) and Land Degradation Neutrality (LDN). Throughout this work with countries, national experts often found that existing land degradation and LPD maps did not reflect the reality on the ground, prompting requests for support and the need for regional assessments, such as the Overview of LDN in Central Asia and Eastern Europe[52] that FAO developed. In response to these challenges, WOCAT-CDE and FAO co-developed an algorithm for estimating LPD that is easily parametrized and adaptable to diverse input datasets. The FAO-WOCAT strategy for LPD mapping is based on the recommendations of the GPG and includes the use of an official legend with five categories, while offering flexibility for users to adjust parameters and methods as needed. This approach, built on open code, FAIR data principles, and easy accessibility, was developed as a Google Earth Engine (GEE) code[53] and integrates concepts from the Trends.Earth methodology, as well as the JRC algorithm. The development process emphasized co-creation with countries, leveraging previous efforts and lessons learned to ensure the approach effectively addresses the identified challenges.

The FAO-WOCAT Land Productivity Dynamics (LPD) algorithm v2 is the latest code version expanded to accommodate a larger variety of input datasets derived from MODIS at 250m or Landsat at 30m. It has been tested with diverse vegetation indexes, such as NDVI, EVI, EVI2, SAVI, and ESPI. It also allows to use different annual integration methods, including filters to remove clouds/outliers (moving windows with Median, Maximum and spatiotemporal Savitzky-Golay) and climate de-coupling with different EO products and analysis. The algorithm evaluates land productivity using three metrics: Steadiness, State, and Initial Biomass. Additional parameters were added in the version 2 that allow to better calibrate local conditions and biological meaning of the results.

Steadiness assesses long-term productivity trends by combining trend direction (from a Mann-Kendall analysis and statistical test) and net change (from a version of Multi Temporal Image Differencing analysis modified to include a significance level parameter). Results classify pixels into four classes (ST1–ST4), reflecting strong decline to strong improvement.

State detects recent changes by comparing the average productivity of the initial and final periods (using percentile distributions). Significant change is defined by the number of quantiles jumps (set as ±2 by default), with categories: Negative, Stable, or Positive. Given that significant change can sometimes be detected in relatively stable time series, it is important to consider other parameters to add biological meaning to the metric. To account for sensitivity on high/low ranges of NDVI extra parameters are used: 1.- Small absolute NDVI changes (e.g. <0.05 NDVI) can be interpreted as Stable; 2.- Small percentage changes (e.g. < 10%) can be interpreted as Stable.

Initial Biomass is a simple metric to reflect the baseline capacity of an ecosystem to support life and sustain productivity. It describes the average NDVI level at the beginning of the monitored time window (e.g first 3 years). It is usually divided into three categories: low, medium and high. It assumes that areas with higher initial biomass are generally more productive and resilient, whereas areas with low initial biomass indicate more arid or extreme conditions with lower resilience.

These three metrics generate 36 combinations, which are reclassified into five standard LPD categories (Figure 3.9).

[52] FAO. 2022. Overview of land degradation neutrality (LDN) in Europe and Central Asia. Rome. https://doi.org/10.4060/cb7986en

[53] Garcia, C. L., & Teich, I. (2022). FAO-WOCAT Land Productivity Dynamics indicator. Zenodo. https://doi.org/10.5281/zenodo.10849367

Steadiness	ST1 (Trend- & MTID-)			ST2 (Trend- or MTID- & Trend 0)			ST3 (Trend 0 or Trend + & MTID -)			ST4 (Trend + & MTID+)		
Intitial Biomass	Low	Medium	High	Low	Medium	High	Low	Medium	High	Low	Medium	High
State Neg.	1	2	3	10	11	12	19	20	21	28	29	30
State neutral	4	5	6	13	14	15	22	23	24	31	32	33
State Pos.	7	8	9	16	17	18	25	26	27	34	35	36

Declining | Moderate Decline | Stable but Stressed | Stable | Improving

Fig. 3.9: Combinations derived from three productivity metrics (steadiness, initial biomass and state) in the FAO WOCAT LPD algorithm, and how they reclassified into five standard Land Productivity Dynamics (LPD) categories (colour coded).

Users can explore a range of parametrizations with the FAO WOCAT LPD v2 leading to broad land degradation/improving maps to more priority area focus maps. For the 2026 reporting process FAO-WOCAT produced global maps at 250m resolution based on MODIS (see Annex 1). High resolution FAO WOCAT LPD v2 maps at 30m covering SIDS were also developed by International Research Center of Big Data for Sustainable Development Goals (CBAS)[54], Apacheta, The Partnership Initiative for Sustainable Land Management (PISLM) and Conservation International (CI)[55].

These three main LPD algorithms, and the variations in how they are parameterized, can lead to significantly different results in the characterization of land productivity dynamics. Such variability underscores the importance of context-specific analysis and highlights the need for careful selection and adaptation of methodologies. In the next subsection, we present a practical workflow designed to help countries identify the most representative LPD dataset for their national context, ensuring robust and meaningful assessments.

3.2.3- Verifying results and selecting the most representative LPD dataset

LPD maps are typically generated by multi-annual time series analysis of vegetation indices derived from satellite data. As discussed in previous sections, the resulting LDP maps are sensitive to the choice of input datasets and parameterization of the chosen algorithmic approach leading to different LPD maps for the same area of interest. The challenge, therefore, is to select an approach that produces an LPD map that best reflects national land productivity trends. This section provides guidance for countries and users in following a workflow that enables them to obtain the most representative LPD dataset, based on approaches that have already been successfully implemented.

Choosing the most reliable LPD map is essential for ensuring the accuracy of the final land degradation assessment and the estimation of SDG Indicator 15.3.1. It is also a critical step in monitoring progress towards Land Degradation Neutrality (LDN). Ideally, verification should be conducted for all LPD categories, including areas showing declining productivity, early signs of decline, stable but stressed conditions, and stable or increasing productivity. However, this section focuses on providing examples of datasets that can be used to verify trends of declining and increasing productivity. The verification

[54] Xiaosong Li & Tong Shen. Land Productivity Dynamics Product of Small Island Developing States (30 meters Resolution), International Research Center of Big Data for Sustainable Development Goals (CBAS). Big Earth Data Center, CAS, 2025. DOI: https://doi.org/10.12237/casearth.686dc91f24e15709b381ae4e

[55] García, C. L., Raviolo, E., Francis, R., Maharaj, T., Zvoleff, A., Antunes Daldegan, G.,Pozzi Tay, E. F., Paredes-Trejo, F., Noon, M. & James, C. (2025). A 30m Land Productivity Dynamic Dataset for SIDS computed from Mixed Landsat Time Series and FWv2 model [Data set]. Zenodo. https://doi.org/10.5281/zenodo.15276519

workflow is different from validation in that it does not aim to provide a quantitative accuracy assessment of LPD maps but rather to compare alternative LPD datasets and identify the one that best represents national conditions. In the case of LDP, this will likely involve the comparison of results from using different input datasets and algorithms. These examples are not exhaustive, and each country and expert group is encouraged to think creatively based on available local knowledge and datasets.

In order to determine whether LPD maps are accurately detecting improvements and declines in productivity in areas where restoration activities or degradation processes have occurred, additional datasets can be used. These can be polygon or point datasets representing locations that have experienced a loss or a gain in productivity during the assessment period, or any other data or information available that will help the users qualitatively assess changes in productivity. Examples of such areas include:

Areas with land cover changes that lead to a reduction of productivity: certain land cover changes typically impact negatively on productivity, for example, forest loss is a type of land cover change that generates, in most cases, a decrease in productivity[56]. Many countries have national or subnational maps of deforestation that identify and characterize such areas. These maps can be used to verify if the alternative LPD maps indeed capture the expected declines in productivity.

*Example at national scal*e: Argentina used a national dataset produced by the country's Management Unit of the Forest Assessment System (UMSEF) of the National Forest Agency. This dataset contained 43,614 plots (ranging in size from 5 to 1,000 ha) where loss of forest lands and loss of other woodlands occurred (at least 80% of forest cover was lost). The ability of different LPD maps to represent declining trends in Argentina was compared using such a dataset[57]. The results indicated that different LPD models performed differently in different regions and vegetation types. In temperate grasslands and shrublands (Espinal) and subtropical moist forests (Paranaensis forests), models using the ESPI time series were more effective in detecting declining productivity due to deforestation.

Example at global scale: land cover datasets were also used to verify a global 30 m resolution LPD map[58]. Specific land cover transitions that lead to a reduction in land productivity and that occurred during key years at the start and end of the monitoring period were identified. A total of 4,345 sample points were randomly selected globally to represent various land change processes, such as forest loss. For urbanization, urban expansion data[59] was used to assess if the LPD map identified declining land productivity trends in those areas (Figure 3.9). In this case, the LPD map evaluated identified typical declining productivity processes in more than 80% of these areas.

[56] Hansen, M.C.; Potapov, P.V.; Moore, R.; Hancher, M.; Turubanova, S.A.; Tyukavina, A.; Thau, D.; Stehman, S.V.; Goetz, S.J.; Loveland, T.R.; et al. High-Resolution Global Maps of 21st-Century Forest Cover Change. Science 2013, 342, 850

[57] Teich, I.; Gonzalez Roglich, M.; Corso, M.L.; García, C.L. *"Combining Earth Observations, Cloud Computing, and Expert Knowledge to Inform National Level Degradation Assessments in Support of the 2030 Development Agenda"*. Remote Sensing (2019) 11(24), 2918. https://doi.org/10.3390/rs11242918

[58] Li, X., Shen, T., Garcia, C.L. et al. A 30-meter resolution global land productivity dynamics dataset from 2013 to 2022. Sci Data 12, 555 (2025). https://doi.org/10.1038/s41597-025-04883-3

[59] City Mayors data http://citymayors.com/statistics/urban_growth1.html

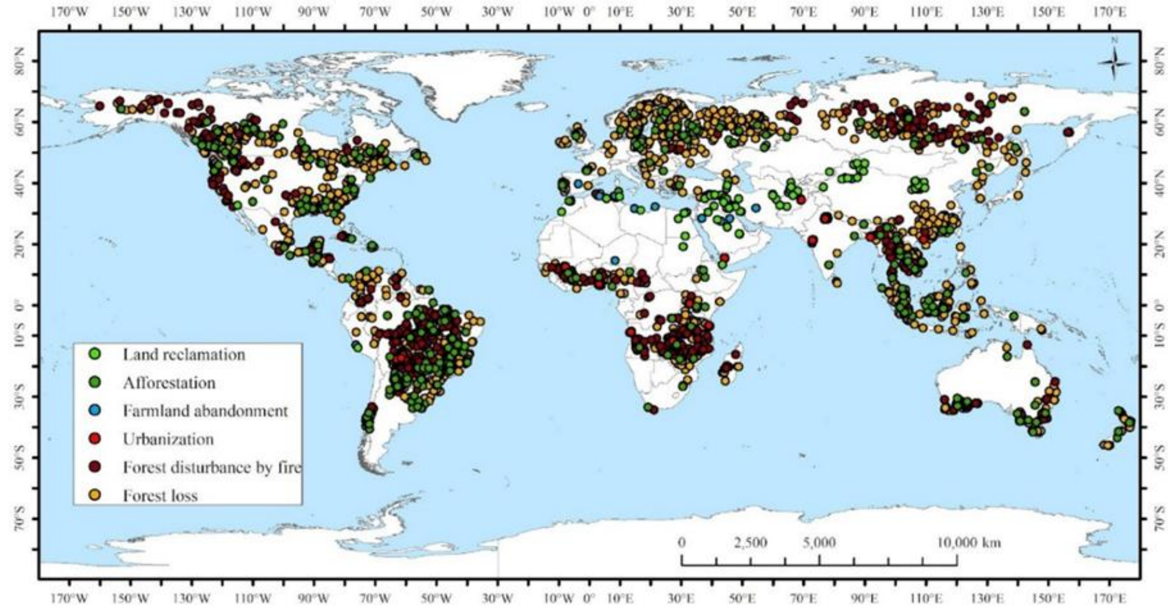


Figure 3.9: Map with the distribution of points used for validation of 30 m LPD map. Source: Li et al., 2025

Areas affected by fires: areas affected by fires often experience a decline in productivity, particularly in forested regions. Many countries have national burned area maps that can be used to assess whether LPD maps correctly detect these declines. Additionally, global datasets, such as the MODIS burned area product, provide valuable data for verification. However, fire impacts on productivity vary depending on fire intensity and severity, ecosystem type, and recovery dynamics. In some cases, vegetation may naturally regenerate after a fire, meaning long-term productivity loss is not always expected. This is especially relevant in rangelands and croplands, where fire is commonly used as a land management practice to stimulate fresh vegetation growth in grazing areas or to clear land for cultivation. Therefore, when using burned area datasets for verification, it is essential to account for fire severity and post-fire recovery patterns to ensure an accurate interpretation of productivity trends.

Mining Activity Data: Mining areas should exhibit declining productivity trends, provided mining activity was ongoing during the LPD monitoring period. For example, Bhutan used mining area datasets to verify LPD maps for national reporting to UNCCD during the 2022 reporting process. Experts from the Department of Geology and Mines identified different mining sites that were active during the LPD assessment period to compare the ability of alternative LPD maps to detect the loss of productivity in such areas. They found that some LPD maps did not detect the expected declining trends, which allowed them to select more appropriate LPD models.

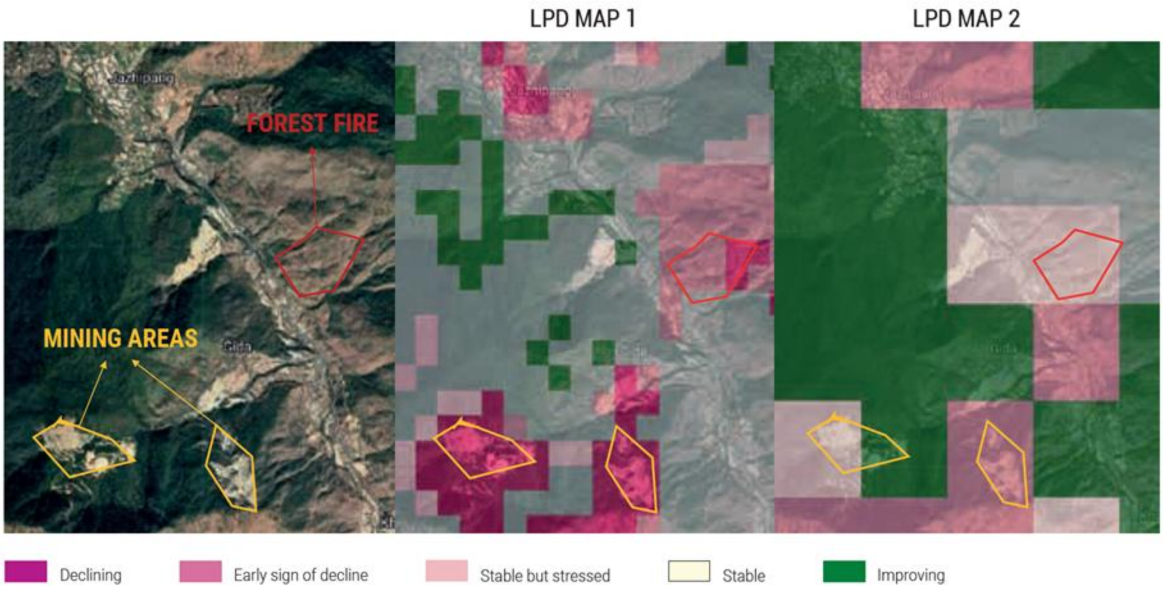


Figure 3.10: The figure shows the same area: the map on the left shows known areas of forest fires and mining in Bhutan, while in the centre and right are two alternative LPD maps that were compared. The centre map aligns best with the situation shown in the ground data (left map). Source: The Land Story. Country experience with reporting on land degradation and drought (UNCCD and WOCAT, 2024).

Verifying positive trends in land productivity is just as important as confirming negative trends. Although areas with increasing productivity are not directly used for estimating SDG indicator 15.3.1, it is crucial to accurately map them for LDN assessments, particularly for counterbalancing degraded areas. Additionally, accurate mapping of improvements in land condition is essential in the context the UN Decade on Ecosystem Restoration, and to monitor progress towards Target 2 (Restore 30% of all degraded Ecosystems) of the Kunming-Montreal Global Biodiversity Framework (KMGBF). To verify and compare the ability of alternative LPD maps to identify improved areas, different datasets can be used. These include:

Restoration and Sustainable Land Management (SLM) areas: if restoration or SLM has taken place in specific areas, an improvement in land productivity should be expected. However, the level of impact of such practices on land productivity will depend on various aspects, including the type of practice implemented, the type of degradation being addressed and the time since the interventions took place. A study conducted at global scale[60] used 1,063 globally distributed SLM technologies from WOCAT Global SLM database[61] to assess their impact on trends in land productivity sub-indicator. The study found that LPD maps detected improvements in areas where SLM was implemented (Figure 3.11). However, it also highlighted that at least 10 years were needed after the start of the implemented action for interventions to show measurable impacts on productivity. Additionally, some SLM practices were not detected by remote sensing, underscoring the importance of integrating remotely sensed data with expert knowledge for assessing and monitoring progress toward LDN.

[60] Gonzalez-Roglich, M., Zvoleff, A., Noon, M., Liniger, H., Fleiner, R., Harari, N., & Garcia, C. (2019). Synergizing global tools to monitor progress towards land degradation neutrality: Trends.Earth and the World Overview of Conservation Approaches and Technologies sustainable land management database. *Environmental Science & Policy*, 93, 34–42. https://doi.org/10.1016/j.envsci.2018.12.019

[61] https://qcat.wocat.net/en/wocat/

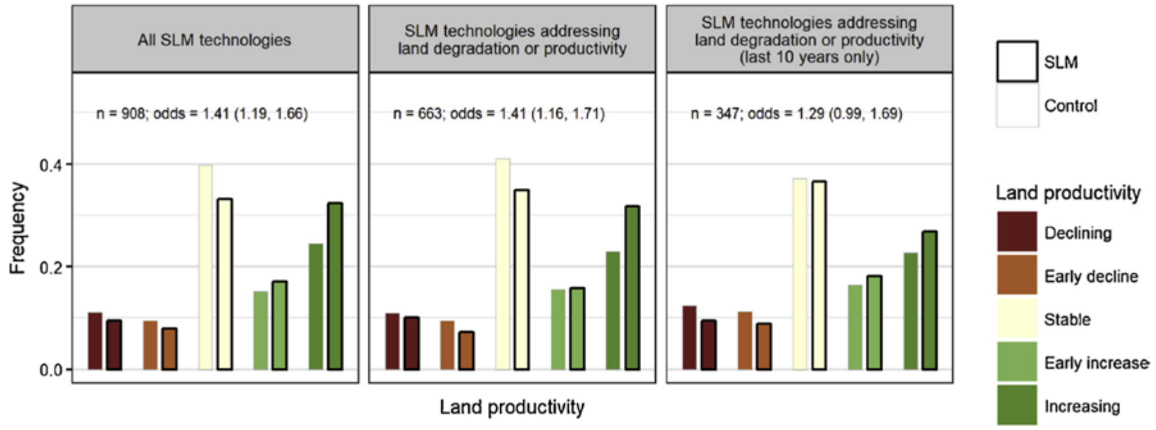


Figure 3.11: Relative frequency of each of 5 LPD classes in areas with SLM technologies and similar sites without SLM. When only SLM technologies with less than 10 years of implementation are considered (right), the difference between sites with SLM and control sites was not statistically significant (right). "n" indicates sample size, and "odds" indicates the odds ratio for an ordinal logistic regression (with 95% confidence intervals). Source: Roglich et al. 2019.

The Framework for Ecosystem Restoration Monitoring (FERM)[62] is a geospatial platform and registry of restoration initiatives that could eventually be leveraged for verifying the accuracy of LPD maps. As the official monitoring platform for tracking global progress and disseminating best practices for the UN Decade on Ecosystem Restoration, FERM supports countries in reporting restored areas for GBF Target 2.

Areas with land cover changes that lead to an increase of productivity: conversely to deforestation, there are land cover transitions that are expected to impact positively on land productivity. Therefore, if such areas can be identified, they can be used to verify increasing productivity trends. For example, in the aforementioned global LPD validation study, afforestation transitions were used to confirm positive trends in LPD maps (Table 3.5). Interestingly the percentage of areas with forest gain that indeed showed positive trends in land productivity was much lower than the areas with forest loss showing the expected decline in productivity (58% versus 84%). This probably relates to the fact that restoration efforts tend to take more time than the degradation processes to manifest, and may not be detectable with the duration of the time series used for the LPD maps .

PROCESS	TYPES OF VALIDATION POINTS	VALIDATION POINTS	POINTS W/DECLINING OR EARLY SIGNS OF DECLINE	ACCURACY
Forest loss	GLC_FCS30D transition from forest to others LCLUC transition from forest to others	2,589	2,182	84.28%
Forest disturbance by fire	GLC_FCS30D transition from forest to others LCLUC transition from forest to others Wildfire occurrences from 2016 to 2022	652	610	93.56%
Farmland abandonment	GLC_FCS30D transition from cropland to bare land LCLUC transition from cropland to bare land	24	22	91.67%
Urbanization	GLC_FCS30D transition from others to urban LCLUC transition from others to urban	1,080	865	80.09%

62 https://ferm.fao.org/

PROCESS	TYPES OF VALIDATION POINTS	VALIDATION POINTS	POINTS W/DECLINING OR EARLY SIGNS OF DECLINE	ACCURACY
Afforestation	GLC_FCS30D transition from others to forest LCLUC transition from others to forest	309	180	58.25%
Land reclamation	GLC_FCS30D transition from bare land to cropland LCLUC transition from bare land to cropland	90	51	56.67 %

Table 3.5: Consistency verification between typical processes of land cover change and a 30 m global LPD map. Source: Li et al. 2025.[63]

Protected Areas: protected areas, such as National Parks and Nature Reserves, are generally expected to show increasing land productivity over time. As a result, protected area maps can serve as a useful tool for verifying positive land productivity trends. However, this verification should be done with caution, as there are several reasons why a protected area may not exhibit an increasing trend. First, if an area was already in good conservation status when it was designated as protected, it may have reached an ecological equilibrium, leading to a stable productivity trend rather than an increase. In such cases, the lack of change does not indicate degradation but rather long-term ecosystem stability. Second, not all designated protected areas are actively managed or enforced. Some may still experience unsustainable practices, such as illegal logging, grazing, fire events or land conversion, which could prevent productivity from improving or even lead to declining trends. Therefore, it is crucial for experts to identify specific national protected areas where recovery is expected over the period covered by the LPD map. To support this verification, global datasets such as the World Database on Protected Areas (WDPA)[64] can be used. The WDPA provides comprehensive information on protected areas worldwide, including government-designated national parks, areas recognized under regional and international conventions, privately protected lands, and indigenous and community-conserved territories.

As a general recommendation, and regardless of whether verifying declining or increasing productivity trends, it is crucial to use reliable datasets. It is better to have fewer, well-curated polygons (ensuring proper temporal alignment) than to use many polygons that may not accurately represent expected productivity changes. The process of polygon delineation can become complex and excellent guidelines have been published for best practice such as through the TerraFund for AFR100[65] initiative.

The previously introduced datasets offer valuable quantitative and qualitative insights into land productivity trends, helping countries select the most reliable LPD map. By improving the accuracy of land degradation assessments, these datasets contribute to more confident decision-making for achieving LDN and better estimations of SDG indicator 15.3.1. However, to enhance accuracy and ensure the results alignment with local knowledge, countries should undertake a verification process that combines local knowledge, alternative datasets, and spatial assessments. Such a workflow is presented below and has been successfully implemented by multiple countries serving as a guide to improve SDG indicator 15.3.1. The key steps of the workflow include: (1) establishing a multidisciplinary group of experts, (2) providing training and capacity building, (3) deciding whether a subnational analysis is necessary, (4) exploring alternative LPD datasets, (5) identifying verification

[63] Table 3 Consistency verification between typical processes of land cover change and LPD.
[64] United Nations Environment Program's World Conservation Monitoring Center (UNEP-WCMC) (2021). Protected areas map of the world. Available at: www.protectedplanet.net
[65] https://terramatchsupport.zendesk.com/hc/en-us/articles/23804849298203-Webinar-Training-on-Creating-Sites-on-TerraMatch-Collecting-Geospatial-Polygons

data and expert knowledge, (6) comparing the performance of alternative LPD maps, and (7) selecting the most representative LPD map for national reporting.

Workflow for selecting the most representative LPD Map

Step 1: Establishing a Multidisciplinary Group of Experts

A well-rounded expert group is essential to ensure that diverse perspectives are incorporated into the analysis. This group should include representatives from academia, government institutions, and various sectors such as forestry, agriculture, livestock, and urban planning. While GIS or remote sensing expertise is not a requirement, members should have a deep understanding of land degradation and restoration dynamics. This includes soil scientists, ecologists, and land users who can provide insights into areas that have experienced degradation or improvement. Different countries have taken varied approaches to structuring their expert groups. For instance, during the 2022 reporting process, Panama has organized experts based on hydrological basins, while Bosnia and Herzegovina has included representatives from different administrative regions. Ensuring gender balance and the inclusion of Indigenous Peoples and Civil Society Organizations (CSOs) is also crucial. This inclusive approach not only provides a more comprehensive representation of the country's realities but also fosters a sense of ownership among stakeholders, increasing the likelihood that the results will be effectively used for decision-making (Figure 3.12).

Figure 3.12: Participatory assessment of LPD maps for the estimation of SDG indicator 15.3.1 in different countries (Kenya, Turkiye, Bhutan, Panama)

Step 2: Training and Capacity Building

Once the expert group is established, it is important to ensure they have a clear understanding of LPD maps: what they represent, how they are estimated, and why different datasets may produce varying results. Training sessions can be conducted through participatory workshops or virtual meetings, utilizing available resources[66]. If specific tools are to be used for comparing LPD maps, training should also include practical exercises on their application. Capacity building ensures that all participants have the necessary knowledge to contribute effectively to the identification of the best available LPD map.

[66] https://wocat.net/en/wocat-media-library/land-degradation-neutrality-training-materials/

Step 3: Determining the Need for a Subnational Analysis

In many cases, national-level LPD assessments may not sufficiently capture the diversity of land productivity trends across different ecological zones. Countries with highly diverse landscapes may benefit from conducting a subnational analysis by defining regions where alternative vegetation indices (VIs) or differently parameterized LPD models can be applied. When conducting subnational assessments, it is recommended that the same delineation is used for all three SDG 15.3.1 subindicators, that the number of regions remains manageable (ideally fewer than five), and that their boundaries align with recognizable administrative or ecological units. These areas should be clearly mapped and documented.

Step 4: Exploring Alternative LPD Datasets

Since it is difficult to determine in advance which input dataset and algorithm will be the most appropriate, experts should explore alternative LPD maps before selecting a map for reporting. These maps can be generated using different global LPD algorithms, such as FAO-WOCAT LPD, JRC, or Trends.Earth, and by using various LPD input datasets. It is important to note that these are not fixed products, but tools and methodologies that can (and should) be parameterized to reflect local conditions. However, given the vast number of possible combinations, a preselection process is necessary to ensure feasibility. Comparing an excessive number of maps would make it impractical to analyze and interpret the results effectively. During the 2022 reporting process, many countries compared five different LPD datasets (Figure 3.13). This number provided a reasonable balance, offering diversity in estimations while remaining manageable for analysis. However, the selection of maps to be compared should be determined in advance through a participatory process involving the expert group. As a general rule, it is advisable to always include the UNCCD default dataset and ensure that the selected maps produce different results to allow meaningful comparisons. Additionally, key characteristics of the datasets should be carefully considered. For example, in some countries, it is essential to account for climate correction methods to adjust for the impact of precipitation variability.

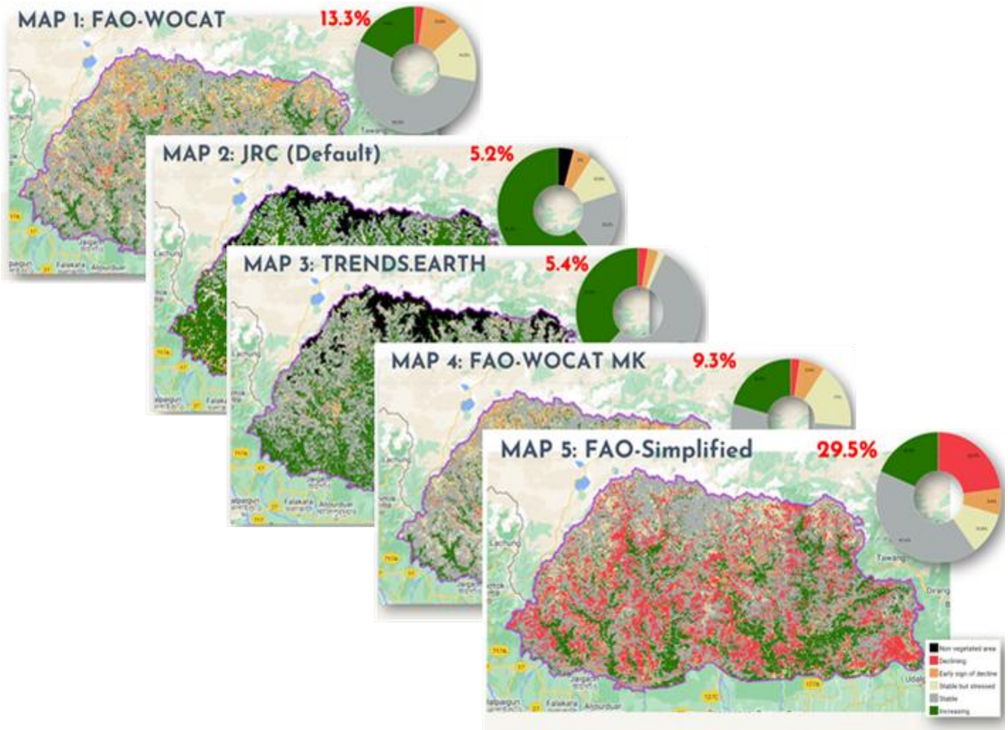
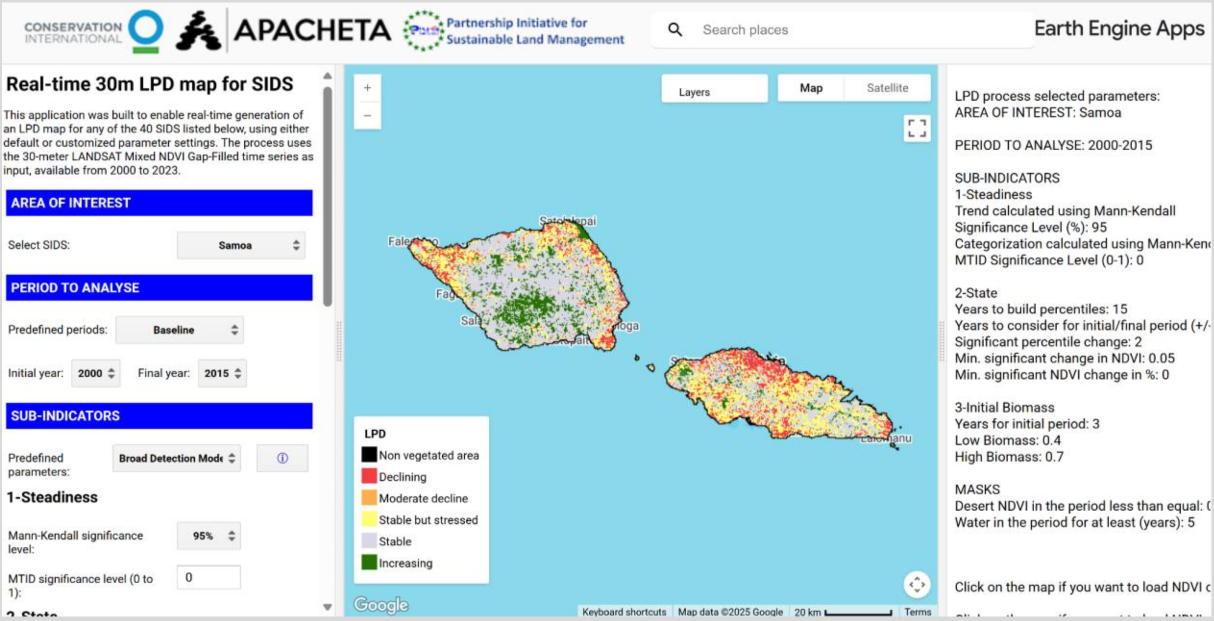


Figure 3.13: Alternative LPD maps compared by Bhutan experts during the 2022 Reporting Process. Source: WOCAT 2023.

BOX 3.4:
Real Time LPD App global and SIDS version

Given the large amount of possible alternative LPD parametrizations, different tools were developed to easily visualize alternative LPD parametrizations and help countries identify the best available LPD map. The global App [Real Time LPD App][67] allows users to compute global LPD maps for any period between 2001-2023 with MODIS data with 250m resolution (NDVI, EVI and ESPI) as input datasets. Countries can explore different parametrization approaches on the FAO-WOCAT v2 LPD model, changing the algorithm sensitivity to obtain broad degradation maps or focus on priority areas. Together with Conservation International (CI) and The The Partnership Initiative for Sustainable Land Management (PISLM) a [high-resolution version for SIDS][68] was developed for 40 SIDS to parametrize and visualize the FAO-WOCAT v2 LPD model using as source the 30m Mixed Landsat Image NDVI Time series as input dataset[69].



Real-time 30m LPD map for SIDS. Source: PISLM, CI and Apacheta 2025. Licensed CC BY 4.0 by Apacheta, CI and PISLM.

Step 5: Identifying Verification Data and Expert Knowledge

As previously presented, various ancillary datasets can be used to assess and compare the reliability of different LPD datasets. Verification data may include extensive spatial datasets containing multiple polygons as well as localized expert knowledge. One effective approach is to compile a list of sites where degradation (with an expected decrease in productivity) or restoration (with an increase in productivity) has been observed, allowing experts to evaluate whether these areas are accurately represented in the different LPD maps. If georeferenced data is unavailable, experts can use tools such

[67] https://apacheta.projects.earthengine.app/view/lpd-realtime

[68] https://apacheta.projects.earthengine.app/view/lpd-realtime-sids

[69] García, C. L., Raviolo, E., Francis, R., Maharaj, T., Zvoleff, A., Antunes Daldegan, G.,Pozzi Tay, E. F., Paredes-Trejo, F., Noon, M. & James, C. (2025). A 30m Land Productivity Dynamic Dataset for SIDS computed from Mixed Landsat and FWv2 model [Data set]. Zenodo. https://doi.org/10.5281/zenodo.15276519

as the FAO-WOCAT LDN Decision Support Systems (LDN-DSS)[70] or Google Earth to manually identify these areas. As a general recommendation, the selection of verification datasets should prioritize:

- High-quality, validated datasets to ensure accuracy.
- Temporal alignment with the LPD assessment period to maintain consistency.
- The combination of data with expert knowledge to enhance reliability.

Step 6: Comparing the Performance of Alternative LPD Maps

The comparison of different LPD datasets should be done through a participatory process, ideally in a workshop setting. If a subnational assessment has been conducted, comparisons should be performed separately for each region. When using large verification datasets, automated methods can be employed to quantify the percentage of areas where each LPD map correctly identifies degradation or improvement. Additionally, visual comparison of LPD maps has proven to be a valuable tool, as demonstrated by the use of FAO-WOCAT LPD Comparison Apps[71] (Figure 3.14). These apps allow stakeholders to explore spatial patterns interactively, validate known hotspots and brightspots, and discuss the strengths and weaknesses of each dataset. For instance, Panama used an LPD Comparison Tool to assess five different maps, ultimately selecting an LPD dataset derived from Trends.Earth. Similarly, Bosnia and Herzegovina experts chose the FAO-WOCAT LPD map for their national report. For the 2026 reporting process an LPD comparison app with alternative LPD datasets, including 30m resolution LPD datasets was developed for SIDS[72]. In addition, a global LPD comparison App for all UNCCD Parties will be developed by WOCAT, facilitating future assessments.

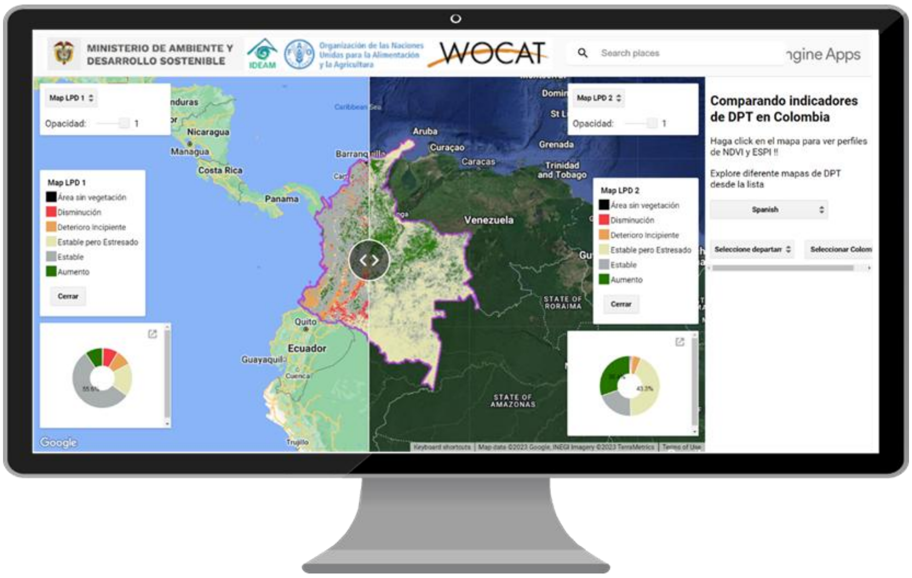


Figure 3.14: FAO WOCAT LPD Comparison App developed and used by Colombia during the 2022 Reporting Process. Source:

[70] Teich, I., Harari, N., Caza, P., Henao-Henao, J.P., Lopez, J.C., Raviolo, E., Díaz-González, A.M., González, H., Bastidas, S., Morales-Opazo, C. and García, C.L. (2023), "An interactive system to map land degradation and inform decision-making to achieve Land Degradation Neutrality via convergence of evidence across scales: a case study in Ecuador". Land Degradation and Development. https://doi.org/10.1002/ldr.4645

[71] wocat.net/en/ldn/wocatapps/

[72] https://apacheta.projects.earthengine.app/view/compare-lpd-sids

Step 7: Selecting the Most Representative LPD Map

Based on the discussions and analyses, experts should select the LPD map that best represents national land productivity trends. If different maps are chosen for different regions, countries are encouraged to merge these into a single national dataset for reporting purposes. The final LPD map should be well-documented, including minutes from workshops, a list of participating experts, and a justification for the selection. Proper metadata should also be included to ensure transparency and reproducibility.

By following this workflow, countries can improve the accuracy of their LPD assessments and ensure that their reports to the UNCCD are robust, credible, and aligned with both scientific data and local expertise.

BOX 3.5 Convergence of Evidence

The principle of convergence of evidence is fundamental to robust land degradation mapping, as it enables the integration of multiple independent data sources to improve the reliability and confidence of assessments. Rather than relying on a single indicator, this approach considers the combined signals from various datasets to identify areas of degradation or improvement. The World Atlas of Desertification (WAD) pioneered this method at the global scale, demonstrating how spatial overlap and consistency across indicators can highlight critical degradation hotspots. Building on this concept, FAO and WOCAT have operationalized convergence of evidence in more than 40 countries by codeveloping LDN Decision Support Systems, making it accessible to practitioners through tools that guide the integration of diverse national data layers for local and national decision-making. By embracing this principle, countries and projects can generate more credible, and policy-relevant information to support action towards Land Degradation Neutrality (LDN).

3.3 Enhancements for Assessing Trends in Soil Organic Carbon

This subsection highlights key aspects of estimating trends in soil organic carbon (SOC) while showcasing how countries improved their estimations in the 2022 reporting process. The methodology remains consistent with the guidance provided in GPG v2, which offers a comprehensive explanation of the approach. As outlined in GPG v2 and UNCCD Decision 22/COP.11, SOC stock remains the primary metric for assessing carbon stocks.

Assessing SOC changes is particularly challenging due to the high spatial variability of soil properties, the time and cost required for representative soil surveys, and the limited availability of SOC time series data in most regions. Ideally, SOC changes would be estimated directly by comparing SOC maps from the beginning and end of the period (baseline and/or reporting period). However, this is often not feasible, as SOC maps are typically derived from legacy data collected through different sampling campaigns, measurement techniques, and depths, making it difficult to establish SOC levels for a specific year, especially at the national scale.

The Tier 1 approach, based on assessing SOC changes in areas where land cover changes occurred, will remain the methodological basis for the default datasets in the 2026 reporting process. However, as outlined in GPG v2, countries are encouraged to use national datasets and methodologies to reduce bias and uncertainty and improve accuracy and reliability in the estimations. Many countries improved their estimations by maintaining the same methodological approach but incorporating national datasets, both for reference SOC stocks and conversion factors. This enhancement increases data quality and is classified as a Tier 2 approach. However, it still relies on land cover change as the primary driver of SOC change detection. Ideally, countries should advance to Tier 3 methods, which capture SOC changes through calibrated and validated process-based models.

3.3.1 Combined Land Cover / SOC method (Tier 1 and 2 methods)

This subsection describes the methodology used to estimate the default dataset for this sub-indicator (Tier 1) in order to clarify in which ways countries can enhance these estimations. The default dataset was produced by Conservation International using global SOC data and algorithms implemented in Trends.Earth, applying the combined land cover/SOC method. The methodology is structured into four key steps:

1. **Establish SOC reference values**
2. **Map Land Cover Changes for SOC change Estimation**
3. **Calculate SOC Changes**
4. **Identify Significant SOC Changes**

For each step, we will provide examples of how countries have improved their estimations by integrating national SOC and land cover data or using national conversion factors, thus upgrading to Tier 2 methods.

STEP 1: Establish SOC reference values

Since most countries do not have SOC maps for multiple years, default estimates of SOC stock change for reporting are derived using a modified Intergovernmental Panel on Climate Change (IPCC) Tier 1 methodology for compiling national greenhouse gas inventories for mineral soils. This methodology relies on a single reference SOC map to estimate changes based on land cover transitions. While this reference map does not influence the classification of areas as degraded, improved, or stable due to SOC trends, it is crucial for understanding the spatial distribution of SOC, setting baseline values for different land types, understanding the magnitude of change in terms of SOC stocks and identifying priority areas for intervention.

The default reference map used in the reporting process is the SoilGrids 250m carbon stock map, which estimates SOC stocks for the top 30 cm of soil. This map, produced by International Soil Reference and Information Centre (ISRIC), was developed using approximately 150,000 soil profiles and 158 remote sensing-based soil covariates, analyzed with machine learning techniques such as random forests and gradient boosting. However, countries are encouraged to use alternative datasets, including global or national SOC maps, to improve accuracy. For example, Türkiye used a national SOC map developed through the Soil Organic Carbon Model and Mapping Project, an initiative involving multiple national agencies. Similarly, countries like Ecuador, Colombia, and Bosnia and Herzegovina have relied on their SOC maps developed for the Global Soil Organic Carbon Map (GSOCmap) with support from the Global Soil Partnership (GSP) and FAO. The GSOCmap is another important reference dataset, created through a participatory approach where countries developed national SOC maps under the guidance of the Intergovernmental Technical Panel on Soils and the GSP Secretariat (see Box 3.6). For more details on available SOC datasets and their limitations, refer to Section 5 of GPG v2.

BOX 3.6

THE GLOBAL SOIL ORGANIC CARBON MAP: A COUNTRY DRIVEN APPROACH

The Global Soil Organic Carbon Map (GSOCmap) is the first-ever country-driven global assessment of soil organic carbon (SOC) stocks. Developed through a participatory approach, this initiative enabled countries to compile and integrate all available soil data at the national level, strengthening their technical capacities in the process. The map was prepared by member countries, under the guidance of the Intergovernmental Technical Panel on Soils and the Global Soil Partnership Secretariat. Countries agreed on the methodology to produce the map and were trained on modern tools and methodologies to develop national maps. The Global Soil Partnership then gathered all national maps to produce the final product, ensuring a thorough harmonization process.

The GSOCmap estimates SOC stocks from 0 to 30 cm depth and serves as a valuable tool for global and national monitoring efforts. A total of 76 countries contributed national SOC maps, covering approximately 65% of the world's land area. The map was produced following the GSOCmap Guidelines[73] and is based on 1,079,617 soil profiles and sampling locations. However, the density of sampling data varies significantly across countries, with many nations incorporating soil observations from before 1990 to ensure full territorial coverage.

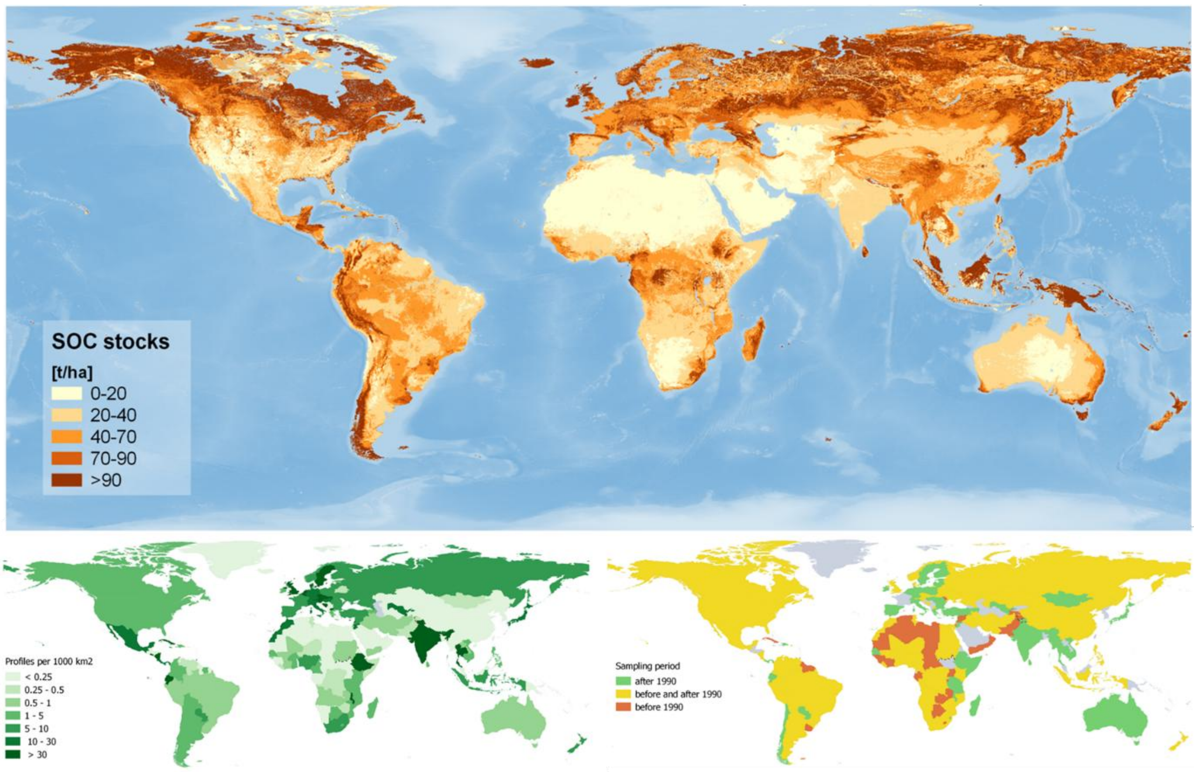


Figure XX: GSOC Map version 1.5.0 (above), density of point data per country (below left) and sampling period of the SOC data used for the GSOC map (below right). Source: FAO, 2020, [74] licenced under CC BY-NC-SA 3.0 IGO by FAO.

A key achievement of the GSOCmap is that **many countries reinforced their national capacities and chose to use this dataset to estimate SDG indicator 15.3.1**, rather than relying on global products such as the SoilGrids SOC map. This highlights the growing importance of **country-led efforts in soil data collection and mapping** to improve SOC monitoring and reporting.

[73] https://openknowledge.fao.org/server/api/core/bitstreams/0e9e6885-076e-4ff1-92fb-787449f11094/content

[74] FAO and ITPS. 2020 Global Soil Organic Carbon Map V1.5: Technical Report. Rome, FAO. https://openknowledge.fao.org/server/api/core/bitstreams/392badd9-cf0e-43c9-aaf7-75d0c0abc662/content

STEP 2: Map land cover changes for SOC change estimation

Under the Tier 1 methodology, IPCC-derived land use change factors should be used to estimate SOC stock losses and gains under different land use and management transitions. However in the absence of global land use change datasets corresponding to these factors, the default SOC change data relies largely on land cover maps. Changes in SOC stocks are modeled using land cover conversion factors as proxies for land use, meaning that accurate identification of land cover transitions is essential for reliable results. When the Tier 1 approach is used, the accuracy of this sub-indicator depends largely on the quality of the land cover transitions map, making it crucial to use the best available data to classify and track land cover changes over time.

For the default dataset used in SOC stock change estimation, seven land cover classes, adapted from the IPCC land use categories, are used: tree covered areas, grasslands, croplands, wetlands, artificial surfaces, other lands, and water bodies. These classes are selected because conversion factors are available for transitions among them, allowing for estimations of SOC changes. The ESA Climate Change Initiative (CCI) Land Cover maps are used to map land cover transitions as the default dataset. However, this approach heavily relies on global land cover datasets, which may not always reflect national realities.

As discussed in Section 3.1, many countries have national land cover maps that may offer higher accuracy and better classification detail. In cases where national maps or reclassified regional/global maps provide a more country-specific representation of degradation processes, countries are encouraged to use them for SOC change estimation. However, in order to apply SOC conversion factors, the land cover classifications must be aligned with the seven default categories. If a country has nationally determined SOC conversion factors for the national land cover legend, then it is acceptable to use additional land cover categories. If using the default conversion factors, land cover maps must be reclassified into the seven standard categories.

The ESA CCI Land Cover maps, used in the default dataset, provide annual land cover data, allowing for precise identification of the specific year when land cover transitions occurred. However, most national land cover datasets do not have annual updates. In cases where only two maps are available (one at the start and one at the end of the reporting period), it is recommended to assume that land cover change occurred towards the beginning of the period. While this assumption may overestimate the duration of land cover impacts on SOC stocks, it remains a valid approach for estimating SOC trends.

As an example, for the 2022 reporting process, Bhutan used the ESA CCI land cover dataset but reclassified the land cover categories to better align with national conditions. Additionally, Bhutan used a national SOC map, allowing for a more precise estimation of SOC trends and an upgrade to a Tier 2 approach. This demonstrates how combining improved land cover classification with national SOC data enhances the reliability of SOC trend assessments.

STEP 3: Calculate SOC changes

To estimate changes in soil organic carbon (SOC) stocks, conversion coefficients for land cover transitions are applied. The UNCCD has provided standardized global conversion factors based on an extensive literature review. The default conversion factors represent the proportional change in SOC stocks over a 20-year period following a land cover conversion. Table 3.6 shows the default conversion factors. In this table each cell represents a conversion factor, which indicates the proportional change in SOC stocks 20 years after a land cover change. The cells with a value of "1" (light yellow) indicate that no change in SOC stocks occurs. Cells with values lower than 1 (purple) indicate SOC loss after conversion. Cells with values higher than 1 (green) indicate SOC gains after land cover change. Values of 2 for example correspond to a doubling of SOC stocks after 20 years, this corresponds to areas transitioning from artificial or bare lands to vegetated land cover types, suggesting significant carbon sequestration potential.

LU coefficients	Forest	Grasslands	Croplands	Wetlands	Artifical areas	Bare lands	Water bodies
Forest	1	1	f	1	0.1	0.1	1
Grasslands	1	1	f	1	0.1	0.1	1
Croplands	1/f	1/f	1	1/0.71	0.1	0.1	1
Wetlands	1	1	0.71	1	0.1	0.1	1
Artifical areas	2	2	2	2	1	1	1
Bare lands	2	2	2	2	1	1	1
Water bodies	1	1	1	1	1	1	1

Table 3.6: Land Use Conversion Factors for Soil Organic Carbon (SOC) Stock Changes. Source: Trends.Earth User Guide,[75] licenced under CC BY 4.0 by Conservation International.

Since the rate of SOC sequestration is influenced by environmental factors such as precipitation, evaporation, solar radiation, and temperature, it is not reasonable to apply the same conversion factor to vastly different climatic conditions. For instance, SOC loss due to land conversion in a cold and dry region will occur at a different rate than in a hot and humid region. To account for this regional variability, especially in land cover transitions involving cropland, different sets of conversion factors are assigned based on climate zones:

- Temperate Dry (f= 0.80)
- Temperate Moist (f= 0.69)
- Tropical Dry (f= 0.58)
- Tropical Moist (f= 0.48)
- Tropical Montane (f= 0.64)

Example of calculation of SOC changes

For example, if a wetland is converted into cropland, the default conversion factor is 0.71 (Table 3.3.1). This means that after 20 years, the SOC stock in that area will be 71% of its original value. Suppose that the wetland initially had 60 tonnes of SOC per hectare, then after 20 years, the SOC stock will be:

$$SOC_{\text{final}} = SOC_{\text{initial}} \times CF$$

$$SOC_{\text{final}} = 60 \times 0.71 = 42.6 \text{ tonnes per hectare}$$

However, since the reporting periods to the UNCCD are not a fixed 20-year period, it is necessary to estimate the annual rate of SOC change and adjust it for the specific reporting period. This is outlined in Equation 5.2 of GPG v2 for the calculation of SOC change per year. Then SOC change over any given period (T years) can be estimated as:

$$SOC_{\text{change}} = \left(\frac{SOC_{\text{final}} - SOC_{\text{initial}}}{20}\right) \times T$$

[75] https://docs.trends.earth/en/latest/for_users/index.html

When annual land cover data is available, it becomes possible to identify the specific year in which a land cover change occurred, allowing for more precise estimation of the number of years since the change (T). This is the case in the calculation of SOC changes in Trends.Earth when using the default datasets, as they are based on annual ESA CCI land cover data. This approach also enables better tracking of multiple land cover changes within the period. In such cases, all land cover transitions and the corresponding changes in SOC are estimated individually and cumulatively accounted for, ensuring that total SOC change reflects the sum of all transitions over time. However, in many cases only the initial and final land cover maps are available, and it is not possible to know in which year the change occurred. In such cases, a good practice is to assume that the land cover change took place in the middle of the period. For example, if the period spans 16 years, it is assumed that the change happened between years 8 and 9, resulting in T=8 years since the land cover change. If the period length is an odd number, such as 15 years, the period is divided by two (7.5 years); in Trends.Earth, this value is rounded up to 8.

Applying the previous equation to a 16-year reporting period, we calculate:

$$SOC_{\text{change}} = \left(\frac{42.6 - 60}{20}\right) \times 8$$

$$SOC_{\text{change}} = (-0.87) \times 8 = -6.96 \text{ tonnes per hectare}$$

This means that, over a 16-year period, SOC stocks in this area would decrease by 6.96 tonnes per hectare due to the conversion from a wetland to a cropland.

This example highlights the importance of using reliable and regionally appropriate conversion factors to estimate SOC trends. The default global dataset applies conversion factors based on broad climatic regions, using a global map to distinguish major climate zones. However, to improve accuracy, countries are encouraged to refine these factors using national data. For example, Türkiye developed country-specific conversion factors by analyzing its national SOC map and CORINE land cover map. By calculating the ratio of SOC stocks across different land cover classes, Türkiye was able to generate conversion factors tailored to local conditions. National experts further reviewed and adjusted these values, determining, for instance, that the conversion factor for artificial surfaces transitioning to tree-covered areas was significantly higher than the default global estimate.

		Target Landcover						
		Tree-covered	Grassland	Cropland	Wetland	Artificial	Other land	Water body
Original Landcover	Tree-Covered	1	0,9	0,6	1	0,1	0,2	1
	Grassland	1,1	1	0,7	1	0,1	0,2	1
	Cropland	1,4	1,3	1	1,4	0,1	0,2	1
	Wetland	1	1	0,7	1	0,1	0,2	1
	Artificial	3	2,5	2	2	1	1	1
	Other land	2	2	2	2,3	1	1	1
	Water body	1	1	1	1	1	1	1

Table 3.7: Land Use Conversion Factors for Soil Organic Carbon (SOC) Stock Changes estimated by Turkiye for the 2022 UNCCD Reporting process. Source: The Land Story. Country experiences with reporting on land degradation and drought (UNCCD and WOCAT, 2024).

Further refinements can be achieved through subnational stratification, where conversion factors vary based on subnational regions. Countries are encouraged to explore these refinements to improve the accuracy of their SOC trend estimates and better reflect their national circumstances. Countries that choose to use national conversion factors or apply a subnational approach to estimate trends in soil organic carbon (SOC) should ensure that these methodologies are well-documented, transparently reported, and validated. Proper documentation should include a clear description of the data sources, calculation methods, and any adjustments made to reflect local conditions. Additionally, the estimation of these national or subnational conversion factors should follow the IPCC guidelines[76] and undergo validation processes, at a minimum through participatory approaches that engage national experts, researchers, and relevant stakeholders. This ensures that the factors used reflect local knowledge and land-use dynamics.

STEP 4: Identify significant SOC changes

Once the conversion factors and land cover transitions have been identified, the change SOC stocks over the period is calculated by comparing the SOC at the end of period and SOC at the beginning of the period, which corresponds to the end of the baseline. For the Tier 1 approach, areas experiencing a SOC loss of 10% or more are classified as potentially degraded, while areas with a SOC gain of 10% or more are considered potentially improved. This 10% threshold is a suggested starting point but can be refined based on national data, expert knowledge, country-specific conditions and dataset-specific conditions e.g. if the 10% is within the known margin of error for a given dataset.

To determine whether an area has experienced a significant SOC change, the percentage change is calculated as follows:

$$\%\Delta SOC = \frac{SOC_{\text{final}} - SOC_{\text{initial}}}{SOC_{\text{initial}}} \times 100$$

Using the example from the previous step, where SOC decreased by **6.96 tonnes per hectare**:

$$\%\boldsymbol{\Delta SOC} = \left(\frac{53.04 - 60}{60}\right) \times 100 = \mathbf{-11.6}\%$$

Since this change exceeds the 10% loss threshold, the area is classified as potentially degraded. Similarly, an area where SOC has increased by more than 10% would be classified as potentially improved, reflecting gains in natural capital. While this threshold-based approach provides an initial classification, expert assessment is crucial to validate results and identify potential false positives and false negatives.

[76] IPCC 2006, 2006 IPCC Guidelines for National Greenhouse Gas Inventories, Prepared by the National Greenhouse Gas Inventories Programme, Eggleston H.S., Buendia L., Miwa K., Ngara T. and Tanabe K. (eds). Published: IGES, Japan.

BOX 3.7

Why the Reference SOC Map does not affect the classification of trends in SOC

When applying the Tier 1 method to determine whether an area has experienced a significant change in SOC stocks, a threshold-based approach is applied. Areas where SOC has decreased by 10% or more are classified as potentially degraded, while areas with an increase of 10% or more are classified as potentially improved. This classification depends on the land cover transition, the associated conversion factor, and the number of years since the change occurred. **Notably, the absolute initial SOC stock does not influence this determination because it cancels out in the calculation of SOC change as a proportion of the initial value.** This means that the classification of degradation or improvement is driven entirely by the relative impact of land cover transitions and the duration of the reporting period rather than the original SOC stock itself. The following explanation provides the mathematical basis for this.

Given equation:

$$\left(\frac{(SOC_{\text{initial}} \times CF) - SOC_{\text{initial}}}{20}\right) \times T \ \leq \ SOC_{\text{initial}} \times 0.1$$

Left side of the equation shows:

- $SOC_{\text{initial}} \times CF$ represents the SOC stock **after 20 years** (where CF is the conversion factor).
- The difference $(SOC_{\text{initial}} \times CF) - SOC_{\text{initial}}$ represents the **total SOC change over 20 years**.
- Dividing by 20 gives the **annual rate of SOC change**.
- Multiplying by t (the number of years since the land cover change) gives the **SOC change over t years**.

Thus, the left-hand side represents the total SOC change over the reporting period.

Right side of the equation shows:

- $SOC_{\text{initial}} \times 0.1$ represents a **10% change** in the initial SOC stock, which serves as the threshold to determine whether an area has undergone significant SOC loss or gain.

Factor Out SOC initial

Rewriting the left-hand side:

$$\left(\frac{SOC_{\text{initial}} \times (CF - 1)}{20}\right) \times T$$

Since SOC_{initial} is **present in both terms**, we see that it cancels out when we compare with the threshold:

$$\frac{(CF - 1) \times T}{20} \leq 0.1$$

This shows that whether an area is classified as **degraded or improved depends only on**:

1. The **conversion factor (CF)** associated with the land cover transition.
2. The **number of years (T)** since the land cover change.

Conclusion

- The initial SOC stock does not influence whether an area is classified as degraded or improved.
- The key drivers are the **land cover transition (which determines CF) and the duration of change**.
- If ((CF−1) × T) / 20 is **less than -0.1**, then the area is degraded.
- If ((CF−1) × T) / 20 is **greater than 0.1**, then the area is improving.

This reinforces the importance of **accurate conversion factors and appropriate timeframes** in estimating SOC trends.

3.3.2 Alternative methods to estimate changes in SOC

The previously presented approach, which combines land cover and SOC methods, only detects changes in SOC in areas where land cover changes occur. However, it is equally crucial to detect and model SOC changes in areas where land cover remains stable. Tier 3 methods, such as calibrated and validated ecosystem (process-based) modeling, offer a more comprehensive solution. These methods link models with country-specific spatial dataset, such as soil maps, land use, climate, and agricultural activity, providing a higher level of accuracy for estimating changes in SOC stocks. These approaches deliver more precise insights into SOC dynamics and therefore can improve the estimations of SDG indicator 15.3.1.

In this section, we will introduce two key strategies that countries adopted in the 2022 reporting process using Tier 3 methods. These strategies involve the use of SOC sequestration potential maps and the integration of other nationally determined indicators, such as salinization and erosion, to estimate changes in SOC.

GSOC Sequestration Potential Maps

One advanced approach to estimating soil organic carbon (SOC) changes involves integrating SOC sequestration potential maps with ancillary data on soil characteristics. These maps, such as the Global Soil Organic Carbon Sequestration Potential Map (GSOCseq), offer spatially explicit estimates of SOC changes based on various factors, including soil properties, land management practices, and climate. By overlaying these maps with land cover data, countries can refine their SOC stock estimates, going beyond the default conversion factors typically used in standard assessments.

The Rothamsted Carbon model, or RothC[77], is a widely used tool for modeling the turnover of organic carbon in the topsoil. The model considers soil clay content, current SOC levels, and climate data (temperature, precipitation, and evapotranspiration), as well as plant cover and net primary production. Based on these inputs, RothC simulates carbon fluxes across five key SOC compartments: 1) Inert Organic Matter (IOM), 2) Decomposable Plant Material (DPM), 3) Resistant Plant Material (RPM), 4) Microbial Biomass (BIO), and 5) Humified Organic Matter (HUM). The model also accounts for the ratio of DPM to RPM, which is determined by vegetation type, and how carbon flows from these compartments to HUM and BIO, with these fluxes constrained by the clay content in the soil. This model was used as the basis of the Global Soil Organic Carbon Sequestration Potential Map an initiative led by FAO. The primary goal of GSOCseq is to predict the spatial variation of SOC stocks under current land management by the year 2040 and compare this with projections under various SSM scenarios.

For instance, Colombia developed a national SOC sequestration potential map using its 2017 national SOC stock map. The country leveraged the widely adopted RothC model to project SOC sequestration potential through 2040. This projection enabled Colombia to identify areas experiencing SOC gains or losses during the 2022 reporting process. By comparing the SOC stock estimates from the year 2000 with the projected 2040 sequestration potential, Colombia was able to assess ongoing changes and potential risks to SOC stocks, offering more precise insights into future trends.

Incorporating national indicators such as Salinization and Soil erosion

Beyond land cover changes, SOC stocks are influenced by degradation processes such as erosion and salinization, which can significantly affect carbon storage in soils. Tier 3 methods can incorporate these factors to enhance the accuracy of SOC change estimates.

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[77] https://www.rothamsted.ac.uk/rothamsted-carbon-model-rothc

Colombia provides a compelling example of this approach. The country utilized national maps of soil erosion (from 2011) and salinization (from 2017) to improve SOC degradation assessments (Figure 3.15). Areas classified as undergoing severe or very severe erosion or salinization were considered at high risk of SOC losses. By integrating this information with the SOC sequestration potential map, Colombia identified areas where SOC stocks were declining by more than 5% and classified them as degraded. Similarly, areas with projected SOC gains exceeding 5% were marked as improving.
This refined approach revealed significant differences compared to estimates based solely on global default data. Specifically, Colombia's national-level assessment indicated that SOC degradation affected nearly 10 times more area in the baseline period and approximately 90 times more area in the reporting period compared to the results obtained using UNCCD's default dataset.

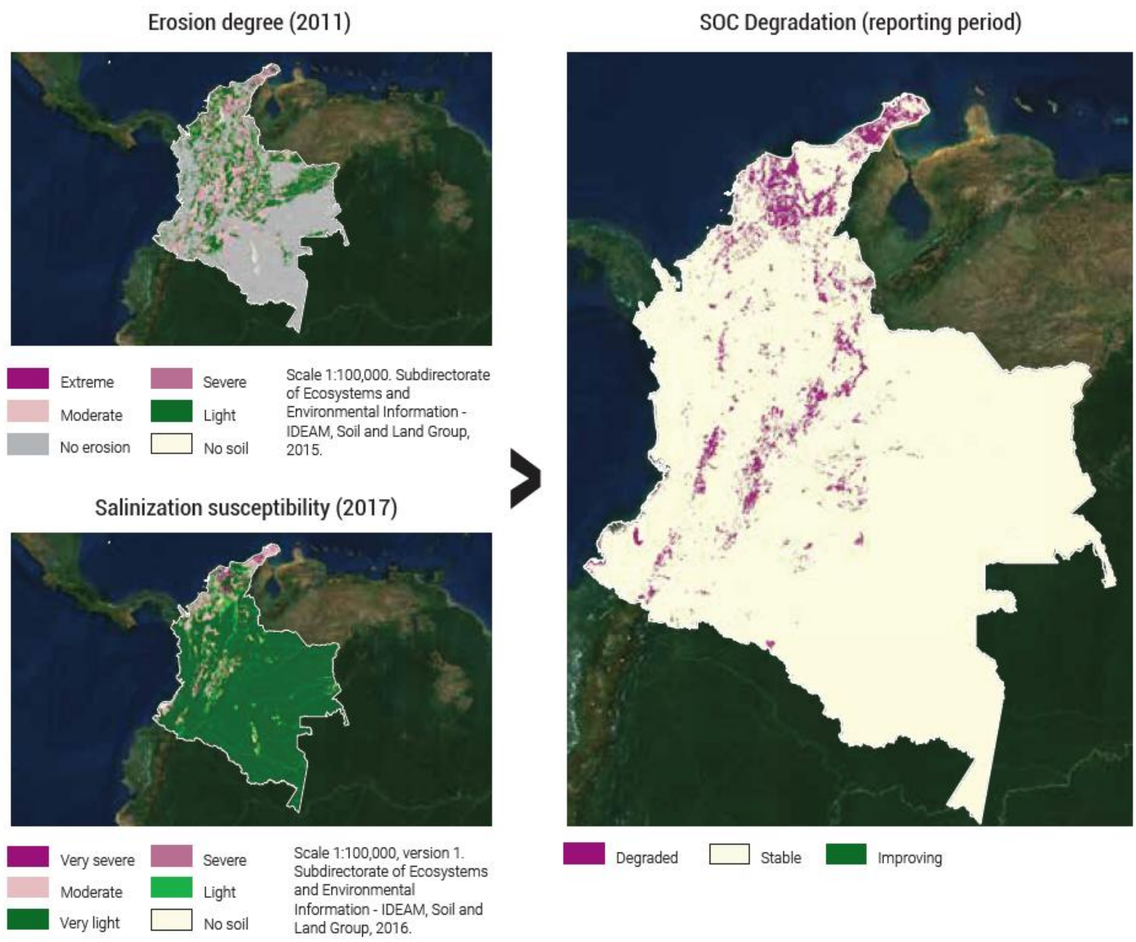

Figure 3.15: National maps showing the degree of soil erosion and salinization susceptibility (left) were used to identify areas in continental Colombia experiencing SOC changes (right). These changes were then estimated using SOC sequestration potential maps. Source: Thee Land Story. Country experiences with reporting on land degradation and drought (UNCCD and WOCAT, 2024).

The methdological enhancements described in this section underscore the progress made since the release of GPG Version 2, reflecting both the evolving data landscape and the increasing technical capacity of countries to tailor methodologies to their specific contexts. By integrating new global and national datasets, refining sub-indicator estimation workflows, and incorporating country-led innovations, the approaches detailed in this section aim to improve the reliability of land degradation assessments and estimations of SDG indicator 15.3.1, proportion of degraded land. Importantly, these enhancements also foster more meaningful stakeholder engagement and promote the use of evidence-based decision-making to achieve LDN.

CONCLUSIONS AND WAY FORWARD

CONCLUSIONS AND WAY FORWARD

This Addendum to the Good Practice Guidance for SDG Indicator 15.3.1 represents a step forward in improving the methodological foundation for monitoring land degradation and tracking progress towards achieving LDN by 2030. Developed through a collaborative and iterative process informed by the experience of countries, technical experts, and international partners, this Addendum addresses key gaps identified during the 2022 UNCCD reporting process and aligns the guidance with new datasets, tools, and analytical approaches.

The enhancements introduced respond directly to the evolving needs of countries as they continue to implement the UNCCD 2018–2030 Strategic Framework and contribute to the achievement of SDG Target 15.3. These updates are not only technical in nature but also reflect an increasing emphasis on usability, transparency, national ownership, and policy relevance. By providing additional clarity on how to assess land condition over time, monitor both degradation and improvement, and track progress toward neutrality using spatially explicit methods, this Addendum aims to support more robust, evidence-based decision making and reporting.

Key conclusions include:

- **Improved temporal consistency**: a simplified approach to integrating land condition assessments over reporting processes, using clearly defined reporting periods and status mapping, enables more consistent time-series analysis of SDG Indicator 15.3.1.
- **Enhanced understanding of land condition dynamics**: By distinguishing between recent and baseline degradation and improvement, the expanded Status Matrix allows for a more detailed interpretation of temporal change. This facilitates better targeting of land restoration interventions.
- **Operationalization of counterbalancing**: For the first time, detailed guidance is provided on applying the counterbalancing principle to assess progress toward LDN. This approach ensures that new degradation is matched by equivalent gains in natural capital within the same land type, thereby supporting the goal of "no net loss" and promoting land-use planning that considers progress towards LDN.
- **Support for country-driven approaches**: This Addendum encourages the use of nationally verified datasets and local expertise, reinforcing national ownership of the monitoring and reporting process.
- **Integration with global tools and platforms**: The methodologies described in the Addendum will be implemented as executable code in free and open-access software such as Trends.Earth, ensuring that the guidance is not only theoretically sound but also practically implementable.
- **Strengthened basis for sustainable land management and policy**: By enabling identification of spatial patterns of degradation and improvement, and quantification of changes in natural capital, this Addendum empowers countries to link monitoring outcomes with real-world interventions and offers valuable tools for planning, implementing, and evaluating sustainable land management practices.

Looking Ahead

As the global community approaches the 2030 deadline for achieving the Sustainable Development Goals, the need for timely, accurate, and actionable information on land condition has never been greater. Countries are increasingly investing in monitoring systems, data infrastructure, and institutional capacity to meet this demand. This Addendum builds on the theoretical and methodological basis outlined in version 1 and 2 of the GPG and supports these efforts by providing clear, practical, and scalable guidance that is responsive to both technical advancements and on-the-ground realities.

However, the guidance provided here is not static. Just as land systems are dynamic, so too must be the frameworks we use to monitor them. Future updates to the GPG and the UNCCD Strategic Framework guided by continued consultation, country feedback, and advancements in Earth Observation and geospatial analysis, will be essential to keep pace with change and ensure continued relevance. Among the areas identified for future development are:

- Improved integration of socio-economic and land tenure data;
- Accounting for climate-related impacts on land degradation; and
- Refinement of methodologies for complex regional geographies, such as hyper arid zones, urban areas, and heterogeneous landscapes.

In conclusion, the GPG Addendum represents a critical tool for supporting national and global efforts to achieve SDG target 15.3. It offers countries the clarity and flexibility needed to adapt the global framework to national contexts, while maintaining the rigor and comparability essential for international reporting. While the Addendum is primarily designed to assist national reporting officers in compiling consistent and credible data for official reporting, it is also a valuable resource for researchers and software developers who require an in-depth understanding of SDG Indicator 15.3.1. These users play a vital role in supporting national-level monitoring, reporting, tool development, and research related to land degradation and LDN. By enhancing the technical capacity of these diverse stakeholders, the Addendum contributes to more informed decision-making in advancing sustainable land management, protecting biodiversity, improving livelihoods, and enhancing resilience in the face of global environmental change.