SEN4LDN

LAND DEGRADATION NEUTRALITY

D5.2

Product Validation Report

Version 2.0

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0.2	Draft	28 August 2024	Draft, focus on validation plan (§2)
1.0	Final	2 September 2024	Final version containing the validation plan
2.0	Final	15 January 2025	Final version including validation results

Table of contents

List of figures

List of tables

Key takeaway messages

- The SEN4LDN project aims to improve land degradation neutrality monitoring using high-resolution Sentinel data, focusing on land cover and land productivity trends in Uganda, Portugal, and Colombia.
- The land cover map achieved the highest accuracy in Colombia (90.1% ± 3.4%) and the lowest in Uganda (69.6% ± 5.5%), with significant confusion between vegetation types in Uganda.
- The land cover change map in Uganda showed good performance in detecting forest changes, achieving an overall accuracy of 73.7% at the change vs. no change level.
- SEN4LDN's change detection in Portugal was more conservative compared to the national COSc product, while its estimates in Colombia were more logical compared to the MapBiomas product.
- Validation of land productivity trends indicated high internal consistency, particularly in Portugal and Uganda, with some challenges in Colombia due to atmospheric and topographical factors.

Summary

The SEN4LDN project, funded by the European Space Agency, aims to enhance the monitoring of land degradation neutrality (LDN) by leveraging high-resolution Sentinel data. The project focuses on improving the spatial and temporal resolution of data required for effective land degradation (LD) monitoring, addressing the challenges posed by varying regional conditions and the need for local stakeholder involvement.

The Product Validation Report (D5.2) outlines the validation methodology and results for the SEN4LDN products, focusing on land cover (LC) and land productivity trends in Uganda, Portugal, and Colombia. The validation of SEN4LDN products focuses on land cover and land cover change (LCC) maps, as well as trends in land productivity. The validation procedures include several aspects. For the validation of land cover, the primary validation data is derived from the global land cover validation dataset, initially generated for the Copernicus Land Monitoring Service (CLMS). This dataset employs stratified random sampling and includes 21,752 primary sampling units (PSUs) globally. For Uganda, a separate validation dataset was collected due to insufficient samples in the global dataset. Land cover change was validated directly in Uganda using a stratified random sampling design and indirectly in Colombia and Portugal by comparing SEN4LDN LCC maps with national products (MapBiomas in Colombia and COSc in Portugal). The validation of trends in land productivity focuses on the trend and performance products, including visual checks, internal consistency analysis, and indirect validation through qualitative cross-comparison with global products derived from CLMS GDMP 300m.

The SEN4LDN land cover maps showed varied performances across the three countries. The highest overall accuracy was achieved in Colombia (90.1% ± 3.4%), with high accuracies in mapping trees, low vegetation, and wetlands. The overall accuracy in Portugal was 87.0% ± 6.5%, with good performance in mapping crops and low vegetation. The lowest accuracy was observed in Uganda (69.6% ± 5.5%), with significant confusion between low vegetation, trees, and crops. The map performed well in mapping wetlands but had low accuracy for built-up areas and other classes due to limited validation data.

In Uganda, the land cover change map achieved an overall accuracy of 73.7% at the change vs. no change level and 72.9% for specific transition classes. The map performed well in detecting forest-related changes (deforestation and reforestation) but underestimated other changes.

Indirect validation over Colombia and Portugal showed that SEN4LDN LCC maps had a higher percentage of stable/unlikely change areas compared to national products. In Colombia, the SEN4LDN map estimated a more logical change area compared to MapBiomas, while in Portugal, it was more conservative compared to COSc.

The validation of trends in land productivity included visual checks, internal consistency analysis, and indirect validation. Systematic visual analysis indicated no significant spatial artefacts, except for the effect of persistent cloud coverage in some areas of Colombia and Uganda. High internal consistency was found for the products over Portugal and Uganda, with slightly lower consistency in Colombia due to atmospheric and topographical factors. Qualitative cross-comparison with CLMS GDMP 300m showed good agreement between the temporal profiles of TPROD and GDMP, confirming the trend coefficient and trend class.

In conclusion, the SEN4LDN project successfully developed and validated high-resolution land cover and land productivity products for Uganda, Portugal, and Colombia. Overall, the SEN4LDN products demonstrated strong performance in monitoring land degradation neutrality, providing valuable insights for SDG 15.3.1 reporting. The report highlights the importance of local stakeholder involvement in product development and validation, ensuring that the final products meet user requirements and are usable for sustainable development monitoring.

List of abbreviations

ATBD	Algorithm Theoretical Baseline Document
B	Mean Bias
BRDF	Bidirectional Reflectance Distribution Function
CEO	Collect Earth Online
CLMS	Copernicus Land Monitoring Service
COSc	Carta Ocupacao do Solo Conjuntural
DMP	Dry Matter Productivity
DW	Dynamic World
EO	Earth Observation
EU	European Union
EVI2	2-band Enhanced Vegetation Index
FAPAR	Fraction of Absorbed Photosynthetically Active Radiation
GLC	Global Land Cover
GMR	Geometric Mean Regression
GPP	Gross Primary Productivity
HR	High Resolution
ICOS	Integrated Carbon Observation System
IPCC	Intergovernmental Panel on Climate Change
LAI	Leaf Area Index
LC	Land Cover
LCC	Land Cover Change
LD	Land Degradation
LDN	Land Degradation Neutrality
LSP	Land Surface Phenology
MAD	Median Absolute Deviation
MD	Median Deviation
MODIS	Moderate Resolution Imaging Spectroradiometer
MR	Medium Resolution
NBAR	Nadir BRDF-Adjusted Reflectance
NDVI	Normalized Difference Vegetation Index
NPP	Net Primary Production
PPI	Plant Phenology Index
PSU	Primary Sampling Unit
RB	Requirement Baseline
RMSD	Root Mean Squared Distance
SDG	Sustainable Development Goal
SEN4LDN	Sentinels for Land Degradation Neutrality
SSU	Secondary Sampling Unit
STD	standard deviation (of the bias)
TPROD	Total Productivity
UNCCD	United Nations Convention to Combat Desertification
VI	Vegetation Index
VPP	Vegetation Phenology and Productivity

WP	Work Package

1 Introduction

1.1 Scope and objectives

The 2030 Agenda for Sustainable Development is fundamentally based on 17 Sustainable Development Goals (SDG) which are targets agreed upon by the UN members regarding various interlinked objectives that must be ensured to achieve sustainable development. These range from combating poverty, ensuring access to education, to economic development and the protection of life on water and land.

Diminished overall productivity and reduced resilience in the face of climate and environmental change, have made addressing land degradation a global priority formalized by the United Nations Convention to Combat Desertification (UNCCD) and the SDG. To this end, the 2030 Agenda for Sustainable Development defined target 15.3 of SDG 15, called '*Life on Land*', that strives to reach Land Degradation Neutrality (LDN) by 2030.

Efficient monitoring of LD requires constant monitoring of various biophysical and biochemical characteristics of the land. These disturbances can range from rapid land cover change (e.g., fire or logging) to continuous and slower degradation of soil and land quality [1]. While monitoring these at larger scale becomes a logistical impossibility if not using Earth Observation (EO) data, there are still a number of challenges and opportunities to address particularly related with increasing spatial and temporal resolution and diversity of sensor types [2]. Sentinels for Land Degradation Neutrality (SEN4LDN) aims to address these two limitations by developing and showcasing a novel approach for improving both the spatial and temporal resolution of the data required for LD monitoring. While LDN is agreed between the SDG signatories, each region/country will have its own specific challenges and drivers of LD and therefore the inclusion of local partners in the product development is extremely important. These stakeholders will provide insights on the user requirements and feedback on the final product and its actual usability for SGD 15.3.1 reporting.

The objective of SEN4LDN Work Package 4 (WP4) is to produce large-scale demonstration products over the selected pilot sites and conduct a comprehensive validation of the output products. This deliverable aims to present the product validation plan and the qualitative validation results of the output products.

1.2 Document structure

The document is structured as follows:

- Chapter 2 describes the methodology of product validation.
- Chapter 3 provides the validation results on pilot sites.
- Conclusions are summarized in Chapter 4.

1.3 Related documents

- D1.2 Requirement Baseline (RB)
- D3.2 Algorithm Theoretical Baseline Document (ATBD)

Public deliverables of the SEN4LDN project are available on https://esa-sen4ldn.org/en/deliverables.

2 Validation methodology

2.1 Introduction

The validation of SEN4LDN products focuses in first instance on the validation of land cover and land cover change maps. Table 1 shows the requirements for land cover and land cover change characterization accuracy in the three SEN4LDN early adopter countries.

Table 1: Accuracy requirement on land cover and land cover change

Country	Requirement on land cover	Requirement on land cover change
Colombia	Verification with field data, report, and publication for Colombia.	Some areas are very dynamic, LCC is expected in those areas.
Portugal	Minimum requirement of accuracy 82%, target 90%.	No specific requirements indicated.
Uganda	Accuracy as high as possible, 80% is desired.	No specific requirements indicated.

Also output products of the trend in land productivity sub-indicator will be validated, focusing on trend and performance products. From the user consultation, no specific requirements were derived for the validation of trends in land productivity.

The next sections describe the validation procedures, methods and reference data used.

2.2 Validation of trends in land cover

2.2.1 Validation of land cover

The primary validation data that is used for validation of land cover is the global land cover validation dataset that was initially generated for validating the Copernicus Land Monitoring Service (CLMS) Land Cover products.

This dataset is based on probability sampling to allow a design-based inference of map accuracies. The validation dataset is based on stratified random sampling, employing a global stratification [3]. Globally there are 149 strata divided over seven (sub)continents, consisting of 21,752 primary sampling units (PSUs) [4]. This dataset was used for validating land cover maps of Colombia and Portugal. For Uganda, a separate validation dataset was collected. The spatial distribution of the validation sites over Colombia and Portugal are shown in Figure 1.

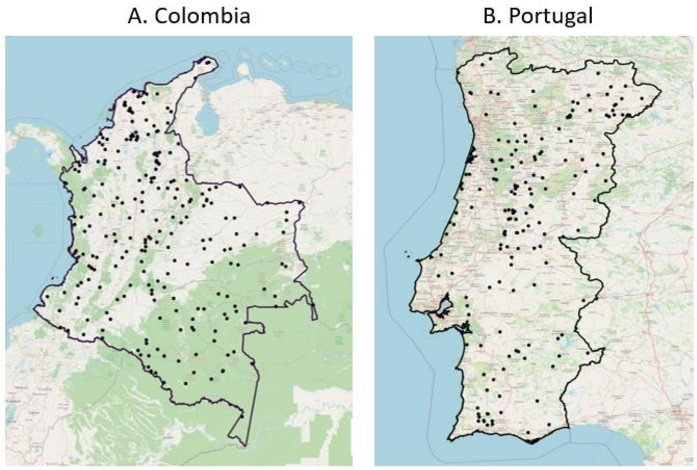


Figure 1: Spatial distribution of the global validation sample sites for A. Colombia and B. Portugal.

Each PSU (covering an area of 100 m × 100 m) was divided into 10 × 10 small blocks (henceforth called SSU: secondary sampling unit). Since the reference land cover elements were collected at 10 m × 10 m SSU level, the dataset is compatible with assessing land cover maps with 10-100 m resolutions.

For the thematic representation, the generic land cover elements recorded at each SSU include trees (phenology and leaf types), shrubs, grass, crops, built-up areas, bare area, lichens/mosses, open water, snow & ice, and regularly flooded areas. The land cover elements were defined according to the United Nations Land Cover Classification System (LCCS) [5]. An example of labelling the land cover of SSUs within a PSU is provided in Figure 2.

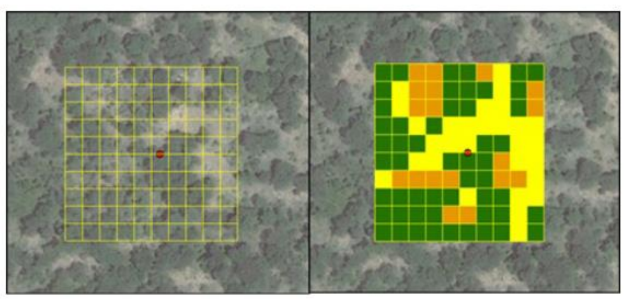


Figure 2: Screenshot of an example sample interpretation (green – trees, orange – shrubs, yellow –grassland)

More detailed information on the validation data can be found in [4].

The reference land cover information corresponds to 2021. The reference land cover is also available for these locations for the year 2019, with additional ~10,000 PSU locations. All 100 secondary sampling units were used for the validation. Following the one-stage cluster sampling, a stratified cluster estimator was used to assess the accuracy by accounting for sampling area weights. This study intended to validate the most recent SEN4LDN map based on the available validation data, i.e., 2021, and in case there are not sufficient validation samples available for 2021, the data from 2019 was supplemented. The total number of sample sites used to validate land cover in Portugal and Colombia is listed in Table 2.

In Uganda, the global validation dataset does not have sufficient samples, which may result in unstable accuracy estimates. Therefore, for the validation of land cover in Uganda, we used a different validation dataset, collected for land cover change validation explained in section 2.2.2. From this dataset, we used the land cover labels for the year 2023 with the area-weighted accuracy estimation for stratified sampling.

To ensure that the map and validation data are thematically comparable, we reclassified both their legends to the Intergovernmental Panel on Climate Change (IPCC) categories: forest land, cropland, low vegetation (grassland and shrubs), wetlands (incl. open water), settlements, and other lands. Table 3 provides an overview of the harmonized and original classes.

Table 2: Number of PSU and SSU available in the country for the validation of land cover

Country	Year of data	Number of PSUs	Number of SSUs	Validation data source
Colombia	2021	185	18500	Global validation dataset
Portugal	2019 & 2021	172	17200	Global validation dataset
Uganda	2023	750	750	LCC validation data (§2.2.2)

Table 3: Legend harmonization for validation data and SEN4LDN product

IPCC class		SEN4LDN		Reference data	
Code	Name	Code	Name	Code	Name
1	Forest land	10	Tree cover	11, 12	Closed forest, Open forest
		95	Mangroves		
2	Cropland	40	Cropland	40	Cropland
3	Low vegetation	20	Shrubland	20	Shrubs
		30	Grassland	30	Herbaceous vegetation
4	Wetlands	80	Permanent water bodies	80	Open water
		90	Herbaceous wetland	90	Wetland herbaceous vegetation
5	Settlements	50	Built-up	50	Urban/built up
6	Other lands	60	Bare / sparse vegetation	60	Bare/sparse vegetation
		70	Snow and ice	70	Snow and ice
		100	Moss and lichen		

2.2.2 Validation of land cover change

LCC was validated directly and indirectly. For direct LCC validation, the change validation dataset was specifically collected for Uganda. Uganda was chosen as it has insufficient number of validation samples in the global land cover validation dataset. In addition, the area is challenging in terms of land cover classification and change detection due to heterogenous landscapes. For Colombia and Portugal, SEN4LDN LCC maps were indirectly validated by comparing the LCC with available national products in Colombia and Portugal.

2.2.2.1 Direct validation of land cover change for Uganda

Sampling stratification

Stratified random sampling design was used to collect LCC validation data in Uganda (Figure 3). For stratification, high spatial resolution (10 meters) Global Land Cover (GLC) products were used. For this purpose, we selected GLC products with consistent annual output: ESRI (ArcGIS) and Dynamic World (DW by Google). Here, LCC between 2019 and 2023 is considered. This stratification is different from the SEN4LDN LC change maps. As such, this allowed us to collect validation data while the Sen4LDN maps were being generated.

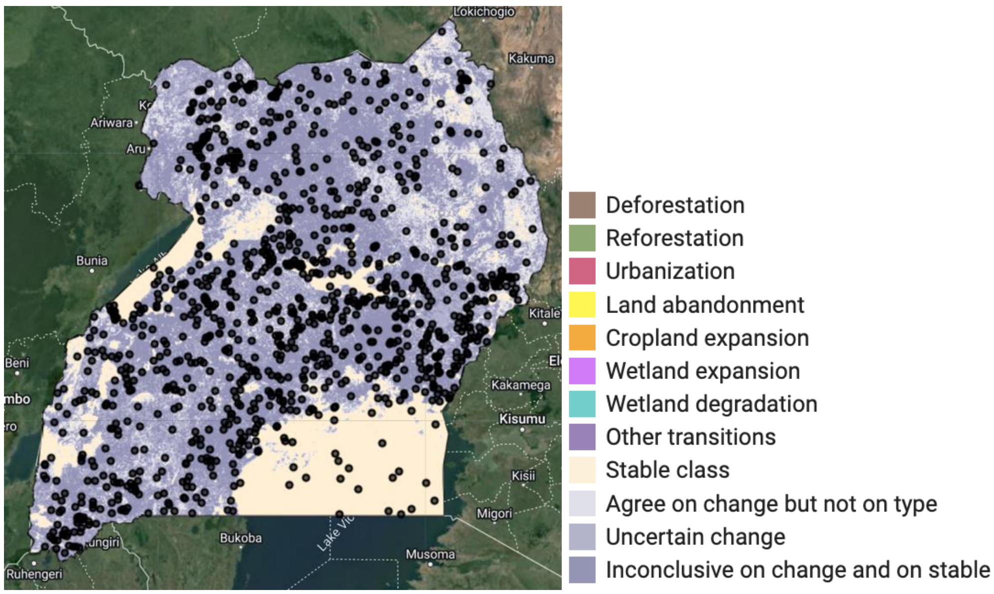


Figure 3: Distribution of stratified random samples in Uganda based on 8 change strata, stable class and 3 uncertainty strata.

To derive a consistency among the GLC maps, we harmonized the original land cover classes for the two products and further aligned with IPCC categories: forest land, cropland, low vegetation (grassland and shrubs), wetlands (incl. open water), settlements, and other lands. To improve the temporal consistency of the maps and reduce falsely detected change areas, we introduced stable classes between 2018-2019 and 2022-2023 for each GLC product. Stable class means the land cover type is the same for two consecutive years (e.g., 2018 and 2019). Unstable areas with different land cover types in the two consecutive years were recorded. Afterward, the algebraic differentiation for time discrepancy of 2019 and 2023 enabled the detection of the classes transition process (or LCC) within each GLC product and introduced 8 change strata at this stage. To further increase the change credibility in the stratification, we focused on the agreement on LCC between DW and ESRI for the final map output. During this stage, an additional stable-no change stratum and 3 uncertainty strata of different levels were added.

When selecting the sample, we used equal allocation of sample sites in each change stratum to ensure even coverage of sample units across different strata based on the final stratification map. For achieving more precise estimates, the strata with a larger area proportion were allocated 100 sample units each, while those with a smaller proportion accounted for 50 sample sites per stratum. A total of 750 stratified sample units were selected for Uganda (Table 3).

Each sampling point represents a 10x10 meter pixel-based block. Table 3 shows the list of LCC change or transition strata and allocated sample units.

Table 3: Stratification and corresponding sample size for LCC validation in Uganda

LCC or transition	N of pixels	Percentage	N sample units
Deforestation	20128949	0.83	50
Reforestation	121649	0.01	50
Urbanization	2039711	0.08	50
Land abandonment	239184	0.01	50
Cropland expansion	1818769	0.07	50
Wetland expansion	2782229	0.11	50
Wetland degradation	47510	0.00	50
Other transitions	87793	0.00	50
Stable no change	1136626775	46.73	100
Maps agree on change but not on the type	6648771	0.27	50
Uncertain change	329602281	13.55	100
Inconclusive on change and stable	932195743	38.33	100
Total	**2432339364**	**100**	**750**

Sample interpretation interface and data collection

The reference dataset was collected using the online, free-access platform Collect Earth Online (CEO), which serves as a tool for interpreting land cover surface images. Integrated tools such as GeoDash were customized within the platform to include supportive time series diagrams and image composites that assist visual interpretation. Additionally, KML plots for each sample could be downloaded for external review to enhance analysis quality. For sample analysis, experts had flexibility in choosing from various imagery options, including Mapbox Satellite, Planet Monthly, Planet NICFI Public (Pantropics only), and Sentinel-2.

Interpretation contained two phases: first, experts were allocated randomly selected sample sites for visual identification. In the second phase, the quality check was done by review experts. The two Ugandan experts are Prof. Moses Isabirye and Joram Bahati of the University of Butisema. The review experts are the WU authors.

Figure 4 illustrates that each sample point comprises a central 10x10 meter block and a larger 30x30 meter unit block. Experts are requested to identify land cover types for the years 2019 and 2023 using additional tools such as Google Earth Pro (for historical imagery), Esri Wayback, the Normalized Difference Vegetation Index (NDVI) time series graphs in Google Earth Engine, and GeoDash (Figure 5). Land cover labels such as open water, trees, grass, crops, urban areas, shrubs, wetlands, and others can be assigned to the 10x10 meter square. If the majority land cover in the 30x30 meter box differs from that of the central square, the appropriate label was selected. Experts needed to determine whether a change occurred between 2019 and 2023; if so, the new land cover class was interpreted within the 10x10 meter block and 30x30m block. Finally, experts indicated their confidence level in the interpretation based on image quality and site clarity.

After the interpretation process by local experts, we conducted quality checks by offering feedback on incorrectly assigned labels to the experts. After two rounds of revision, the 750 samples were guaranteed to have a high quality for validation. Accuracies were calculated both at the change vs. no change level and for the transition classes by checking the agreement between the map and the reference labels.

Figure 4: Snapshot of the visual interpretation platform in Collect Earth Online

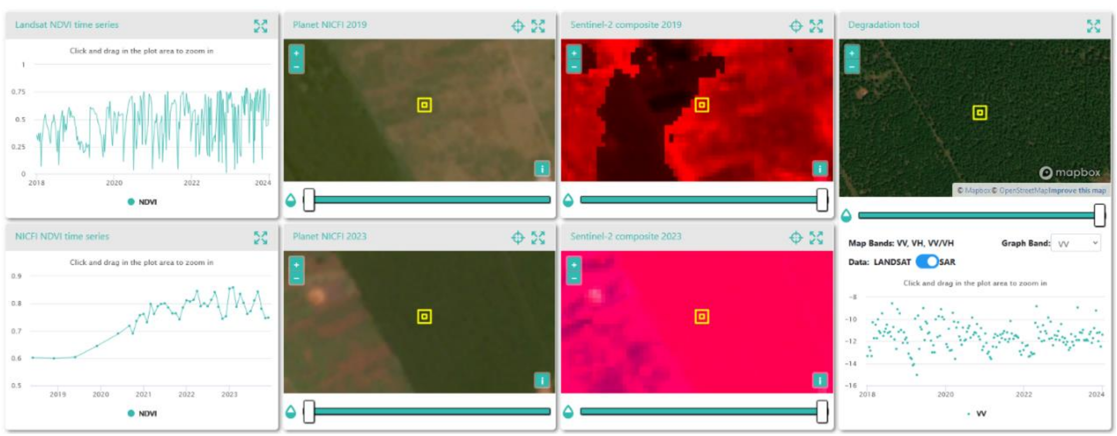


Figure 5: Screenshot of the Geodash tool in CEO depicting NDVI time series, planet images, Sentinel false colour composites for 2019-2023

2.2.2.2 Indirect validation of land cover change

The land cover change (LCC) maps of Colombia and Portugal were indirectly validated through a comparison with the national LCC maps of the two countries. The MapBiomass product of Colombia and the Conjuctural Land Occupation map (COSc - Carta Ocupacao do Solo Conjuntural) of Portugal were used for this purpose (Figure 6). The maps are described in detail below.

A. Portugal: COSc map **B. Colombia: MapBiomas map**

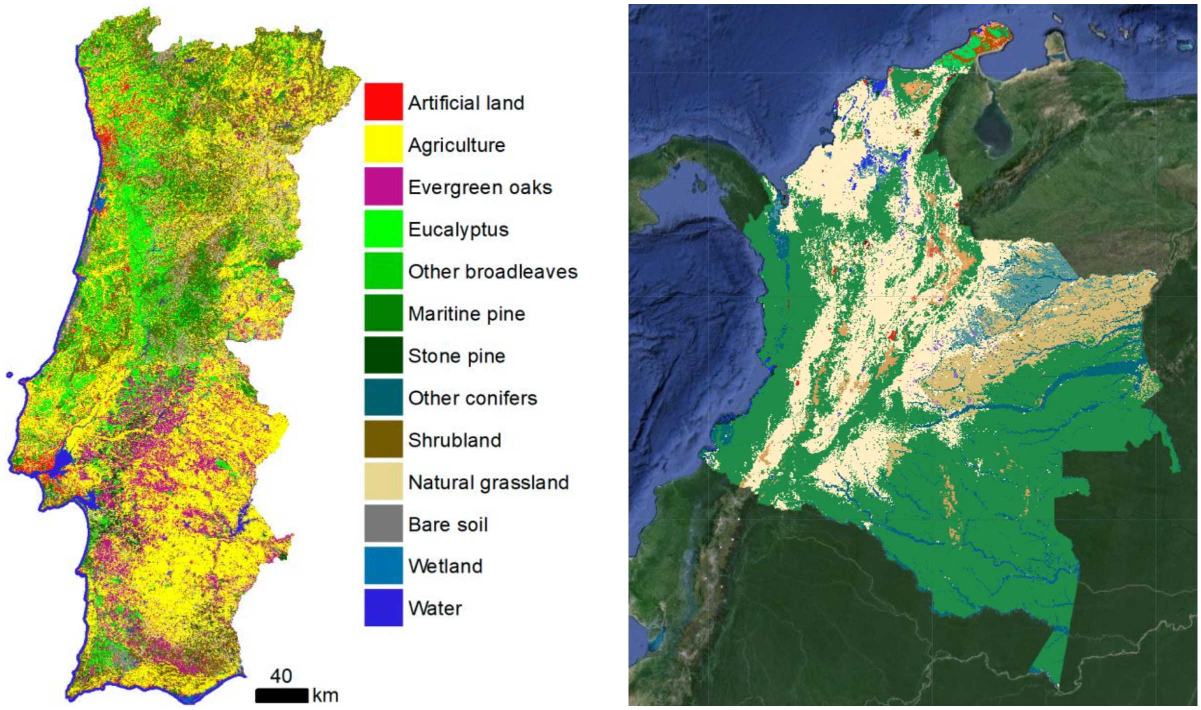


Figure 6: National land cover maps: A. COSc land cover 2018 for Portugal [6]*, and B. MapBiomas land cover 2019 for Colombia* [7]*. Legend of MapBiomas can be referred to Table 5.*

Conjuctural Land Occupation map (Portugal)

The COSc is a land cover product for Portugal [8], covering the years 2018, 2020, 2021, 2022, and 2023. The dataset, derived from Sentinel-2 satellite imagery, has a spatial resolution of 10 meters. The classification approach includes a supervised image classification using the Random Forest algorithm, enhanced by post-classification analysis incorporating expert knowledge. The COSc dataset delineates thirteen land cover classes (Table 4), including key tree species prevalent in Portugal. The overall accuracy of the 2018 map is 81.3 ± 2.1%. A visualization of the map is shown in Figure 6A.

As COSc does not have data for 2019, this study evaluated the LCC in Portugal for the period 2020 – 2023. The legend of the product was harmonized to match the SEN4LDN transition classes. Agreement between the COSc map and the SEN4LDN product were compared for detailed LCC classes, and the area percentage of each class was calculated per product.

Table 4: Land cover classes mapped by the COSc map [6].

Level 1	Level 2	Level 3	Level 3 Class Description
Artificial land	Artificial land	Artificial land	Impervious surfaces such as residencies, industries, and roads.
Agriculture	Agriculture	Agriculture	Temporary and permanent crops, managed grassland, and lawns.
Forest trees	Broadleaves	Evergreen oaks	Cork oak (Quercus suber) and Holm oak (Quercus rotundifolia).
		Eucalyptus	Eucalyptus (Eucalyptus spp.)
		Other broadleaves	Broadleaves other than evergreen oaks and eucalyptus.
	Conifers	Maritime pine Stone pine Other conifers	Maritime pine (Pinus pinaster). Stone pine (Pinus pinea). Conifers other than maritime and stone pines.
Shrubland and Natural grassland	Shrubland	Shrubland	Small and tall shrubs. Additionally, includes shrub regeneration after a burn event.
	Natural grassland	Natural grassland	Spontaneous herbaceous vegetation. Additionally, includes herbaceous regeneration in forest clear-cuts and burnt areas.
Bare soil	Bare soil	Bare soil	Rocks, sand, and bare soil. Additionally, includes clear cuts and burnt areas with no vegetation (<25% vegetation cover).
Wetland and Water	Wetland and Water	Wetland and Water	Vegetation temporarily covered by salt or brackish water. Permanent water.

MapBiomas Collection 1.0 (Colombia)

The MapBiomas Colombia product is the outcome of MapBiomas Amazon project for monitoring the Amazon region [7]. The Collection 1.0 covers the period 1985-2022. The product has a 30 m resolution and is generated from Landsat images using the Random Forest classifier. The overall accuracy of the maps is around 82.4%. A total of 21 thematic classes are mapped in the product (Table 5)[1]. Figure 6B shows the MapBiomas product for the year 2019.

As MapBiomas Colombia does not have data for 2023, this study evaluated the LCC for the period 2019 – 2022. Legend of the product was harmonized to match the SEN4LDN transition classes. Agreement between the MapBiomas and the SEN4LDN product was compared for the LC transition classes and area percentage of each transition type was calculated per map.

[1] For a detailed definition of the classes, users are referred to https://colombia.mapbiomas.org/wp-content/uploads/sites/3/2024/07/LEGEND-DESCRIPTION-MAPBIOMAS-COLOMBIA-COLLECTION-1-Documentos-de-Google.pdf. The data can be accessed through Google Earth Engine (https://code.earthengine.google.com/?scriptPath=users%2Fmapbiomas%2Fuser-toolkit%3Amapbiomas-user-toolkit-lulc.js).

Table 5: Land cover classes of the MapBiomas Colombia product. Source: MapBiomas (2020).

COLLECTION 1 – CLASSES	ID	New Color
1. Forest formation	1	
1.1. Forest	3	
1.2. Mangrove	5	
1.3. Flooded forest	6	
1.4. Wooded sand vegetation	49	
2. Natural non forest formation	10	
2.1. Wetland	11	
2.2. Grasslands/ herbaceous	12	
2.3. Hypersaline tidal flat	32	
2.4. Rocky outcrop	29	
2.5. Herbaceous sand vegetation	50	
2.6. Other non forest formation	13	
3. Agricultural and livestock area	14	
3.1. Forest plantation	9	
3.2. Palm oil	35	
3.3. Mosaic of agriculture and pasture	21	
4. Non-vegetated area	22	
4.1. Beach, dune and sand spot	23	
4.2. Infrastructure	24	
4.3. Mining	30	
4.4. Other non-vegetated area	25	
5. Water body	26	
5.1. River, lake or ocean	33	
5.2. Aquaculture	31	
5.3. Glacier	34	
6. Not observed	27	

2.3 Validation of trends in land productivity

2.3.1 Overall procedure

Vegetation productivity is defined as the seasonal accumulated production of green biomass as estimated from a satellite-derived index, that expresses the density and health of plant life, providing indicators of photosynthetic activity and overall ecosystem functionality. The total sum of this index between the start and end of seasons (Total productivity, TPROD) indicates the green biomass production. The maximum seasonal value (MAXV) indicates the potential productivity as a basis for the performance estimation.

Land productivity, and losses of productivity in connection with land degradation, can be estimated based on the trend, state and performance of vegetation productivity ([5], [6], [7]) The trend measures the rate and direction of change of land productivity over a time period. The state compares the productivity to historical productivity, and the performance compares the local productivity to similar land units over a large area.

In SEN4LDN, the trend is estimated for the period 2018-2023 at 10 m spatial resolution. The resulting *Trendval* displays the value of the slope coefficient of this trend, thus the amount of change over time. The discrete *Trendclass* shows areas of strong negative trend, weak negative trend, no trend, weak positive and strong positive trend. The continuous *Perfval* performance indicator and discrete *Perfclass* are computed by comparing local pixel values with the average across large areas. The *Trendclass* and *Perfclass* are combined in the *LPD*, whereas the *Trendval* and *Perfval* are combined in the *LPDval*.

Validation of the trends in land productivity products will concentrate on the following SEN4LDN output products:

- *Trendval*: values of trend coefficient of productivity (2018-2023)
- *Trendclass*: classes indicating trend / no trend
- *Perfval*: Maximum performance 2021-23 over the land cover class reference
- *Perfclass*: Classes of performance indicating degradation / no degradation
- *LPDval*: Continuous values of land productivity degradation
- *LPD*: Classes of degradation / no degradation by combining trend and performance

The validation procedures include:

- **Visual checks** to evaluate whether spatial artefacts are present in the products.
- **Internal consistency analysis** based on samples in the Sentinel-2 tile overlap areas, since trends in land productivity products are processed per Sentinel-2 tile. The analysis is based on statistical consistency of continuous variables (*Perfval* and *LPDval*), and on a contingency matrix analysis of discrete classes (*Trendval*, *Perfclass* and *LPDclass*). *Trendclass* is excluded from this analysis, because of the very high occurrences of 0-values (i.e. no or no significant trend detected), which cause high skewedness in the data.
- **Indirect validation** through qualitative cross-comparison with global products derived from CLMS DMP 300m.

The possibility to perform direct validation based on comparison with FLUXNET data was evaluated and not retained. Only for one FLUXNET site in Western Spain (ES-Abr: Albuera[2], latitude: 38.701839, longitude: -6.785881) an overlap with the SEN4LDN trends in land productivity products is found. However, for this site, no FLUXNET data is available after 2020. It is therefore not relevant to compare this data source with the SEN4LDN products that were generated for the time series 2018-2023.

2.3.2 Reference data

CLMS GDMP 300m version 1

The CLMS Gross Dry Matter Productivity (GDMP) product represents the total amount of dry matter fixed by land plants per unit time through photosynthesis. A substantial fraction of GDMP supports plan autotrophic respiration. GDMP represents the above and belowground part of plants. Every 10-days estimates are available in near real time at global scale in the spatial resolution of about 300 m from January 2014 to June 2020 based upon PROBA-V data with version 1.0 and from July 2020 onwards based upon Sentinel-3 data with version 1.1. To compare this 300 m product with the 10 m resolution SEN4LDN products, pixel extractions on 1x1 300 m pixel are compared to average (or dominant) pixel extractions over 30x30 10 m pixels. Sampling is described in §2.3.4.2.

2.3.3 Validation criteria and metrics

2.3.3.1 Spatial consistency

Spatial consistency refers to the realism and repeatability of the spatial distribution of retrievals over the globe. A first qualitative check of the realism and repeatability of spatial distribution of retrievals and the absence of strange patterns or artefacts (e.g., missing values, stripes, unrealistic values, etc.) can be achieved through systematic visual analysis of maps.

2.3.3.2 Temporal consistency

Temporal consistency refers to the realism of the inter-annual temporal variations. The temporal evolution of TPROD is qualitatively analysed over selected sites.

2.3.3.3 Error evaluation

Accuracy, Precision and Uncertainty (APU) are quantified by several metrics reporting the goodness of fit between two products.

- Accuracy is the degree of the "closeness of the agreement between the result of a measurement and a true value of the measurand" [15]. Commonly, accuracy represents systematic errors and often is computed as the statistical mean bias (B), i.e. the difference between the short-term average measured value of a variable and the true value.
- Precision or repeatability is the "closeness of the agreement between the results of successive measurements of the same measurand carried out under the same conditions of measurement" [15]. Precision represents the dispersion of product retrievals around their expected value and

[2] https://www.europe-fluxdata.eu/home/site-details?id=ES-Abr

can be estimated by the standard deviation (STD) of the difference between retrieved satellite product and the corresponding reference estimates.

- Uncertainty is a "parameter, associated with the result of a measurement that characterizes the dispersion of the values that could reasonably be attributed to the measurand" [15]. Uncertainty includes systematic and random errors and can be estimated by the Root Mean Squared Distance (RMSD).

In addition to these metrics, other statistics are useful to evaluate the goodness of fit between two datasets including linear model fits. For this purpose, orthogonal regression, such as Geometric Mean Regression (GMR), is computed because orthogonal regression is specifically formulated to handle error in both of the x and y variables [16]. Other metrics are used, such as number of samples (N), indicative of the power of the validation, or the correlation coefficient (R, estimated as Pearson coefficient), which indicates descriptive power of the linear accuracy test.

2.3.4 Sampling

2.3.4.1 Sampling for internal consistency analysis

To evaluate the internal consistency of the *Trendclass*, *Perfval*, *Perfclass*, *LPD* and *LPDval* products, a random sample of points, with minimum distance of 100m, was generated in each Sentinel-2 (horizontal or vertical) tile overlap area. An example of this random sample is shown in Figure 7. Pixel values for these samples are used for pairwise intercomparison between adjacent Sentinel-2 tiles. This results in a maximum sample size between 2400 and 6980, depending on the region of interest (see Table 6).

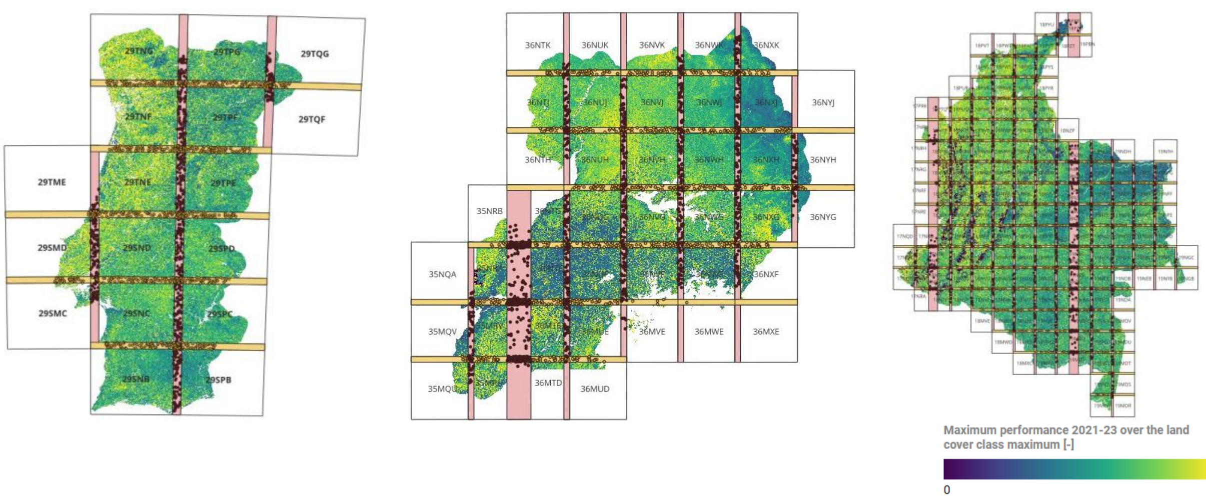


Figure 7: Random sample of points in each horizontal and vertical Sentinel-2 tile overlap area; over Portugal (left), Uganda (centre), Colombia (right). The figure background shows Perfval *(Maximum performance 2021-23 over the land cover class reference).*

Table 6: Number of random point samples in Sentinel-2 tile overlap areas

Country	Number of horizontal overlap areas	Number of vertical overlap areas	Number of samples per overlap area	Maximum sample size
Portugal	13	11	200	2400
Uganda	34	42	40	3040
Colombia	147	202	20	6980

2.3.4.2 Sampling for indirect validation

For qualitative cross-comparison with an external product, a number of expert-based samples were identified per country under study. The number of points identified is 75 for Portugal, 154 for Uganda and 164 for Colombia.

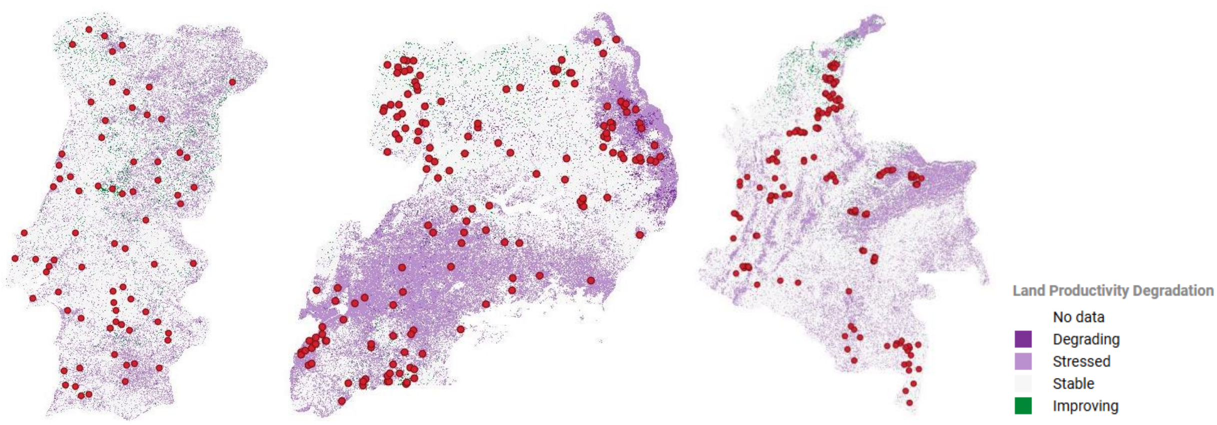


Figure 8: Expert based sample of points for indirect validation over Portugal (left), Uganda (centre), Colombia (right). The figure background shows LPD *(Classes of degradation / no degradation by combining trend and performance).*

3 Validation Results

3.1 Validation of trends in land cover

3.1.1 Validation results of land cover

Table 7 shows the accuracies for the validation of SEN4LDN land cover maps in the three countries. The highest overall accuracy was achieved in Colombia (90.1% ± 3.4%, 95% CI), followed by Portugal (87.0% ± 6.5%) and Uganda (69.6% ± 5.5%); thus, the overall accuracy varied in different countries. The confusion matrices of the three countries can be found in Annex A.

Among the six LC types, trees, low vegetation, and wetlands (including open water and herbaceous wetlands) were mapped with a higher accuracy in the three countries. The SEN4LDN map also had high accuracies in mapping crops in Portugal, while in Uganda and Colombia, the producer's accuracy for crops was low, indicating a higher omission error of this class. Low vegetation (including grass and shrubs) had considerable confusion with trees and crops in Uganda by checking the confusion matrix (Table 16 in Annex A). The map performed well in mapping built-up in Colombia, while in Portugal and Uganda, the accuracy of built-up was low. The low accuracy may relate to the limited sample points for this class. Through visual checks (Figure 9), it can be found that built-up areas were well captured by the SEN4LDN LC maps. The "Other" class (including bare/sparse vegetation, snow & ice, and moss/lichen) was mapped with relatively low accuracies in the three countries, which is also caused by the limited validation data for this type.

Table 7: Accuracies for the validation of SEN4LDN land cover maps in Uganda, Portugal, and Colombia. UA and PA represent the user's accuracy and the producer's accuracy, respectively. The validated map was 2023 for Uganda, 2021 for Colombia, and 2019 and 2021 maps were collectively assessed for Portugal.

Class	Uganda			Portugal			Colombia		
	UA (%)	PA (%)	Sampling units	UA (%)	PA (%)	Sampling units	UA (%)	PA (%)	Sampling units
Trees	60.2	77.6	95	83.3	88.5	6392	92.5	98.1	9720
Crops	70.6	49.1	212	89.1	99.8	878	99.8	8.6	556
Low vegetation	63.0	74.3	253	88.7	78.2	8280	86.6	87.8	6172
Wetland	93.7	90.9	161	98.9	92.5	1479	71.9	87.2	916
Built-up		0.0	14	1.8	46.2	13	96.0	73.9	385
Other	9.6	0.3	15	15.9	78.2	158	85.4	23.5	751
Overall accuracy (%)	**69.6±5.5**			**87.0±6.5**			**90.1± 3.4**		

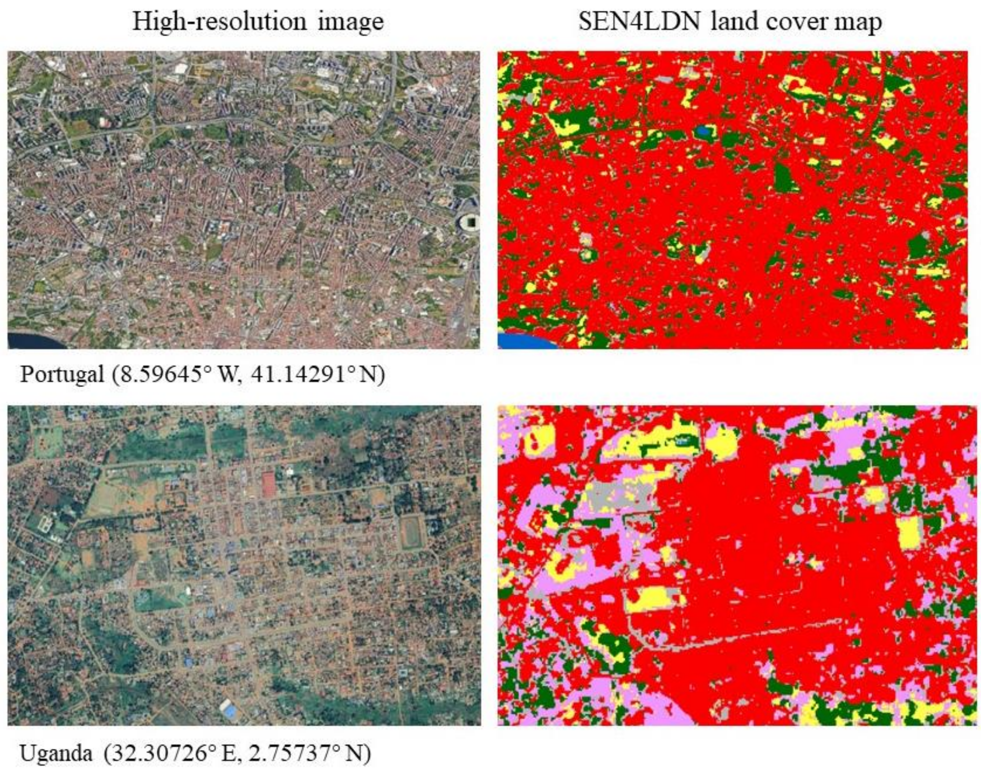


Figure 9: Mapping of built-up by SEN4LDN land cover map in Portugal and Uganda

3.1.2 Validation results of land cover change

3.1.2.1 Direct validation in Uganda

The SEN4LDN LCC map achieved an overall accuracy of 73.7% at the change vs. no change level in Uganda. From Table 8, it can be observed that No change areas were overestimated at the cost of Change. The producer's accuracy of Change was 18.1%, indicating considerable omission of this class.

Table 8: Confusion matrix for land cover change map in Uganda at Change vs. No change level

Class		Reference				
		Change	**No Change**	Correct	Total	UA (%)
Map	**Change**	**41**	12	41	53	77.4
	No Change	185	**512**	512	697	73.5
	Correct	41	512			
	Total	226	524			
	PA (%)	18.1	97.7			
	Overall Accuracy (%)					**73.7**

For the transition classes, the SEN4LDN LCC map achieved an overall accuracy of 72.9% (Table 9) in Uganda. The highest producer's accuracy, indicating how well the classification captures the pixels that should be labeled as a certain class without missing them, was achieved by the Wetland establishment class (100%), followed by Stable/Unlikely change (97.7%) and Reforestation (51.0%), and the highest user's accuracy, indicating the reliability of the class being correctly identified without assigning a pixel a classification that is not accurate, was achieved by the Reforestation class (83.3%), followed by Deforestation (75.0%) and Stable/Unlikely change (73.5%). Therefore, the map performed relatively well in detecting changes related to forest gain (Reforestation) and loss (Deforestation).

Consistent with the observation at change vs. no change level, Table 9 shows that the SEN4LDN map tended to overestimate Stable/Unlikely change. The reference data comprised the full range of transition classes (10 specific change classes), while the SEN4LDN map only identified 7 of them, with Inundation, Withdrawal of agriculture, and Urban expansion classes being missed. It should be noted that some transition classes were not well reflected in the LCC validation data due to the quality of the stratification. Although 10 transition classes were stratified using the existing global maps for validation data collection, the observed transition sample size was low for urban transitions, inundation, and wetland transitions. Thus, the accuracy estimates cannot be reliable for these transitions.

Table 9: Confusion matrix for land cover change map in Uganda for transition classes

Class			Reference													
			0	1	2	3	4	5	6	101	102	103	104	Correct	Total	UA (%)
Map	**Stable/Unlikely change**	0	**512**	10	28	6	6	27	2	24	18	0	64	512	697	73.5
	Deforestation	1	1	**6**	1	0	0	0	0	0	0	0	0	6	8	75.0
	Vegetation loss	2	2	0	**2**	3	0	1	0	0	0	0	0	2	8	25.0
	Urban expansion	3	0	0	0	**0**	0	0	0	0	0	0	0	0	0	-
	Inundation	4	0	0	0	0	**0**	0	0	0	0	0	0	0	0	-
	Withdrawal of agriculture	5	0	0	0	0	0	**0**	0	0	0	0	0	0	0	-
	Wetland drainage	6	0	0	0	0	0	0	**0**	0	1	0	0	0	1	0.0
	Reforestation	101	5	0	0	0	0	0	0	**25**	0	0	0	25	30	83.3
	Vegetation establishment	102	1	0	0	0	0	0	0	0	**1**	0	0	1	2	50.0
	Wetland establishment	103	2	0	0	0	0	0	0	0	0	**1**	0	1	3	33.3
	Agricultural expansion	104	1	0	0	0	0	0	0	0	0	0	**0**	0	1	0.0
	Correct		512	6	2	0	0	0	0	25	1	1	0			
	Total		524	16	31	9	6	28	2	49	20	1	64			
	PA (%)		97.7	37.5	6.5	0.0	0.0	0.0	0.0	51.0	5.0	100.0	0.0			
	Overall Accuracy (%)															**72.9**

3.1.2.2 Indirect validation in Portugal and Colombia

Compared with the MapBiomas product in Colombia and the COSc map in Portugal, SEN4LDN LCC maps had a higher percentage of Stable/Unlikely change areas (Table 10). In Colombia, the mapped change area accounts for 6.9% by MapBiomas and 1.2% by SEN4LDN, respectively. Both maps had similar estimation on the area of Urban expansion and Wetland establishment, namely < 0.05% of the total area. The two maps have a large discrepancy in the mapping of Deforestation and Wetland drainage, which MapBiomas estimated much more percentage of areas for the two types than SEN4LDN. From Figure 10, it can be observed that MapBiomas indeed overestimated Wetland drainage (Figure 10a) and Deforestation (Figure 10b).

In Portugal, the characterized change area accounts for 9.5% by COSc and 3.1% by SEN4LDN, respectively. Considering that this represents only a 3-year period (2020-2023), SEN4LDN map's estimate seems to be more plausible. Compared with the COSc map, SEN4LDN was able to detect Urban expansion, Inundation, Wetland drainage, and Wetland establishment that were not detected by COSc (Table 10). The COSc map had a high percentage of area for Vegetation loss (3.4%), while this class was estimated to take 0.6% of the total area according to SEN4LDN. From Figure 11a, it can be seen that COSc overestimated vegetation losses. The same observation has been found for Vegetation establishment, which can be seen from Figure 11b.

Table 10: Comparison of change area proportions estimated by COSc and SEN4LDN in Portugal, and by MapBiomas and SEN4LDN in Colombia. Note that the 0.0% does not equal to 0 as the percentages are shorted to one digit.

Class name	Colombia		Portugal	
	MapBiomas	SEN4LDN	COSc	SEN4LDN
Stable/Unlikely change	93.1%	98.8%	90.5%	96.9%
Deforestation	2.1%	0.6%	1.0%	1.3%
Vegetation loss	0.3%	0.1%	3.4%	0.6%
Urban expansion	0.0%	0.0%	-	0.0%
Inundation	0.7%	0.0%	-	0.0%
Withdrawal of agriculture	0.4%	0.0	1.1%	0.0
Wetland drainage	1.4%	0.0%	-	0.0%
Reforestation	1.2%	0.4%	0.8%	0.6%
Vegetation establishment	0.1%	0.0%	2.9%	0.2%
Wetland establishment	0.0%	0.0%	-	0.0%
Agricultural expansion	0.6%	0.0%	0.3%	0.5%

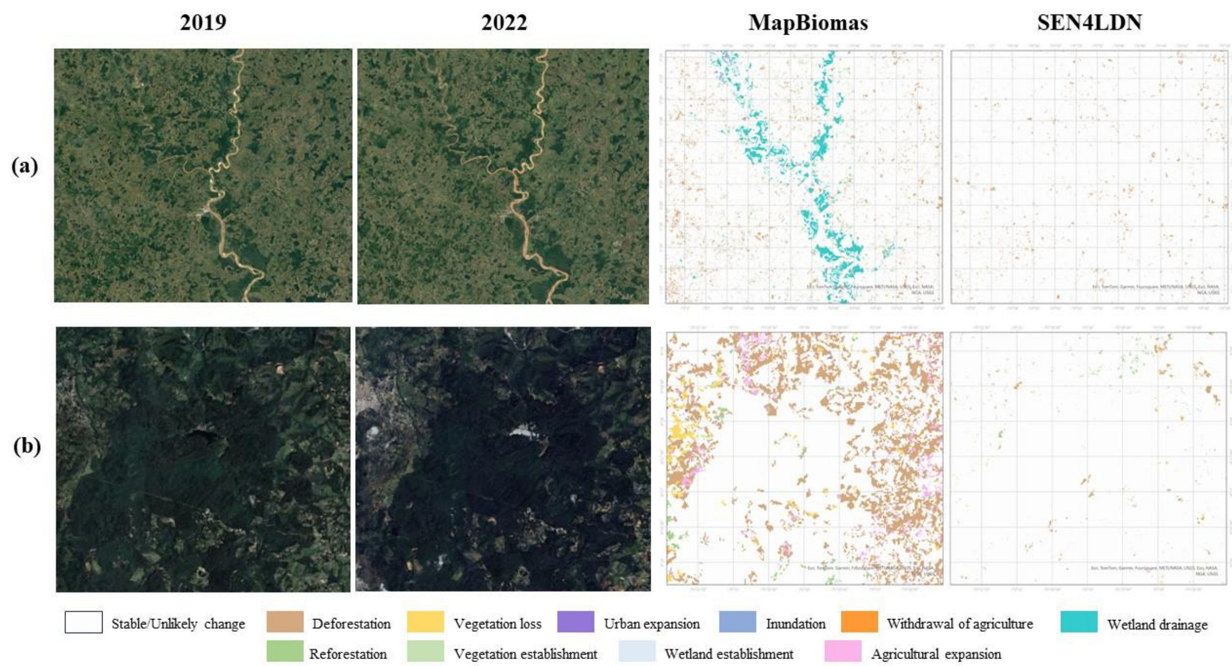


Figure 10: Comparison between MapBiomas and SEN4LDN in Colombia

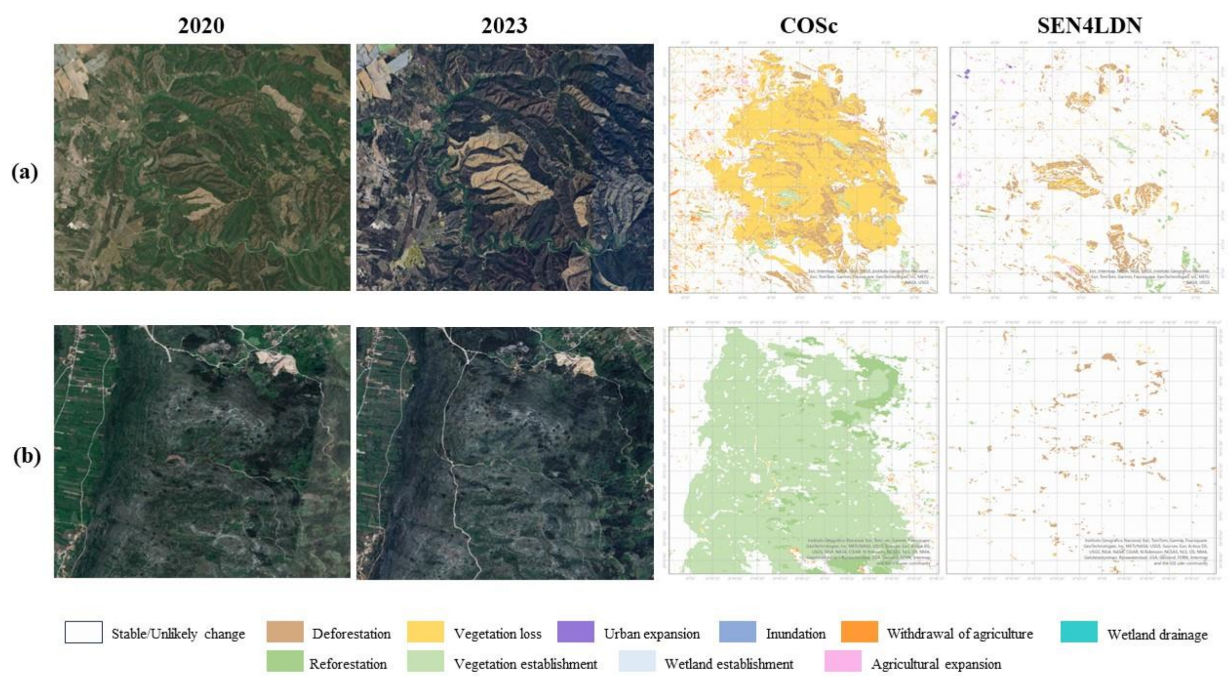


Figure 11: Comparison between COSc and SEN4LDN in Portugal

3.2 Validation of trends in land productivity

3.2.1 Visual checks

Systematic visual analysis and checks were performed by exploring the products for trends in productivity on the SEN4LDN Google Earth Engine Application[3], to evaluate the spatial consistency of the trends in productivity output products.

The *Perfval* product seems to suffer from persistent cloud coverage (and possibly also omission of clouds in the cloud detection), for example in the coastal and mountainous areas of Colombia and the Ruwenzori mountains at the Western border of Uganda (Figure 12). These pixels are labelled as 'degrading' in the *Perfclass* product. Because there is no significant trend detected, in the *LPD* product, the pixels will be labelled as 'Stressed'.

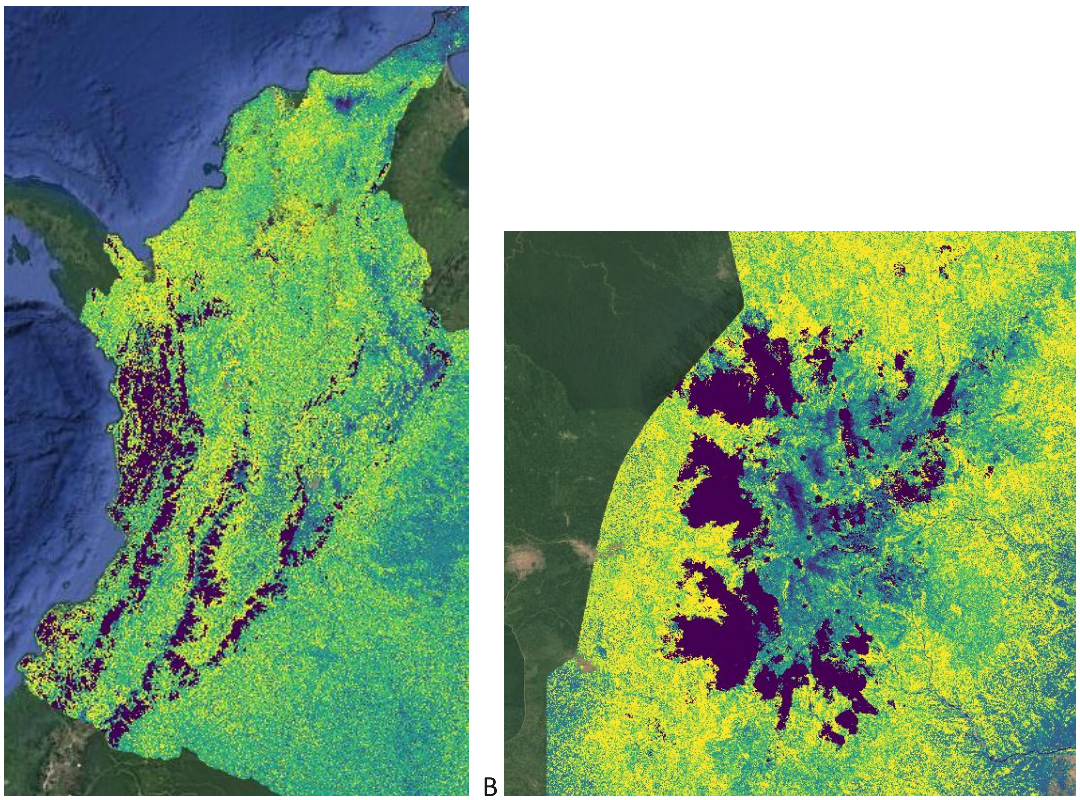
A

B

Figure 12: Effect of persistent cloud cover in A. coastal and mountainous areas of Colombia, and B. Ruwenzori mountain area in West Uganda, on the Perfval *product.*

No other artefacts (e.g., missing values, stripes, unrealistic values, etc.) were found during the visual checks. It must be noted that, although processing is done on Sentinel-2 tile basis, no tile border artefacts are visible in the country wide products. This means that spatial consistency of the SEN4LDN trends in productivity output products is high.

[3] https://vitorsveg.users.earthengine.app/view/sen4ldn

3.2.2 Internal consistency analysis

Internal consistency analysis is based on extractions over random point samples in the Sentinel-2 tile overlap areas. The analysis is based on statistical consistency of continuous variables (*Perfval* and *LPDval*), and on a contingency matrix analysis of discrete classes (*Trendclass*, *Perfclass* and *LPD*).

3.2.2.1 Statistical consistency of continuous variables

Statistical consistency analysis is based on the comparison of frequency histograms, the bias frequency histogram and the scatter density plots with results of GMR regression and APU statistics. Overall, very good consistency is found both for *Perfval* (Figure 13) and *LPDval* (Figure 14). Bias histograms peak at 0.0 bias, and the regression lines are close to the 1:1 line. There is some scatter on the regression plots, most pronounced for the Colombia case. This is possibly an effect of remaining (undetected) clouds in the Sentinel-2 inputs. Also the tile-based atmospheric correction could have larger effects in Colombia because of larger variations in atmospheric components and more pronounced topography.

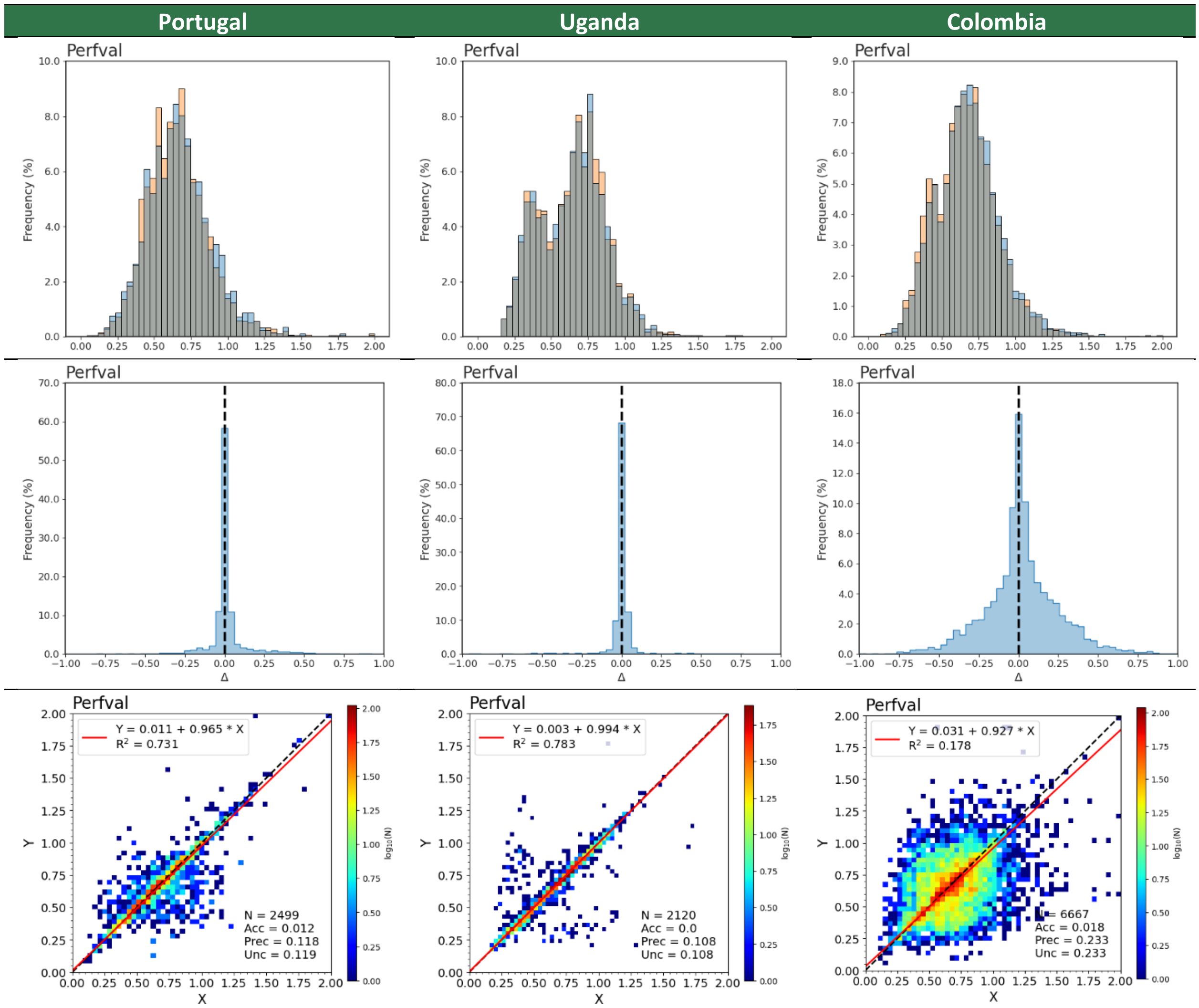


Figure 13: Frequency histograms (top), bias frequency histograms (middle) and scatter density plots (bottom) of Perfval *over Portugal (left), Uganda (centre) and Colombia (right) to evaluate internal consistency over Sentinel-2 tile overlap areas.*

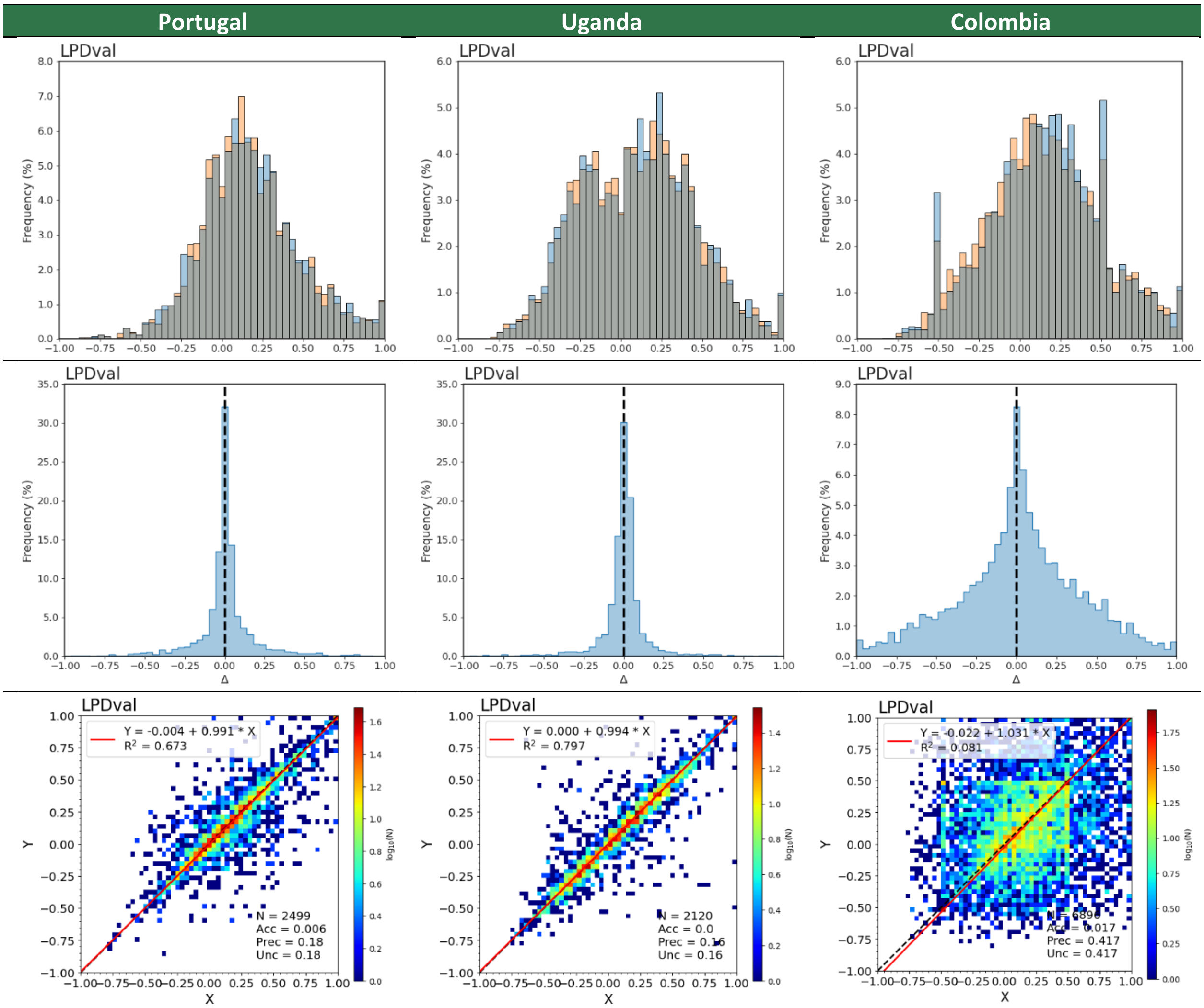


Figure 14: Frequency histograms (top), bias frequency histograms (middle) and scatter density plots (bottom) of LPDval *over Portugal (left), Uganda (centre) and Colombia (right) to evaluate internal consistency over Sentinel-2 tile overlap areas.*

3.2.2.2 Contingency analysis of discrete clases

The contingency matrices in Table 11-

Table 13 show overall very high consistency of *Trendclass*, *Perfclass* and *LPDclass* over the Sentinel-2 tile overlap areas, with overall accuracies that are in general well above 90%. For *Perfclass* and *LPDclass*, however, the results for Colombia are slightly lower, with overall accuracies of 76% and 77%. It is at this point not clear what this originates from. Possibly, in Colombia there are larger effects of tile-based atmospheric correction differences or spurious effects of remaining (undetected) clouds.

Table 11: Contingency matrix for the internal consistency analysis of Trendclass

	Portugal			Uganda			Colombia		
Class	Degr.	Stable	Impr.	Degr.	Stable	Impr.	Degr.	Stable	Impr.
Degrading	**37**	23	0	**67**	27	0	**12**	85	3
Stable	23	**2255**	49	31	**1927**	18	84	**6498**	85
Improving	23	39	**73**	0	16	**34**	0	105	**24**
Overall accuracy (%)			**93.8**			**95.7**			**94.8**

Table 12: Contingency matrix for the internal consistency analysis of Perfclass

	Portugal		Uganda		Colombia	
Class	Degrading	Stable	Degrading	Stable	Degrading	Stable
Degrading	**471**	95	**493**	47	**828**	884
Stable	87	**1843**	42	**1164**	772	**4412**
Overall accuracy (%)		**92.7**		**94.9**		**76.0**

Table 13: Contingency matrix for the internal consistency analysis of LPDclass

	Portugal				Uganda				Colombia			
Class	Degr.	Str.	Stab.	Impr.	Degr.	Str.	Stab.	Impr.	Degr.	Str.	Stab.	Impr.
Degrading	**23**	2	7	0	**50**	8	10	0	**7**	8	16	0
Stressed	10	**523**	96	0	7	**666**	39	1	4	**876**	870	4
Stable	13	71	**1699**	7	8	38	**1242**	10	14	688	**4654**	17
Improving	0	1	9	**38**	0	0	5	**36**	0	3	24	**11**
Overall accuracy (%)				**91.4**				**94.1**				**77.1**

3.2.3 Indirect validation

Indirect validation is done through qualitative comparison of the temporal evolution of average TPROD, the average *Trendval*, *Perfval* and *LPDindex*, and the dominating *Trendclass*, *Perfclass* and *LPDclass* of 30x30 pixel windows on sampling points as specified in §2.3.4.2. These are compared with 1x1 pixel extractions of CLMS Gross Dry Matter Productivity at 300m resolution (see §2.3.2).

Profiles are shown for sites in Portugal (Figure 15 – Figure 17), Uganda (Figure 18 – Figure 20) and Colombia (Figure 21 – Figure 23), with degrading (Figure 15, Figure 18, Figure 21), stable (Figure 16, Figure 19, Figure 22) resp. improving (Figure 17, Figure 20, Figure 23) land productivity.

In some cases, apparent land cover change at the end of the time series is not reflected in the *Trendval* or *Trendclass* (e.g. Figure 16A, Figure 21A). Overall, however, very good agreement is found between the temporal profiles of TPROD and the CLMS GDMP. Visual interpretation of the temporal profiles mostly confirms the trend coefficient (*Trendval*) and trend class (*Trendclass*).

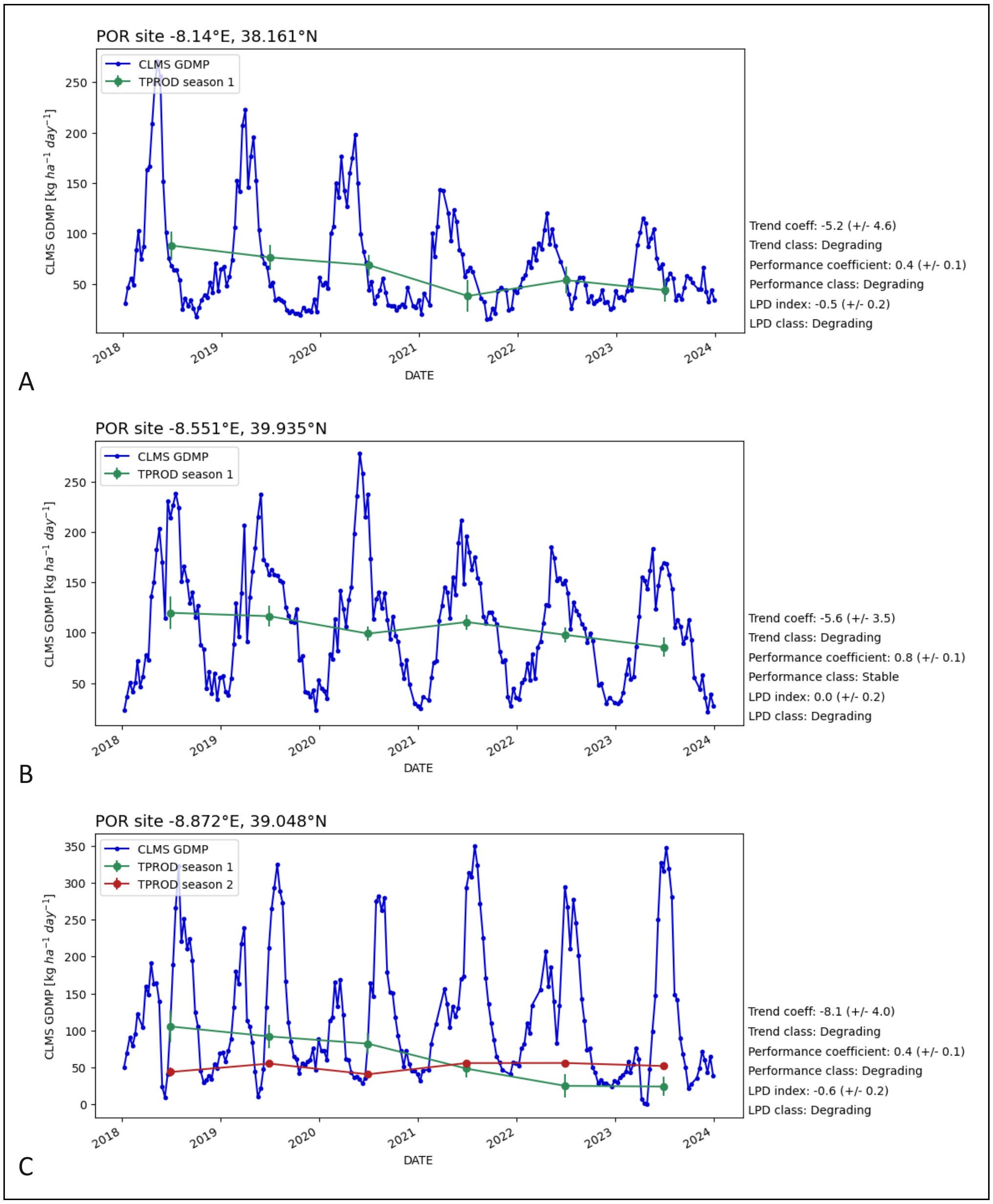


Figure 15: Indirect validation over a few sample sites in Portugal with degrading land productivity. Sentinel-2 derived TPROD [EVI · day] is plotted on the same axis as GDMP [kg ha^{-1} day^{-1}].

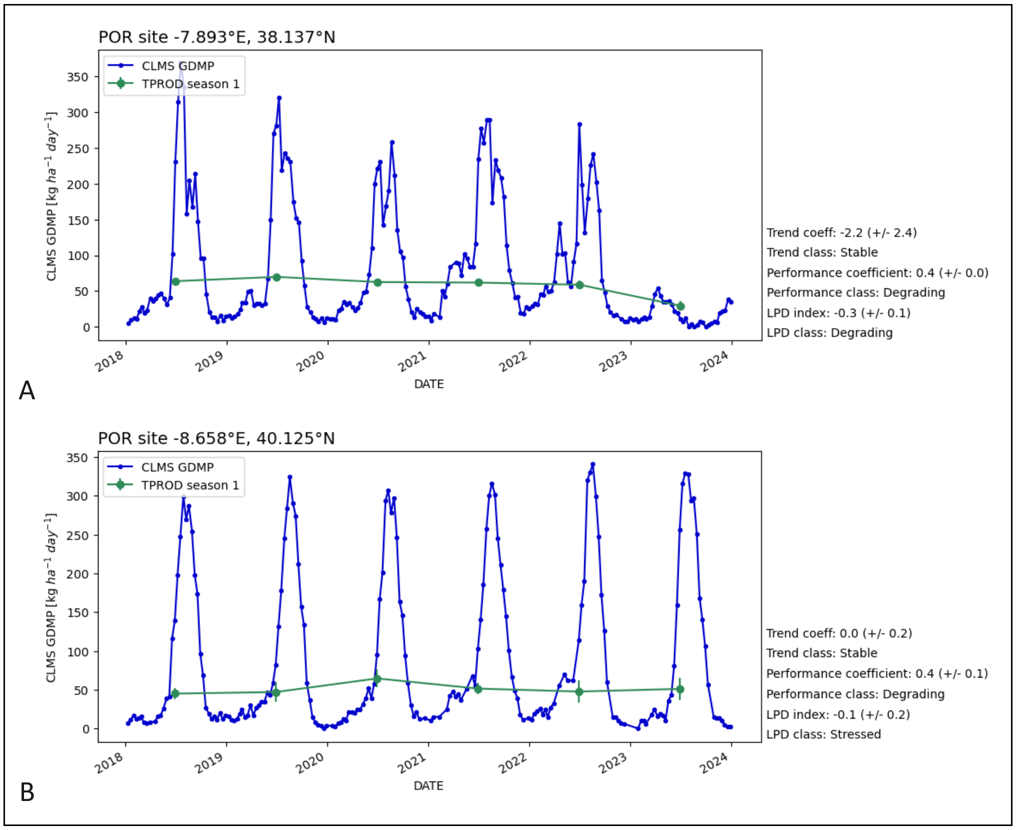
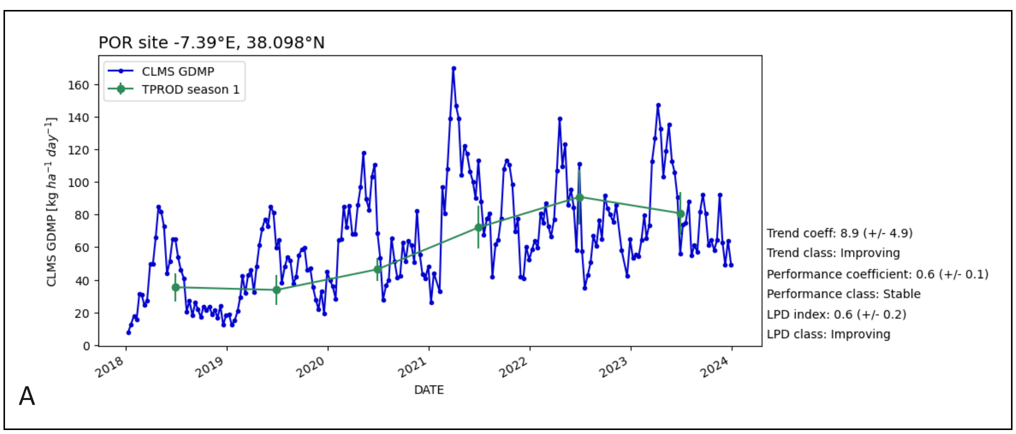


Figure 16: Indirect validation over a few sample sites in Portugal with stable land productivity. Sentinel-2 derived TPROD [EVI · day] is plotted on the same axis as GDMP [kg ha^{-1} day^{-1}].



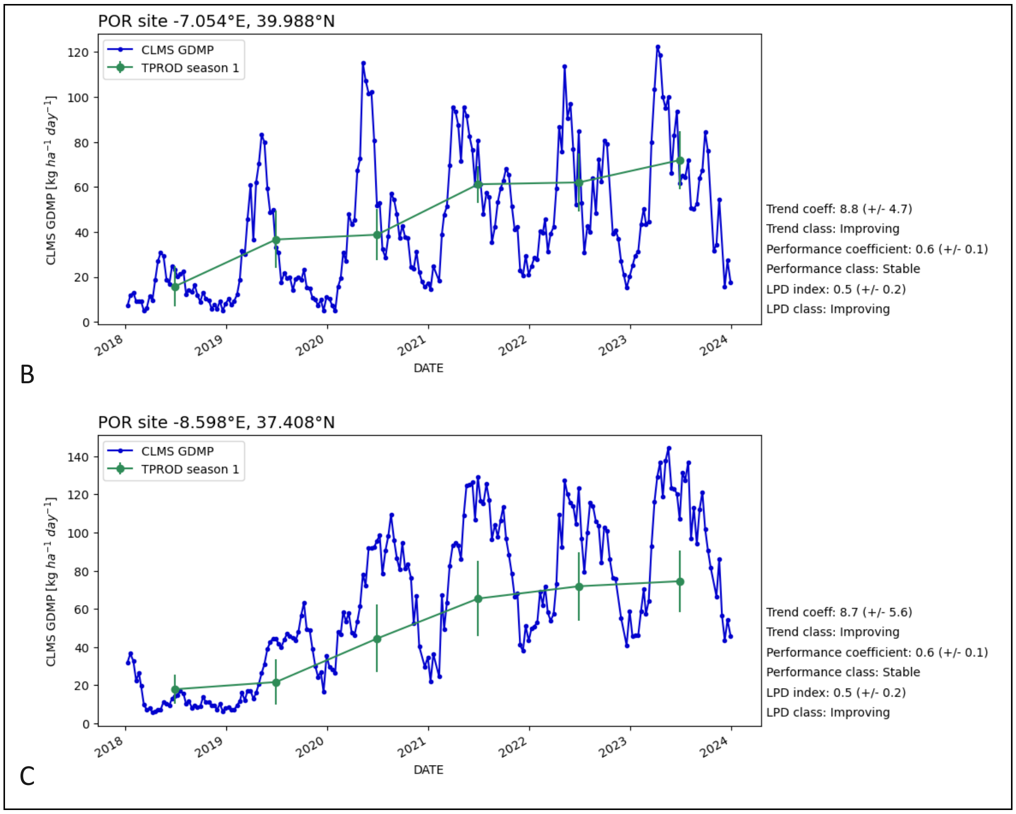
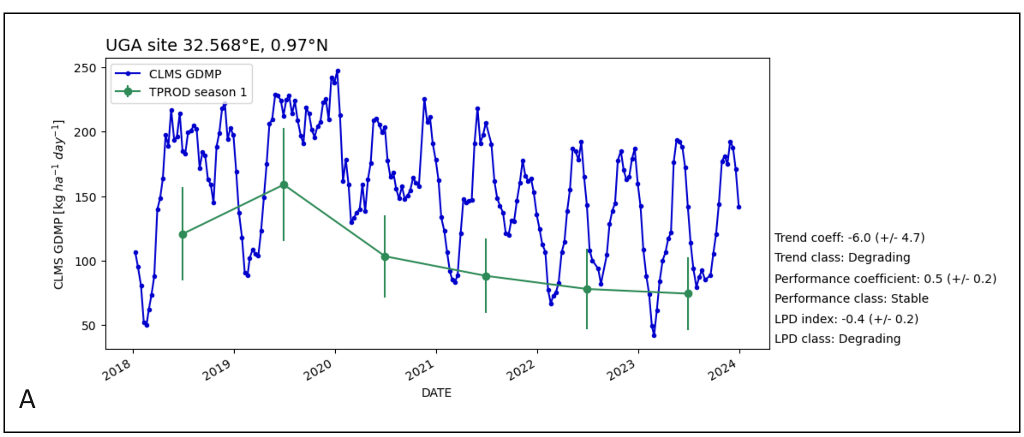


Figure 17: Indirect validation over a few sample sites in Portugal with improving land productivity. Sentinel-2 derived TPROD [EVI · day] is plotted on the same axis as GDMP [kg ha^{-1} day^{-1}].

3.2.3.1 Uganda



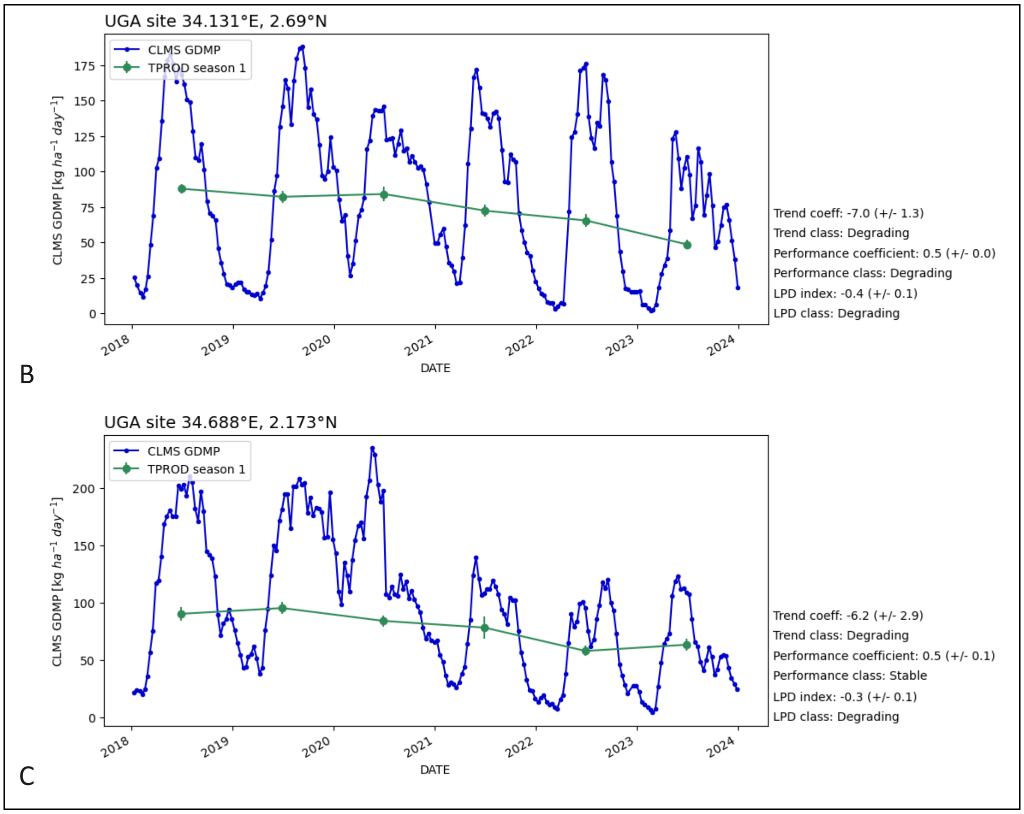
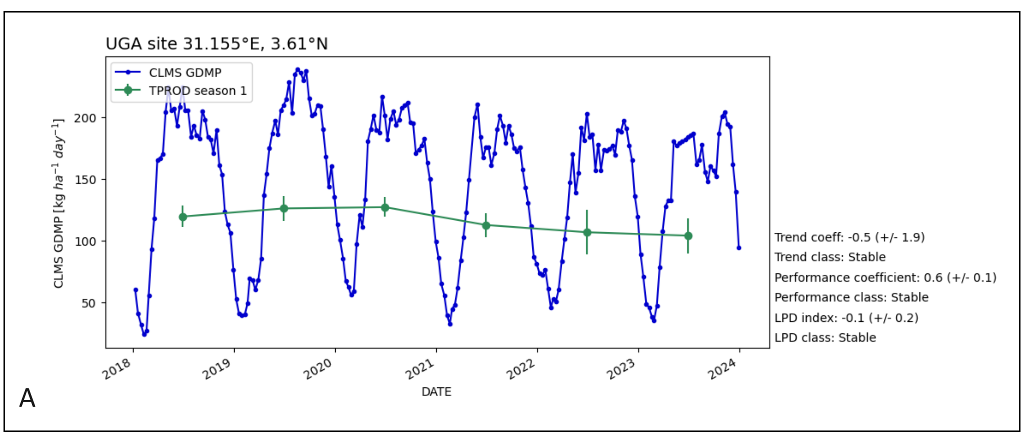


Figure 18: Indirect validation over a few sample sites in Uganda with degrading land productivity. Sentinel-2 derived TPROD [EVI · day] is plotted on the same axis as GDMP [kg ha^{-1} day^{-1}].



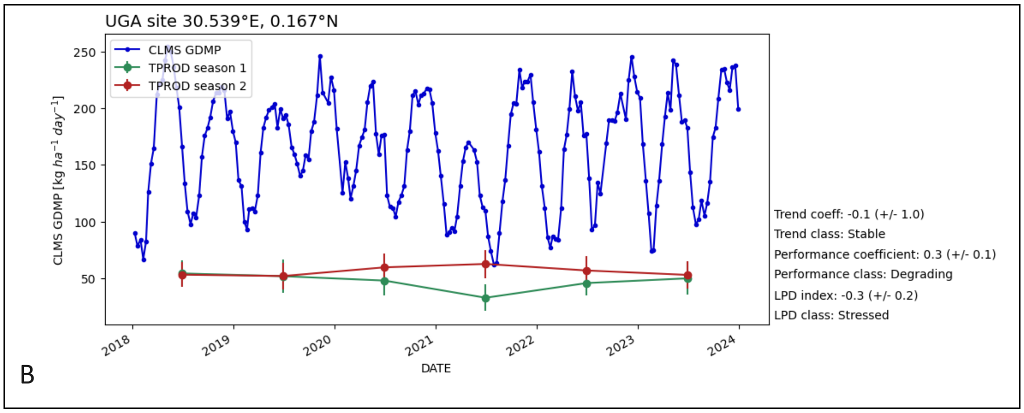
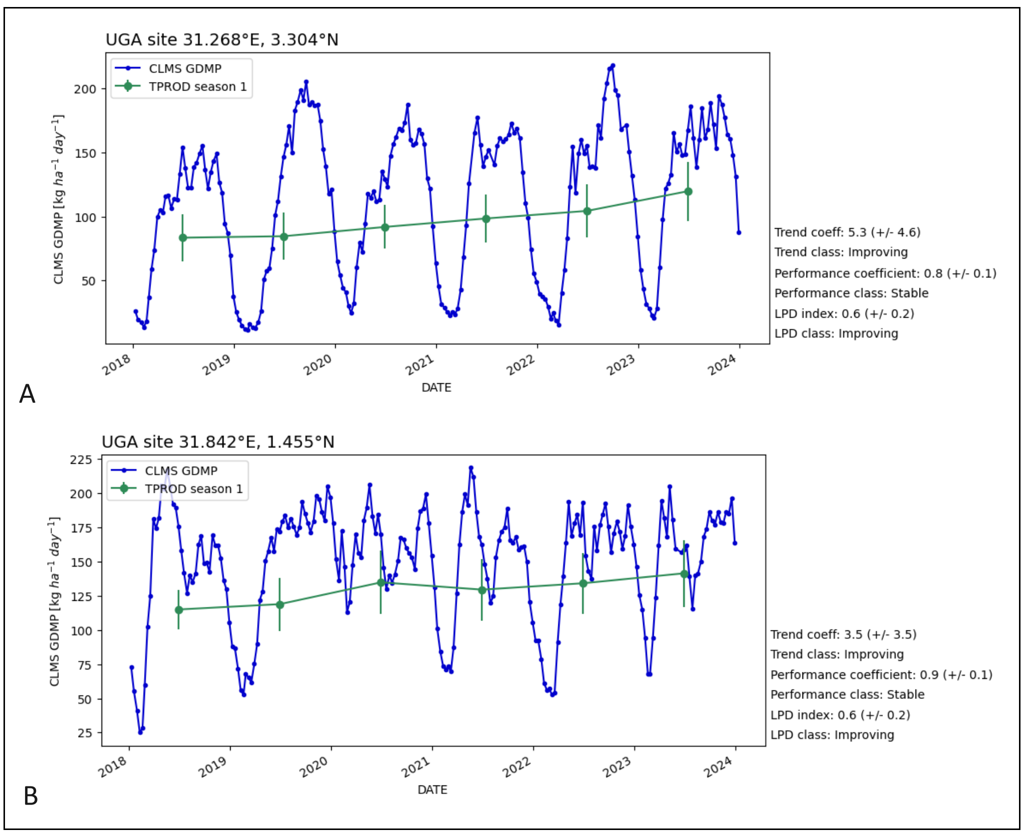


Figure 19: Indirect validation over a few sample sites in Uganda with stable land productivity. Sentinel-2 derived TPROD [EVI · day] is plotted on the same axis as GDMP [kg ha^{-1} day^{-1}].



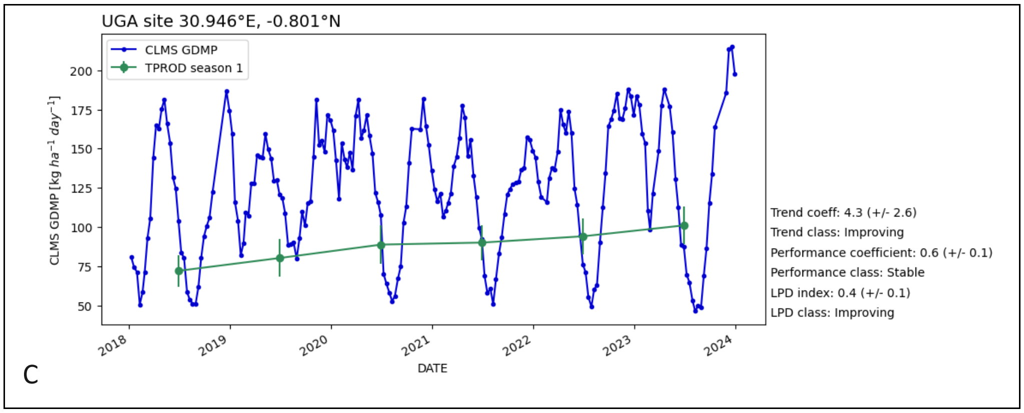
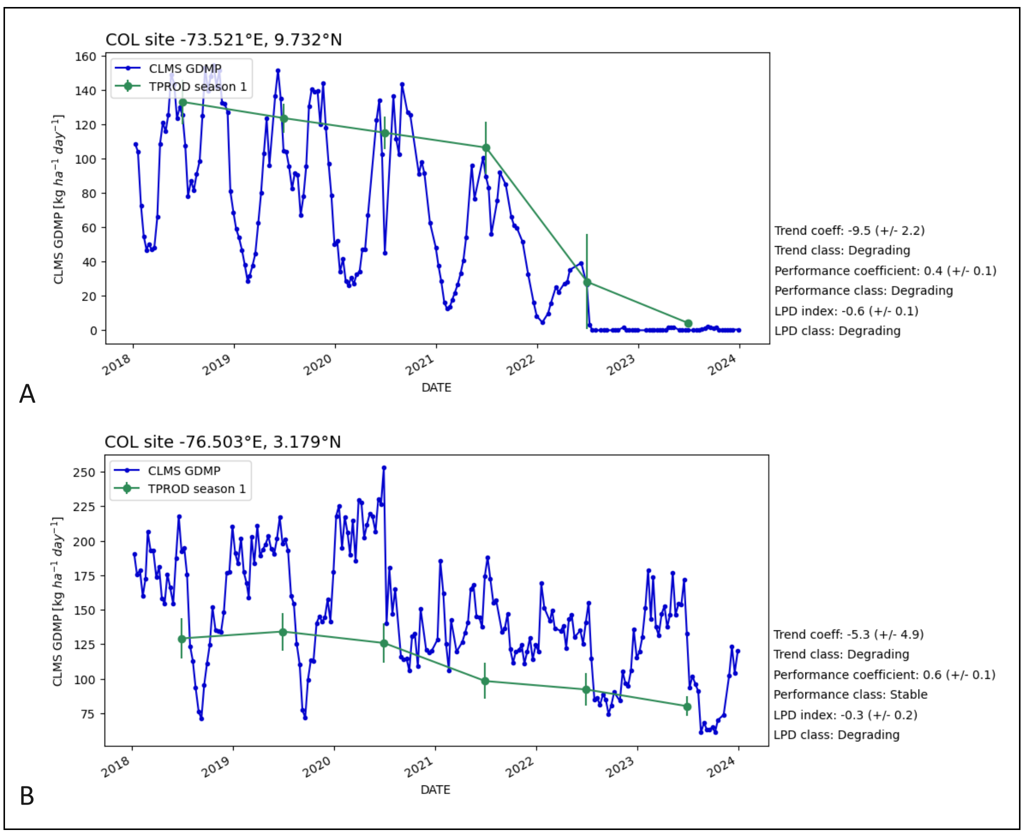


Figure 20: Indirect validation over a few sample sites in Uganda with improving land productivity. Sentinel-2 derived TPROD [EVI · day] is plotted on the same axis as GDMP [kg ha^{-1} day^{-1}].



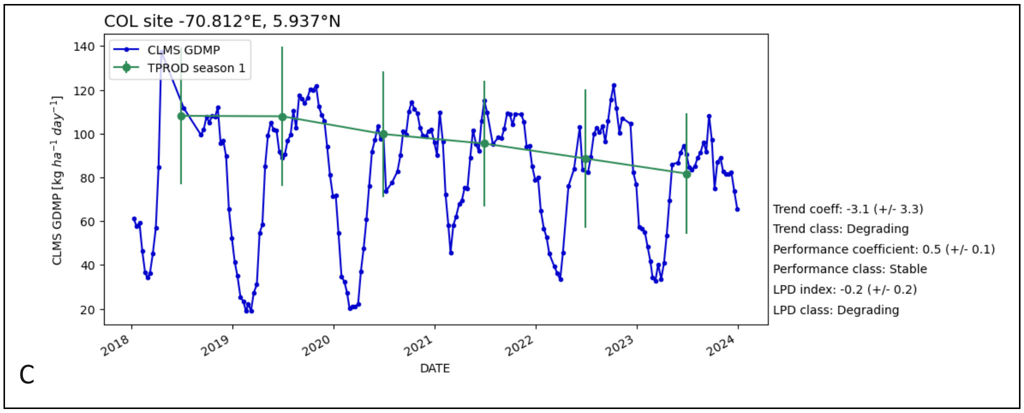


Figure 21: Indirect validation over a few sample sites in Colombia with degrading land productivity. Sentinel-2 derived TPROD [EVI · day] is plotted on the same axis as GDMP [kg ha^{-1} day^{-1}].

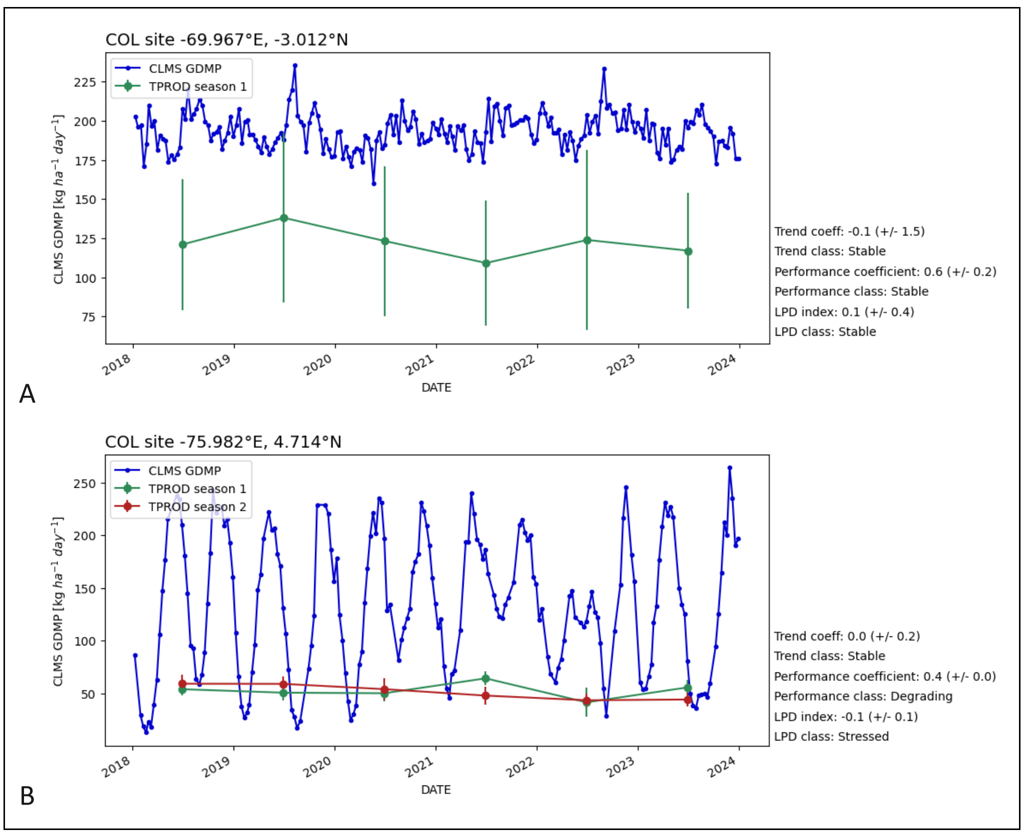


Figure 22: Indirect validation over a few sample sites in Colombia with stable land productivity. Sentinel-2 derived TPROD [EVI · day] is plotted on the same axis as GDMP [kg ha^{-1} day^{-1}].

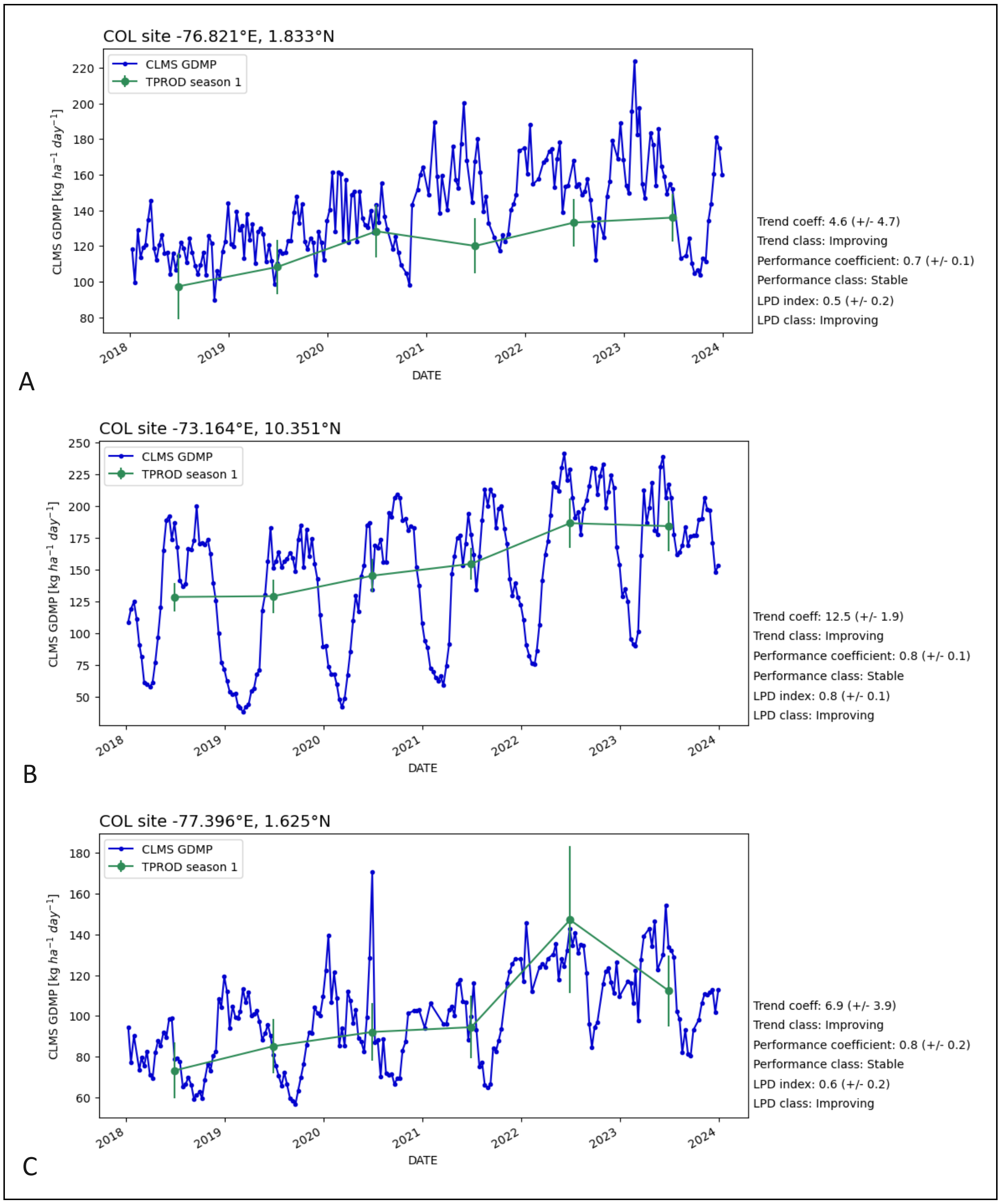


Figure 23: Indirect validation over a few sample sites in Colombia with improving land productivity. Sentinel-2 derived TPROD [EVI · day] is plotted on the same axis as GDMP [kg ha^{-1} day^{-1}].

4 Conclusions

With independent validation, the SEN4LDN land cover maps showed varied performances in the three demonstration countries, namely Uganda, Portugal, and Colombia. The LC map achieved the highest overall accuracy in Colombia (90.1% ± 3.4%), while the lowest accuracy in Uganda (69.6% ± 5.5%). In terms of the land cover classes, wetlands (i.e., open water and wetland herbaceous vegetation), trees, and low vegetation were mapped with higher accuracies among the IPCC classes. However, the SEN4LDN LC map had considerable confusion between low vegetation (i.e., grass and shrubs), trees and crops in Uganda, which is also a common issue in global land cover products [17].

With an independent and direct validation of the land cover change map in Uganda, the SEN4LDN LCC product achieved an overall accuracy of 73.7% at the change vs. no change level, and 72.9% when considering the specific transition classes. The LCC map in Uganda had a good performance in detecting change related to forest, i.e., deforestation and reforestation, as well as stable/unlikely changes. However, the map underestimated considerable changes as well. By comparing SEN4LDN LCC maps with the national LC map-derived changes in Portugal and Uganda, it is observed that SEN4LDN tends to be more conservative in predicting change areas in Portugal compared to the COSc product, while its estimation of change areas in Colombia is more logical compared to the MapBiomas product.

Validation of the SEN4LDN output products on trends in land productivity is based on visual inspection, internal consistency analysis and qualitative indirect validation with external data. Visual inspection indicated no important issues related to spatial consistency, except the effect of persistent cloud coverage over some areas in Colombia and – to a lesser extent – Uganda. This however does not result in erroneous identification of degraded areas in the *LPD* product. Internal consistency of the products was evaluated based on intercomparison and error evaluation of the products of adjacent tiles on a sample in Sentinel-2 tile overlap area. Very high consistency is found for the products over Portugal and Uganda. The results for Colombia are slightly less good, probably related to larger uncertainties in the atmospheric correction, more pronounced topography, and higher cloud coverage. Indirect validation was done through qualitative cross-comparison with an external product from CLMS GDMP 300m to evaluate the temporal consistency of interannual temporal variation. Although there is a large discrepancy in spatial resolution between the SEN4LDN products (10 m) and the CLMS GDMP 300m product, in most cases a good agreement can be found between the temporal evolution of GDMP, the temporal evolution of TPROD and the derived *Trendval* and *Trendclass*.

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Annex A. Confusion matrices for land cover map validation

Table 14: Confusion matrix for the validation of SEN4LDN land cover map in Portugal, expressed in percentages of the total area

Class		Reference								
		Trees	Crops	Low vegetation	Wetland	Built-up	Other	Correct	Total	UA (%)
Map	Trees	**37.5**		6.7	0.8			37.5	45.0	83.3
	Crops	1.5	**12.4**	0.1				12.4	13.9	89.1
	Low vegetation	3.2		**25.7**	0.1			25.7	29.0	88.7
	Wetland			0.1	**11.2**			11.2	11.4	98.9
	Built-up									1.8
	Other	0.2		0.3			**0.1**	0.1	0.7	15.9
	Correct	37.5	12.4	25.7	11.2		0.1			
	Total	42.4	12.4	32.9	12.2		0.1			
	PA (%)	88.5	99.8	78.2	92.5	46.2	78.2			
	Overall accuracy (%)									**87,0±6.5**

Table 15: Confusion matrix for the validation of SEN4LDN land cover map in Colombia, expressed in percentages of the total area

Class		Reference								
		Trees	Crops	Low vegetation	Wetland	Built-up	Other	Correct	Total	UA (%)
Map	Trees	**59.6**	1.2	3.4	0.2			59.6	64.4	92.5
	Crops		**0.3**					0.3	0.3	99.8
	Low vegetation	1.0	1.8	**27.8**	0.1		1.4	27.8	32.1	86.6
	Wetland	0.1		0.5	**1.8**		0.1	1.8	2.5	71.9
	Built-up					**0.1**		0.1	0.1	96
	Other						**0.5**	0.5	0.6	85.4
	Correct	59.6	0.3	27.8	1.8	0.1	0.5			
	Total	60.7	3.3	31.7	2.1	0.2	2.1			
	PA (%)	98.1	8.6	87.8	87.2	73.9	23.5			
	Overall accuracy (%)									**90,1± 3,4**

Table 16: Confusion matrix for the validation of SEN4LDN land cover map in Uganda, expressed in percentages of the total area

Class		Reference								
		Trees	Crops	Low vegetation	Wetland	Built-up	Other	Correct	Total	UA (%)
Map	Trees	**10.1**	1.9	3.7	0.6	0.5		10.1	16.9	60.2
	Crops	0.0	**14.2**	5.9		0.0	0.0	14.2	20.1	70.6
	Low vegetation	2.9	11.8	**28.3**	1.1	0.1	0.6	28.3	45.0	63.0
	Wetland		1.0	0.1	**16.9**			16.9	18.0	93.7
	Built-up								0.0	
	Other		0.0	0.0		0.0	**0.0**	0.0	0.0	9.6
	Correct	10.1	14.2	28.3	16.9		0.0			
	Total	13.1	28.9	38.1	18.6	0.6	0.6			
	PA (%)	77.6	49.1	74.3	90.9	0.0	0.3			
	Overall accuracy (%)									**69.6±5.5**