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GOOD PRACTICE GUIDANCE ADDENDUM

SDG Indicator 15.3.1

Proportion of land that is degraded over total land area

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Disclaimer

Cover photograph

The cover photograph depicts green fields and a dense forested landscape in Malawi, Africa.

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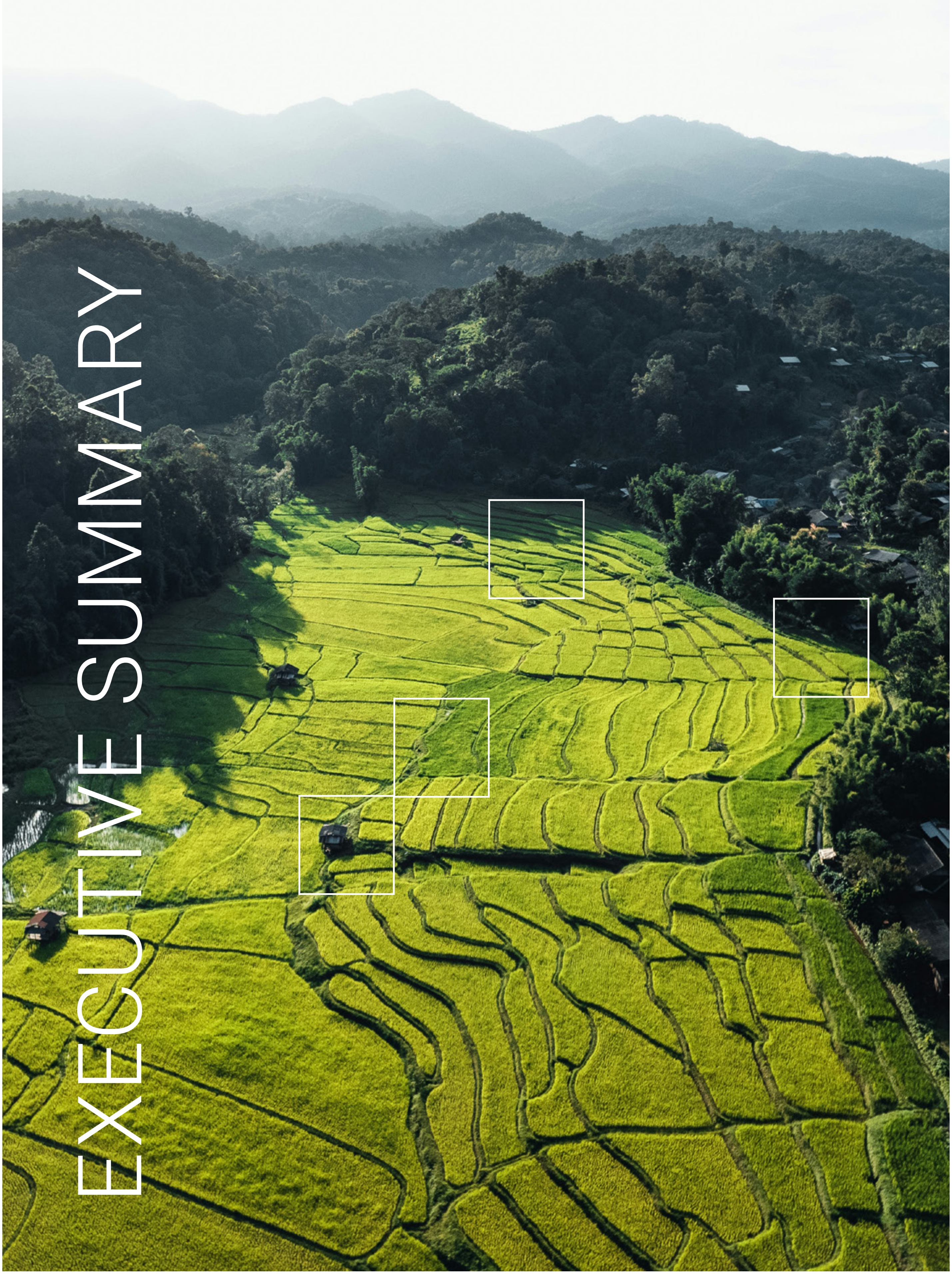
Proportion of land that is degraded over total land area

EXECUTIVE SUMMARY



EXECUTIVE SUMMARY

This addendum to the Good Practice Guidance for SDG Indicator 15.3.1 (GPG) provides updated methodological guidance for countries reporting on Sustainable Development Goal (SDG) Indicator 15.3.1 (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 Approaches and Technologies (WOCAT) (hosted at the Centre for Development and Environment (CDE) of the University of Bern), 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. This updated approach allows for the generation of status maps that reflect land condition at the end of each period by integrating changes relative to the baseline. The second section clarifies the distinction between monitoring SDG Indicator 15.3.1 and assessing progress toward 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. 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 mapping and reporting on land condition. They also reinforce the broader objective of achieving LDN by 2030, supporting evidence-based decision-making, and enhancing national ownership of data and reporting processes.

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GLOSSARY of new and updated terms

Counterbalancing: A process in land degradation neutrality (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 (1OAO) 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 under Sustainable Development Goal (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 United Nations Convention to Combat Desertification reporting cycle.

Reporting process: Periodic submission of reports by Parties in accordance with the four-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 that illustrates 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 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 analysing country data, and estimating regional and global aggregates for inclusion in Sustainable Development Goal (SDG) progress reports. The Good Practice Guidance for SDG Indicator 15.3.1 (GPG), 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 intergovernmentally agreed both as part of the UNCCD monitoring framework (specifically for strategic objective 1),[2] and as part of the global SDG indicator framework.[3] This approach is based on a 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 I.1

SUSTAINABLE DEVELOPMENT GOAL (SGD) 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

SGD 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

15 LIFE ON LAND

1 https://www.unccd.int/sites/default/files/documents/2021-09/UNCCD_GPG_SDG-Indicator-15.3.1_version2_2021.pdf.
2 To improve the condition of affected ecosystems, combat desertification/land degradation, promote sustainable land management and contribute to land degradation neutrality.
3 https://unstats.un.org/sdgs/metadata/files/Metadata-15-03-01.pdf.

Since 2018, and every four years thereafter, countries officially submit their estimations for 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 subregional, regional and global aggregates, and submits them to the United Nations Statistics Division (UNSD). This information is then published in The Sustainable Development Goals Report, including its Extended Report, and the UNSD Global SDG Indicators 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 feedback from country Parties and technical partners, the UNCCD has identified the need to expand and refine Version 2 of the GPG. To address critical aspects that were highlighted as problematic or unresolved during the 2022 reporting process, the UNCCD and the World Overview of Conservation Approaches and Technologies (WOCAT) of the Centre for Development and Environment (CDE) at the University of Bern have led the development of this addendum to the GPG. 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 monitor progress toward LDN 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 Version 2 of the GPG, 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 contains further detail. A **status matrix** is introduced to operationalize the concepts presented in Version 2 of the GPG 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 into 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 that incorporates cloud computing and expert knowledge, a process already adopted by many countries;
- **Updated references to key datasets and tools.** References to datasets and tools 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 assessing, mapping and reporting land condition in alignment with the SDG Indicator 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 on SDG 15.3.1 and strategic objective 1, thereby contributing to more effective monitoring of progress towards SDG Target 15.3 and the achievement of LDN.

The addendum is structured in the following 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 focuses on the timeframe of the data used to assess land condition in each reporting period and how to integrate the period assessment with the baseline. It also provides additional guidelines on how to interpret and visualize changes over multiple reporting processes.

Section 2: Tracking progress towards land degradation neutrality

While Version 2 of the GPG focuses on the methodology for monitoring degraded land (assessing whether it is 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 (i) incorporating the improved land component and the neutrality mechanism into target-setting; (ii) LDN intervention planning; (iii) prioritizing areas for investment; and (iv) 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 and tools related to land cover, land productivity and 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 WOCAT of the CDE, University of Bern, through a consultative process with experts and UNCCD technical partners, including the Apacheta foundation, the Commonwealth Scientific and Industrial Research Organization, Conservation International, the European Space Agency, the Group on Earth Observation-Land Degradation Neutrality Flagship, the Joint Research Centre of the European Commission, the Open Geospatial Consortium, the OpenGeoHub Foundation, and the Sahara and Sahel Observatory.


1
SECTION

SECTION 1
Integrating land condition assessments over time

This section further develops the methods for integrating information on land condition over time. In view of the upcoming 2026 and subsequent reporting processes,[4] additional guidance is provided to clarify the time frame 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.

This 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 subsection intends to clarify the time frames of each reporting period, and the time frames of the datasets used to assess the three sub-indicators in each;

1.2 **Assessing current status:** This subsection 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) for 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.

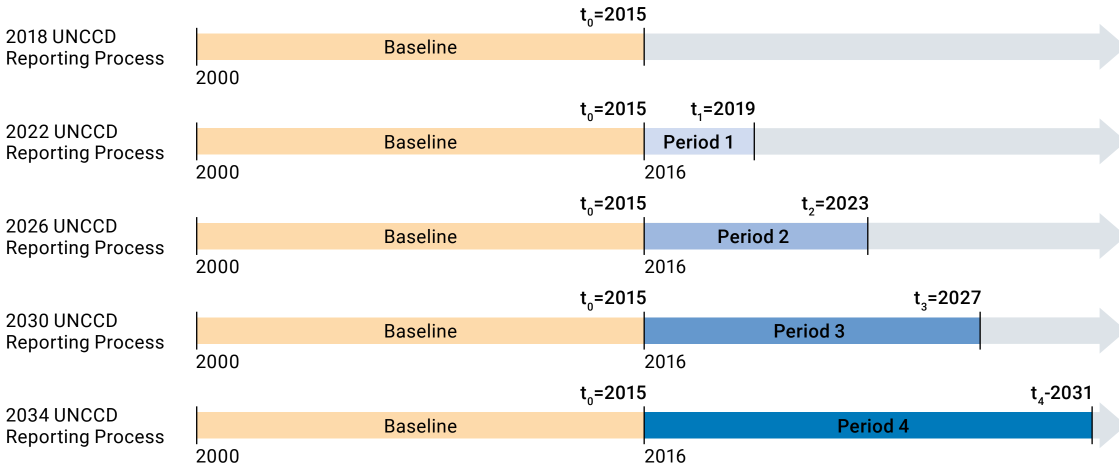
1.1 Assessing changes in land condition during each reporting period (period assessment)

By decision 15/COP.13, Parties approved a four-year frequency for the submission of national reports containing information on the strategic objectives of the 2018–2030 Strategic Framework of the United Nations Convention to Combat Desertification (UNCCD 2018–2030 Strategic Framework). The frequency of reporting on SDG Indicator 15.3.1 was aligned with the four-year frequency of the 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 1 January 2000 to 31 December 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.

After the 2018 reporting process, when the baseline period assessment was conducted, the next UNCCD reporting process was finalized in 2022. Countries reported land condition status and SDG Indicator 15.3.1 for the first reporting period (Period 1), covering 1 January 2016 to 31 December 2019. The results of the Period 1 assessment included the estimation of the proportion of degraded land (i.e. 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 (from1 January 2016) (see figure 1.1).

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 four years) from the last year of the baseline period over which land degradation is assessed.

Figure 1.1
Timeline illustrating the four-year UNCCD reporting frequency for SDG Indicator 15.3.1.



After the baseline period (2000–2015), the first reporting period (Period 1) covers 1 January 2016 to 31 December 2019. Subsequent reporting processes follow every four years, with periods increasing their duration by four years: Period 2 (2016–2023), Period 3 (2016–2027) and Period 4 (2016 to 2031). Each period assessment evaluates changes in land condition through the three sub-indicators of SDG Indicator 15.3.1.

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 Version 2 of the 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. According to 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.

1.1.1 Assessment of trends in land cover in each period

For the baseline period, changes in land cover are determined 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 (see 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 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 the 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 analyse 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 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.

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

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

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.

1.1.2 Assessment of trends in land productivity in each period

Significant change was introduced in GPG Version 2 regarding how trends in land productivity should be assessed. In GPG 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, GPG Version 2 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 data sets, both spanning a 16-year time frame, providing a more reliable basis for evaluating changes in land productivity over time. The time frames 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.

Table 1.2
Initial and final years of the 16-year moving window used to assess changes in land productivity for each reporting period.

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

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 Version 2 and implemented in Trends.Earth, the following three complementary metrics can be used to estimate an LPD data set to assess trends in land productivity:

4. **Trend**: Measures the long-term trajectory of productivity change over a 16-year time series;
5. **State**: Compares current productivity levels in a given area to historical productivity observations (i.e. assessing recent productivity relative to a longer baseline period).
6. **Performance**: Evaluates local productivity in relation to areas in the region with similar productivity potential, providing a benchmark of productivity levels within a comparable context.

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

The Trend metric uses the full time series of 16 years for analysis, as described in table 1.2. This approach remains unchanged from GPG Version 2, 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 3 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. The GPG Version 2 proposes estimating performance over the years since the baseline. However, using a longer time frame (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 potential 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.

Further recommendations and alternative LPD algorithms are presented in section 3.

Table 1.3
Specific time frames recommended to estimate each land productivity metric (Trend, State and Performance) for multiple reporting periods.

Period	Trends in land productivity			
	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

1.1.3 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 UNCCD decision 22/COP.11, the 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, GPG Version 2 presents a range of datasets and processing options, consistent with the Intergovernmental Panel on Climate Change (IPCC) guidelines, supplements and refinements from 2006, 2013 and 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 the minimum requirements call for land cover maps for the starting and end years of the reporting period.

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. Therefore, the same periods used for assessing land cover change should also be applied for SOC changes (see 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 time frame 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 time frames.

Table 1.4
Initial and final years for the assessment of trends in soil organic carbon stocks for each reporting period

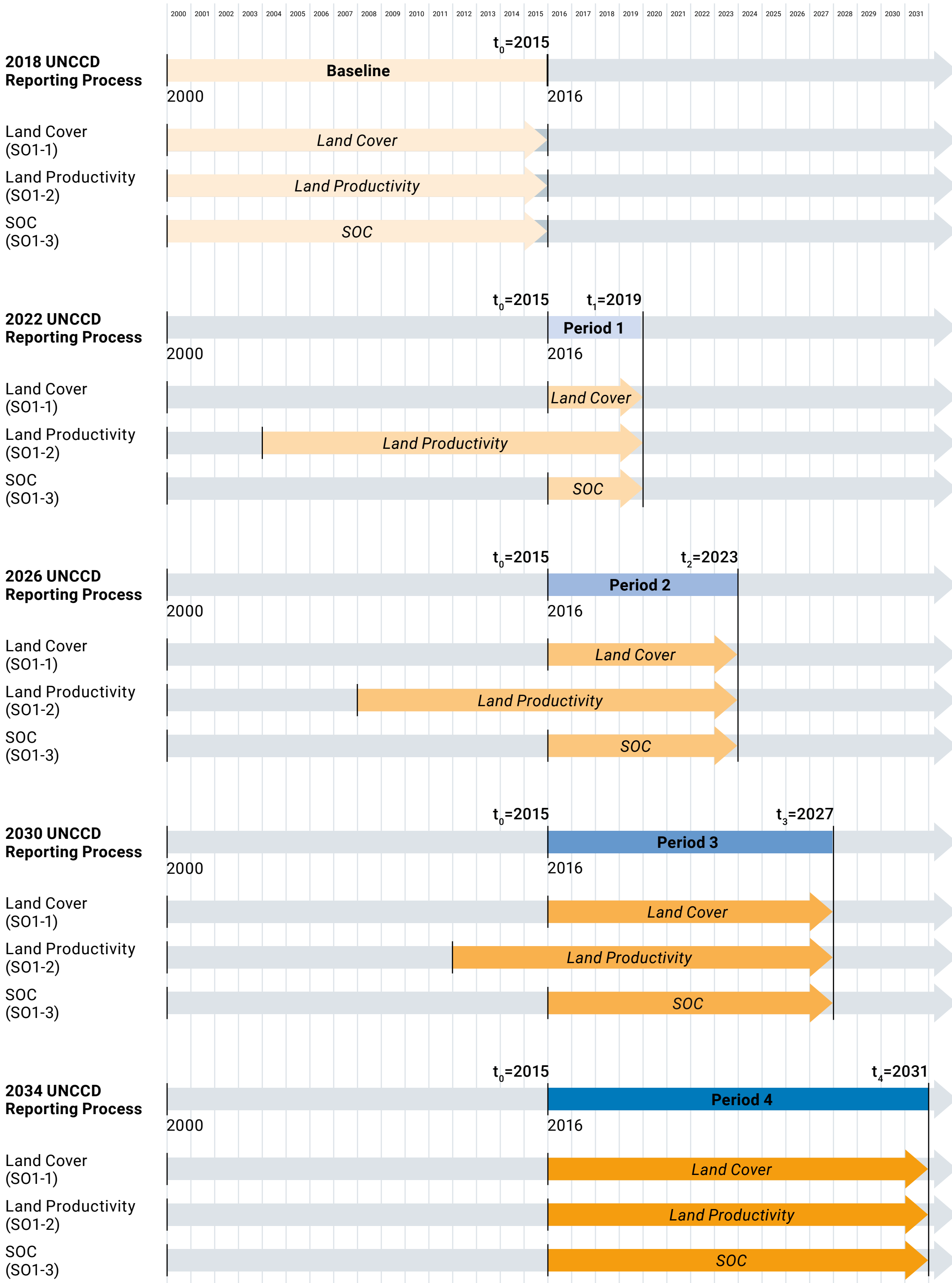
Period	Trends in soil organic carbon stocks	
	Initial year	Final year
Baseline: 2000-2015	2000	2015
Period 1: 2016-2019	2015	2019
Period 2: 2016-2023	2015	2023
Period 3: 2016-2027	2015	2027
Period 4: 2016-2031	2015	2031

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. Section 3 of this addendum presents further recommendations and examples of such approaches.

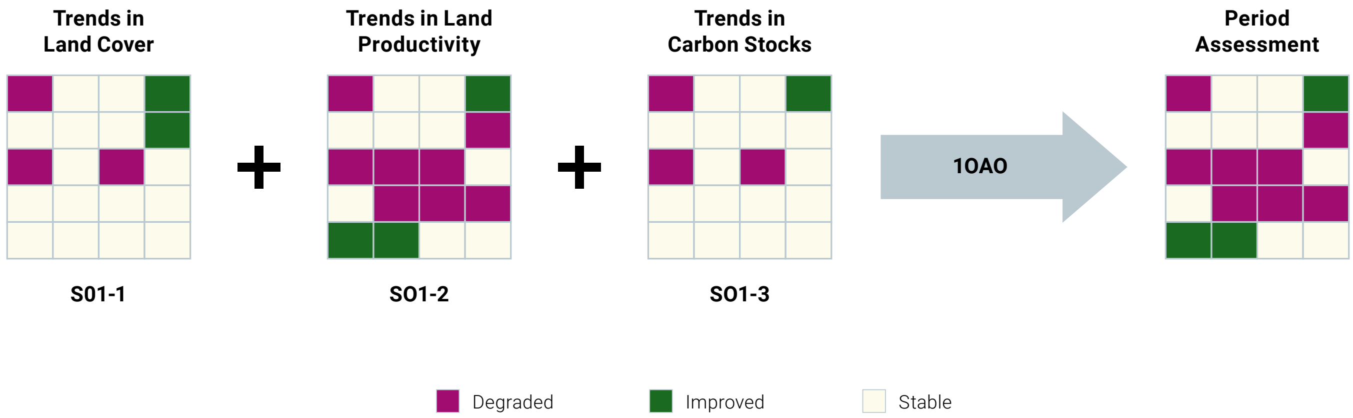
Figure 1.2 graphically illustrates the time frames used for estimating each sub-indicator during the baseline and subsequent reporting processes under the UNCCD framework. For land cover, it shows that the initial year for each reporting period is the end of the baseline. Similarly, for SOC trends, the 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 time frames of the baseline and 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.

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

Figure 1.2
Time frames 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.



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.

Figure 1.3
Application of the one out, all out (1OAO) principle to combine the three sub-indicators for assessing the land condition status for each period.

1.1.4 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 1OAO method in which a considerable reduction or negative change in any one of the three sub-indicators is considered to comprise land degradation (see figure 1.3).

A final map that shows the results of the period assessment is produced for each reporting period. 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 1OAO 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. Subsection 1.2 below 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 GPG, the baseline assessment 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.

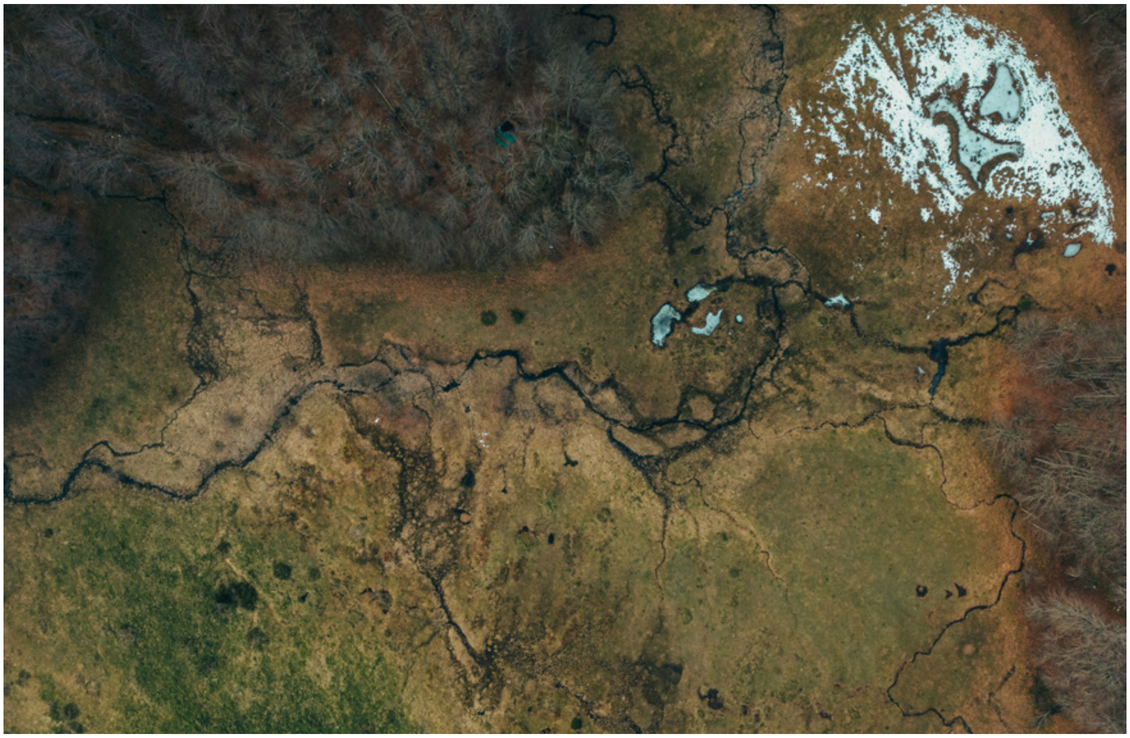
However, in this addendum, the baseline assessment has been expanded to include not only degraded areas, but also land areas that have shown improvement, creating a third category in the original binary baseline map. This expanded baseline assessment simplifies the approach to simultaneously estimate 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 these 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, the status is identical to the period assessment for the baseline period (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 GPG, 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, in estimating SDG Indicator 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 3x3 matrix showing the different possible combinations of changes in land condition between the baseline period and the reporting period. The status matrix (see table 1.5) allows for 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 the 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). Refer to section 2 for further characterization of changes relative to the baseline. 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 (2000-2015). 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 Scientific Conceptual Framework for Land Degradation Neutrality, aimed 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 LDN.

Table 1.5
Status matrix: a 3x3 matrix to assess status (in italics) by comparing the reporting period assessment (columns) and the baseline (rows).

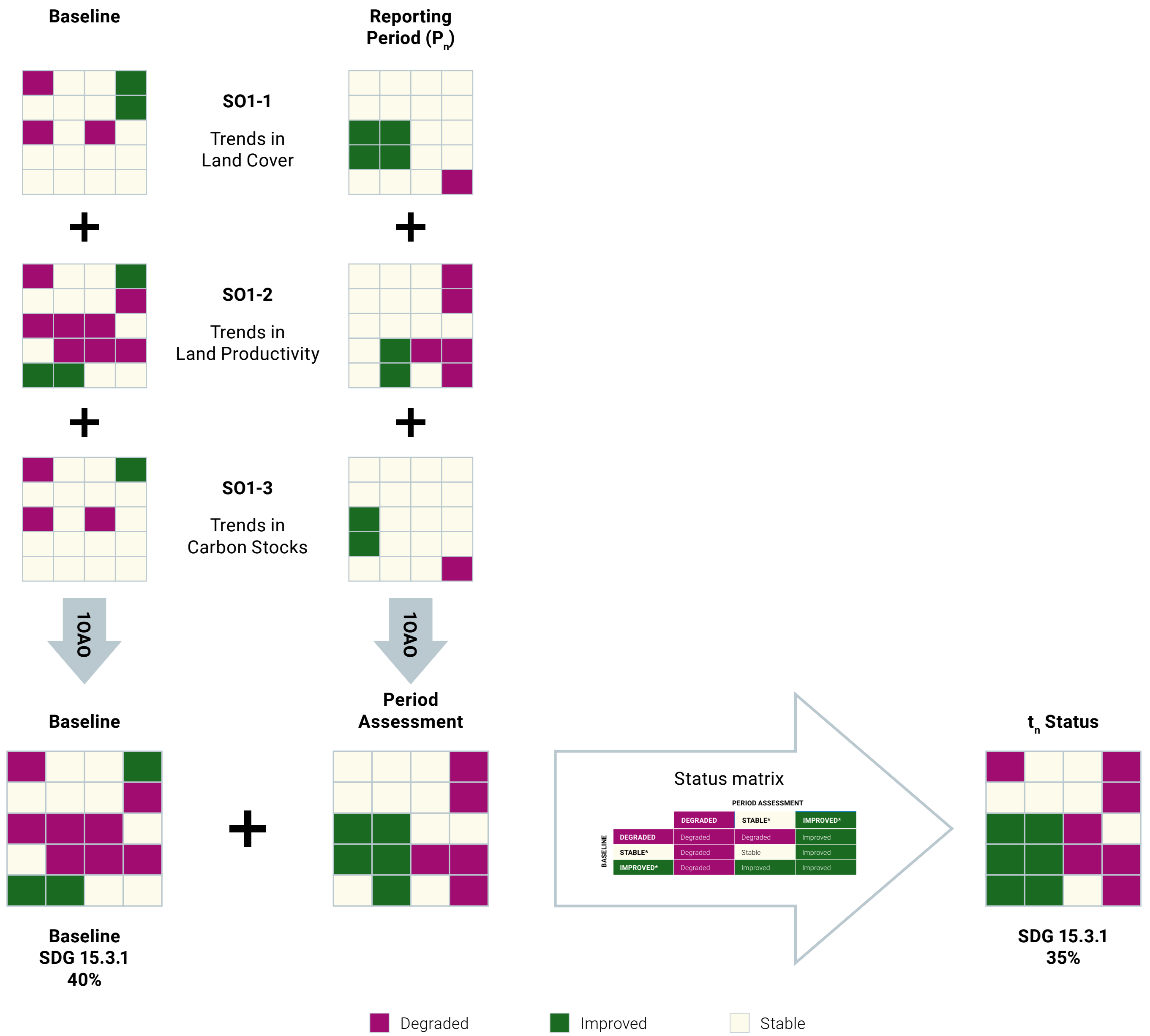
		PERIOD ASSESSMENT		
		DEGRADED	**STABLE***	**IMPROVED***
BASELINE	**DEGRADED**	*Degraded*	*Degraded*	*Improved*
	STABLE*	*Degraded*	*Stable*	*Improved*
	IMPROVED*	*Degraded*	*Improved*	*Improved*

* Not Degraded areas.

The categories 'stable' and 'improved' correspond to not degraded areas.

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 indicators with the baseline using the 3x3 status matrix.

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 four-year period from 2016 to 2019, the status (status 2019) is estimated by comparing the reporting period assessment with the baseline using the 3x3 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 3x3 status matrix. Figure 1.4 shows this process.



For subsequent reporting periods, the same process is applied to determine the land status. Table 1.6 shows the data sets used for each period to obtain the period assessment and status. 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.

Table 1.6
Years used for the estimation of each of the three sub-indicators across reporting periods.

UNCCD reporting process	Reporting period	Period assessment: 1OAO applied on the three sub-indicators			Status
		Land cover maps	Land productivity	Change in carbon stocks	
2018	Baseline: 2000-2015	2000-2015	2000-2015	2000-2015	Status 2015 = baseline assessment
2022	Period 1: 2016-2019	2015-2019	2004-2019	2015-2019	Status 2019 = baseline + 2016-2019 assessment
2026	Period 2: 2016-2023	2015-2023	2008-2023	2015-2023	Status 2023 = baseline + 2016-2023 assessment
2030	Period 3: 2016-2027	2015-2027	2012-2027	2015-2027	Status 2027 = baseline+ 2016-2027 assessment
2034	Period 4: 2016-2031	2015-2031	2016-2031	2015-2031	Status 2031 = baseline + 2016-2031 assessment

The combination of these using the one out, all out (1OAO) principle generates the period assessments. The final column indicates how the resulting assessments are then compared with the baseline using the 3x3 status matrix to determine the status for each period.

1.3 Tracking change over multiple reporting processes

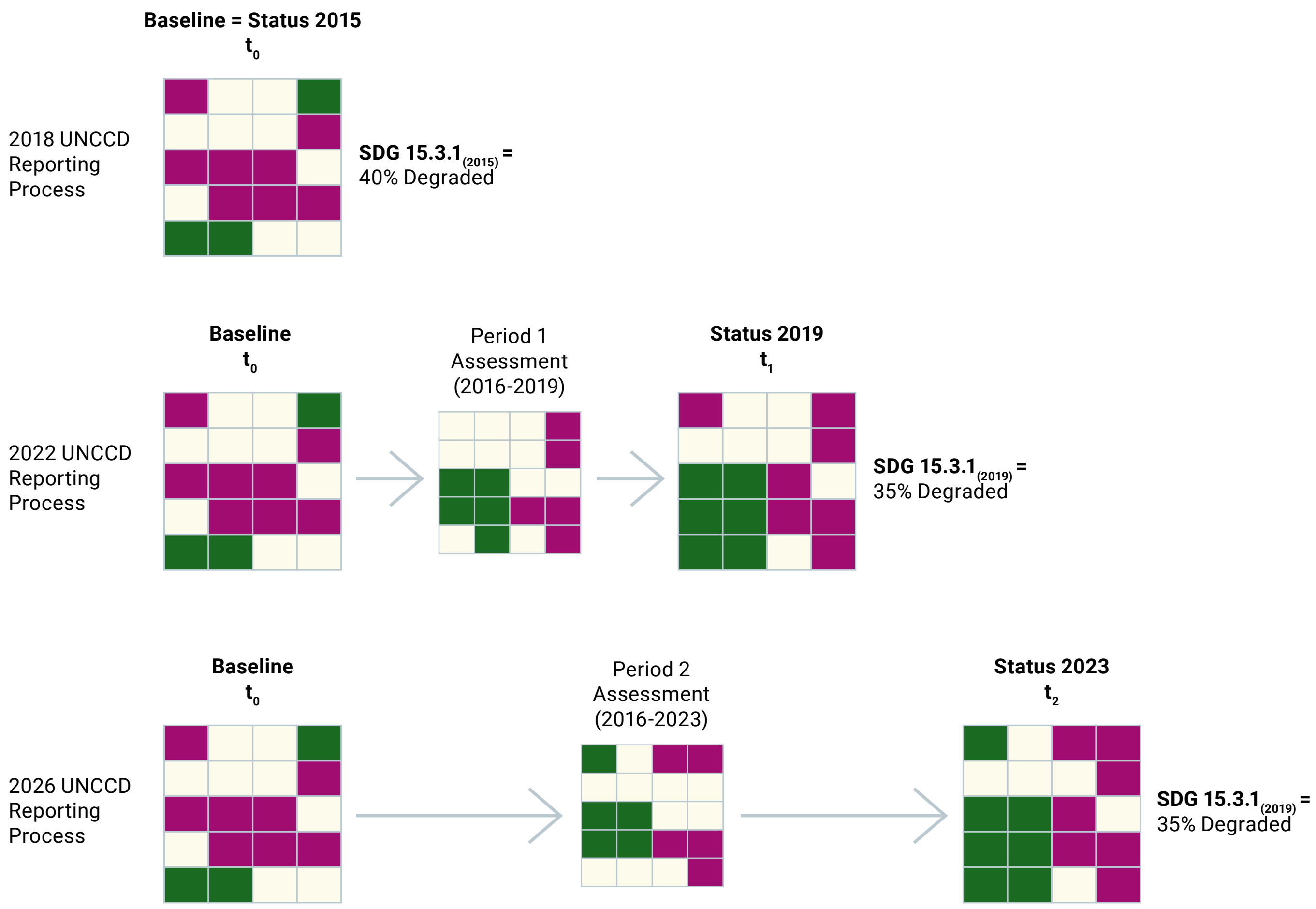
The reporting process for SDG Indicator 15.3.1 requires tracking changes in land degradation every four years. At the time of publication of this addendum, countries have submitted their estimates for SDG Indicator 15.3.1 twice: once for the baseline period (t_0: 2000–2015) in 2018 and once for the first 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 Sustainable Development Goals Report, including its Extended Report, and the UNSD Global SDG Indicators 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, it is recommended that countries recalculate and resubmit all baseline and Period 1 estimates for strategic objective 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 analyse 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.

Figure 1.5
Status maps showing land condition over three reporting periods: the baseline period (t_0), Period 1 ((t_1; 2016–2019) and Period 2 (t_2; 2016–2023).

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 square kilometres (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 1.5 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).



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.

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.

Period	Degraded Area SDG Indicator 15.3.1	
	(km²)	(%)
t_0	8	40
t_1	7	35
t_2	7	35
t_n	...	...

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 SDG 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).

$$\Delta D_n = ((D_{tn} - D_{t0}) / A_{t0}) \times 100$$

(Eq. 1)

Where,

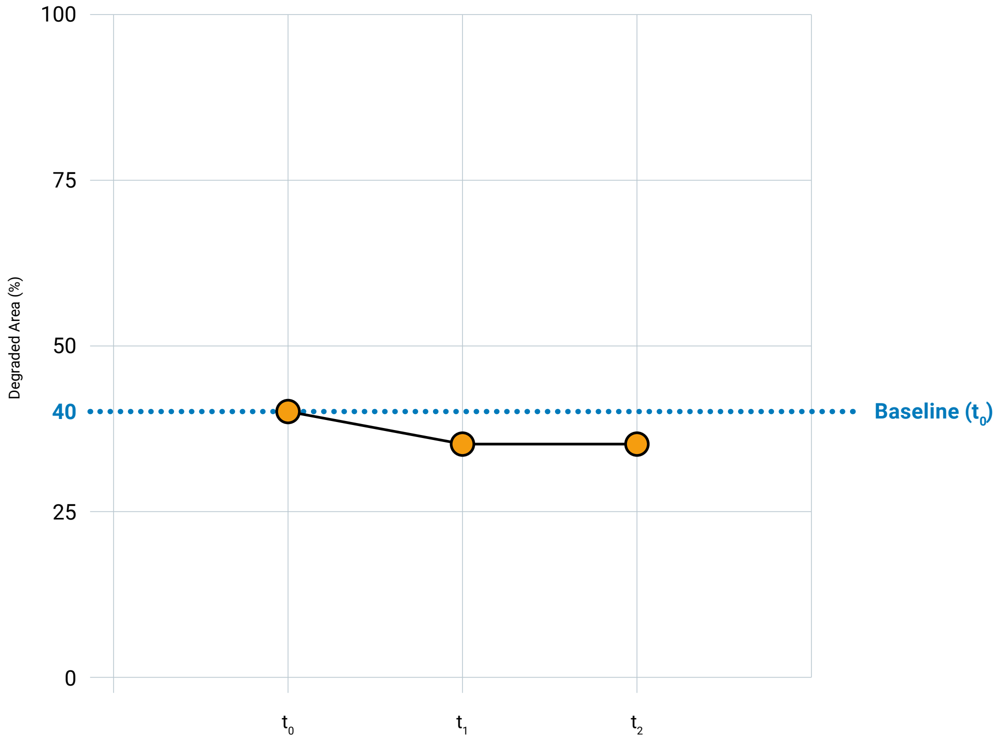
- ΔD_n is the percentage change in the area of degraded land from the baseline period t_0 to the most recent reporting period tn, relative to the total land area at baseline.
- D_{tn} is the area of degraded land in the most recent reporting period.
- D_{t0} is the area of degraded land in the baseline period.
- A_{t0} is the total land area at the baseline.

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 (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 indicates an increase in the extent of degraded land compared to the baseline period, which is undesirable as it shows increased degradation. In all these calculations, the land area being assessed is assumed to remain constant (e.g. if the area compared between n and 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.

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 km² and percentage points, following the estimations presented in table 1.7.

Period	ΔD	
	(km²)	(%)
t_1	-1	-5
t_2	-1	-5
t_n	…	…

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.



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 (see figure 1.6).

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, which discusses methodologies for spatially explicit analyses.

Monitoring changes in SDG Indicator 15.3.1 does not equate to monitoring progress towards LDN. SDG Indicator 15.3.1 offers a simplified framework, focusing on the three sub-indicators, for assessing changes in the proportion of land degradation. 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

SECTION 2
Tracking progress towards land degradation neutrality

In the context of global efforts to achieve the SDGs, particularly SDG Target 15.3 aimed at achieving LDN, 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 GPG 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 and experts in tracking the balance between degradation and improvements in land condition spatially over time to monitor progress towards their national LDN commitments and for planning interventions to achieve LDN.

In this context it is essential to differentiate between SDG Indicator 15.3.1 (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 counter-balancing 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 3x3 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.

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 (see 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 (see 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).

Each type of change represented in the expanded version of the status matrix (see table 2.1) is detailed below. The table captures the nine possible combinations in the 3x3 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, persistent or baseline improvement or degradation. This classification into seven categories helps in understanding whether the observed changes represent new developments that have occurred during the current assessment period or not.

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).

		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*

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 the 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 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 for implementing 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, more time might be needed to detect improvement in the indicators.

Stable to stable = Stability (S)

- **Change description**: Areas that have consistently remained stable since 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 the implementation of sustainable land management (SLM) 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)

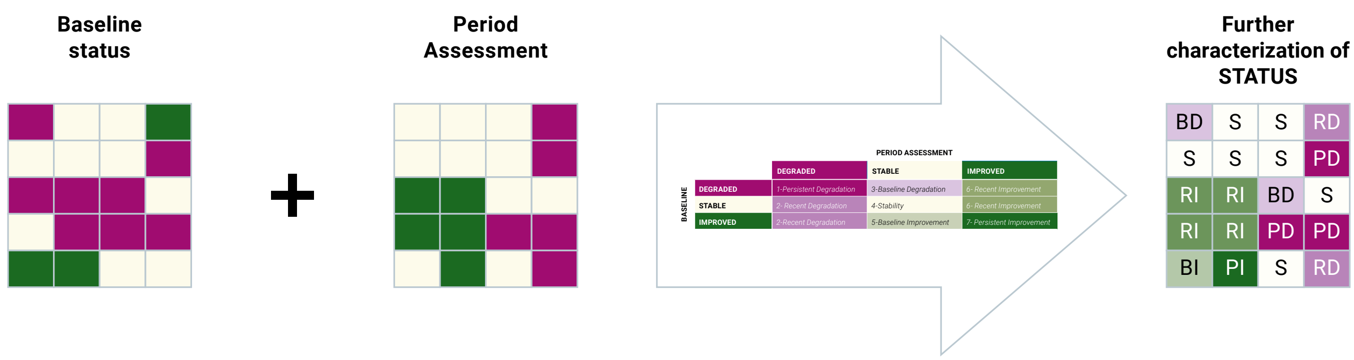
- **Change description**: Areas that were stable during the baseline assessment but have recently shown improvement in land condition.
- **Interpretation**: There has been a positive change and natural capital has been gained. This could be the result of the successful implementation of SLM practices 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 (see figure 2.1). Using the expanded status matrix (see table 2.1), the area's land condition has been analysed 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 baseline degradation (BD), as well as 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 per cent. During the reporting period, 5 pixels experienced degradation processes, while 5 pixels showed improvement. By analysing 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, thus the final SDG 15.3.1 is 35 per cent. Out of these 7 degraded pixels, 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 analysis shows that though some areas have improved, recent degradation has affected a significant proportion of the land.

Figure 2.1
Example of further characterization of land degradation and land improvement.



The further characterization of land degradation and land improvement 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).

BOX 2.1

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

The monitoring of LDN is focused on neutrality, that is ensuring that a 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.

2.2.1 SDG 15.3.1 and 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 Indicator 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, for counterbalancing, only the degradation and improvements that have occurred since the baseline should be taken into account to assess whether neutrality has been achieved.

2.2.2 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

9 Orr et al., 2017.

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 include ecosystem type maps.[11] Countries can utilize their own national data to define land types more accurately across different scales.

Planning allows for anticipation of future natural capital losses and the implementation of targeted actions to balance these losses with planned gains. This is why integrated land use planning is regarded as the mechanism to achieve LDN.[12]

2.2.3 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 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 to the baseline. Table 2.2 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.

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 The Group on Earth Observations is currently developing a Global Ecosystems Atlas, which will integrate high-quality global, regional and national ecosystem maps into a single, accessible online resource.

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. UNCCD, Bonn, Germany.

Table 2.2
Categories of land condition according to the expanded status characterization and their usage for the estimation of SDG Indicator 15.3.1 (binary classification) and for counter-balancing (gains and losses of natural capital).

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	x
PERSISTENT IMPROVEMENT	Not-degraded	✓ (GAIN)
RECENT IMPROVEMENT	Not-degraded	✓ (GAIN)
BASELINE IMPROVEMENT	Not-degraded	x
STABILITY	Not-degraded	x

2.2.4 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 the GPG and section 1 of this addendum)

After defining the baseline, subsequent assessments are conducted at each assessment 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 assessment period, the area is classified as degraded.

STEP 3. Expanded status matrix to calculate new status

The new status of the land after the reporting period is determined using the expanded status matrix to compare the baseline and period assessment (see table 2.1). 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:

$$\Delta_{LDN}^{i} = \mathrm{A}_{gains}^{i} - A_{losses}^{i}$$

(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 persistent 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 $\Delta_{LDN}^{i} = 0$, there is no net loss, meaning LDN has been achieved for that land type.
- If $\Delta_{LDN}^{i} > 0$, there has been a net gain of natural capital, and LDN has not only been achieved but exceeded for that land type.
- If $\Delta_{LDN}^{i} < 0$, 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 for all land types. This means:

$$\forall_i, \Delta_{LDN}^{type} \geq 0$$

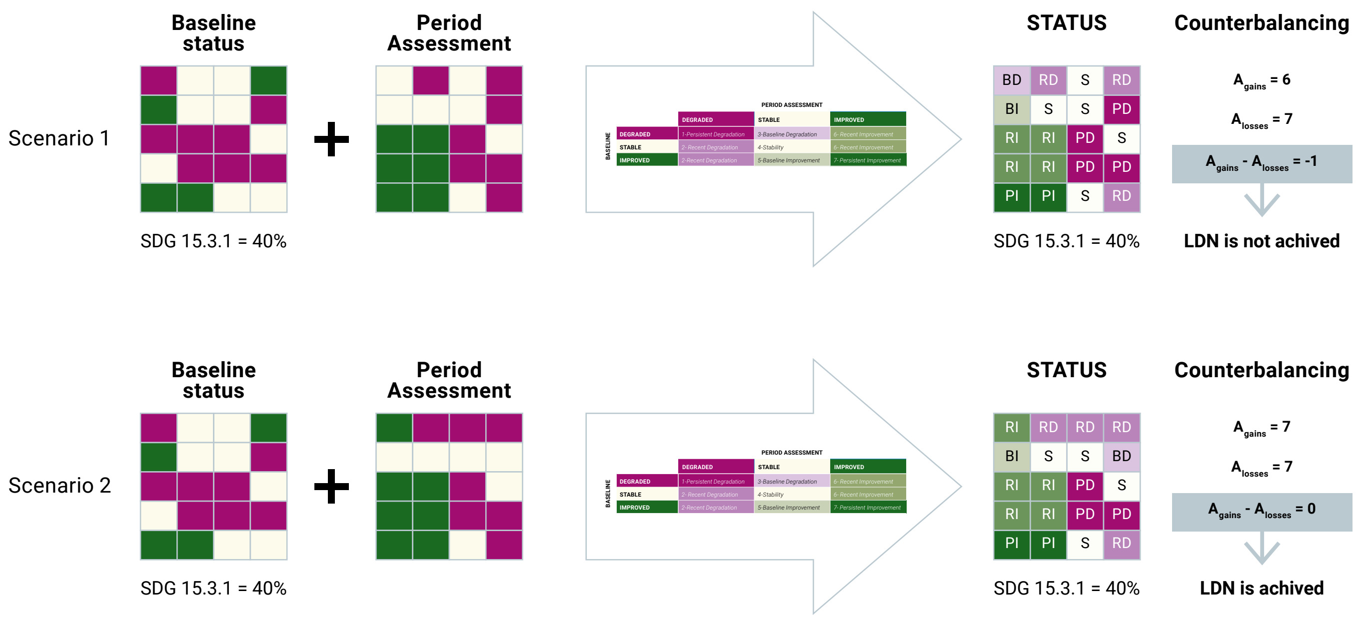
(Eq. 3)

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

Figure 2.2 shows an example 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% of degraded 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 per cent, since 40 per cent of the total land area is degraded at baseline.

In the first scenario, degradation occurs in 7 pixels (7 km²) during the reporting period, 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 per cent degradation. However, 7 of these degraded pixels correspond to recent degradation, while only 1 pixel corresponds to baseline 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 baseline improvement. 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 –1 km². This negative value indicates that LDN was not achieved. Although the SDG Indicator 15.3.1 remained constant at 40 per cent 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 per cent, just as it was in the first scenario. However, 7 pixels correspond to recent degradation, and 1 pixel remains as baseline 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 (i.e. 7 km² of gains minus 7 km² of losses), the result is 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 per cent. 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. In this framework, the intensity of land degradation and land improvement is not explicitly measured. Therefore, it is assumed to remain constant across time and space. While this assumption simplifies the analysis, it does not fully reflect real-world variability in the magnitude or rate of degradation and recovery processes. A more detailed assessment of intensity would require additional data and methodological refinements.

3

SECTION

SECTION 3
Enhancements of datasets and methodologies

This section focuses on strengthening datasets and methodologies to improve the selection of the most suitable data products across different contexts. It presents newly available global datasets on land cover, land productivity and SOC, along with country experiences in comparing and identifying the most representative options. Furthermore, it showcases workflows developed by national experts that enhance data verification and accuracy through the use of cloud computing, interactive web applications for dataset comparison, and subnational approaches to estimate sub-indicators. Building on the methodological framework outlined in GPG Version 2, this section also provides updated insights from the 2022 reporting process, incorporating innovative datasets, tools, and lessons learned from practical implementation.

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 LPD, such as those developed by the Joint Research Center (JRC) of the European Commission, Conservation International (CI) and the Food and Agriculture Organization of the United Nations (FAO)-WOCAT, 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.

3.1 Enhancements for assessing trends in land cover

To assess changes in land cover under the LDN framework,[13] 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 Version 2 (titled "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 appendix to GPG Version 2, 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.

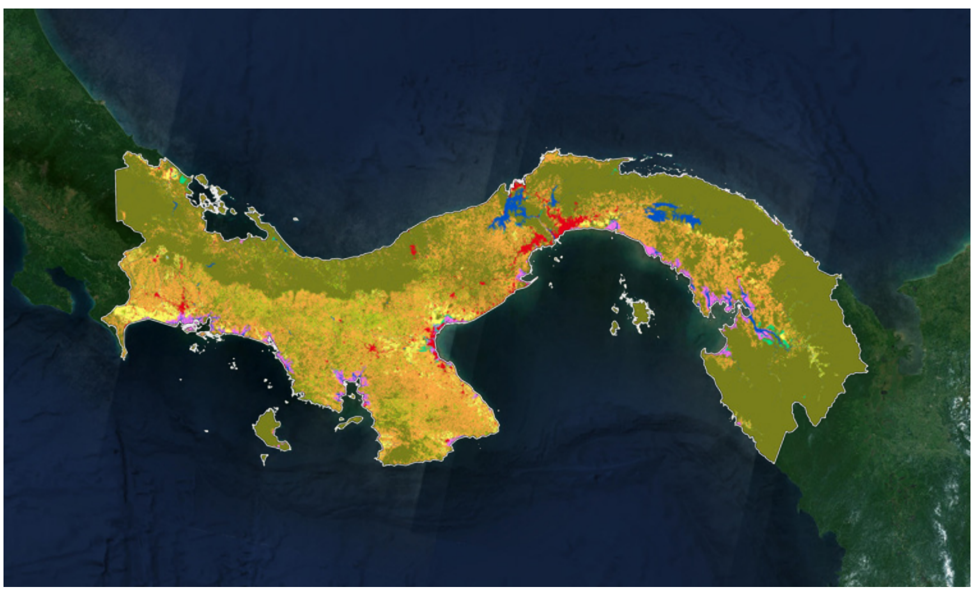
13 Orr, B.J., A.L. Cowie, V.M. Castillo Sanchez, P. Chasek, N.D. Crossman, A. Erlewein, G. Louwagie, M. Maron, G.I. Metternicht, S. Minelli, A.E. Tengberg, S. Walter and S. Welton. 2017. Scientific Conceptual Framework for Land Degradation Neutrality. A Report of the Science-Policy Interface. UNCCD, Bonn, Germany.

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 the Land Cover Legend Registry[14] may support this process. Another challenge when not using global default datasets 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 (see figure 3.1), as detailed in a recent publication showcasing country experiences with reporting on land degradation and drought.[15] 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.

Figure 3.1
Panama land cover map used for the 2022 reporting cycle with a legend containing nine classes.



Using a national land cover map series, Panama added two additional classes (mangrove and thicket) to the default legend that are important to capture information on national land degradation processes.
The national border displayed on this map was provided by the Government of Panama

Source: Panama 2022 National Report to the UNCCD, licenced under CC BY-NC 2.0.

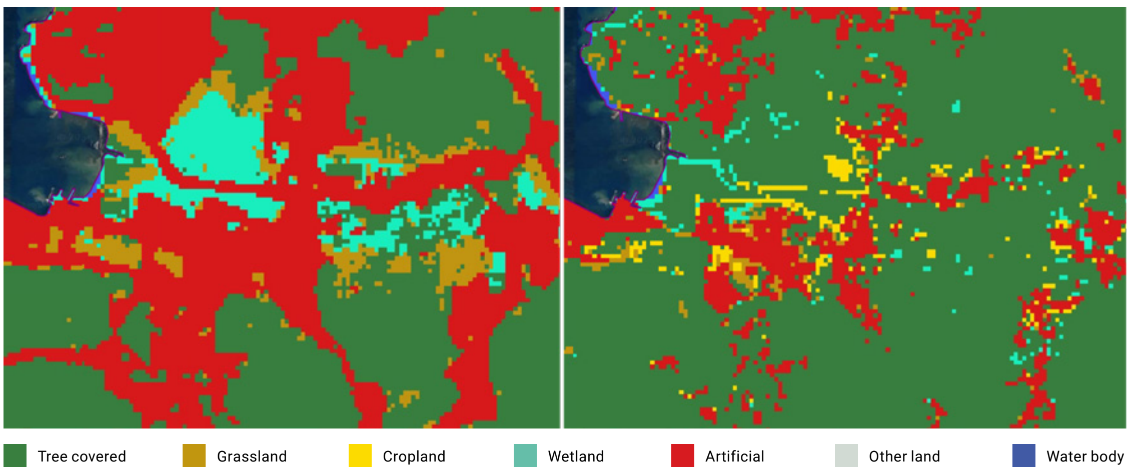
14 Mushtaq, F., Di Gregorio, A., Tchana, E., Ghosh, A., Jalal, R., O'Brien, D., Mosca, N., Tefera, M. & Henry, M. 2023. Land Cover Legend Registry (LCLR) – Functionalities and legend preparation. User guide. Rome, FAO.

15 UNCCD and WOCAT, 2024. The Land Story. Country experiences with reporting on land degradation and drought. UNCCD, Bonn, Germany; WOCAT and CDE, University of Bern, Switzerland.

In cases where national datasets are unavailable, regional datasets can be more representative than global datasets. For instance, Coordination of Information on the Environment (CORINE) Land Cover maps, which are freely accessible with 100m 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 (CLC) maps would yield more accurate results than ESA CCI. Given the available years, Türkiye used the 2000 and 2012 CLC maps for the baseline period (2000–2015) and the 2012 and 2018 CLC 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 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 datasets[16] (available for 2000, 2005, 2010, 2015 and 2020) and the Global Land Cover – Fine Classification System at 30-meter resolution with Dynamics (GLC_FCS30D)[17] product (available every five years from 1985 to 2000, and then annually up to 2022). Both products have a 30m spatial resolution. All global datasets exhibit differences in the 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 (see figure 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.[18]

Figure 3.2
Screenshot of Global Land Analysis and Discovery (GLAD) (left) and GLC_FCS30D (right) of the same area (south of Castries, Saint Lucia), showing considerable differences, especially in urban and peri-urban areas.



Source: Land Cover Comparison Tool for SIDS (https://apacheta.projects.earthengine.app/view/compare-lct-sids, Apacheta and the Partnership Initiative for Sustainable Land Management (PISLM) 2025). Licensed under CC BY 4.0 by Apacheta and PISLM.

16 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.

17 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.

18 García, C. L., Pozzi Tay, E. F., Raviolo, E., Paredes-Trejo, F., Francis, R. and 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.

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 the FAO-WOCAT Applications for Land Cover Comparison,[19] can facilitate this process by enabling users to compare datasets, analyse 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,[20] was developed (Apacheta and the Partnership Initiative for Sustainable Land Management (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 that are suitable for SDG Indicator 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.

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

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 (GLAD) Land Cover	University of Maryland	Landsat 5, 7, and 8 scenes	Global	30 m	11 classes	2000, 2005, 2010, 2015 and 2020
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

19 wocat.net/en/ldn/wocatapps.

20 García, C. L., Pozzi Tay, E. F., Raviolo, E., Paredes-Trejo, F., Francis, R. and 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.

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 on this step is covered comprehensively in the GPG Version 2. 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 (see box 3.1).

The default UNCCD land cover legend comprising seven broad land cover classes: tree-covered areas, grasslands, croplands, artificial surfaces, 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 2022 UNCCD reporting process.[21] 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 socioeconomic 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 a 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 seven-class legend described above 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 included 36 classes but was reclassified into the seven UNCCD default categories for aggregate reporting. However, these 36 land cover classes can be reclassified differently to capture key land degradation processes at the national level. This approach was also taken by some countries during the UNCCD 2022 reporting process. For example, Bhutan and Bosnia and Herzegovina[22] 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 and grasslands. 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 the ESA CCI dataset (see 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 (see table 3.3).

21 UNCCD and WOCAT, 2024. The Land Story. Country experiences with reporting on land degradation and drought. UNCCD, Bonn, Germany; WOCAT and CDE, University of Bern, Switzerland.

22 UNCCD and WOCAT, 2024. The Land Story. Country experiences with reporting on land degradation and drought. UNCCD, Bonn, Germany; WOCAT and CDE, University of Bern, Switzerland.

Table 3.2
Bhutan's reclassifications of ESA CCI land cover classes.

Original			Default	BTN	Workshop
ID		Colour	ID Category	ID Category	ID BTN
0	No Data				
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, needleleared, 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, needleleared, 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 Bare land	7 Bare land	6 Bare land
201	Consolidated bare areas		6 Bare land	7 Bare land	6 Bare land
202	Unconsolidated bare areas		6 Bare land	7 Bare land	6 Bare land
210	Waterbodies		7 Waterbody	8 Waterbody	7 Waterbody
220	Permanent snow and ice		6 Bare Land	7 Bare Land	6 Bare Land

Three alternative reclassifications are shown: (1) Default reclassification into 7 UNCCD classes; (2) classification into 8 classes, differentiating shrublands; and (3) a 7-class reclassification including shrublands but merging wetlands with water bodies, which was agreed during the participatory workshop. Source: FAO E-learning course: Using land cover information to monitor progress on SDG 15 (UNCCD and FAO, 2024).

Table 3.3
Bosnia and Herzegovina's reclassifications of ESA CCI Land Cover classes to differentiate maquis (shrublands) and its correspondence to the 7 UNCCD default classes.

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 post-flooding		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 (15-40%)		Forest
	Tree cover, needleleaved, evergreen, closed to open (>15%)		Forest
	Tree cover, needleleaved, evergreen, closed (>40%)		Forest
	Tree cover, needleleaved, evergreen, open (15-40%)		Forest
	Tree cover, needleleaved, deciduous, closed to open (>15%)		Forest
	Tree cover, needleleaved, deciduous, closed (>40%)		Forest
	Tree cover, needleleaved, deciduous, open (15-40%)		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	Waterbody	Waterbody
	Permanent snow and ice		

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 Sustainable Development Goal 15

In 2024 the United Nations Convention to Combat Desertification, the Group on Earth Observations Land Degradation Neutrality Flagship, the Deutsche Gesellschaft für Internationale Zusammenarbeit (GIZ) and the Food and Agriculture Organization of the United Nations developed an e-learning course, in collaboration with other partners such as the World Overview of Conservation Approaches and Technologies and the Centre for Development and Environment, 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 SDG Indicators 15.3.1 (Proportion of land that is degraded over total land area) and 15.4.2 (including its sub-indicators: Mountain Green Cover Index and Proportion of degraded mountain land).

It is free, open to all and can be accessed here.[23]

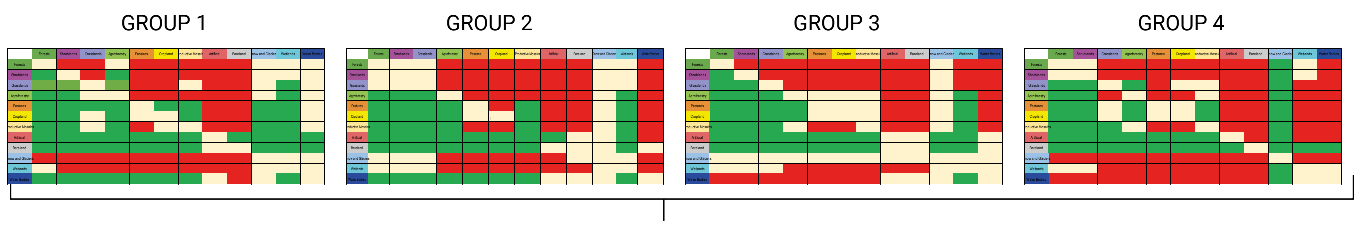
23 https://elearning.fao.org/course/view.php?id=1098.

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.*

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, socioeconomic, 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,[24] as exemplified by the páramo ecosystem in Colombia. National land cover maps that 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.[25] On the other hand, in humid lowland regions, experts generally viewed the conversion of grasslands to forests as a positive trend (see figure 3.3).



	Forests	Shrublands	Grasslands	Agroforestry	Pastures	Cropland	Artificial	Prodoctive Mosaics	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

Source: FAO E-learning course: Using land cover information to monitor progress on SDG 15 (UNCCD and FAO, 2024).

24 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.

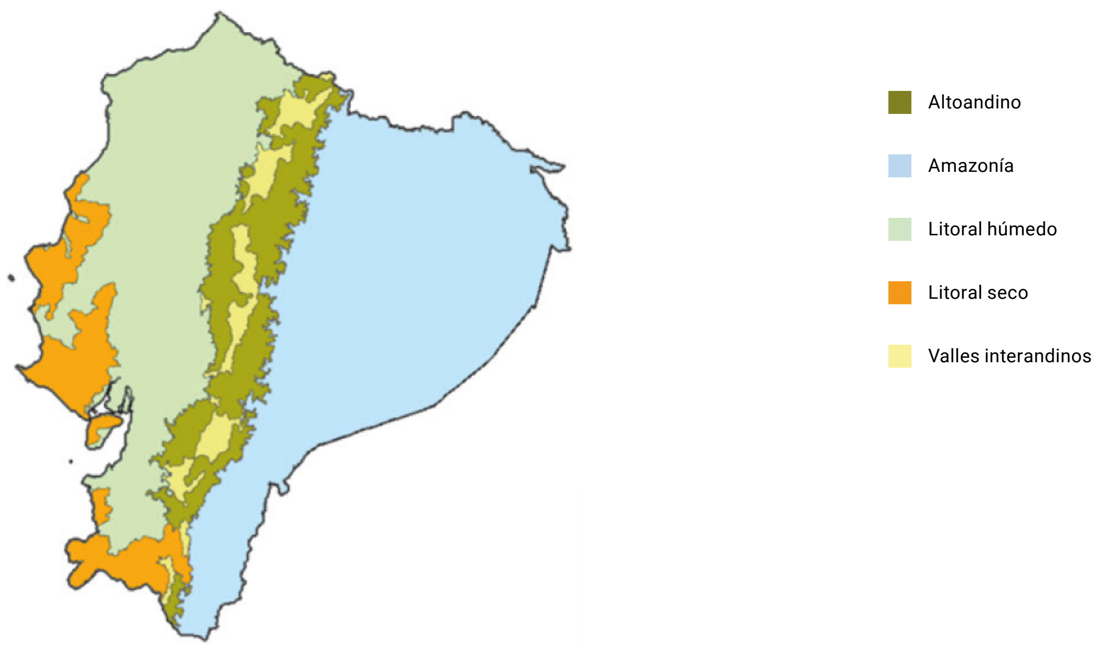
25 Murad, C.A., Pearse, J. and Huguet, C. Multitemporal monitoring of páramos as critical water sources in Central Colombia. Sci Rep 14, 16706 (2024). https://doi.org/10.1038/s41598-024-67563-z.

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 the estimation of SDG Indicator 15.3.1. 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 socioeconomic 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 (see figure 3.4).[26] The proposed zoning included:

- *Litoral seco*: Areas with ustic or aridic moisture regimes;
- *Litoral húmedo*: Evergreen forests from the west Andean montane forests to the Pacific coast;
- *Altoandino*: Glaciers, páramos and high altitude ecosystems (nival and subnival bioclimatic zones);
- *Valles interandinos*: Inter-Andean valley ecosystems, excluding the *altoandino* and *litoral seco*;
- *Amazonía*: Evergreen forests from the Andean Montane East to the Amazon basin.

Figure 3.4
Ecuador's subnational stratification for the estimation of SDG Indicator 15.3.1.



Source: CONDESAN and WOCAT, 2025.[27]

26 García C. L., Teich I., Metzler E. and Peralvo M., 2025. Colaboración entre WOCAT y CONDESAN para el monitoreo nacional de la degradación de la tierra en Ecuador 2023-2025. Reporte técnico final. WOCAT y CDE, Universidad de Berna, Suiza; CONDESAN, Quito, Ecuador. https://wocat.net/documents/1411/NDT_Ecuador_WOCAT_CONDESAN.pdf.

27 García C. L., Teich I., Metzler E. and Peralvo M., 2025. Colaboración entre WOCAT y CONDESAN para el monitoreo nacional de la degradación de la tierra en Ecuador 2023-2025. Reporte técnico final. WOCAT y CDE, Universidad de Berna, Suiza; CONDESAN, Quito, Ecuador. https://wocat.net/documents/1411/NDT_Ecuador_WOCAT_CONDESAN.pdf.

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 socioeconomic 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 assessments of land cover trends, 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 Version 2 and further elaborates on a workflow to obtain a representative map of trends in land productivity. As in the GPG Version 2, land productivity refers to the biological productive capacity of the land: the principal source of the food, fibre 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 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 LPD crucial for mapping land degradation, estimating SDG Indicator 15.3.1 and tracking progress towards LDN.

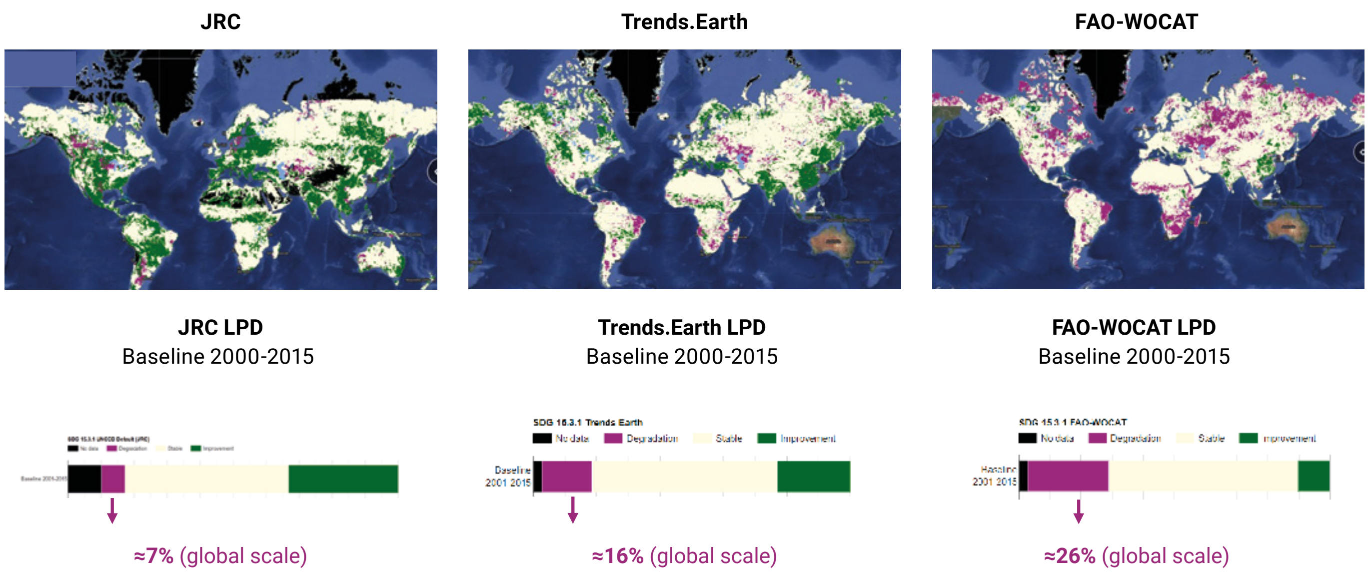
In this context, the concept of land productivity should not be confused with agricultural productivity. Agricultural productivity refers to the output of agricultural products, such as crops per unit of input (such as land, labour or fertilizer). In contrast, trends in land productivity aims to identify 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 kilogram (kg)/hectare (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 LPD (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 Version 2.

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. and 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.

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 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 algorithms 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 the comparison of these datasets and the selection by countries of the most suitable datasets for reporting SDG Indicator 15.3.1, an interactive application[33] was developed by CI, FAO and WOCAT under the Global Environment Facility-funded global Tools4LDN Project (see 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. A new updated version of this tool is under development for the 2026 reporting process,[34] for which 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 the extent of land degradation for the baseline period using different LPD maps.



Source: Tools4LDN LPD product comparison: (https://maps.tools4ldn.org/) (CI, WOCAT and FAO, 2022). Licensed under CC BY 4.0.

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.
32 https://docs.trends.earth/en/latest/for_users/downloads/index.html.
33 Tools4LDN LPD product comparison: https://maps.tools4ldn.org/ (CI, WOCAT and FAO, 2022).
34 https://apacheta.projects.earthengine.app/view/compare-sdg. (Ed note: Website did not work 3/11)

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 analyse this time series and generate the LPD map). For example, the FAO-WOCAT LPD algorithm can be applied on either a Landsat-derived Normalized Difference Vegetation Index (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 algorithms (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 a 30m resolution NDVI time series and LPD maps for SIDS, such as the ones developed by the by International Research Center of Big Data for Sustainable Development Goals (CBAS)[35] and PISLM-CI-Apacheta.[36] 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 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.

35 Xiaosong Li and Tong Shen. Land Productivity Dynamics Product of Small Island Developing States (30 meters Resolution), CBAS. Big Earth Data Center, CAS, 2025. DOI: https://doi.org/10.12237/casearth.686dc91f24e15709b381ae4e. (Ed note: Website did not work 3/11)

36 García, C. L., Raviolo, E., Francis, R., Maharaj, T., Zvoleff, A., Antunes Daldegan, G.,Pozzi Tay, E. F., Paredes-Trejo, F., Noon, M. and 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.

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. Section 1 of this addendum, particularly table 1.3, describe the initial and final years to assess changes in land productivity for each reporting period. These periods are defined to be 16 years, in concordance with the moving window described in GPG Version 2. However, this sub-indicator can be used to assess land degradation for other purposes besides 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 NDVI, the Enhanced Vegetation Index (EVI) and the 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 other things. 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 infrared normalized difference band math that can be obtained from most optical sensors like MODIS data at a 250m spatial resolution or from Landsat data at a 30m resolution. Selecting a VI 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 VI 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.[37] For example, for regions with dense plant canopies and high biomass, EVI and Enhanced Vegetation Index 2 (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.

In areas where vegetation cover is sparse, such as hyperarid 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, 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 VIs 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.

37 Antunes Daldegan, G., Noon, M., Zvoleff, A. and 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.

Table 3.4
Summary of main vegetation indices used to assess land productivity trends.

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.

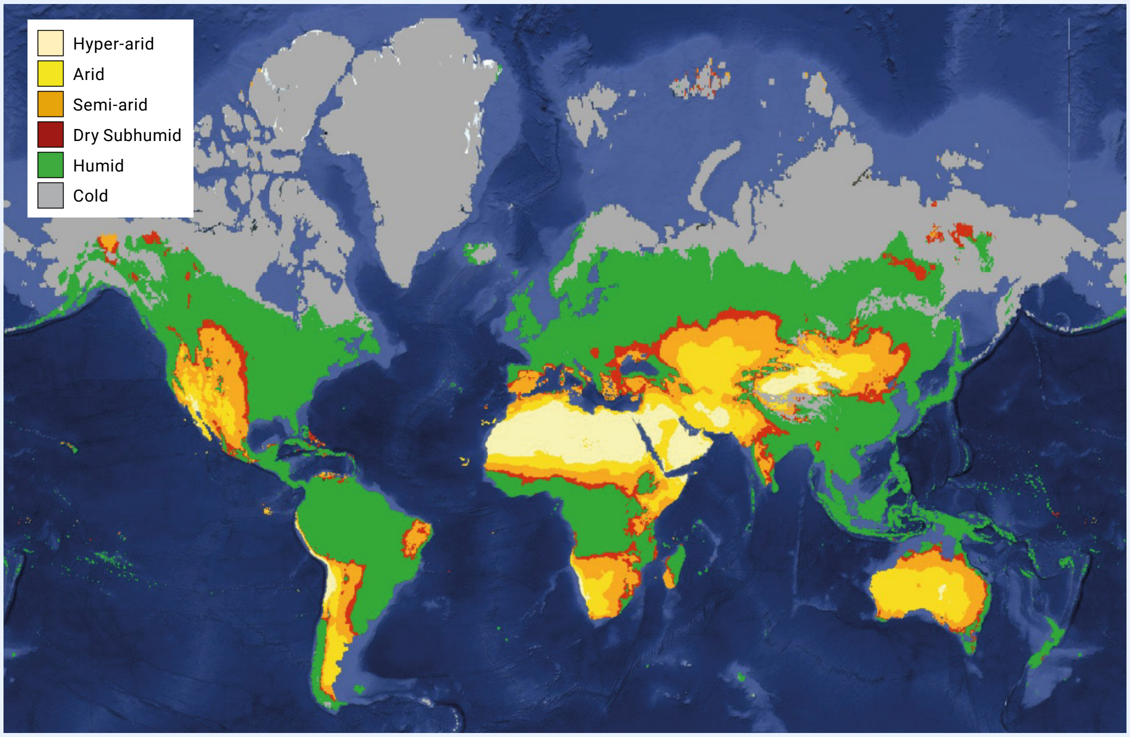
Source: Review by the Tools4LDN project https://doi.org/10.5281/zenodo.4162290, licensed under CC BY 4.0 by Conservation International.

BOX 3.2

Global efforts to enhance the assessment of land productivity trends in hyperarid areas

Hyperarid regions cover nearly 10% of the global land area (see figure B3.2), with approximately 30 United Nations Convention to Combat Desertification (UNCCD) member countries having land classified as hyperarid. 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 sub-indicator "Trends in land productivity", as low vegetation cover in hyperarid 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 land productivity dynamics (LPD) datasets often lack data on these regions or classify them as "stable" or "no data", significantly impacting national reporting on land degradation to the UNCCD and global Sustainable Development Goal Indicator 15.3.1 assessments. The inability to accurately assess land productivity trends in hyperarid zones hampers efforts to identify degradation hotspots, prioritize land-based interventions, mobilize resources and monitor the impact of restoration efforts.

Fig B3.2.
Global aridity index map for 2000–2024. The areas considered to be hyperarid account for about 9 per cent of the global land area.



Source: produced by C.L. Garcia (Apacheta 2025)[38] using the TerraClimate dataset.[39]. Licensed under CC BY 4.0.

38 https://code.earthengine.google.com/2db1f27ab2df447f4b4466f9ea46729e.
39 Abatzoglou, J.T., S.Z. Dobrowski, S.A. Parks and 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

To address this issue, Saudi Arabia's Ministry of Environment, Water and Agriculture of Saudi Arabia and National Center for Vegetation Cover Development (NCVC) convened an international workshop on 26–28 August 2024, bringing together leading experts to discuss key challenges in monitoring LPD in hyperarid environments and identify practical steps toward improving methodologies. These discussions led to the identification of four key pathways to address this challenge:

1. Stocktaking of alternative and innovative solutions for hyperarid 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 hyperarid 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 vegetation indices, such as the soil-adjusted vegetation index (SAVI) or soil-adjusted total vegetation index (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 hyperarid zones through improved ground-based data collection is essential for validating satellite-derived results.

3. Promoting a user-centred 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.

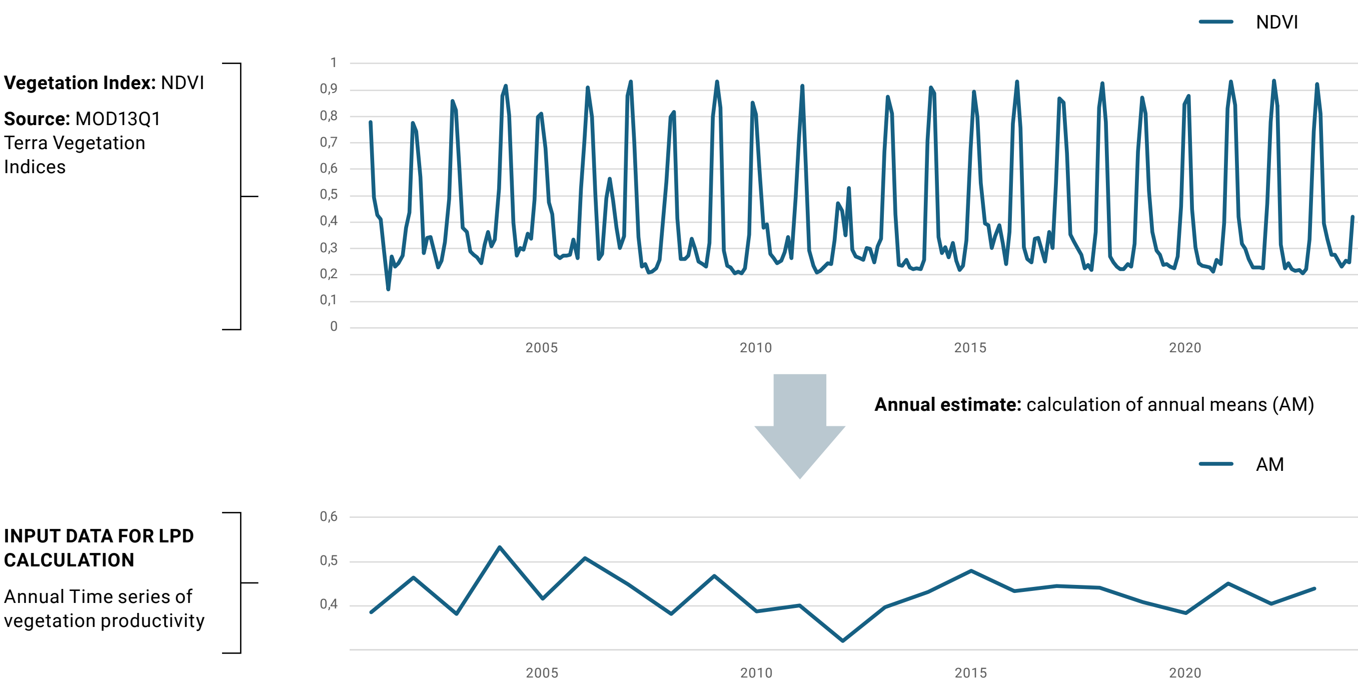
4. Building institutional partnerships and a community of practice. Addressing LPD challenges in hyperarid regions requires sustained collaboration. The workshop facilitated discussions among international organizations and universities on leveraging expertise and developing structured institutional 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 VI and 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 analyse actual long-term changes in LPD. 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.

Figure 3.6 shows an example of the process for obtaining an LPD input dataset (for one area/pixel) by estimating annual averages. In this example, NDVI was selected as the VI and the satellite data source is the MOD13Q1 Terra Vegetation Indices,[40] which provide 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 and used as an annual productivity proxy and LPD input dataset.

Fig. 3.6
Example of the process to obtain an LPD input dataset (for one area/pixel) from a Normalized Difference Vegetation Index time series derived from MODIS for the period 2001–2021.



40 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.

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 AM. 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 analyse trends or combined to create new indices. For example, the Ecosystem Services Productivity Index (ESPI)[41] integrates both the NDVI AM and the intra-annual CV.[42] While the ESPI does not directly measure ecosystem services, it helps differentiate land cover types with similar annual NDVI values, such as croplands and pastures.[43] Croplands typically exhibit higher intra-annual variability than pastures, resulting in lower ESPI values.

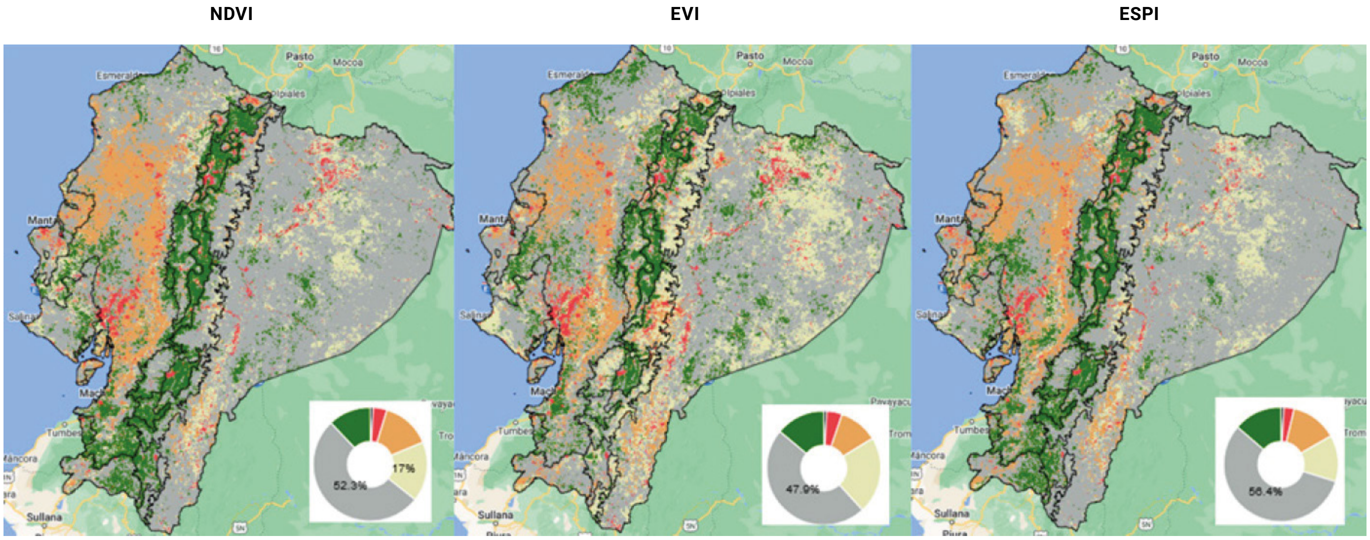
While NDVI remains the most widely used vegetation index due to its advantages, alternative indices may offer better sensitivity in specific environments. This is particularly relevant for ecologically diverse countries, where subnational stratification may be necessary to account for extreme biomass variation. In such cases, using different vegetation indices (e.g. EVI or SAVI) for different subregions can improve the accuracy of land productivity assessments and provide a more detailed understanding of LPD. 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 on Ecuador, figure 3.7 presents three LPD maps generated from time series of the 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.[44] For instance, in the humid littoral zone, the EVI and ESPI-based maps more accurately reflected known areas of degradation and restoration.

41 Paruelo, J.M.; Texeira, M.; Staiano, L.; Mastrángelo, M.; Amdan, L.; and 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.

42 ESPI = AM * (1 – CV).

43 Teich, I.; Gonzalez Roglich, M.; Corso, M.L.; and 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.

44 García C. L., Teich I., Metzler E., Peralvo M., 2025. Colaboración entre WOCAT y CONDESAN para el monitoreo nacional de la degradación de la tierra en Ecuador 2023-2025. Reporte técnico final. WOCAT y CDE, Universidad de Berna, Suiza; CONDESAN, Quito, Ecuador.



Source: WOCAT and CONDESAN 2025, licensed by CC BY 4.0 by WOCAT and CONDESAN.

Figure 3.7
LPD maps for the period 2000–2024 using different input LPD datasets (NDVI, EVI and ESPI annual means).

An overview of key ready-to-use VI datasets available from various satellite missions, including Landsat, MODIS, Visible Infrared Imaging Radiometer Suite (VIIRS), and Copernicus, is provided in table 3.5. 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 other VIs can be calculated at different time steps.

As the MODIS instruments aboard the United States of America's National Aeronautics and Space Administration (NASA) 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 VIs vegetation indices, is critical. MODIS has served as the default source for 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 VIIRS, onboard the Joint Polar Satellite System platforms operated by NASA and the National Oceanic and Atmospheric Administration (NOAA) of the United States. VIIRS offers similar observational capabilities and will continue the legacy of MODIS with compatible spatial and temporal resolutions. While VIIRS does not provide the EVI, a key MODIS-based metric, it supports alternative vegetation indices that can be used to sustain long-term LPD assessments. VIIRS instruments aboard the Suomi Polar-orbiting Partnership satellite, NOAA-20, and NOAA-21 will extend the Earth observation record, and platforms such as NASA's Global Imagery Browse Services and Worldview are working to ensure the continuity and accessibility of comparable visualization products. Although the loss of MODIS's morning overpass (Terra) introduces a temporal observation gap, the 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.

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
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[45]	NDVI	30m	2000-2023	Annually

Table 3.5
Global Vegetation Index Datasets

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

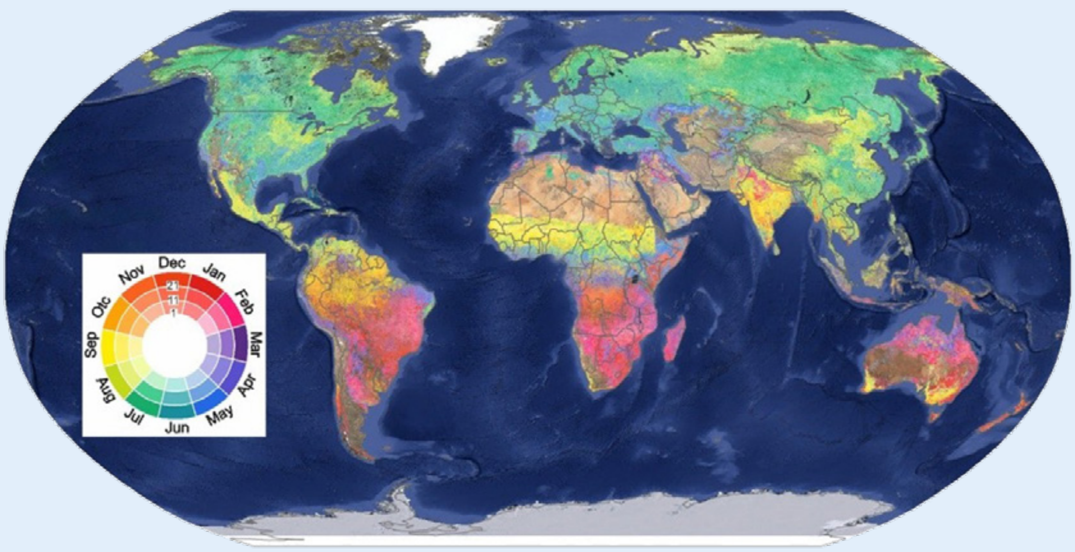
BOX 3.3

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/Ocean and Land Colour Instrument (OLCI) imagery. While this dataset currently cannot be used directly for monitoring Sustainable Development Goal (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.

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.

Figure B3.3:
Global map of the date of the peak of growing season (season maximum date).



Source: Global Land Surface Phenology 2023 — Copernicus Land Monitoring Service

3.2.2 The LPD algorithm: parametrizing and estimating LPD models

As previously noted, once the LPD input dataset is prepared, it must be analysed 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 Trends.Earth. The methodology is based on the approach proposed for the World Atlas of Desertification (WAD),[46] developed by the 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 Trends.Earth. In addition, FAO and WOCAT developed an alternative approach that leverages strength from both the JRC and Trends.Earth algorithms. For the 2022 reporting cycle, these three main LPD algorithms (JRC, Trends.Earth and FAO-WOCAT) were used globally to assess LPD.

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 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,[47] but also with higher-resolution 30-meter Landsat data.[48] 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.[49] 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 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 LPD algorithm

The JRC LPD algorithm[50] 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), both the baseline and the first reporting period (2004–2019) were estimated for the 2022 reporting process. 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.

46 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].

47 Paredes-Trejo, F.; Barbosa, H.A.; Daldegan, G.A.; Teich, I.; García, C.L.; Kumar, T.V.L.; and 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.

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

49 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.

50 https://doi.org/10.1016/j.ecolind.2021.108386.

The methodology for generating the JRC LPD dataset was originally developed and implemented in R as part of the LPDynR package, which is available on GitHub.[51] Recently, JRC translated this methodology into Python to align it with broader data science practices and support the increased accessibility and scalability of the toolset.

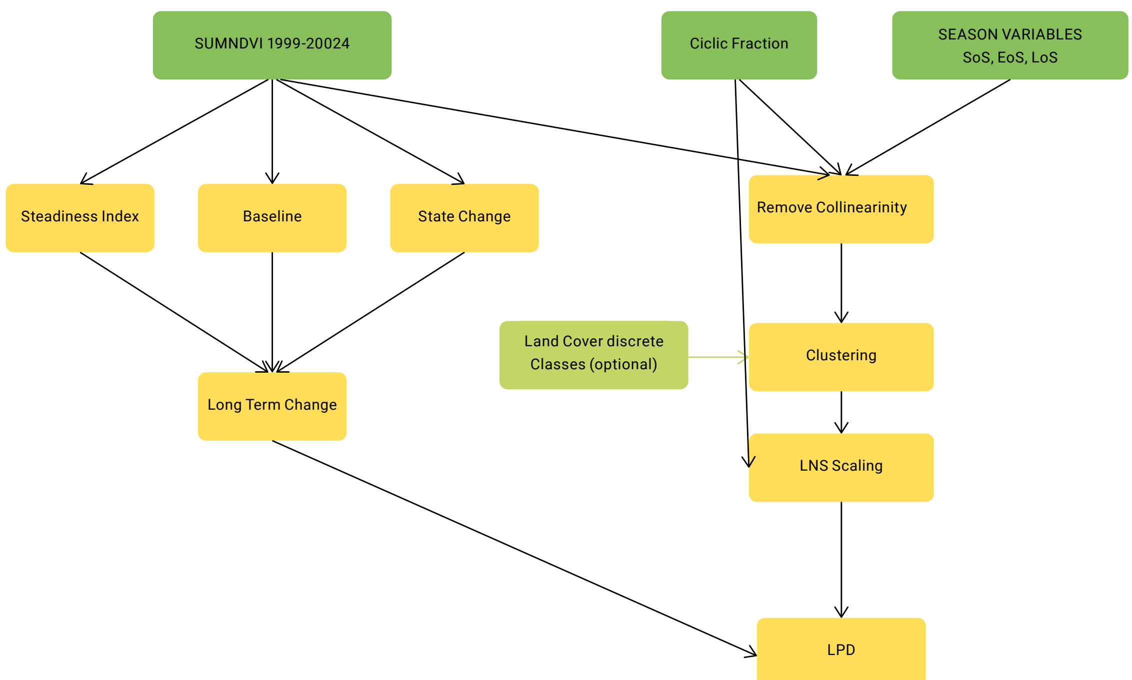
The JRC LPD indicator is constructed by integrating two main components: the long-term change map and the current status map (see figure 3.8). The long-term change map integrates three types of information: the steadiness index (tendency of change), the baseline productivity level (starting condition) and the change in productivity state (shift in condition over time). While the ong-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. This helps identify areas that may show positive trends but are still underperforming relative to their ecological potential.

The steadiness index (4 classes), the baseline level (3 classes) and the state change (3 classes) are combined to generate the long-term change map. 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.

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

Figure 3.8
JRC LPD processing workflow.



Source: JRC.

51 https://github.com/xavi-rp/LPDynR.

For the **baseline productivity level**, each pixel's productivity at the start of the time series (e.g. 2000–2002) is classified as 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).

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). The tool uses clustering algorithms to group 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 EFT 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 per cent 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 productivity 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 and conservation efforts, and standardized reporting under international sustainability frameworks such as UNCCD's LDN initiative and SDG Indicator 15.3.1.

Parametrization of the 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 per cent in drylands at global level), while *highprodProp* defines the threshold for high productivity (commonly set at 10 per cent). 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 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

The Trends.Earth LPD algorithm closely aligns with the methodology outlined in GPG Version 2. 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; if positive, they are considered potential improvements, and if negative, they 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 (see box 3.4).

BOX 3.4

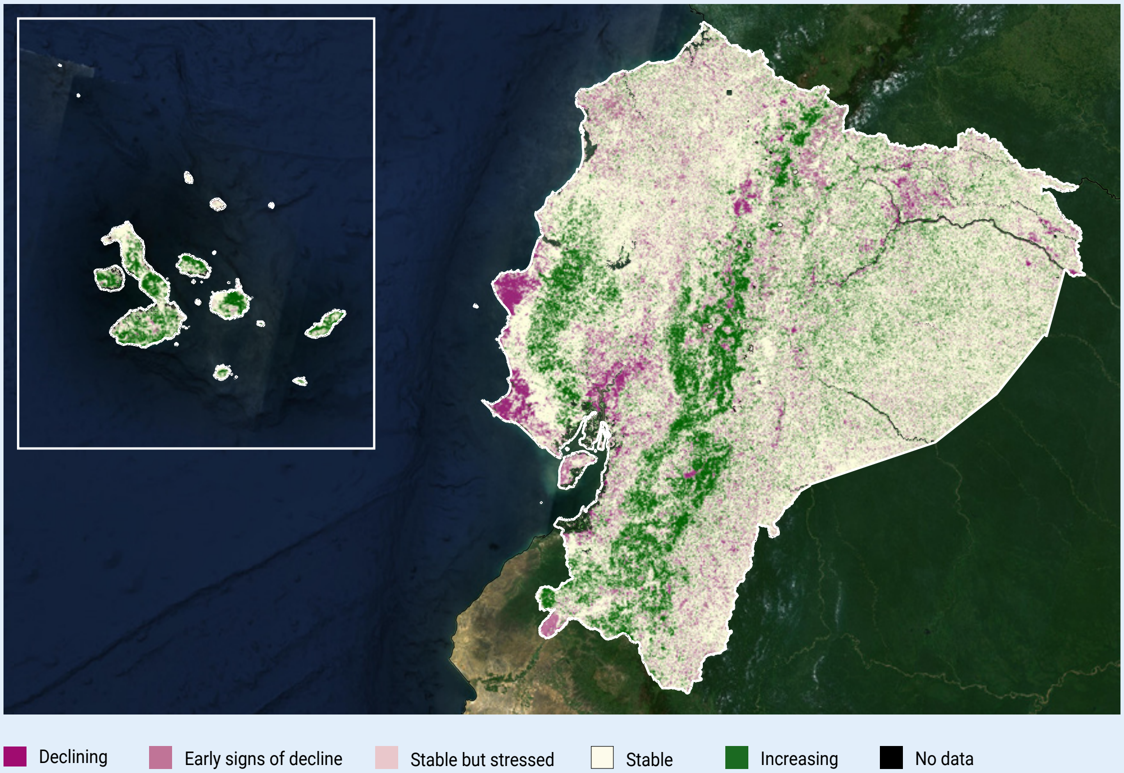
Applying climate correction to land productivity dynamics using Trends.Earth

For the 2022 reporting process, Ecuador applied a climate correction to the land productivity dynamics (LPD) 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 (RESTREND) method.

The results of this method are very sensitive to the specific precipitation dataset adopted as well as 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 B3.4
Ecuador LPD 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, licensed 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 three 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 suggests potential improvement.
- Small changes suggest 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 300m resolution and soil taxonomy units provided by SoilGrids at 250m resolution using the United States Department of Agriculture (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 five LPD classes. The GPG Version 2 introduced the possibility of combining these metrics in different ways (see table 4.5 in the GPG Version 2 document). 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 3.9 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.

Figure 3.9
Recommended aggregation of productivity metrics into five land productivity dynamics classes and three land productivity degradation classes.

Aggregating Land Productivity metrics

Trend	State	Performance	5 Classes	3 Classes
Improving	Improving	Stable	Increasing	Improving
Improving	Improving	Degrading	Increasing	Improving
Improving	Stable	Stable	Increasing	Improving
Improving	Stable	Degrading	Increasing	Improving
Improving	Degrading	Stable	Increasing	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	Stable but stressed	Stable
Stable	Degrading	Stable	Moderate Decline	Degrading
Stable	Degrading	Degrading	Declining	Degrading
Degrading	Improving	Stable	Declining	Degrading
Degrading	Improving	Degrading	Declining	Degrading
Degrading	Stable	Stable	Declining	Degrading
Degrading	Stable	Degrading	Declining	Degrading
Degrading	Degrading	Stable	Declining	Degrading
Degrading	Degrading	Degrading	Declining	Degrading

Source: Trends.Earth User Guide,[52] licensed under CC BY 4.0 by Conservation International (https://creativecommons.org/licenses/by/4.0).

FAO-WOCAT LPD algorithm

Both FAO and WOCAT have played a fundamental role in supporting numerous countries in their efforts to implement the UNCCD, particularly through the execution of Global Environment Facility projects related to SLM and 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 Land Degradation Neutrality in Europe and Central Asia[53] developed by FAO. In response to these challenges, WOCAT 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 (data should be findable, accessible, interoperable, and reusable), and easy accessibility, was developed as a Google Earth Engine (GEE) code[54] and integrates concepts from the Trends.Earth methodology as well as the JRC algorithm. The development process emphasized

52 https://docs.trends.earth/en/latest/for_users/index.html.
53 FAO. 2022. Overview of Land Degradation Neutrality (LDN) in Europe and Central Asia. Rome. https://doi.org/10.4060/cb7986en.
54 Garcia, C. L., and Teich, I. (2022). FAO-WOCAT Land Productivity Dynamics Indicator. Zenodo. https://doi.org/10.5281/zenodo.10849367.

co-creation with countries, leveraging previous efforts and lessons learned to ensure the approach effectively addresses the identified challenges.

A second version of the FAO-WOCAT LPD algorithm is the latest version of the code, which was expanded to accommodate a larger variety of input datasets derived from MODIS at 250m or Landsat at 30m. It has been tested with diverse VIs, such as NDVI, EVI, EVI2, SAVI and ESPI. It also allows for (i) the use of different annual integration methods, including filters to remove clouds/outliers (moving windows with median, maximum and spatiotemporal Savitzky-Golay filters); and (ii) climate decoupling using different Earth observation products and analysis. The algorithm evaluates land productivity using three metrics: steadiness, state, and initial biomass. Additional parameters were added in version 2 of the FAO-WOCAT LPD that allow for the better calibration of local conditions and the biological meaning of the results. A description of each metric is presented below:

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 a multi-temporal image differencing analysis modified to include a threshold). 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 quantile jumps (set as ±2 by default) grouped into the following 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 in high/low ranges of NDVI, extra parameters can be used: a threshold in terms of absolute NDVI change (e.g. NDVI <0.05 can be interpreted as stable); and a threshold in terms of percentage changes (e.g. changes < 10% can be interpreted as stable).

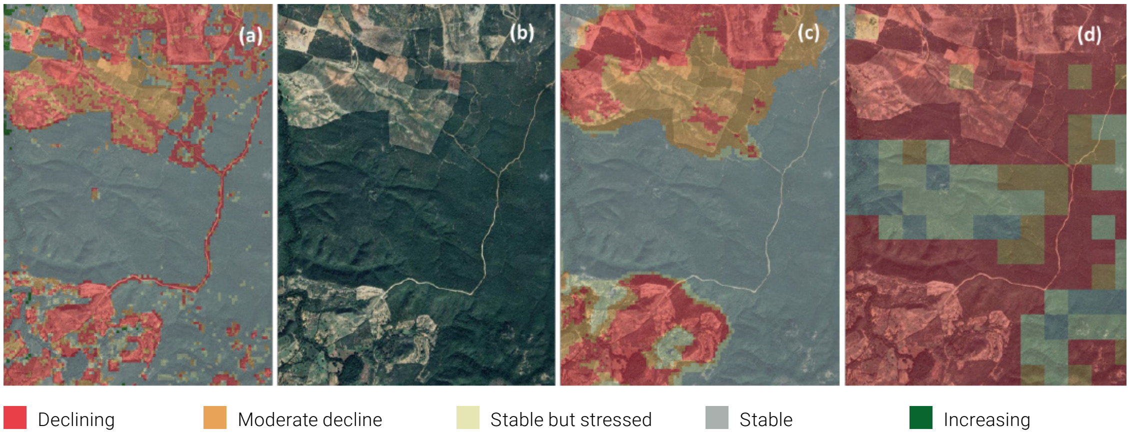
Initial biomass is a simple metric to reflect the baseline capacity of an ecosystem to support life and sustain productivity. It describes the average NDVI level at the beginning of the monitored time window (e.g. first three years). It is usually divided into three categories: low, medium and high. 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 (see Table 3.6).

Table. 3.6
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 categories.

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		Increasing			

Fig. 3.10
Comparison of land productivity dynamics outputs generated using the FAO-WOCAT algorithm with different NDVI time series and spatial resolutions for the same area.



(a) Mixed Landsat 30m (pure Landsat) product; (b) High-resolution imagery; (c) HiLPD (MODIS–Landsat fusion at 30m); and (d) MODIS 250m resolution.

Users can explore a range of parametrizations with the FAO-WOCAT LPD v2 algorithm, from maps showing broad land degradation/improvement to maps customized for priority areas. 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 the International Research Center of Big Data for Sustainable Development Goals (CBAS),[55] Apacheta, PISLM and CI[56] (see figure 3.10).

These three main LPD algorithms and the variations in how they are parameterized can lead to significantly different results in the characterization of LPD. Such variability underscores the importance of context-specific analysis and highlights the need for the 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.

55 Xiaosong Li and Tong Shen. Land Productivity Dynamics Product of Small Island Developing States (30m resolution), CBAS. Big Earth Data Center, CAS, 2025. DOI: https://doi.org/10.12237/casearth.686dc91f24e15709b381ae4e.

56 García, C. L., Raviolo, E., Francis, R., Maharaj, T., Zvoleff, A., Antunes Daldegan, G.,Pozzi Tay, E. F., Paredes-Trejo, F., Noon, M. and 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.

3.2.3 Verifying results and selecting the most representative LPD dataset

LPD maps are typically generated by a multi-annual time series analysis of VIs derived from satellite data. As discussed in previous sections, as any indicator, the resulting LPD 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 on 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 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 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.

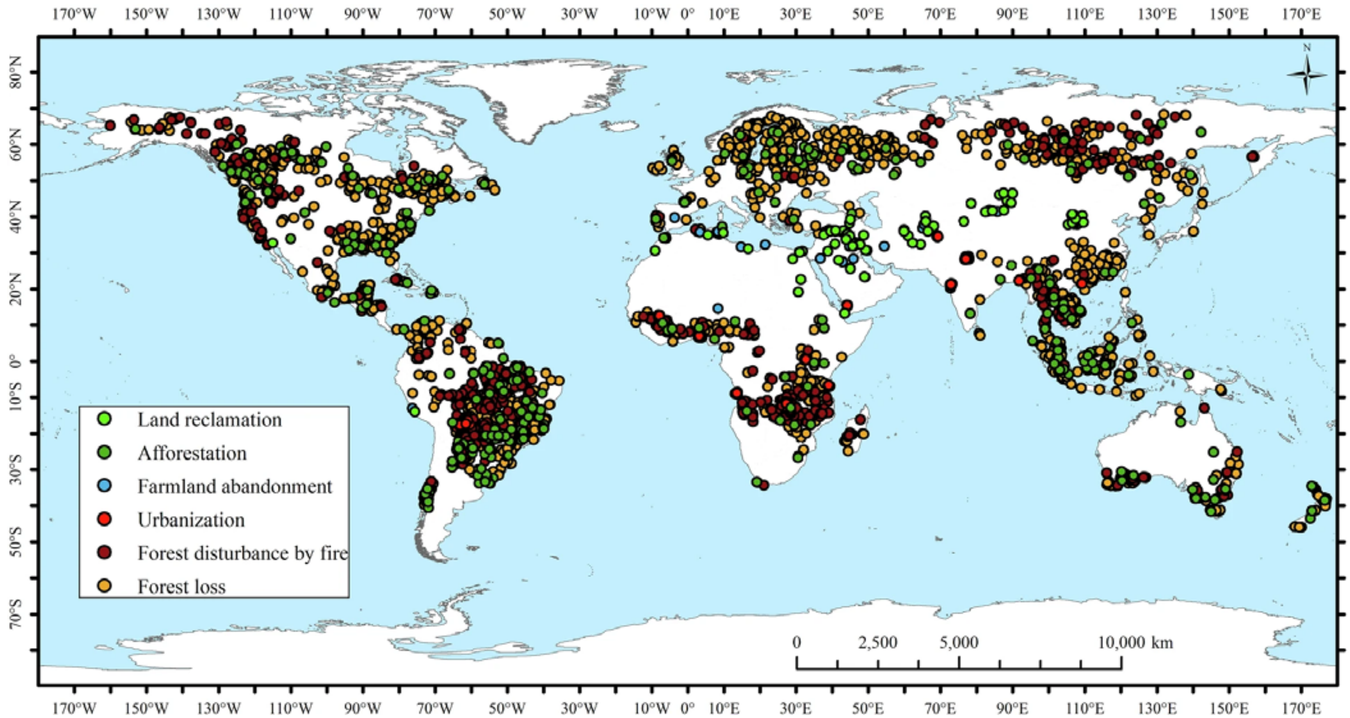
In order to determine whether LPD maps are accurately detecting improvements and declines in productivity in areas where restoration activities or degradation processes have occurred, additional datasets can be used. These can be polygon or point datasets representing locations that have experienced 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.[57] 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 scale: Argentina used a national dataset produced by the country's Management Unit of the Forest Assessment System 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 per cent of forest cover was lost). The ability of different LPD maps to represent declining trends in Argentina was compared using such a dataset.[58] The results indicated that different LPD models performed differently for different regions and vegetation types. In temperate grasslands and shrublands (*espinal*) and subtropical moist forests (*paraná* forests), models using the ESPI time series were more effective in detecting declining productivity due to deforestation.

57 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.

58 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.



Source: Li et al., 2025.

Figure 3.11 *Map with the distribution of points used for the validation of a 30m LPD map.*

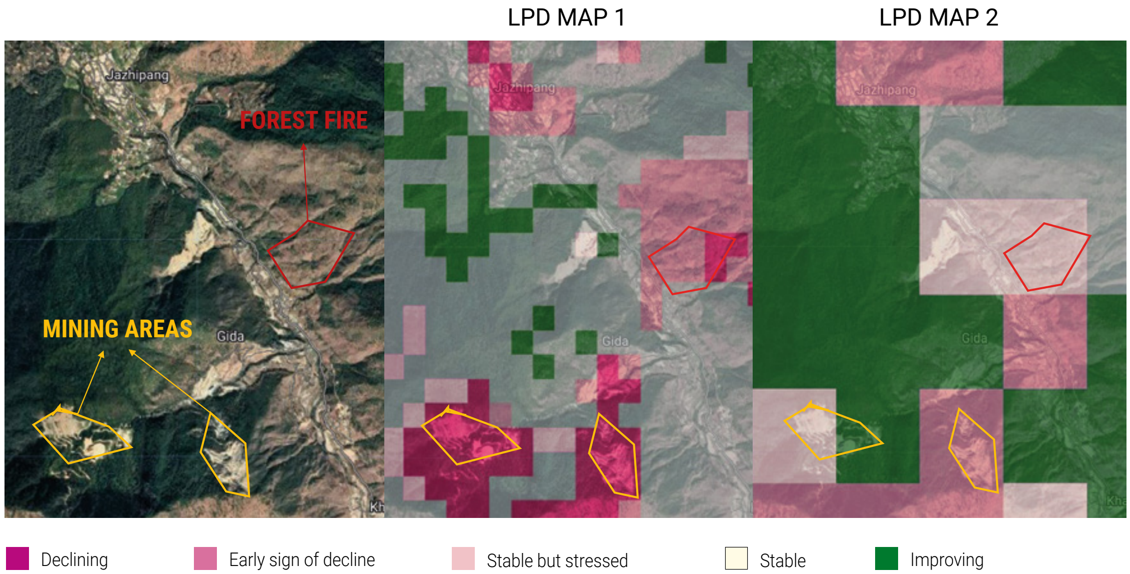
Example at global scale: Land cover datasets were also used to verify a global 30m resolution LPD map.[59] Specific land cover transitions that led to a reduction in land productivity and that occurred during key years at the start and end of the monitoring period were identified. A total of 4,345 sample points were randomly selected globally to represent various land change processes, such as forest loss. For urbanization, urban expansion data[60] was used to assess if the LPD map identified declining land productivity trends in those areas (see figure 3.11). In this case, the LPD map evaluated typical declining productivity processes in more than 80 per cent of these areas.

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.

59 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.

60 City Mayors data: http://citymayors.com/statistics/urban_growth1.html.

Figure 3.12
Impact of Mining in Areas of Bhutan on Local Land Productivity Dynamics. The figure shows the same area; the map on the left shows known areas of forest fires and mining in Bhutan, while the centre and right show 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).

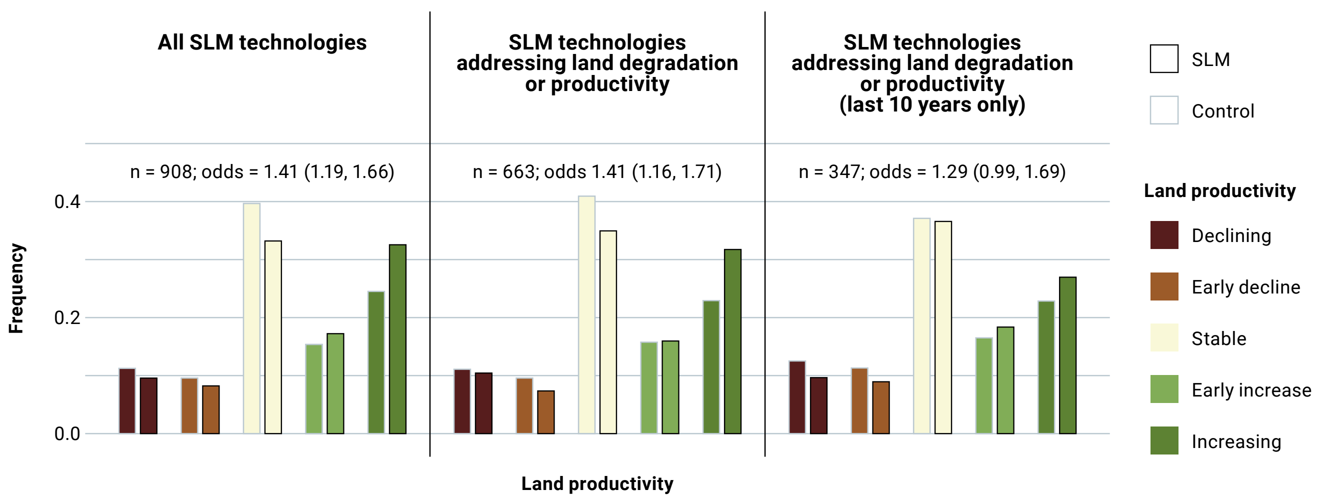
Mining activity data: Mining areas should exhibit declining productivity trends, provided mining activity was ongoing during the LPD monitoring period. For example, Bhutan used mining area datasets to verify LPD maps for national reporting to UNCCD during the 2022 reporting process (see figure 3.12). 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.

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 of the United Nations Decade on Ecosystem Restoration (2021–2030), and to monitor progress towards Target 2 of the Kunming-Montreal Global Biodiversity Framework (Restore 30% of all degraded ecosystems). Different datasets can be used to verify and compare the ability of alternative LPD maps to identify improved areas. Such datasets include:

Restoration and 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 amount of time since the interventions took place. A study conducted at global scale[61] used 1,063 globally distributed SLM technologies from the WOCAT Global SLM database[62] to assess their impact on the sub-indicator for trends in land productivity. The study found that LPD maps detected improvements in areas where SLM was implemented (see figure 3.13). 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.

The Framework for Ecosystem Restoration Monitoring (FERM)[63] 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 United Nations Decade on Ecosystem Restoration (2021–2030), FERM supports countries in reporting restored areas for Kunming-Montreal Global Biodiversity Framework Target 2.

Figure 3.13
Relative frequency of each of five 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.

61 Gonzalez-Roglich, M., Zvoleff, A., Noon, M., Liniger, H., Fleiner, R., Harari, N. and Garcia, C. (2019). Synergizing global tools to monitor progress towards land degradation neutrality: Trends.Earth and WOCAT Global SLM database. *Environmental Science & Policy*, 93, 34–42. https://doi.org/10.1016/j.envsci.2018.12.019.
62 https://qcat.wocat.net/en/wocat/.
63 https://ferm.fao.org/.

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 (see table 3.7).

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 per cent versus 84 per cent). 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 .

Table 3.7
Consistency verification between typical processes of land cover change and a 30m global LPD map.

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	2,589	2,182	84.28%
	LCLUC transition from forest to others			
Forest disturbance by fire	GLC_FCS30D transition from forest to others	652	610	93.56%
	LCLUC transition from forest to others			
	Wildfire occurrences from 2016 to 2022			
Farmland abandonment	GLC_FCS30D transition from cropland to bare land	24	22	91.67%
	LCLUC transition from cropland to bare land			
Urbanization	GLC_FCS30D transition from others to urban	1,080	865	80.09%
	LCLUC transition from others to urban			
Afforestation	GLC_FCS30D transition from others to forest	309	180	58.25%
	LCLUC transition from others to forest			
Land reclamation	GLC_FCS30D transition from bare land to cropland	90	51	56.67 %
	LCLUC transition from bare land to cropland			

Source: Li et al. 2025.[64]

64 Table 3 Consistency verification between typical processes of land cover change and LPD.

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. Global datasets such as the World Database on Protected Areas (WDPA)[65] can be used to support this verification. 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 one is 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 on best practice, such as through the TerraFund for AFR100[66] 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, which serves as a guide to improve SDG Indicator 15.3.1, is presented below and has been successfully implemented by multiple countries. 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 data and expert knowledge; (6) comparing the performance of alternative LPD maps; and (7) selecting the most representative LPD map for national reporting.

65 United Nations Environment Programme's World Conservation Monitoring Centre (UNEP-WCMC) (2021). Protected areas map of the world. Available at: www.protectedplanet.net.

66 https://terramatchsupport.zendesk.com/hc/en-us/articles/23804849298203-Webinar-Training-on-Creating-Sites-on-TerraMatch-Collecting-Geospatial-Polygons.

3.2.4 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 geographic information systems (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 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 (see figure 3.14).

Figure 3.14
Participatory assessment of LPD maps for the estimation of SDG Indicator 15.3.1 in different countries (Kenya, Türkiye, Bhutan and 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.[67] 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.

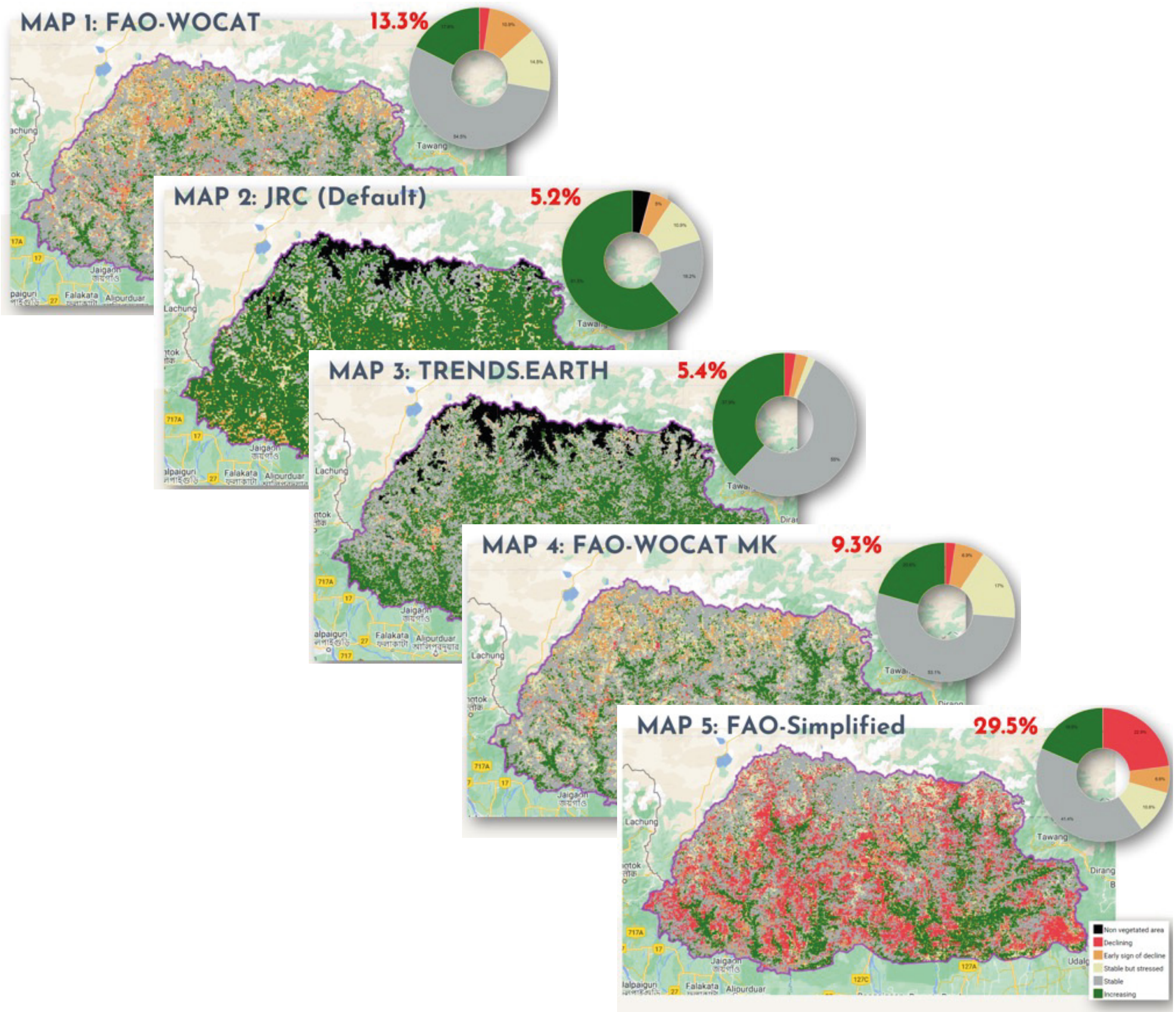
Step 3: Determining the need for a subnational analysis

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 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 sub-indicators, 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 analyse and interpret the results effectively. Two tools for cloud-based real time parametrization were developed to facilitate the parametrization of the FAO-WOCAT LPD (see box 3.5). During the 2022 reporting process, many countries compared five different LPD datasets (see figure 3.15). 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.

67 https://wocat.net/en/wocat-media-library/land-degradation-neutrality-training-materials/.



Source: WOCAT 2023.

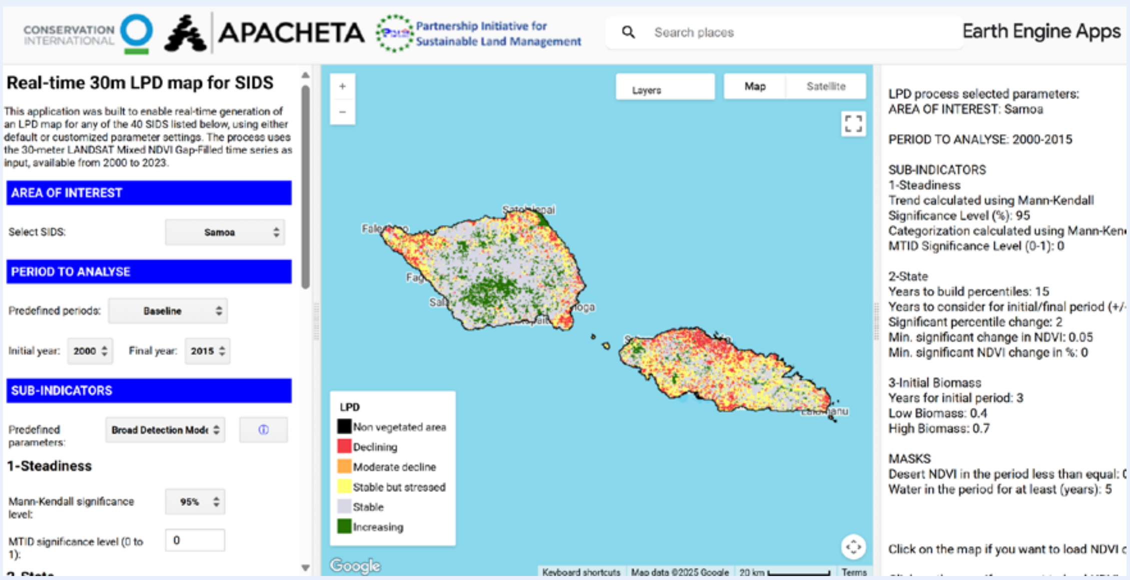
Figure 3.15
Alternative LPD maps compared by experts from Bhutan during the 2022 reporting process.

BOX 3.5

Real Time LPD Application (global and SIDS version)

Given the multitude 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 Real Time LPD App[68] allows users to compute global LPD maps for any period between 2001–2023 with MODIS data (250m resolution; NDVI, EVI and ESPI) as input datasets. Countries can explore different parametrization approaches on the FAO-WOCAT LPD model (version 2), changing the algorithm sensitivity to obtain broad degradation maps or focus on priority areas. Together with Conservation International (CI) and the Partnership Initiative for Sustainable Land Management (PISLM), a high-resolution version for SIDS[69] was developed for 40 SIDS to parametrize and visualize the FAO-WOCAT LPD model (version 2) using the 30m mixed Landsat image NDVI time series as an input dataset.[70]

Fig B3.5
Real-time 30m LPD map for SIDS.



68 https://apacheta.projects.earthengine.app/view/lpd-realtime.
69 https://apacheta.projects.earthengine.app/view/lpd-realtime-sids.
70 García, C. L., Raviolo, E., Francis, R., Maharaj, T., Zvoleff, A., Antunes Daldegan, G.,Pozzi Tay, E. F., Paredes-Trejo, F., Noon, M. and 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.

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 as the FAO-WOCAT LDN Decision Support Systems[71] 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 the FAO-WOCAT LPD comparison apps[72] (see figure 3.16 and box 3.6). 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.[73] In addition, a global LPD comparison app for all UNCCD Parties was developed by CI and Apacheta,[74] facilitating future assessments.

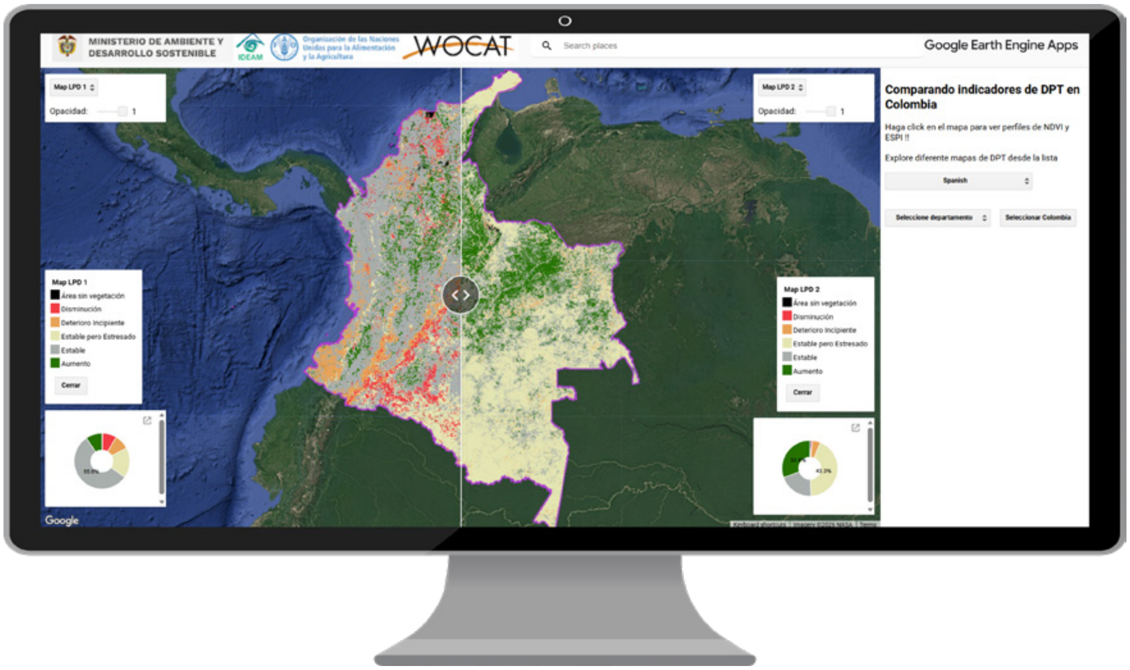
71 Teich, I., Harari, N., Caza, P., Henao-Henao, J.P., Lopez, J.C., Raviolo, E., Díaz-González, A.M., González, H., Bastidas, S., Morales-Opazo, C. and García, C.L. (2023), "An interactive system to map land degradation and inform decision-making to achieve Land Degradation Neutrality via convergence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

72 wocat.net/en/ldn/wocatapps/.

73 https://apacheta.projects.earthengine.app/view/compare-lpd-sids.

74 https://apacheta.projects.earthengine.app/view/compare-lpd.

Figure 3.16
FAO WOCAT LPD comparison app developed and used by Colombia during the 2022 Reporting Process.



Source: WOCAT, 2022.LPD Comparison Tool Colombia

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 3.6

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 pioneered this method at a 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,[75] 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, policy-relevant information to support action towards 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 Version 2, which offers a comprehensive explanation of the approach. As outlined in GPG Version 2 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 IPCC 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 Version 2, 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.

75 Teich, I., N. Harari, P. Caza, et al. 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 & Development 34: 4475–4487. https://doi.org/10.1002/ldr.4645.

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 CI 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:

Establish SOC reference values

Map land cover changes for SOC change estimation

Calculate SOC changes

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 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 centimetres of soil. This map, produced by the International Soil Reference and Information Centre, was developed using approximately 150,000 soil profiles and 158 remote sensing-based soil covariates, analysed 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 3.7). For more details on available SOC datasets and their limitations, refer to section 5 of GPG Version 2.

BOX 3.7

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 in 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 centimetre 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[76] 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.

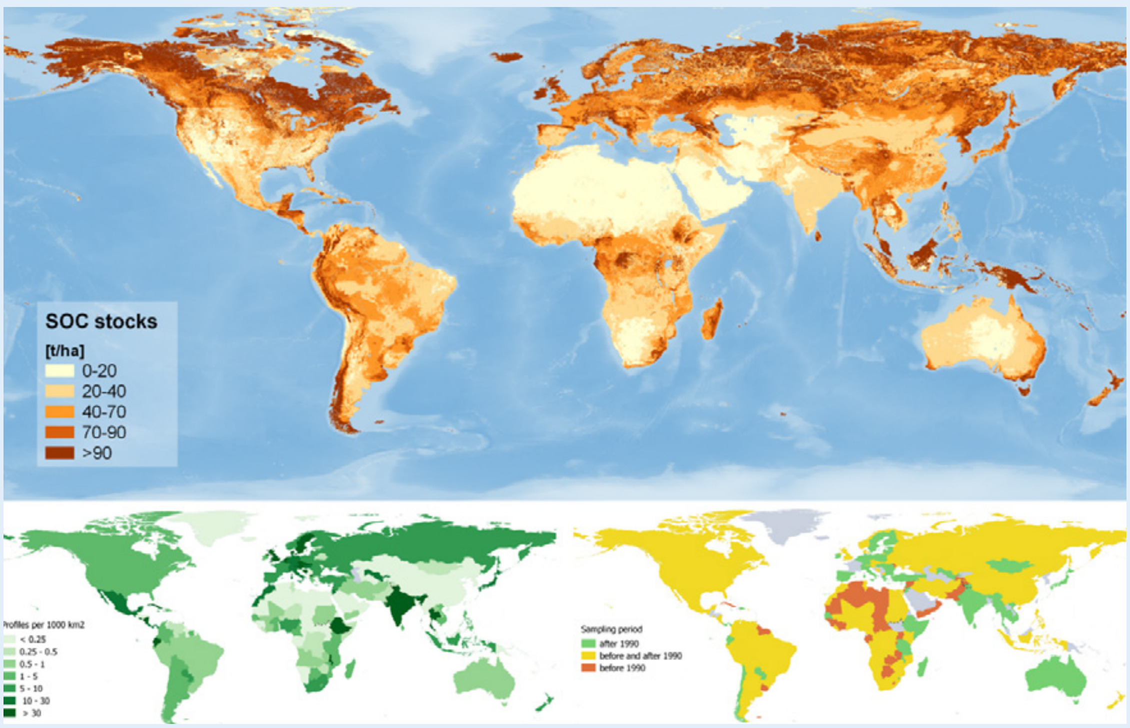


Figure B3.7
GSOCmap version 1.5.0 (top), density of point data per country (bottom left) and sampling period of the SOC data used for the GSOCmap (bottom right).

Source: FAO, 2020, [77] 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.

76 https://openknowledge.fao.org/server/api/core/bitstreams/0e9e6885-076e-4ff1-92fb-787449f11094/content.
77 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

IPCC-derived land use change factors should be used under the Tier 1 methodology 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 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

Conversion coefficients for land cover transitions are applied to estimate changes in SOC stocks. 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 3.8 shows the default conversion factors. In table 3.8, 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.

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

Table 3.8
Land use conversion factors for soil organic carbon stock changes.

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

Source: Trends.Earth User Guide,[78] licenced under CC BY 4.0 https://creativecommons.org/licenses/by/4.0 by Conservation International.

78 https://docs.trends.earth/en/latest/for_users/index.html.

For example, if a wetland is converted into cropland, the default conversion factor is 0.7 (see table 3.11). This means that after 20 years, the SOC stock in that area will be 71 per cent 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 fixed 20-year periods, 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 Version 2 for the calculation of SOC change per year. Then SOC change over any given period (T years) can be estimated as:

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

When annual land cover data is available, it becomes possible to identify the specific year in which a land cover change occurred, allowing for a 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, only the initial and final land cover maps are available in many cases, 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 analysing 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 (see Table 3.9). 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.

Original land cover		Target land cover						
		Tree-covered	Grassland	Cropland	Wetland	Artificial	Other land	Water body
	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

Source: The Land Story. Country experiences with reporting on land degradation and drought (UNCCD and WOCAT, 2024).

Table 3.9
Land use conversion factors for soil organic carbon stock changes estimated by Türkiye for the 2022 UNCCD reporting process.

Further refinements can be achieved through sub-national 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 SOC trends 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[79] 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. Box 3.8 provides greater detail on the relative importance of land cover change in determining SOC change trends compared to the reference SOC stock value.

79 IPCC, 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: Institute for Global Environmental Strategies, Japan.

STEP 4: Identify significant SOC changes

Once the conversion factors and land cover transitions have been identified, the change in SOC stocks over the period is calculated by comparing the SOC at the end of period and the SOC at the beginning of the period, which corresponds to the end of the baseline. For the Tier 1 approach, areas experiencing an SOC loss of 10 per cent or more are classified as potentially degraded, while areas with an SOC gain of 10 per cent or more are considered potentially improved. This 10 per cent 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 per cent 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 per cent loss threshold, the area is classified as potentially degraded. Similarly, an area where SOC has increased by more than 10 per cent 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.

BOX 3.8

Why the reference SOC map does not affect the classification of trends in SOC

When applying the IPCC 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 per cent or more are classified as potentially degraded, while areas with an increase of 10 per cent 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 is canceled 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:

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

The 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 results in the annual rate of SOC change.
- Multiplying by T (the number of years since the land cover change) results in the SOC change over T years.

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

The 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.

If $SOC_{initial}$ is factored out, the revised left side of the equation shows:

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

Since SOC_{initial} is present in both terms, it is canceled out when compared 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. IPCC 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 datasets, 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.

This section 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.

Global Soil Organic Carbon Sequestration Potential Maps

One advanced approach to estimating 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 Maps (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,[80] 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; (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 (GSOCseq) 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 Sustainable Soil Management 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.

80 https://www.rothamsted.ac.uk/rothamsted-carbon-model-rothc.

Incorporating national indicators such as salinization and soil erosion

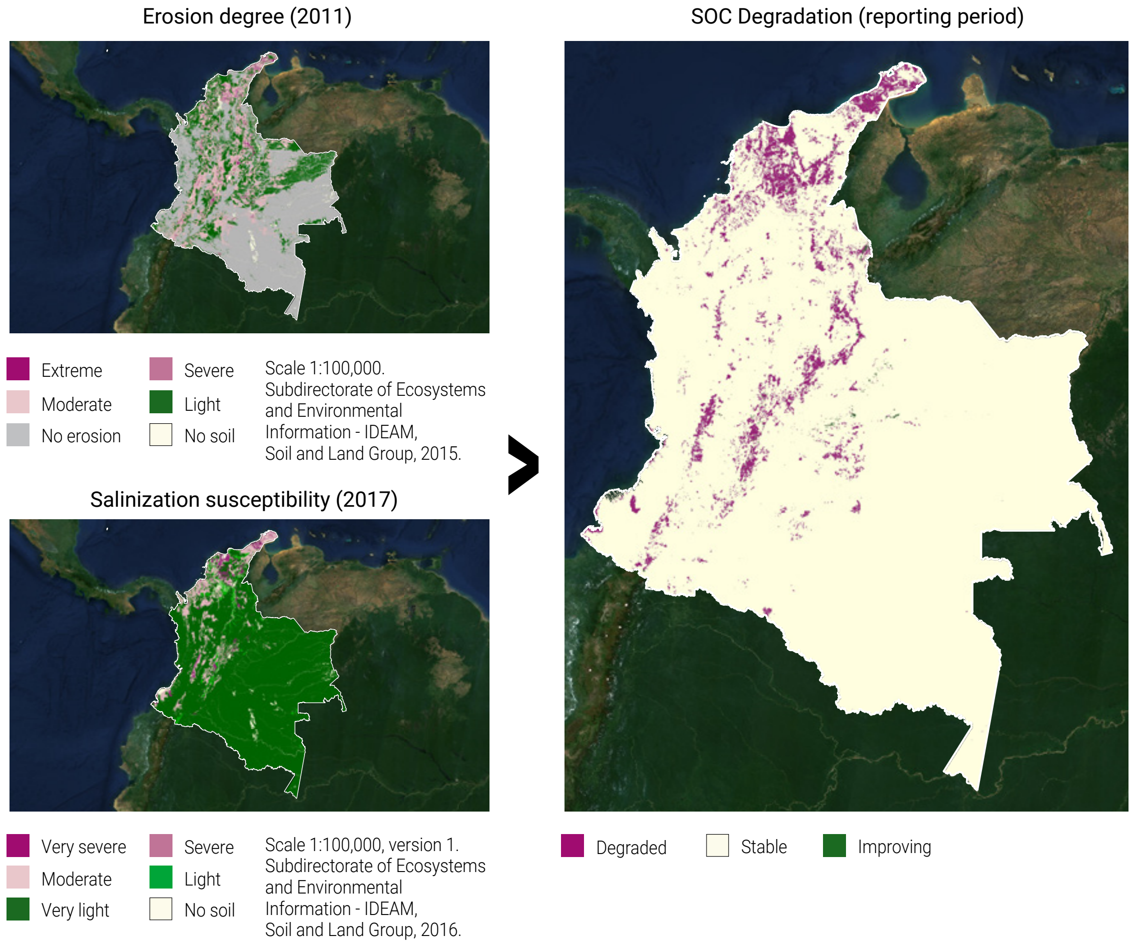
Beyond land cover changes, SOC stocks are influenced by degradation processes such as erosion and salinization, which can significantly affect carbon storage in soils. Tier 3 methods can incorporate these factors to enhance the accuracy of SOC change estimates.

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 (see figure 3.17). 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 per cent and classified them as degraded. Similarly, areas with projected SOC gains exceeding 5 per cent 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.

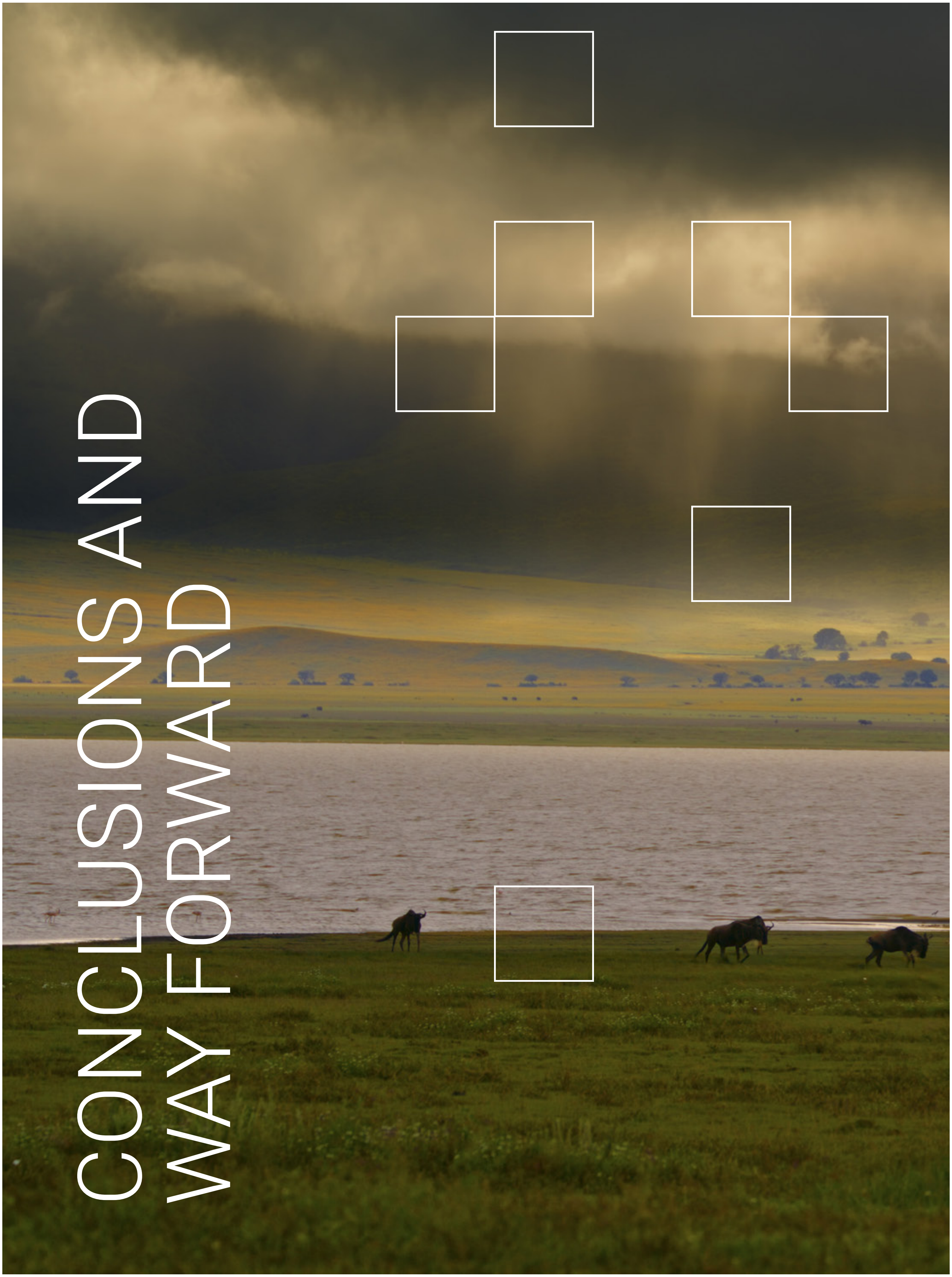
The methdological enhancements described in this section underscore the progress made since the release of GPG Version 2, reflecting both the evolving data landscape and the increasing technical capacity of countries to tailor methodologies to their specific contexts. By integrating new global and national 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.

Figure 3.17
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: The Land Story. Country experiences with reporting on land degradation and drought (UNCCD and WOCAT, 2024).

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 SLM and policy: By enabling the 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 SLM practices.

Looking ahead

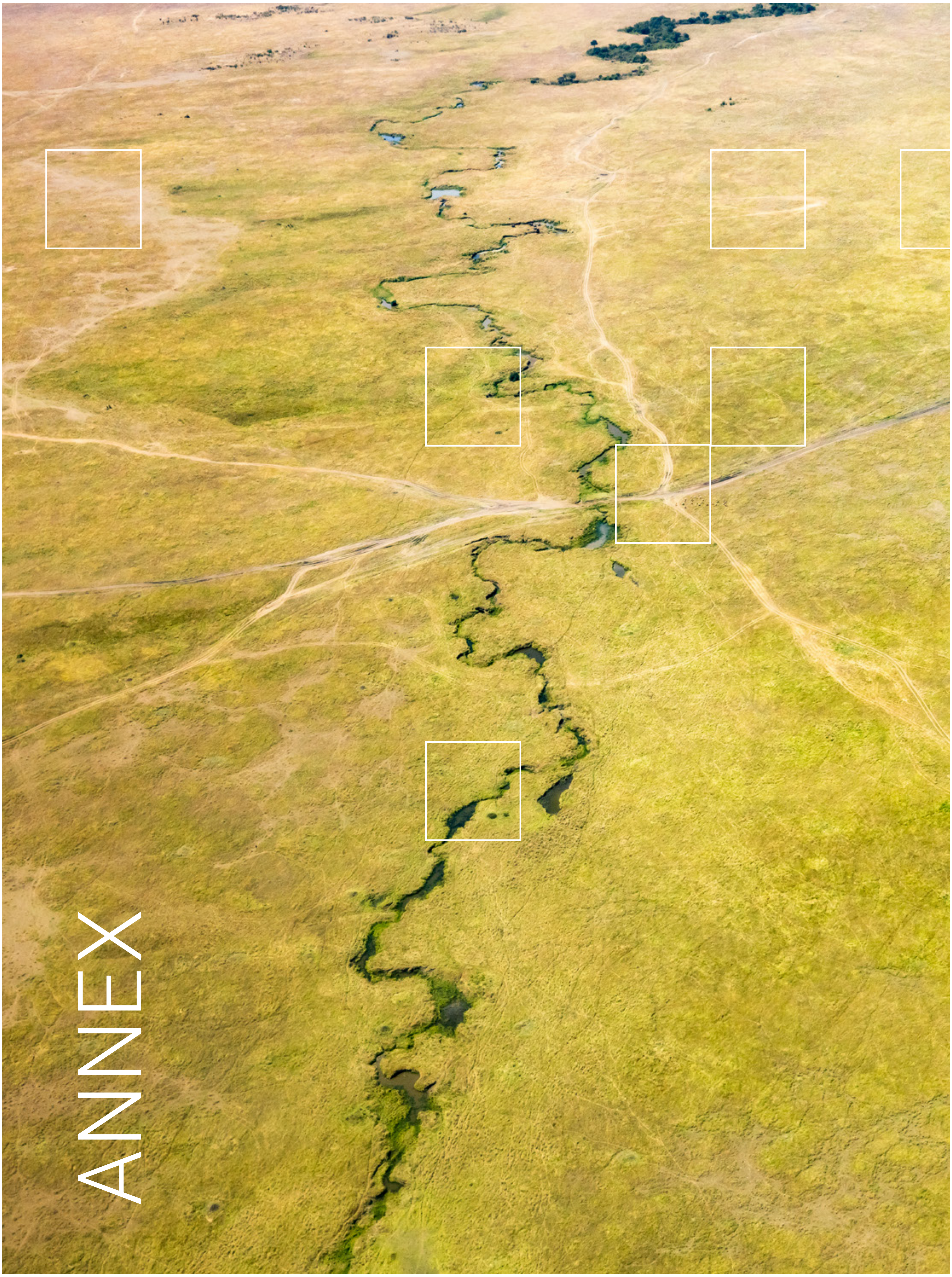
As the global community approaches the 2030 deadline for achieving the SDGs, the need for timely, accurate, and actionable information on land condition has never been greater. Countries are increasingly investing in monitoring systems, data infrastructure, and institutional capacity to meet this demand. 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 socioeconomic and land tenure data;
- Accounting for climate-related impacts on land degradation; and
- Refinement of methodologies for complex regional geographies, such as hyperarid zones, urban areas and heterogeneous landscapes.

In conclusion, the 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 rigour 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 SLM, protecting biodiversity, improving livelihoods and enhancing resilience in the face of global environmental change.

ANNEX



Annex:
Default versions of globally available LPD maps

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This annex builds upon section 3 of the addendum to the Good Practice Guidance for SDG Indicator 15.3.1 (GPG), which introduced the different algorithms for land productivity dynamics (LPD). Although each algorithm allows users to customize parameters according to their specific needs, a default version of each was developed by the Joint Research Centre (JRC) of the European Commission, Conservation International and the Food and Agriculture Organization of the United Nations (FAO)-World Overview of Conservation Approaches and Technologies (WOCAT). These default versions enable a comparable assessment of land productivity changes at the global level. The objective of this annex is therefore to document the default parametrization of each LPD method, detailing the corresponding data sources, input parameters, and processing assumptions to ensure reproducibility and transparency. The annex also presents the results derived from these default global analyses, illustrating how the different algorithms capture spatial and temporal trends in land productivity.

Default Joint Research Centre dataset

Input data:

- Satellite/sensor: A time series of composited Normalized Difference Vegetation Index (NDVI) images obtained from different satellite sensors, including SPOT-VEGETATION (SPOT-VGT) (1998–2013), PROBA-VEGETATION (PROBA-V) (2014–2020), and Sentinel-3 Ocean and Land Color Instrument (OLCI) (2020–present).
- Vegetation index: NDVI
- Annual statistic: Cumulative annual NDVI (the integral of the area under the annual seasonality curve)

The input dataset required for running the JRC LPD tool consists **primarily of a time series of raster data representing vegetation productivity**, along with optional supplementary layers that enhance the ecological and analytical context of the assessment. The core input is a multi-band raster in which each band corresponds to a specific year's productivity value, typically derived from satellite-based indices such as NDVI. These values often represent annual integrals or seasonal summaries (for example, SumNDVI) and are assumed to reflect the total vegetation productivity for each pixel in each year.

This multi-band raster must maintain consistent spatial resolution, projection, and extent across all bands. Each band must be ordered chronologically, and the starting year is defined relative to the band index through parameters in the tool. The time series should cover a sufficient number of years to support the selected processing intervals, normally 16 years for standard baseline and reporting windows used in United Nations Convention to Combat Desertification (UNCCD) reporting. The raster must be free of inconsistencies in alignment or resolution, and while the tool handles missing data (e.g. NaNs), a high-quality and complete dataset is preferable.

In addition to the main productivity raster, the tool may incorporate **a land cover classification map**. This layer provides categorical information on the type of land cover present at each location and is used to stratify the clustering process during the creation of ecosystem functional types (EFTs). The land cover map must match the productivity raster in projection, resolution, and spatial extent. Using land cover information allows the tool to constrain ecological classification within homogeneous land categories, enhancing the ecological realism and interpretability of the resulting EFTs.

Users may also supply additional raster datasets containing relevant environmental or vegetation metrics. These ancillary layers, such as phenological indicators (start or end of growing season, growing season length) or other biophysical variables, are used in the optional multicollinearity filtering step. In this step, the tool calculates temporal averages and correlation matrices among all variables and retains only those that are sufficiently independent, thus improving the quality of inputs for clustering or regression tasks.

During processing, the tool generates an EFT raster by clustering pixels with similar productivity characteristics. This intermediate product is essential for the local net scaling (LNScaling) step, where the current productivity of each pixel is evaluated in the context of similar ecosystems. The EFT raster, while derived internally, must remain spatially consistent with the original productivity dataset in terms of extent and resolution.

A critical aspect of the input setup is the correct association between raster bands and calendar years. The tool uses parameters such as the starting year and year range to determine which bands correspond to which years in the time series. This mapping is essential for correctly computing temporal trends, state changes, and ecological baselines.

The input dataset for the LPD tool is designed to be flexible yet requires well-prepared and harmonized data layers. These include a multi-year productivity raster as the central input, an optional land cover map for stratified analysis, and other variables that support optional steps such as collinearity filtering and ecological classification. Together, these inputs form the foundation for a robust, spatially explicit assessment of LPD.

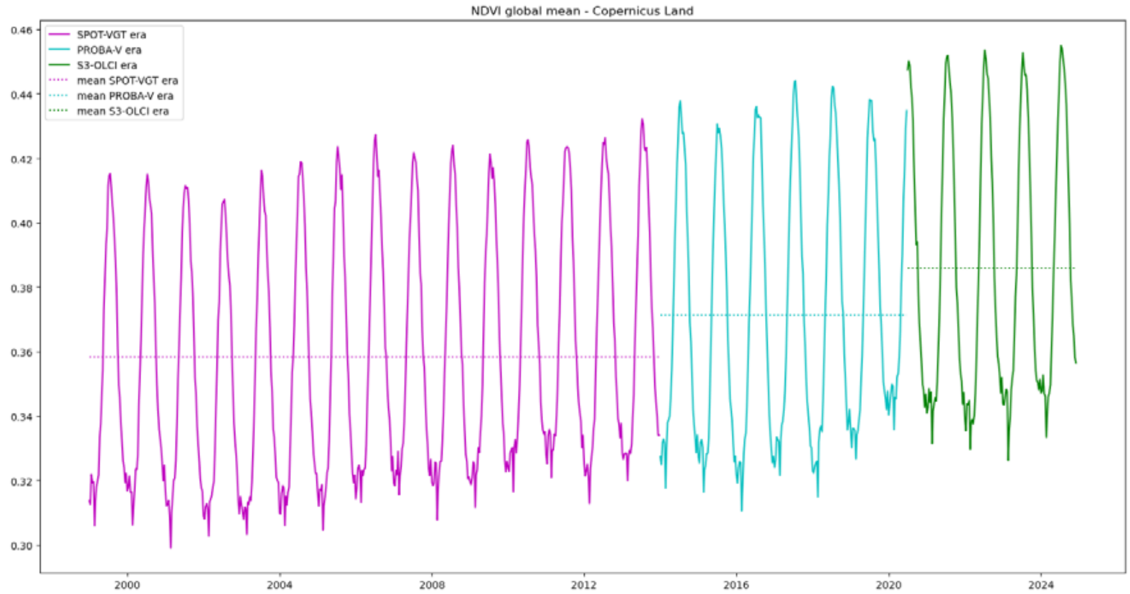
An NDVI time series derived from different satellites

The SumNDVI layer is a key input in the LPD workflow, representing the cumulative annual NDVI for each pixel. It is derived from a series of dekadal or composited NDVI images obtained from different satellite sensors, including **SPOT-VGT (1998–2013), PROBA-V (2014–2020) and Sentinel-3 OLCI (2020–2024)** (see figure A1). These datasets provide long-term continuity, but they also introduce a critical challenge: systematic inconsistencies between sensors due to differences in spectral sensitivity, radiometric behaviour, and acquisition geometry. In particular, NDVI values from SPOT-VGT and PROBA-V are not directly comparable with those from OLCI. If left uncorrected, this sensor transition introduces artificial jumps or discontinuities in the NDVI time series, which can significantly distort trend analyses and long-term productivity assessments. To mitigate this issue, a sensor-specific correction is applied to data from SPOT-VGT and PROBA-V. The correction consists of a linear transformation:

$NDVI_{corrected} = NDVI - 0.0130/0.958$

This adjustment normalizes the NDVI values from SPOT-VGT and PROBA-V, aligning them with the expected scale and dynamic range of the OLCI NDVI. The transformation is applied to each pixel, and all values outside the physical range (–1.0 to 1.0) are masked out. For OLCI data, which already conform to the current processing standard, only invalid or placeholder values (e.g. 2) are filtered, with no additional rescaling applied.

Figure A1
Time series of NDVI derived from SPOT-VGT (1998–2013), PROBA-V (2014–2020), and Sentinel-3 OLCI (2020–2024) used for JRC LPD.



Note that the time series are displayed before sensor-specific corrections are applied. Source: JRC.

After correction and masking, all valid NDVI observations for a given year are stacked and processed. Temporal gaps due to clouds or missing acquisitions are addressed using pixel-wise linear interpolation across the time axis. This step ensures temporal continuity and improves the reliability of the annual aggregate. The SumNDVI is then calculated as the total sum of interpolated NDVI values for each pixel across the year. To ensure data quality, a threshold of observation validity is enforced: a pixel must have at least 60 per cent of valid time steps to be included in the final product. Otherwise, it is marked as NoData.

Despite this correction approach, residual inconsistencies across sensors remain a limitation, particularly at the transitions between PROBA-V and OLCI. To resolve this at scale, a new harmonized NDVI time series at 300m resolution is currently being developed and released under the Copernicus Land Monitoring Service. This product includes a fully reprocessed archive of SPOT-VGT and PROBA-V, harmonized with Sentinel-3 OLCI using consistent calibration and processing methods. The resulting dataset provides a seamless, cross-sensor NDVI time series from 1999 to the present.

This harmonized 300m NDVI time series will serve as the official input for the upcoming JRC LPD Version 2. By removing the need for post hoc corrections and ensuring full temporal consistency, it will enable more accurate and spatially detailed assessments of LPD for global, national and local monitoring efforts – fully aligned with the methodological requirements of SDG Indicator 15.3.1 and the UNCCD reporting framework.

Results of the default version of the JRC LPD

The statistics and maps of the JRC LPD analysis for the baseline and the two reporting periods (2000–2015, 2004–2019 and 2008–2023) are presented in table A1 and figure A2.

During the **baseline period** (2000–2015), more than half of the assessed land area (approx. 52.7 per cent, 55.9 million square kilometres (km²)) showed increasing productivity, while around 3.2 per cent (3.36 million km²) exhibited declining productivity, and 1.8 per cent (1.93 million km²) showed moderate decline. Approximately 22.1 per cent (23.4 million km²) of the land was stable but stressed, and 20.2 per cent (21.4 million km²) remained stable.

In the **first reporting period** (2004–2019), the share of land with declining productivity increased to 4.3 per cent (4.52 million km²), while the area under moderate decline expanded to 5.1 per cent (5.39 million km²). The proportion of stable but stressed land also grew moderately to 24.5 per cent (26.0 million km²). Conversely, stable land decreased to 12.3 per cent (13.05 million km²), and land showing increasing productivity remained dominant but slightly declined to 53.9 per cent (57.3 million km²).

By **the second reporting period** (2008–2023), a marked shift was observed: the proportion of stable but stressed land nearly doubled to 45.6 per cent (47.9 million km²), while the share of increasing productivity areas dropped sharply to 26.2 per cent (27.5 million km²). Areas with declining productivity continued to expand, reaching 5.35 per cent (5.62 million km²), although the moderate decline category decreased to 2.7 per cent (2.86 million km²). The extent of stable land rebounded to 20.1 per cent (21.1 million km²).

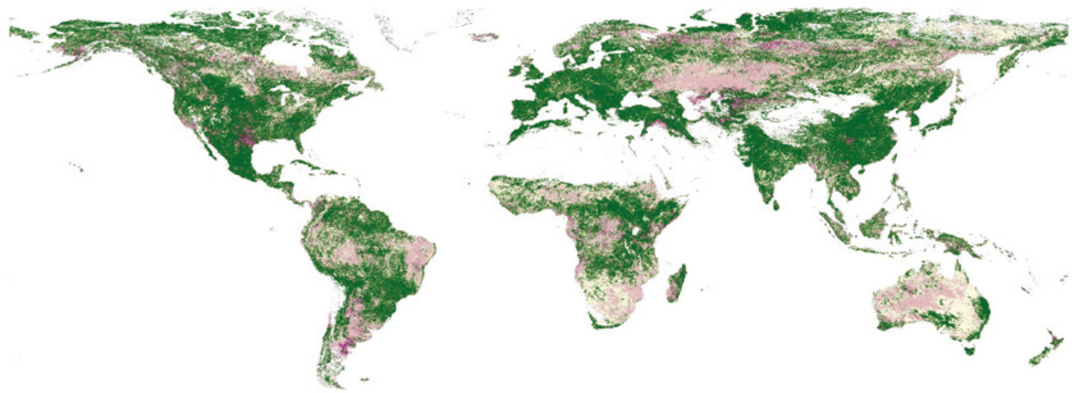
Table A1
Global distribution of JRC LPD classes across the baseline (2000–2015) and two reporting periods (2004–2019, 2008–2023).

LPD class	Baseline period (2000-2015) % and km²	Reporting period 1 (2004-2019) % and km²	Reporting period 2 (2008-2023) % and km²
Declining	≈ 3.17% 3,362,608 km²	≈ 4.26% 4,523,617 km²	≈ 5.35% 5,620,895 km²
Moderate decline	≈ 1.82% 1,930,453 km²	≈ 5.07% 5,387,566 km²	≈ 2.72% 2,860,299 km²
Stable but stressed	≈ 22.07% 23,393,670 km²	≈ 24.46% 26,000,613 km²	≈ 45.63% 47,919,508 km²
Stable	≈ 20.19% 21,404,230 km²	≈ 12.28% 13,050,030 km²	≈ 20.10% 21,116,626 km²
Increasing	≈ 52.74% 55,906,944 km²	≈ 53.93% 57,321,543 km²	≈ 26.20% 27,523,956 km²
No data	449.763.011 km²	449.477.547 km²	450.719.632 km²

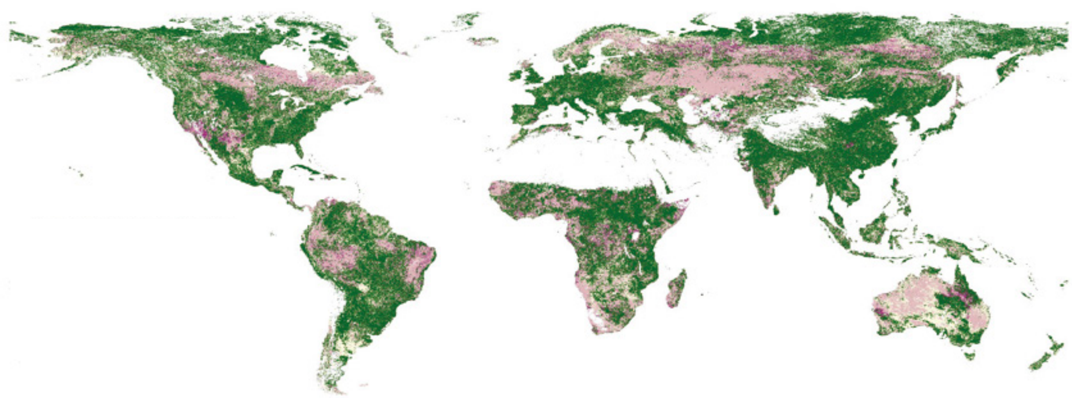
The table shows the proportion (%) and corresponding area (km²) of land under each LPD class.

Figure A2
Global maps of JRC LPD for the baseline (2000–2015) and two reporting periods (2004–2019, 2008–2023)

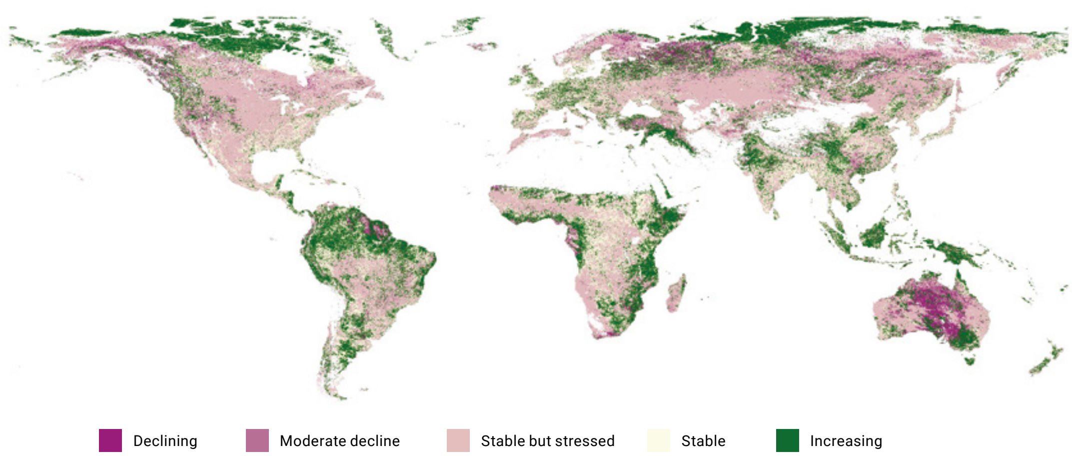
JRC LPD 2000-2015



JRC LPD 2004-2019



JRC LPD 2008-2023



Default Trends.Earth land productivity dynamics dataset

Input data set

Satellite/sensor: Product MOD13Q1 Version 6.1: MODIS Terra Vegetation Indices 16-Day Global at 250m

Vegetation index: NDVI

Annual statistic: Annual mean

Parameters

Trend: The productivity trend metric measures the rate of change in primary productivity over the time period of interest, having a time series of at least 16 years as a requirement according to the GPG Version 2. Trends.Earth asks users to set the starting and ending years of the time series of interest. Additionally, it allows users to apply different climate correction methods, including Rainfall Use Efficiency (RUE), Residual Trend Analysis (RESTREND), Water Use Efficiency (WUE), and several precipitation datasets, as presented earlier in the text.

State: The productivity state metric allows for the detection of recent changes in primary productivity as compared to a baseline period. Users are asked to split the time series of interest into the recent comparison period and the historical baseline.

Performance: The productivity performance metric measures local productivity relative to other similar vegetation types in similar land cover types or bioclimatic regions throughout the study area. For this metric, users are asked to set the starting and ending years of the time series of interest, typically equal to the corresponding years selected for the trend metric.

Results of the default version of Trends. Earth land productivity dynamics

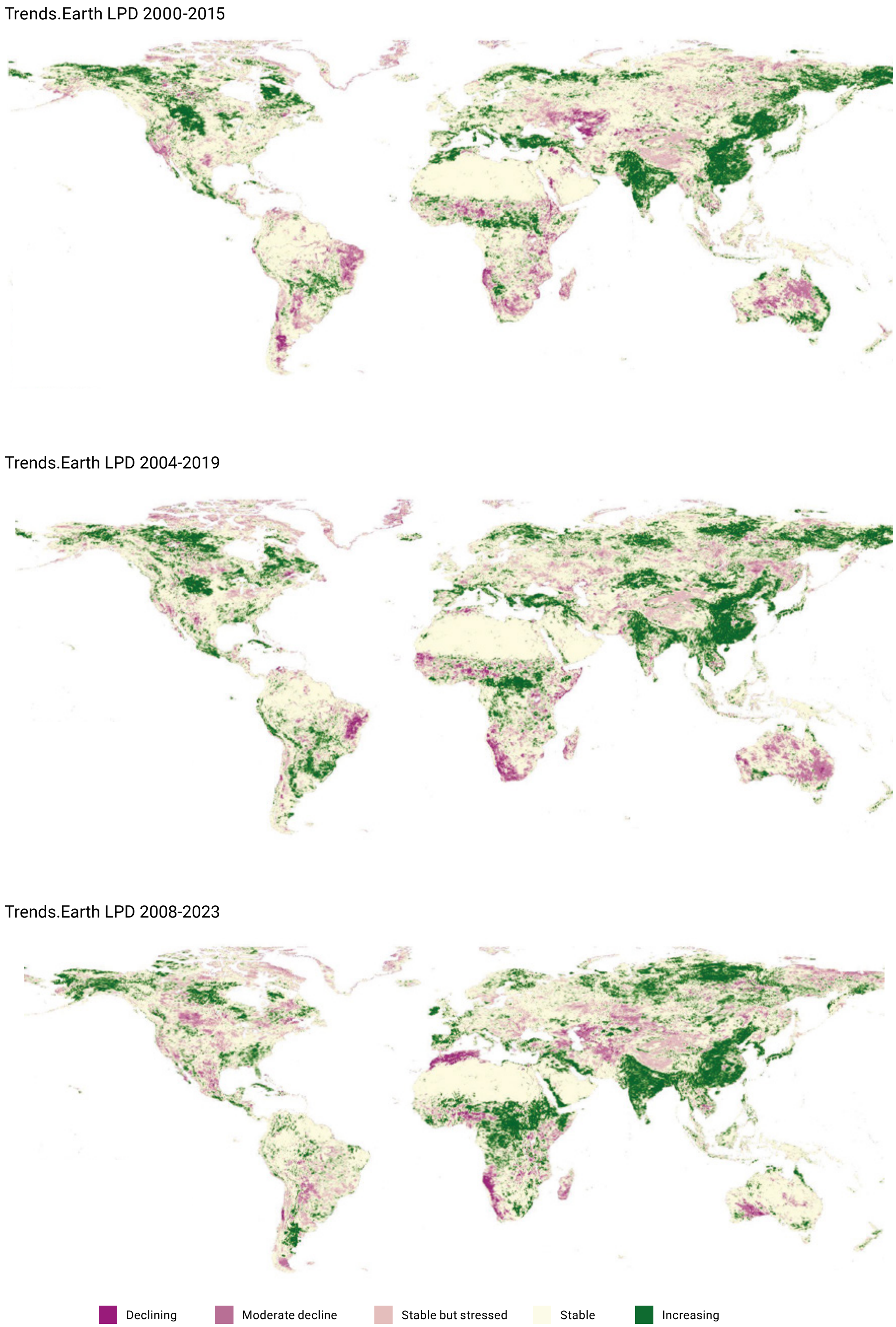
The results of Trends.Earth LPD analysis, presented in table A2 and figure A3, indicate that between the baseline period (2000–2015) and the most recent reporting period (2008–2023), global land productivity patterns show a moderate but consistent improvement. The share of declining productivity areas decreased from 8.37 per cent (10.76 million km²) to 6.97 per cent (8.96 million km²). Moderate decline areas, however, rose slightly from 8.89 per cent to 10.36 per cent, suggesting localized pressures remain in certain regions. The stable but stressed class remained nearly unchanged (around 4 per cent). Meanwhile, stable productivity declined slightly from 58.20 per cent to 55.17 per cent. The increasing productivity class expanded notably, from 20.18 per cent (25.95 million km²) to 23.33 per cent (30.01 million km²), signaling growing areas of improvement.

Table A2
Global distribution of Trends.Earth LPD classes across the baseline (2000–2015) and two reporting periods (2004–2019, 2008–2023).

LPD class	Baseline period (2000-2015) % and km²	Reporting period 1 (2004-2019) % and km²	Reporting period 2 (2008-2023) % and km²
Declining	8.37% 10,764,709 km²	7.53% 9,684,710 km²	6.97% 8,961,289 km²
Moderate decline	8.89% 11,436,439 km²	9.62% 12,371,281 km²	10.36% 13,315,303 km²
Stable but stressed	4.36% 5,605,551 km²	4.33% 5,566,324 km²	4.17% 5,360,848 km²
Stable	58.20% 74,829,053 km²	55.67% 71,578,825 km²	55.17% 70,942,201 km²
Increasing	20.18% 25,945,770 km²	22.85% 29,383,471 km²	23.33% 30,005,078 km²

The table shows the proportion (%) and corresponding area (km²) of land under each LPD class.

Figure A3
Global maps of Trends.Earth LPD for the baseline (2000–2015) and two reporting periods (2004–2019, 2008–2023).



Default FAO-WOCAT dataset

Input data set

Satellite/sensor: Product MOD13Q1 Version 6.1 – MODIS Terra Vegetation Indices 16-Day Global at 250m

Vegetation Index: NDVI

Annual statistic: Annual mean (bad quality pixel values replaced with annual mean value calculated from good quality values for that pixel)

Parameters

The 250m resolution MODIS NDVI was chosen for the global implementation of the FAO-WOCAT Version 2 algorithm.[81] To showcase the importance of parametrizing the algorithm to local conditions, this new version has a set of three different default parametrizations. This allows users to quickly change the algorithm sensitivity to obtain a fit-for-purpose map:

- **Broad detection mode** (high sensitivity). This parametrization, used as the default FAO-WOCAT parametrization in the 2022 reporting process, is less conservative and characterized by a 95 per cent significance level for the steadiness analysis. It features higher sensitivity to subtle or emerging trends, allowing for the detection of changes that may not yet be strongly expressed. This configuration is particularly suitable for broad-scale land degradation or improvement assessments, where the goal is to capture the full spatial extent of potentially affected areas, including those exhibiting only incipient or weak signals of change;
- **Priority area mode** (low sensitivity). This more conservative parametrization applies a 99 per cent significance level for the steadiness analysis. It is designed to identify more evident trends, effectively filtering out minor or short-term fluctuations. By reducing the likelihood of Type I errors (false positives), this mode highlights areas with a high degree of confidence in trend detection, making it particularly relevant for integrated land use planning and for prioritizing areas that require targeted management or intervention;
- **Balanced mode** (medium sensitivity). This parametrization represents an intermediate option that seeks to balance sensitivity and specificity in trend detection. It combines moderate significance thresholds and parameter values to ensure a reasonable detection of genuine trends. The balanced mode is especially useful for assessments where maintaining equilibrium between detecting subtle change signals and avoiding overestimation of change is essential for reliable interpretation.

A careful examination of each parametrization, in consultation with territorial experts and through detailed map analysis, is recommended to fully understand the respective strengths and limitations of each parameterization. For the purposes of this annex, only one default parametrization, corresponding to the broad detection mode, will be shown.

The **Steadiness Index** (tendency of change) is based on a Mann-Kendall analysis with a 95 per cent significance level and a multi-temporal image differencing (MTID) analysis as originally developed by Guo et al. (2008), with a threshold level set to 0 (only shows negative or positive changes).

State (recent productivity performance relative to historical) is calculated from the percentile distribution of the first 15 years of the time series of mean annual NPP, whereby a change in two or more percentiles between the initial and final period is considered significant. The period size is four years, so for the initial and final period, the average of the NDVI for the first and last four years is estimated. If the absolute change is less than 0.05 NDVI, then it is considered not significant since it is such a small value that does not hold biological meaning even if statistically significant. This metric follows a similar approach to the state indicator used in the Trends. Earth LPD; however, different period lengths are used in the FAO-WOCAT LPD broad detection mode.

Initial Biomass (background level of productivity) is based on the average of the three first years of the series, followed by global thresholds being empirically set to low: < 0.4, medium: between 0.4 and 0.7; and high: > 0.7.

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

Masking: The MOD44W Version 6 land/water mask 250m product is used in this case since it is in the same spatial resolution as the input dataset. If water is detected in more than 12 years in the series, then it is considered as permanent water and excluded from the analysis. Hyperarid areas are set to stable and are defined as areas where the NDVI never goes over 0.2 in the 16-day image time series.

Results of the default version of FAO-WOCAT LPD (broad detection mode)

According to the FAO-WOCAT default LPD, across the three assessment periods, land productivity patterns remain relatively stable with gradual improvements (Table A3 and Figure A4). The areas with declining productivity slightly decreased from 6.9 per cent (9.09 million km²) at baseline to 6.0 per cent (7.92 million km²) in the latest period. Moderate decline areas also dropped from 23.8 per cent to 21.1 per cent, reflecting a reduction. Conversely, stable but stressed areas remained steady at around 16 per cent. The stable class, after a drop in the first reporting period (32.6 per cent), increased to 34.3 per cent. The increasing productivity class rose consistently from 19.8 per cent (26.23 million km²) to 22.3 per cent (29.44 million km²), marking a positive trend in land productivity gains over time.

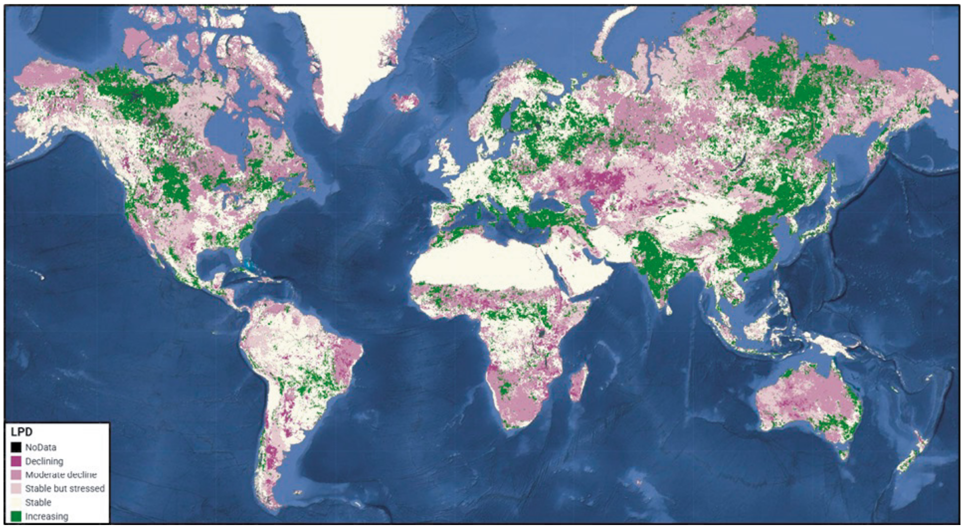
Table A3
Global distribution of FAO-WOCAT LPD (parametrization) classes across the baseline (2000–2015) and two reporting periods (2004–2019, 2008–2023).

LPD class	Baseline period (2000-2015) % and km²	Reporting period 1 (2004-2019) % and km²	Reporting period 2 (2008-2023) % and km²
Declining	6.9% 9,092,982 km²	7.1% 9,369,218 km²	6.0% 7,918,495 km²
Moderate decline	21.7% 28,721,155 km²	23.8% 31,404,550 km²	21.1% 27,825,804 km²
Stable but stressed	15.9% 20,985,499 km²	15.4% 20,417,108 km²	16.3% 21,596,809 km²
Stable	35.7% 47,149,546 km²	32.6% 43,026,299 km²	34.3% 45,392,981 km²
Increasing	19.8% 26,228,001 km²	21.2% 27,960,061 km²	22.3% 29,442,653 km²

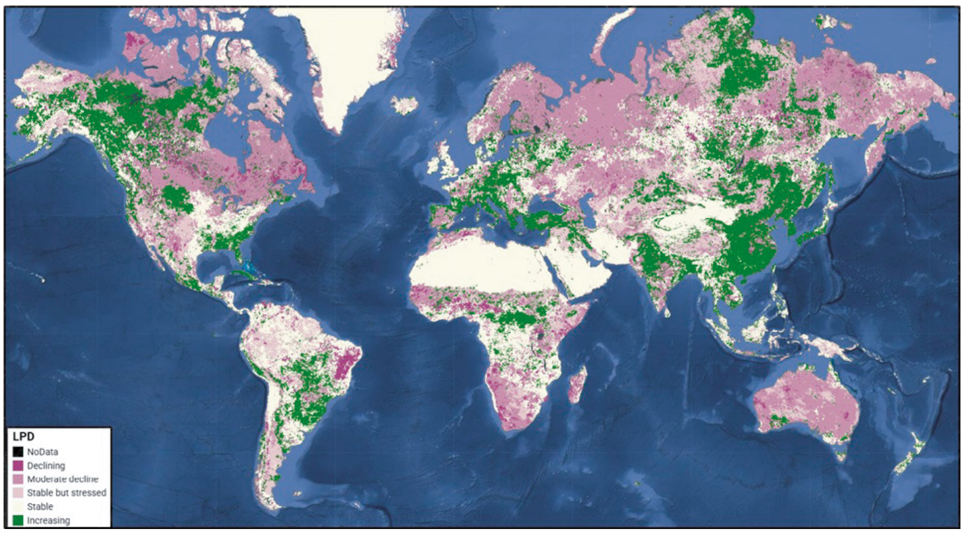
The table shows the proportion (%) and corresponding area (km²) of land under each LPD class.

Figure A4: *Global maps of FAO-WOCAT broad detection mode LPD for the baseline (2000–2015) and two reporting periods (2004–2019, 2008–2023).*

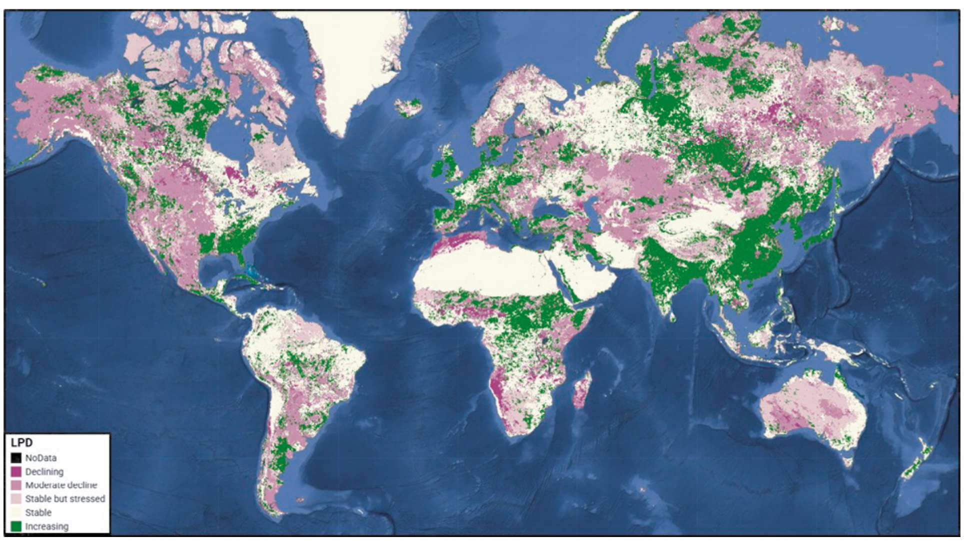
FAO WOCAT LPD 2000-2015



FAO WOCAT LPD 2004-2019



FAO WOCAT LPD 2008-2023



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