Product Specification and Algorithm Theoretical Base Document: Forest & woodland ecosystem condition account

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Submitted by

vito remote sensing	bc3	Ecounting	University of Patras

In collaboration with

Statistisk sentralbyrå Statistics Norway	cbs	ile Institute of Landscape Ecology Slovak Academy of Sciences	University of Patras	Istat, ISPRA
Norway	*Netherlands*	*Slovakia*	*Greece*	*Italy*

DOCUMENT RELEASE SHEET

Role	Name
Book Captain	Dr. Marcel Buchhorn, VITO
Approval (consortium)	Bruno Smets (VITO)
Approval (ESA)	Marc Paganini (ESA)
Contributing Authors	Lori Giagnacovo (VITO), Alessio Bulckaen (BC3), Dr. Stefano Balbi (BC3)
Distribution	Giuseppe Ottavianelli (ESA)
	Early Adopters
	Project Team

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Issue	Issue date	Pages affected	Relevant information
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1.1	2024/09/13	All	First public release
1.2	2024/11/30	5	Added TRL level

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1. Introduction

1.1 Report objectives and approach

The objective of this report is to detail the technical requirements of the selected accounting pilot demonstrators for the PEOPLE-EA project, and hence covers the results of tasks in WP2.1 and WP2.2.

The report first describes the technical specification of the platform, whereafter for each demonstrator account is described:

- the technical specification (e.g., selection of condition indicators and reference levels)
- an overview of potential algorithms to be evaluated during an agile iterative co-design round-robin benchmarking.
- test areas and input datasets necessary to perform the round-robin benchmarking.
- results of the benchmarking, and justification of the selected algorithm.

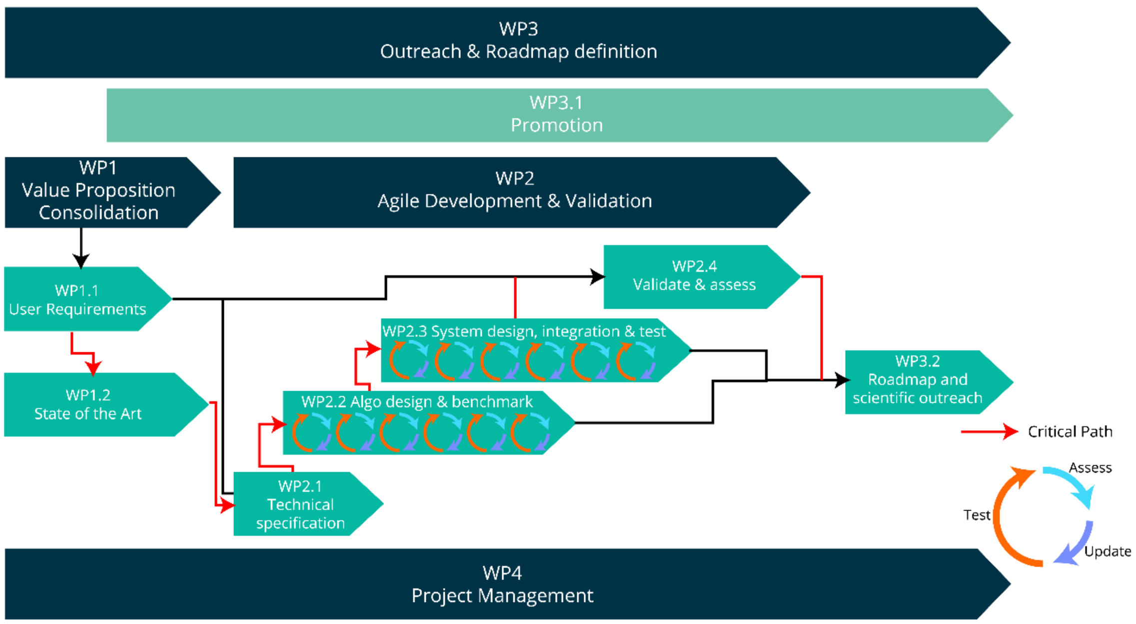

Figure 1: Overview of WP2 agile iterative co-design development cycle

1.2 Scope of work

Table 1 shows the selected pilot demonstrators, and the Early Adopters (countries) where a test-site will be selected to perform the round-robin benchmarking as a co-design activity.

Table 1 Overview of ecosystem account pilot demonstrators

Account	Country	Details / Indicator	Year	Round-robin
Condition - forest	Greece	- Canopy coverage - Standing biomass - Fragmentation - Disturbance	~2020	
	Italy	- Standing biomass - Disturbance (if possible, differentiate between disturbance form fire and from timber harvest) - Fragmentation	~2020	
	Netherlands	- Standing biomass	~2020	X
	Norway	- Standing biomass - Disturbance (three counties)	~2020	
	Slovakia	- Canopy coverage - Standing biomass - Fragmentation - Disturbance (from different causes)	2015-2022	X

Note that the workflow/solution developed is still experimental and not operational, since it is considered to have reach TRL[1] Level-6. This level declares the technology is demonstrated in relevant environment (in this context the Aries4People application and the tests by the Early Adopters) and requires further R&D work as well as being made compliant to the European Statistics Code of Practice (CoP) before being used for official statistical reporting.

[1] TRL defines the Technology Readiness Level ranging from 1 (basic principles observed) up to 9 (actual system proven in operational environment).

1.3 About ecosystem condition accounts

Ecosystem condition reflects the state or quality of an ecosystem type measured in terms of its abiotic, biotic and landscape characteristics (United Nations, 2021). Measuring ecosystem condition over time provides insights in the development of the health of the ecosystem as a function of, for instance, human use, ecological variability, and climate change (United Nations, 2021; Vallecillo Rodriguez et al., 2022). The ecosystem condition itself is described by the combination of various ecosystem condition indicators which are derived from condition variables.

Ecosystem condition variables are quantitative metrics describing individual properties or characteristics of an ecosystem asset. In SEEA EA ecosystem characteristics are structured along a standard Ecosystem Condition Typology (ECT)(Commission et al., 2018; United Nations, 2021). The ECT is first organized by Groups of characteristics: Abiotic (A), Biotic (B), and Landscape level (C), thereafter subdivided into a second level. For each ecosystem type, one or more variables for each of the SEEA EA ECT classes should be measured to provide a comprehensive assessment of ecosystem condition.

Group A: **Abiotic ecosystem characteristics**	Class A1. **Physical state characteristics**: physical descriptors of the abiotic components of the ecosystem (e.g. soil structure, water availability)
	Class A2. **Chemical state characteristics**: chemical composition of abiotic ecosystem compartments (e.g. soil nutrient levels, water quality, air pollutant concentrations)
Group B: **Biotic ecosystem characteristics**	Class B1. **Compositional state characteristics**: composition / diversity of ecological communities at a given location and time (e.g. presence/abundance of key species, diversity of relevant species groups)
	Class B2. **Structural state characteristics**: aggregate properties (e.g. mass, density) of the whole ecosystem or its main biotic components (e.g. total biomass, canopy coverage, annual maximum NDVI)
	Class B3. **Functional state characteristics**: summary statistics (e.g. frequency, intensity) of the biological, chemical, and physical interactions between the main ecosystem compartments (e.g. primary productivity, community age, disturbance frequency)
Group C: **Landscape level characteris-tics**	Class C1. **Landscape and seascape characteristics**: metrics describing mosaics of ecosystem types at coarse (landscape, seascape) spatial scales (e.g. landscape diversity, connectivity, fragmentation)

Figure 2: Ecosystem Condition Typology (ECT) of the SEEA-EA (adapted from Vallecillo Rodriguez et al. (2022))

The definition of an ecosystem condition reference state by setting condition indicator baselines allows monitoring. Therefore, good ecosystem condition will be considered when it presents good physical, chemical, and biological condition, or good physical, chemical and biological quality with self-reproduction or self-restoration capability, in which species composition, ecosystem structure and ecological functions are not impaired (cf. definition of the Taxonomy Regulation (EU) 2020/8528).

2. Forest & Woodland ecosystem condition accounts

Forest ecosystems are a critical component of the world's biodiversity, but pressures like deforestation and forest degradation contributes significantly to the ongoing loss of biodiversity and increasing effects of climate change (Maes et al., 2023). Despite European forests are expanding and accumulating biomass, several pressures such as eutrophication, drought, and tree cover loss remain high and continue to undermine the condition of forests (Grammatikopoulou & Vackarova, 2021). Therefore, the regular generation of forest ecosystem condition accounts can help to monitor the forest condition and support the forest management.

The forest condition accounting chapter is split into the following subsections: a literature review to the state-of-the-art in forest condition account generation and the usage of EO data including the technical specification to the generation of forest condition accounts in the PEOPLE-EA project; description of the test areas for which the forest condition accounts are generated and tested; a short feedback of the round-robin benchmarking; the following three chapters describe the chosen methods and algorithms for the implementation of forest condition variable, indicators and index accounts within the PEOPLE-EA project; a short description of the ARIES for PEOPLE-EA explorer as the main distribution system for forest condition accounts in the project; an uncertainty estimation and a closing summary.

Please note: the forest condition account was chosen to be implemented in the ARIES for PEOPLE-EA explorer (app) and all datasets / accounts are therefore available for the whole EU28 at Tier-1 and for Tier-2 for selected areas.

2.1 Literature review / Technical specification

The here presented approaches to assess forest condition follow rigorously the guidelines of the SEEA EA Framework (United Nations, 2021). Setting up a SEEA EA compliant forest condition account requires delineating an accounting area and defining a forest typology, selecting forest condition variables, establishing upper and lower reference levels for these variables, and aggregating these variables to a single value or index (Maes et al., 2023; United Nations, 2021).

The delineation of the accounting area and the definition of the forest typology is part of the ecosystem extent account generation. Therefore, this chapter focus of the following three steps to implement a forest ecosystem condition account:

- Step 1: definition and selection of ecosystem condition variables.
- Step 2: definition of the reference conditions and rescaling of the variables to ecosystem condition indicators which range between 0 and 1.
- Step 3: aggregation of the indicators into a single ecosystem condition index using indicator specific weights.

The spatial, temporal and statistical analysis of the forest condition index and the single forest condition indicators finally create the forest condition account per geographical unit. An uncertainty analysis is carried out to evaluate the meaningfulness of the approach.

Please note: three key publications regarding methodology to map and assess forest ecosystem conditions are used within the PEOPLE-EA project. Where Commission et al. (2018) give a comprehensive overview of overall 59 forest condition indicators that have been agreed with EU member states and experts to map and assess forest condition under Action 5 of the EU Biodiversity Strategy to 2020. The publication of Vallecillo Rodriguez et al. (2022) analyses in detail existing datasets including their spatial and temporal resolution as input for these forest condition variables.

Finally, Maes et al. (2023) presents a first attempt for an international statistic standard to account for forest condition over whole Europe.

2.1.1 Ecosystem condition variables candidates

A key criterion for selecting forest condition variables is replicability and repeatability of the underlying data sources. Moreover, within the PEOPLE-EA project condition algorithms to generate forest condition variables based on remote sensing (RS) data are preferred. Table 2 provides an overview of the algorithm/dataset options for a pre-selection of condition variables to generate forest condition indicators mainly based on RS methods or datasets. The pre-selected condition variables aim to be a representative number of variables and cover the full list of the SEEA ECT classes to ensure that the condition index is built on a solid scientific base.

Within the Tier-1 analysis, we opted to only use condition variables described by existing established datasets covering the whole EU to allow transparency in the EU comparison. At Tier-2 level some of the condition variables can be replaced with alternative calculation algorithms (shown in Table 2) and will be calculated on-demand in the PEOPLE-EA project.

Table 2: Algorithm & dataset options for pre-selected, representative forest condition variables covering all SEEA ECT classes to generate a forest condition index within the PEOPLE-EA project. Note: condition variables with optimal data, already established monitoring systems or data services are highlighted in grey. Variable names in bold mark condition variables requested by the early adopters.

SEEA ECT class	Condition variable	Algorithm option	Status current implementation	Reference articles	Main EO input	Remarks
A1	**Vegetation water content**	NDWI (normalized difference water index) by Gao (1996)	Optimal; RS based; existing dataset with 8-daily temporal resolution and 30m spatial resolution	(Gao, 1996) Landsat-8 Collection 1 Tier 1 8-day NDWI composite courtesy of the U.S. Geological Survey	Landsat	sometime also called NDMI (normalized difference moisture index) due to confusion with NDWI by McFeeters (1996)
A1	**Vegetation water content**	NDWI (normalized difference water index) by Gao (1996)	Optimal; RS based	(Gao, 1996)	Sentinel-2	own implementation needed
A1	**Vegetation water content**	Vegetation optical depth (VOD) – microwave RS	Experimental; RS based	(Holtzman et al., 2021) (Li et al., 2021) (Konings et al., 2021) (Konings et al., 2019)	SMAP; SMOS; QuikScAT	Coarse resolution; Weather independent measurements;
A1	**Vegetation water content**	VV/VH cross ratio and VOD	Experimental; RS based	(Vreugdenhil et al., 2020)	Sentinel-1	European test exists
A1	Soil moisture content	ESA Soil Moisture	Online, but with temporal and spatial constrains	(Babaeian et al., 2019) (Dorigo et al., 2023)	Combination of active and passive sensors	Coarse resolution but consistent product over time and covers 1978 - 2022
A2	Foliar & litter nitrogen concentration	NDNI	Experimental; hyperspectral RS	(Serrano et al., 2002)	EnMAP, HySpex, AVIRS	Foliar nitrogen could be measured but need narrow bands in the 1510nm range

SEEA ECT class	Condition variable	Algorithm option	Status current implementation	Reference articles	Main EO input	Remarks
A2	Soil organic carbon	ESDAC dataset	Modelled; based on test areas	European Soil Data Centre (ESDAC), esdac.jrc.ec.europa.eu, European Commission, Joint Research Centre (Jones et al., 2004) (de Brogniez et al., 2014)	-	Only limited temporal datasets available – OCTOP 2003 and LUCAS 2015); coarse resolution
A2	Soil organic carbon	Hyperspectral RS	Experimental;	(Angelopoulou et al., 2023) (Thomas et al., 2022)	HySpex; PRISMA; EnMAP	No full coverage of EU; only possible where no dense tree cover exists
B1	**Species diversity**	Species richness of threatened forest bird species	Modelled	(Maes et al., 2023)	Article 12 Birds Directive data, modelling approach	10km spatial resolution, dataset exists for 2000, 2006, 2012, 2018
B1	**Species diversity**	Tree species richness	Modelled	(FOREST EUROPE, 2020)		Forest tree species (number of species or species richness), tree sp. composition (index)
B2	Tree cover density	Tree cover density in %	RS input	Copernicus HRL	Sentinel-2	
B2	Deadwood volume	Total deadwood (standing & lying)	Modelled; test sites	(FOREST EUROPE, 2020)		Coarse resolution, sometimes only country scale
B2	Tree height	Vegetation height in m	Lidar input; modelled	(Potapov et al., 2020) (Lang et al., 2023)	GEDI, Sentinel-1, Sentinel-2	Measured in m; GEDI limited to 55deg N, but Sentinel-2 dataset exists with higher resolution

SEEA ECT class	Condition variable	Algorithm option	Status current implementation	Reference articles	Main EO input	Remarks
B2	Biomass volume (growing stock)	Tones/ha	Modelled	(Santoro M. & Cartus O., 2023)	ALOS-2, PALSAR-2, Sentinel-1, GEDI, ICESat	Existing dataset for 2010, 2017,2018,2019, 2020
B2	Leaf Area Index	LAI	Optimal, RS input	Copernicus services		Established service at 300m; can be also calculated with Sentinel-2 at higher resolution
B3	Ecosystem productivity	GDP, NPP	Optimal, RS input; existing dataset	Copernicus services		Established service at 300m;
B3	Ecosystem productivity	VPP	Optimal, RS input; existing dataset	Copernicus services	Sentinel-2	Can be provided on 10m level
B3	Fraction of Photosynthetically active radiation	fPAR	Optimal, RS input	Copernicus services		Can be measured via RS
B3	Drought severity	Anomaly of Vegetation Condition (FAPAR Anomaly):	RS input	(European Commission & JRC, 2021)	MODIS	Coarse resolution. Parameter FAPAR anomaly can be influenced also by other stress factors
B3	Drought severity	Global Aridity Index	Modelled; Online, but with temporal and spatial constrains	(Zomer & Trabucco, 2019)		Coarse resolution, available for 1970 – 2000; model code available
B3	Fire recurrence	Burnt area density	optimal	Copernicus services, EFFIS service		Service since 2014
B3	Burn severity	MOSEV database	Optimal; RS input	pre- and post-fire NBR for each burned pixel and calculation of differenced burn severity indices (dNBR and RdNBR)	MODIS	Medium resolution (500m) of burn severity plus additional indicators for 2000 - 2020

SEEA ECT class	Condition variable	Algorithm option	Status current implementation	Reference articles	Main EO input	Remarks
				(Alonso-González & Fernández-García, 2020) (Alonso-González & Fernández-García, 2021) (Fernández-García & Alonso-González, 2023)		
B3	Burnt area	BAIS2 (Burned Area Index for Sentinel 2)		(Filipponi, 2018)	Sentinel-2	Still experimental and to be tested. Indicator would be burnt area/year (ha/year)
B3	**Green (vegetation) index – ANNUAL MAX. NDVI**	Max NDVI	Optimal; RS input		Sentinel-2	Standard available product at 10m
C1	Forest connectivity	Forest area density as indicator for fragmentation	Optimal, modelled	JRC, GUIDOS toolbox (Maes et al., 2023) (Vogt et al., 2019)		When based on CORINE Dataset exist for 1990, 2000, 2006, 2012, 2018
C1	Landscape naturalness	Degree of naturalness to neighbours	Optimal, modelled	JRC, GUIDOS toolbox (Maes et al., 2023)		When based on CORINE Dataset exist for 1990, 2000, 2006, 2012, 2018

2.1.2 References condition options to specify forest condition indicators

To make condition variables comparable and addable, they must be transferred into conditions indicators. A reference level for each variable is used to transfer the condition variables into condition indicators ranging from 0 to 1 reflecting the condition from degraded to natural/healthy (Maes et al., 2023).

The reference condition can be based on different references levels explained by certain values and goals. The SEEA-EA proposes a list of possible methods for setting the reference levels (United Nations, 2021):

1. Identification of reference sites: minimally disturbed condition ('pristine' ecosystems with no or minimal human disturbance)
2. Modelled condition: for instance, potential vegetation models, historical condition
3. Statistical methods based on ambient distribution:
   a. Least-disturbed condition: the currently best available condition of an ecosystem
   b. Best-attainable condition: expected condition of an ecosystem under best possible
4. management practices and attaining a stable socio-ecological state.
5. Prescribed reference levels
6. Contemporary condition: making use of a baseline year (recent history)
7. Expert opinion
8. Combination of methods listed above.

The following Table 3 shows the best options for forest ecosystem condition reference levels:

Table 3: List of pre-selected option to establish forest ecosystem condition reference levels to transfer forest condition variables into indicators (adapted from Vallecillo Rodriguez et al. (2022))

Reference level	Method	Value system	Remarks
Reference forest site	**Closest natural site method:** *upper bound:* maximum condition variable value of closed protected area or primary forest area with no detected changes in last 20 years *lower bound:* minimum variable value over the whole region *reference year*: actual year	Data driven	was used in the ARIES-4-SEEA system; the lower bound is specified by a too large area; the reference levels are not based on the same reference year
Reference forest site	**Forest ecosystem type split method:** The forest ecosystem is delineated into ecosystem types by forest type and biogeographic regions. *Upper bound:* maximum condition variable value over all protected areas or primary forest areas with no detected changes in last 20 years within each forest ecosystem type *lower bound:* minimum variable value within each forest ecosystem type *reference year*: 2000	Data driven, statistical analysis	Currently implemented in Maes et al. (2023); the usage of the minimum and maximum variable values could be error prone – maybe better using 2nd and 98th percentile, respectively.

Reference level	Method	Value system	Remarks
Contemporary condition	The value of the indicator for the reference year becomes 100%	Reference year	Critical approach in case defined reference year is an outlier year
Prescribed level (aligned to legal targets)	Reference condition is based on specific targets, e.g., all tree species in a good population status is set to 100%	Expert opinion, statistical analysis	The definition of the bounds for each variable depends on external knowledge and can be too subjective.

2.1.3 Aggregation methods for the forest condition index

The aggregation of condition indicators into one condition index is optional within the SEEA EA (United Nations, 2021). The need of providing a final aggregated ecosystem condition index will depend on the specific policy requirements (Vallecillo Rodriguez et al., 2022). Nevertheless, the aggregated condition index can be useful to develop a high-level policy index of ecosystem condition and its changes; whereas looking at individual condition variables and their trends allows identifying the correct actions for improving ecosystem condition (Vallecillo Rodriguez et al., 2022). Table 4 shows methods to aggregate single forest condition indicators into one index.

Table 4: Aggregation methods to combine forest condition indicators into a forest condition index

Name	Method	References	Remarks
Euclidean distance	Euclidean distance (geometric average)	ARIES platform	Each indicator is equally important which can screw the results based on data availability, ETC class presentiveness, and spatial resolution of the single indicators.
Average index	Average of the indicators		Each indicator is equally important which can screw the results based on data availability, ETC class presentiveness, and spatial resolution of the single indicators.
Weighted index	Specific weights for each indicator	Maes et al. (2023)	To define specific weights for each indicator needs expert knowledge but overcome the disadvantages of the average index method.

The definition of the indicator weights in the "weighted index" method can be done solely on expert knowledge or by implementing a scoring approach taking into account conceptual criteria's as see in Figure 3.

Conceptual criteria	Vegetation water content - NDWI	Soil organic carbon	Species richness of threatened forest birds	Tree cover density	Forest productivity – (NDVI)	Forest connectivity	Landscape naturalness
Intrinsic relevance	1	3	7	6	2	5	4
Instrumental relevance	4	5	3	6	7	2	1
Directional meaning	1	3	7	5	2	4	6
Sensitivity to human influence	2	1	7	6	3	5	4
Framework conformity	3	5	7	6	4	2	1
Sum of the ranks	11	17	31	29	18	18	16
Weights	0.08	0.12	0.22	0.21	0.13	0.13	0.11

Figure 3: Example for scoring method to establish weights for each forest condition indicator based on conceptual criteria (adapted from Maes et al. (2023)).

2.1.4 Existing gaps

Gaps in data availability for condition variables

- High resolution variables based on RS only available from 2016 onwards on global scale (<30 m)

Gaps in setting up reference condition

- Definition of the lower bound of the condition indicator; according to the SEEA EA definition those should be set to identify the point of "collapse" of an ecosystem (United Nations, 2021). This requires ecological knowledge in the specific context of the condition variable/indicator and changes per biogeographic zone and forest types.
- Reference values are not available (yet) for High Resolution variables; hence no condition indicators can be calculated for High Resolution variables. This would require having a longer time-series available, either including LandSAT or waiting till 10 years of Sentinel-2 data is available.

Gaps in creating the forest condition index

- The ranking of the forest condition variables within each conceptual criteria to create the weights in the “weighted index” method needs expert knowledge. Moreover, if the chosen condition variables come from the same ETC class then this approach is not representative anymore.

2.2 Test areas

The forest condition index algorithm will be tested on two specific regions in Slovakia and the Netherlands (see Table 5, Figure 4).

Table 5: Test areas for algorithm testing and demonstration

Test site (NUTS)	Area size	Test account	Rationale
NL3 (West Nederland)	10 000 km^2	• Coastal condition • Carbon sequestration	Coastal zone Peatland
SK03 (Stredné Slovensko)	16 000 km^2	• Extent • Forest condition	Prime forest

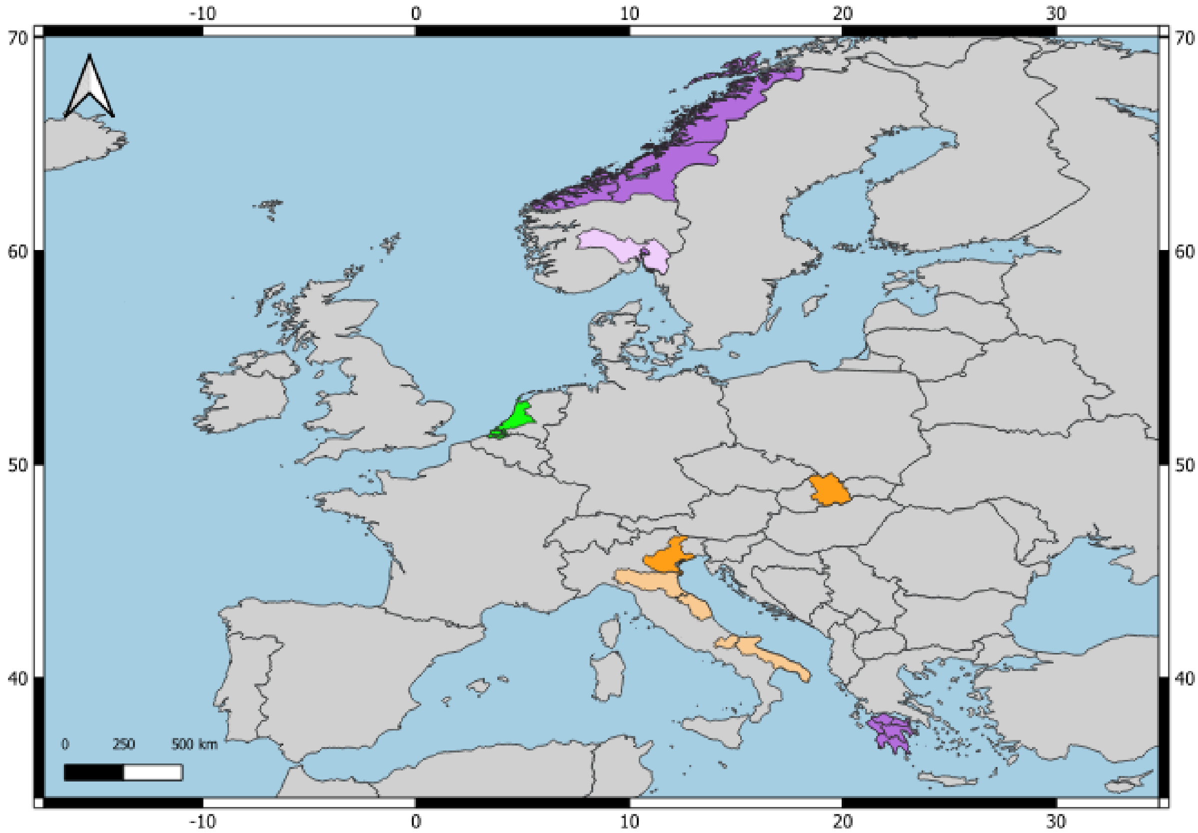

Figure 4: Test sites for algorithm trade-off (NUTS-1 in green, NUTS-2 in orange, NUTS-3 in purple)

2.3 Round-robin results

Preliminary co-design meeting with early adopters in September 2023 highlighted the need of high-resolution output for condition variables and indicators, to capture spatial variability and detail. Especially early adopter NL (the Netherlands) indicated this; high forest diversity in NL needs high resolution EO products. Besides, early adopter SK (Slovakia) clarified that full forest condition accounts are preferred over variable or indicator accounts to showcase usage of EO data in condition accounting. This way, ARIES can show that with openEO support it is possible to automatically generate forest condition indexes and improve the temporal and spatial resolution by usage of improved EO datasets and on-demand processing. By default, ARIES will built-up the best workflow possible based on available resources and uses openEO to get the data and/or models through a UDP/UDF public repository. During the discussion, there was an agreement that the Maes et al. (2023)

approach should not be altered right away since the definition of indicator weights needs a detailed further investigation. In the Tier-1 approach, the Maes et al. (2023) method is followed to enable reproducibility as well as providing yearly time-series instead of 2 timesteps. The spatial detail is set to 100m to enable EU-wide application. As the selection of condition variables/indicators in the Maes et al. (2023) approach is the result of many detailed tests, the addition of other variables/indicators in ARIES would need further in-depth research. Some additional variables that could be investigated for ARIES contained 'NDVI' (B3), 'LAI' (B2), 'Drought severity' (B3), 'Forest fragmentation' (C1) ~ Forest Connectivity, 'Biomass volume' (B2), 'fPAR' (B3), 'Fire recurrence' (B3) and 'Burn severity' (B3). Besides, the possibility was discussed to optimize reference sites to national scale, as Maes et al. (2023) uses all primary/high protected areas within a forest ecosystem type as reference. Then, the forest condition indicators must be nationally evaluated (if provided EU-wide method can be still used on national scale). The current Tier-2 approach is limited to a minimal set of variables (no indicators or index). The spatial detail is set to 10-20m to enable regional accounting. To avoid the use of too many platform resources, this approach is restricted to small areas (e.g., NUTS2). In the next phase, focus on accuracy information is important. For example, error propagation by resampling rasters to align datasets is important information in reporting.
Standing biomass is an important indicator for forest condition accounting as it is for global climate regulation service. There are several outstanding issues related to the reliability of standing biomass and we refer the reader to the ATBD part on global climate regulation to find more details.

The Early Adopters were trained to use the ARIES for PEOPLE-EA explorer platform and give background on the EO models used. Validating the aggregated condition indicator (forest condition index) is difficult, so focus can also be on validating single condition indicators or variables. The following feedback was collected from the Early Adopters in a follow-up meeting. The issues raised are considered for the roadmap towards future updates.

Greece:

- Condition indicators form national life integrated project (spatial resolution 1km) compared to condition indicator of ARIES. Scale differs so not totally comparable. But when overlapping in well-known areas, the indicators seem to correspond well.
- Check NPP was difficult since there is not a lot of data for NPP in Greece. In the next few weeks, data from forest services might deliver some new results to compare with considering NPP.
- Platform sometimes is a bit slow.

Italy:

- No validation possible but tested the application.
- They checked the forest condition index and actual changes in forest (Sentinel-2 images) over several years (2018 and 2022). They found correspondence between the two. Therefore, indicator is valuable to monitor changes. However, also some issues related to input data were discovered, definitely in the boundary zone of forests (e.g., with river next to forest or lake next to forest).
- How to use forest condition index (numerical value) for forest condition accounting? Should we consider threshold values?

Slovakia:

- Focused on some areas where they know there are some problems in the forest (bark beetle outbreak), used the forest condition index to see if they can find expected patterns of decreasing condition. For spruce forest the forest condition index indeed decreased when compared to the past. Results are close to reality.

- They find the index very useful to see the trends, but they would also like to receive directly in the output the main parameters influencing the change. The index is also very sensitive, and therefore it is difficult to interpret the index values without knowing the conditions on the ground. Exceptions are extreme changes such as hollowing/calamity.
- The parameters are lacking a legend, so it is difficult to interpret the results. They do not find it so user-friendly, also work with interpretable colours.
- Recommendations to use CLC+ or extent maps as forest type mapping instead of CORINE?
- Remark: how does the index deal with changes in forest type when calculating forest condition?
- They would like to have the possibility to implement their own data layers (such as ecosystem map) into the system and customize values for weights or thresholds.
- It would be nice to adjust transparency of layers in user interface.

Norway:

- No validation of the computations so far, experts were not available for this. They were able to run the application and generate maps and tables.
- Agreement between Statistics Norway and NINA to perform validation.

The Netherlands:

- Excused from the webinar.

In May 2024, a PEOPLE-EA workshop was organized in Athens, Greece. Here, all early adopters gave presentations with experiences and feedback. Some collected feedback points:

- The forest condition index does not take directly into consideration the phenomenon of forest disturbances due to various phenomena (fires, storms, or insect attacks), but some spectral indices can highlight forest disturbances such as the removal of vegetation. It can be difficult to understand the absolute value of the forest condition index, but the difference can be used to compare different years.
- In some cases, the index is decreasing or increasing although no apparent change in vegetation cover, difficulties in retrieving reasons for that. Unavailability of in situ data about forest condition to perform a quantitative evaluation of accuracy.
- A few errors can be detected in proximity of the border of the forest layers, such as river area, which is probably a limit of input data used for the definition of forest boundaries. Spatial resolution of CORINE limits the assessment of small forest patches.
- Advantages of the ARIES for PEOPLE-EA explorer tool: automatic calculation based on EO that can be performed frequently, good detection of forest removal, possibility to upload national data about land cover.
- The variable ‘Threatened Forest Bird Species Diversity’, extreme low values are found in NL due to the limited number of the bird species in NL. Therefore, the scaled indicator value is not representative of reality, or useful for policy purposes. For them, it is unclear how this species list was derived. Their national data seems more precise and useful to use in their case (based on abundance, which seems more relevant than occurrence).

2.4 Forest condition variables accounts

At Tier-1 level, only established datasets are used to establish a forest condition variable account on national level comparable all over Europe. Therefore, only limited forest condition variables proposed in Table 2 are directly usable. Moreover, the recent publication by Maes et al. (2023) establishing a first European forest condition prototype based on international statistic standards is used as base to create the Tier-1 demonstrator and therefore these variables are used.

To showcase the implementation of remote sensing products, we decided to focus on additional EO variables. Since several possible forest condition variables are interlinked and therefore provide redundant information (e.g., NPP and DMP, NDVI and EVI, …), we selected on criteria like spatial, temporal and thematic resolution.

The integration of the demonstrator on Tier-1 level will be done in the ARIES for PEOPLE-EA explorer and currently includes 13 forest condition variables. All variables based on remote sensing products and not already provided as existing datasets will be calculated in the OpenEO platform and accessed by ARIES in real-time.

On tier-2 level, high resolution datasets for some of the forest condition variables are available to establish a higher spatial refinement. Overall, currently 6 forest condition variables are implemented in the ARIES for PEOPLE-EA explorer. The high-resolution variables are based on Sentinel-2 data and calculated in the OpenEO platform and accessed by ARIES in real-time. Please note due to the availability of Sentinel-2 data, the temporal domain will be limit to 2016 onwards. Moreover, due to the processing intensive generation of these high-resolution condition variables the spatial extent of the Tier-2 account was limited.

2.4.1 overview of implemented forest condition variables

Table 6 provides an overview of the selected Tier-1 and Tier-2 Forest condition variables in the PEOPLE-EA project. The table summarizes for each dataset the dataset origin, applied algorithm, spatial extent, spatial resolution as well as the temporal coverage of the datasets in the explorer.

Table 6: Forest condition variables on Tier-1 and Tier-2 level implemented in the PEOPLE-EA project (Note: Tier-2 variables are marked in grey)

ETC	Variable	Link to dataset or DOI	Spatial Resolution	Spatial Extent	Temporal coverage	Applied algorithm
A.1	Normalized Difference Water Index (NDWI)	GEE Landsat 7 Collection 1 Tier 1 32-Day NDWI Composite GEE Landsat 8 Collection 1 Tier 1 32-Day NDWI Composite	30m	Global	2000-2021	Aggregation to three-annual average; harmonization of Landsat 7 & 8 collections; resampling if needed
A.2	Soil Organic Carbon (SOC)	2003 OCTOP: Topsoil Organic Carbon Content for Europe - Organic carbon content in the first 30 cm of soil	1km	Europe	2003	OCTOP dataset was set for period 2000-2013 and LUCAS dataset used from 2014 onwards; resampling if needed
		2014 LUCAS: Topsoil Soil Organic Carbon (LUCAS) for EU25 (DOI: 10.1111/ejss.12193) - Organic carbon content in the first 30 cm of soil	500m	Europe	2014	
B.1	Threatened Forest Bird Species diversity	Population trend of bird species: datasets from Article 12, Birds Directive 2009/147/EC reporting (2008-2012) (DOI: 7c2dd14f-60b6-4009-aca8-5d20300479a9)	5km	Europe	2000 and 2018	Usage of original dataset provided by Maes et al. (2023); resampling if needed
B.2	Above-ground biomass (AGB)	ESA's Climate Change Initiative Biomass ESA forest carbon monitoring	100m	Global	2010, 2017-2020, 2021	ESA CCI biomass dataset was used for period 2000-2020 and ESA FCM dataset for 2021 onwards; resampling if needed
	Above-ground biomass (AGB)	ESA forest carbon monitoring	20m	Europe	2020, 2021	AGB selection; resampling if needed

ETC	Variable	Link to dataset or DOI	Spatial Resolution	Spatial Extent	Temporal coverage	Applied algorithm
	Leaf Area Index (LAI)	Copernicus leaf area index	300m	Global	2015 to present	Harmonization of 300m and 1km datasets; aggregation to annual average; resampling if needed
			1km	Global	1999 to 2014	
	Leaf Area Index (LAI)	Terrascope Sentinel-2 Leaf Area Index	10m	Europe	2016 to present	This LAI is derived directly from ESA L2A products; applied cloud-screening; LAI generation; aggregation to annual average; resampling if needed
	Plant Phenology Index (PPI)	Copernicus Plant Phenology Index Seasonal Trajectories	10m	EUROPE	2017 to present	Aggregation to annual average; resampling if needed
	Tree cover density	Copernicus HRL tree cover density layer	100m	Europe	2012, 2015, 2018	Year 2012 was used for period 2000-2014; year 2015 for period 2015-2017; year 2018 for 2018 onwards; resampling if needed
B.3	Net Primary Production	Copernicus Dry Matter Productivity and Net Primary Production	300m	Global	2015 to present	Harmonization of 300m and 1km datasets; aggregation to annual sum; resampling if needed; transfer from GDMP to NPP
			1km	Global	1999 to 2014	
	Fraction of Green Vegetation Cover (FCOVER)	Copernicus Fraction of green Vegetation Cover	300m	Global	2015 to present	Harmonization of 300m and 1km datasets; aggregation to annual average; resampling if needed
			1km	Global	1999 to 2014	

ETC	Variable	Link to dataset or DOI	Spatial Resolution	Spatial Extent	Temporal coverage	Applied algorithm
	Fraction of Green Vegetation Cover (FCOVER)	Terrascope Sentinel-2 Fraction of Vegetation Cover	10m	Europe	2016 to present	This FCOVER is derived directly from ESA L2A products; applied cloud-screening; FCOVER generation; aggregation to annual average; resampling if needed
	Fraction of Absorbed Photosynthetic Active Radiation (FAPAR)	Terrascope Sentinel-2 FAPAR	10m	Europe	2016 to present	This FAPAR is derived directly from ESA L2A products; applied cloud-screening; FAPAR generation; aggregation to annual average; resampling if needed
	Drought resistance	European Drought Observatory - Drought Indicator v3 dataset download. 2012 - 2023 documentation	5 km	Europe	2012-2024	Transfer from categorical to quantitative unit; aggregation to annual average; resampling if needed
	Normalized Difference Vegetation Index (NDVI)	Copernicus Normalized Difference Vegetation Index	300m	Global	2021 onwards	Harmonization of 300m and 1km datasets; aggregation to annual average; resampling if needed
			1km	Global	2000 to 2020	

ETC	Variable	Link to dataset or DOI	Spatial Resolution	Spatial Extent	Temporal coverage	Applied algorithm
	Normalized Difference Vegetation Index (NDVI)	Terrascope Sentinel-2 Normalized Difference Vegetation Index	10m	Europe	2016 to present	This NDVI is derived directly from ESA L2A products; applied cloud-screening; NDVI generation; aggregation to annual average; resampling if needed
C.1	Forest Connectivity	Generated using GUIDOS toolbox and Corine landcover dataset. EC CORINE landcover Methodology	100m	Europe	2000, 2006, 2012, 2018	Selected CORINE LC classes were processed with the GUIDOS toolbox algorithm for connectivity
	Landscape Naturalness	Generated using GUIDOS toolbox and Corine landcover dataset. EC CORINE landcover Methodology	100m	Europe	2000, 2006, 2012, 2018	Selected CORINE LC classes were processed with the GUIDOS toolbox algorithm for naturalness
	Forest Fragmentation	Relative Magnitude of Fragmentation (RMF) Data: netCDF (12.57GB)	300m	Global	1992-2020	

2.4.2 Key information of provided variables

Normalized Difference Water Index (NDWI)

The normalized difference water index – as described by Gao (1996) is used to remotely sense vegetation liquid water from space. NDWI is defined as (R860 − R1240) / (R860 + R1240). Both the 0.86-µm and the 1.24-µm channels are located in the high reflectance plateau of vegetation canopies. They sense similar depths through vegetation canopies. Absorption by vegetation liquid water near 0.86 µm is negligible. Weak liquid absorption at 1.24 µm is present. Canopy scattering enhances the water absorption. As a result, NDWI is sensitive to changes in liquid water content of vegetation canopies. Atmospheric aerosol scattering effects in the 0.86–1.24 µm region are weak. NDWI is less sensitive to atmospheric effects than NDVI. NDWI does not remove completely the background soil reflectance effects, similar to NDVI. Because the information about vegetation canopies contained in the 1.24-µm channel is very different from that contained in the red channel near 0.66 µm, NDWI should be considered as an independent vegetation index. It is complementary to, not a substitute for NDVI.

NOTE: the NDWI by Gao (1996) should be not mixed up with the NDWI by McFeeters (1996). Unfortunately, both indices came out in the same year but sense completely different physical properties. McFeeters version is used to monitor changes related to water content in water bodies, using green and NIR wavelengths. Therefore, the NDWI by Gao (1996) is widely also known as NDMI (normalized difference moisture index) by Wilson & Sader (2001).

More information to the provided dataset can be found here: https://www.usgs.gov/landsat-missions/normalized-difference-moisture-index

Applied processing steps: harmonization of Landsat 7 & 8 collections; Aggregation to three-annual average; resampling if needed.

Soil Organic Carbon (SOC)

Chemical properties of the forest topsoil play a key role supporting forest functions and the provision of forest ecosystem services. For example, soil organic carbon (SOC) is key in the nutrient cycle and carbon cycle of forest ecosystems. Therefore, SOC is an important element contributing to enhance the role of forest as carbon sinks. Furthermore, SOC affects forest growth and the forest water cycle. Depending on the tree species and environmental conditions, it may be difficult to accurately define in the field where the mineral soil surface starts as organisms mix highly decomposed organic matter into the upper layers of the mineral matrix (Jones et al., 2005 & de Brogniez et al., 2014).

More information to the OCTOP dataset can be found here: https://doi.org/10.1111/j.1365-2389.2005.00728.x. More information to the LUCAS dataset can be found here: https://doi.org/10.1111/ejss.12193

Applied processing steps: since only two-time steps exist, the OCTOP dataset was set for period 2000-2013 and LUCAS dataset used from 2014 onwards; resampling if needed.

Threatened Forest Bird Species diversity

Richness of threatened forest birds: see also description of forest species richness above. In this case, data available at the EU level (derived from Articles 12 reporting of the BD) present important spatial gaps since not all countries reported bird distributions, and time series are not fully comparable. For this reason, modelling can be applied to provide a consistent spatio-temporal assessment of the forest suitability to host threatened forest birds.

More information can be found in Maes et al. (2023)

Applied processing steps: Usage of original dataset provided by Maes et al. (2023); since only two timesteps exists, the year 2000 dataset was used up to 2017 and then the year 2018 datasets from 2018 onwards; resampling if needed

Above Ground Biomass (AGB)
Above Ground Biomass refers to the living vegetation above the soil, including stem, stump, branches, bark, seeds, and foliage. It is typically measured in terms of mass per unit area, such as Mg/ha.

More information to Tier-1 dataset can be found here: https://climate.esa.int/documents/2148/D2_2_Algorithm_Theoretical_Basis_Document_ATBD_V4.0_20230317.pdf
More information to Tier-2 dataset can be found here: https://www.forestcarbonplatform.org/

Applied processing steps: at Tier-1 ESA CCI biomass dataset was used for period 2000-2020 and ESA FCM dataset for 2021 onwards; at Tier-2 only the years 2020 and 2021 are available; resampling if needed.

Leaf Area Index (LAI)
The Leaf Area Index is defined as half the total area of green elements of the canopy per unit horizontal ground area. The satellite-derived value corresponds to the total green LAI of all the canopy layers, including the understory which may represent a very significant contribution, particularly for forests. Practically, the LAI quantifies the thickness of the vegetation cover.
LAI is recognized as an Essential Climate Variable (ECV) by the Global Climate Observing System (GCOS).

More information to the Tier-1 dataset can be found here: https://land.copernicus.eu/global/sites/cgls.vito.be/files/products/CGLOPS1_ATBD_LAI1km-V2_I1.41.pdf
https://land.copernicus.eu/global/sites/cgls.vito.be/files/products/ImagineS_RP2.1_ATBD-LAI300m_I1.73.pdf
https://land.copernicus.eu/global/sites/cgls.vito.be/files/products/CGLOPS1_ATBD_LAI300m-V1.1_I1.10.pdf
More information to the Tier-1 dataset can be found here: https://docs.terrascope.be/DataProducts/Sentinel-2/references/VITO_S2_ATBD_S2_NDVI_BIOPAR_V200.pdf

Applied processing steps: for Tier 1: Harmonization of 300m and 1km datasets; aggregation to annual average; resampling if needed; for Tier-2: This LAI is derived directly from ESA L2A products; applied cloud-screening; LAI generation; aggregation to annual average; resampling if needed.

Plant Phenology Index (PPI)
The plant phenology index (PPI) is a physically based vegetation index and has a linear relationship with green leaf area index, strong correlation with gross primary productivity, and is shown capable of disentangling remotely sensed plant phenology from snow seasonality. The Seasonal Trajectories PPI is derived from a function fitting of the time-series of the raw PPI values [AD08], thereby acting as a time-series smoothing technique.

More information can be found here: https://land.copernicus.eu/en/technical-library/algorithm-theoretical-base-document-of-seasonal-trajectories-vpp-parameters/@@download/file

Applied processing steps: Aggregation to annual average; resampling if needed.

Tree cover density

Tree cover density is defined as the 'vertical projection of tree crowns to a horizontal earth's surface'. This indicator measures the proportional (percent) forest crown coverage per grid cell at very high resolution of 10 m to 20 m using satellite data. The indicator is produced as part of the Copernicus' High Resolution Layers for 2012, 2015 and 2018.

More information can be found here: https://land.copernicus.eu/en/technical-library/hrl-forest-2018/@@download/file

Applied processing steps: Year 2012 was used for period 2000-2014; year 2015 for period 2015-2017; year 2018 for 2018 onwards; resampling if needed.

Net Primary Production

Dry Matter Productivity (DMP) represents the overall growth rate or dry biomass increase of the vegetation, expressed in kilograms of dry matter per hectare per day (kg DM/ha/day). It is directly related to ecosystem Net Primary Production (NPP), expressed in g $C/m^2/day$. Similarly, the Gross Dry Matter Productivity (GDMP) is directly related to the Gross Primary Production (GPP). The main difference between DMP/NPP and GDMP/GPP is the inclusion of the autotrophic respiration of the vegetation. The following conversions are normally applied: DMP = GDMP * 0.5; NPP = DMP * 0.5 * 0.1; GPP = GDMP * 0.5 * 01

More information can be found here:
https://land.copernicus.eu/global/sites/cgls.vito.be/files/products/CGLOPS1_ATBD_DMP1km-V2_I2.11.pdf
https://land.copernicus.eu/global/sites/cgls.vito.be/files/products/CGLOPS1_ATBD_DMP-NPP300m-V1.1_I1.30.pdf
https://land.copernicus.eu/global/sites/cgls.vito.be/files/products/CGLOPS1_ATBD_DMP300m-V1_I1.12.pdf

Applied processing steps: Harmonization of 300m and 1km datasets; aggregation to annual sum; resampling if needed; transfer from GDMP to NPP.

Fraction of Green Vegetation Cover (FCOVER)

The Fraction of Vegetation Cover (FCOVER) corresponds to the fraction of ground covered by green vegetation. Practically, it quantifies the spatial extent of the vegetation. Because it is independent from the illumination direction and it is sensitive to the vegetation amount, FCOVER is a very good candidate for the replacement of classical vegetation indices for the monitoring of ecosystems.

More information to Tier-1 dataset can be found here:
https://land.copernicus.eu/global/sites/cgls.vito.be/files/products/CGLOPS1_ATBD_FCOVER1km-V2_I1.41.pdf
https://land.copernicus.eu/global/sites/cgls.vito.be/files/products/CGLOPS1_ATBD_FCOVER300m-V1.1_I1.10.pdf
https://land.copernicus.eu/global/sites/cgls.vito.be/files/products/ImagineS_RP2.1_ATBD-FCOVER300m_I1.73.pdf
More information to Tier-2 dataset can be found here:
https://docs.terrascope.be/DataProducts/Sentinel-2/references/VITO_S2_ATBD_S2_NDVI_BIOPAR_V200.pdf

Applied processing steps: at Tier-1: Harmonization of 300m and 1km datasets; aggregation to annual average; resampling if needed; at Tier-2: The FCOVER is derived directly from ESA L2A products; applied cloud-screening; FCOVER generation; aggregation to annual average; resampling if needed.

Fraction of Absorbed Photosynthetic Active Radiation (FAPAR)

The Fraction of Absorbed Photosynthetic Active Radiation (FAPAR) quantifies the fraction of solar radiation absorbed by leaves for the photosynthetic activity. It depends on the canopy structure, vegetation element optical properties, atmospheric conditions, and angular configuration.

More information to Tier-2 dataset can be found here: https://docs.terrascope.be/DataProducts/Sentinel-2/references/VITO_S2_ATBD_S2_NDVI_BIOPAR_V200.pdf

Applied processing steps: The FAPAR is derived directly from ESA L2A products; applied cloud-screening; FAPAR generation; aggregation to annual average; resampling if needed.

Drought resistance

The PEOPLE-EA drought resistance variable is based on the Combined Drought Indicator of the European Drought Observatory. The CDI is an indicator for drought early warning, specifically designed to monitor agricultural drought. Through the combination of spatial patterns of precipitation, soil moisture and greenness vegetation anomalies, the CDI identifies areas at risk of agricultural drought, areas where the vegetation has already been affected by drought and areas in the process of recovery to normal conditions. Accordingly, the CDI classification scheme defines three primary drought classes (Watch, Warning and Alert) and three recovery classes (Temporary Soil Moisture Recovery, Temporary Vegetation Recovery and Recovery).

By converting the drought warning classes into health quantities and aggregating to annual averages, we created an annual drought resistance variable.

More information can be found here: https://edo.jrc.ec.europa.eu/documents/factsheets/factsheet_combinedDroughtIndicator_v3.pdf

Applied processing steps: Transfer from categorical to quantitative unit; aggregation to annual average; resampling if needed.

Normalized Difference Vegetation Index (NDVI)

The Normalized Difference Vegetation Index (NDVI) is a widely used metric for quantifying the health and density of vegetation using sensor data. It is calculated from spectrometric data at two specific bands: red and near-infrared. The index is easy to interpret: NDVI will be a value between -1 and 1. An area with nothing growing in it will have an NDVI of zero. NDVI will increase in proportion to vegetation growth. An area with dense, healthy vegetation will have an NDVI of one 1. Negative values of NDVI (values approaching -1) correspond to water. Values close to zero (-0.1 to 0.1) generally correspond to barren areas of rock, sand, or snow. Lastly, low, positive values represent shrub and grassland (approximately 0.2 to 0.4), while high values indicate temperate and tropical rainforests (values approaching 1).

More information to Tier-1 dataset can be found here: https://land.copernicus.eu/global/sites/cgls.vito.be/files/products/CGLOPS1_ATBD_LTS-STS_NDVI1km-V3_I1.20.pdf
https://land.copernicus.eu/global/sites/cgls.vito.be/files/products/CGLOPS1_ATBD_NDVI300m-V2_I1.20.pdf

More information to Tier-2 dataset can be found here: https://docs.terrascope.be/DataProducts/Sentinel-2/references/VITO_S2_ATBD_S2_NDVI_BIOPAR_V200.pdf

Applied processing steps: at Tier-1: Harmonization of 300m and 1km datasets; aggregation to annual average; resampling if needed; at Tier-2: The NDVI is derived directly from ESA L2A products; applied cloud-screening; NDVI generation; aggregation to annual average; resampling if needed.

Forest Connectivity

Forest connectivity quantifies the degree of spatial intactness of forest cover. The higher the connectivity, the more thriving the forest ecosystem. Forest connectivity can be seen as the opposite of forest fragmentation, i.e., highly connected ≈ little fragmented and vice-versa.

More information can be found here: Maes et al. (2023)

Applied processing steps: Selected CORINE LC classes were processed with the GUIDOS toolbox algorithm for connectivity.

Landscape Naturalness

This indicator derived from the Landscape Mosaic (LM) metric describes landscape composition or the degree of landscape heterogeneity. The LM is based on land cover maps (e.g., CLC). The terrestrial land cover categories are aggregated into three main land cover types, that is, agriculture, natural and developed. Then, relative proportions of these three types are measured for each cell via a moving window algorithm using a fixed neighbourhood area.

More information can be found here: Maes et al. (2023)

Applied processing steps: Selected CORINE LC classes were processed with the GUIDOS toolbox algorithm for naturalness.

Forest Fragmentation

Forest fragmentation is the process of dividing large, uninterrupted forested areas into smaller pieces by human activities such as roads, farms, and transportation corridors. It has far-reaching consequences for biodiversity, carbon storage, and soil health.

More information can be found here: https://portal.geobon.org/ebv-detail?id=4#summary-view

Applied processing steps: resampling if needed.

2.4.3 Usage matrix

Table 7 provides a comprehensive overview how the forest condition variables are used in the PEOPLE-EA project. In summary, all provided forest condition variables at Tier-1 and Tier-2 are viewable, downloadable, and ready to generate annual accounts in the ARIES for PEOPLE-EA explorer. Where no Tier-2 variable are transferred into forest condition indicators, 10 out of the 13 variables are further processed to forest condition indicators and available for viewing, download and account generation in the explorer. Only selected variables are used as raw input for the three available forest condition indices in the project.

Table 7: Usage of the provided forest condition variables in the PEOPLE-EA project

Variable	Tier level	Variable Data	Conversion to indicator	PEOPLE-EA index	NatCom index	Euclidean Distance index
NDWI	1	X	X	X	X	X
SOC	1	X	X	X	X	X
Threatened Forest Bird Species	1	X	X	X	X	X
AGB	1	X	X	X	-	X
AGB	2	X	-	-	-	-
LAI	1	X	X	-	-	-
LAI	2	X	-	-	-	-
PPI	2	X	-	-	-	-
Tree cover density	1	X	X	-	X	-
NPP	1	X	X	X	-	X
FCOVER	1	X	Planned	-	-	-
FCOVER	2	X	-	-	-	-
FAPAR	2	X	-	-	-	-
Drought resistance	1	X	Planned	-	-	-
NDVI	1	X	X	-	X	-
NDVI	2	X	-	-	-	-
Forest connectivity	1	X	X	X	X	X
Landscape naturalness	1	X	X	-	X	-
Forest fragmentation	1	X	-	-	-	-

2.5 Forest condition indicators accounts

Indicators are the rescaled ecological measurements (raw variables) to allow a consistent representation of the dimensions of the conditions captured in the variable. Reference values are used to determine upper and lower bounds used as thresholds to determine the good or bad status for a particular variable in the same type of forest (aka forest with similar characteristics). The goal of the indicator is to compare the results of a particular variable against other dimensions of condition in the same type of forest, or against results for the same variable in a different area.
Within the PEOPLE-EA project we decided to use the "Forest ecosystem type split method" as described in Table 3 and applied by Maes et al. (2023) in their demonstrator study.

Therefore, the first step is to define the forest topology – normally done in the extent accounting – and then to define the reference areas for setting the upper and lower bounds for the rescaling of the variables. We decided to use the reference year 2000 as base year. When the variable dataset doesn't include the year 2000, we have set the closest recent year to the reference year 2000.

2.5.1 Forest typology – Forest ecosystem types

European forests are classified analysing the information from the Corine land cover dataset, used to distinguish varieties of forests, and the European bioregions dataset, to identify main ecological areas in Europe. Their combination, following the definition of Maes et al. (2023) results in 44 forest types.

The following datasets were used to obtain this classification:

- Forest landcovers from Corine accounting adjusted layers for year 2000 (raster file): https://www.eea.europa.eu/en/datahub/datahubitem-view/a55d9224-a326-4cb1-9b9c-3a324520341a?activeAccordion=1069872%2C1069948
- European bioregion zones from the European Environment Agency catalogue of geospatial data sets: https://sdi.eea.europa.eu/data/def7ac06-7d3f-4da5-880c-a76a73953cfc .

European forests have been initially categorized based on their landcover forest class, as per the Corine dataset, which distinguishes 4 types of forest:

- Broad-leave forest (311) - https://land.copernicus.eu/content/corine-land-cover-nomenclature-guidelines/html/index-clc-311.html
- Coniferous forest (312) - https://land.copernicus.eu/content/corine-land-cover-nomenclature-guidelines/html/index-clc-312.html
- Mixed forest (313) - https://land.copernicus.eu/content/corine-land-cover-nomenclature-guidelines/html/index-clc-313.html
- Transitional woodland & shrub (324) - https://land.copernicus.eu/content/corine-land-cover-nomenclature-guidelines/html/index-clc-324.html

The classes of forest described above, are combined with the information on the European bioregion zones, used to define 11 bioregions. Please note, normally only 10 bioregions, but as described in Maes et al. (2023) the Scandinavian Alpine zone was differentiated from the rest of the Alpine bioregion for its characteristics, and covers the forest in the Scandinavian mountains on the border between Norway and Sweden. The 11 bioregions are:

- Alpine,
- Arctic,
- Atlantic,
- Black Sea,
- Boreal,
- Continental,
- Macaronesian,
- Mediterranean,
- Pannonian,
- Steppe regions
- Alpine (Scandinavia)

Figure 5 visualizes the Forest ecosystem typology identifying 44 forest ecosystem types which are implemented as the geographic intersection between 11 biogeographic regions and four forest classes, derived from Corine Land Cover. The legend lists all forest types. Naming simply refers to the combination of region and forest class.

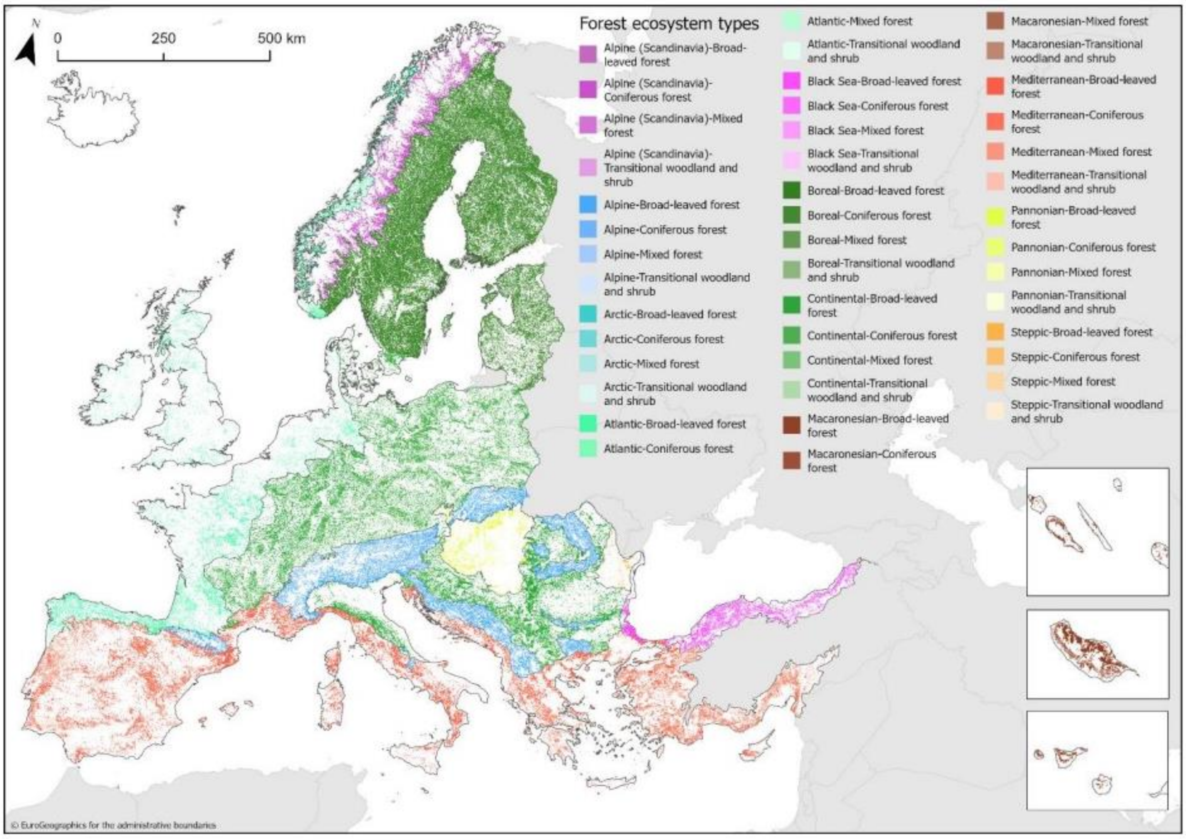

Figure 5: 44 forest ecosystem types forming the forest typology for the European forest condition accounts. Image and forest ecosystem types follow Maes et al. (2023). Image is a direct reprint of the supplemental material of the Maes et al. (2023) article.

2.5.2 Definition reference areas

Within each forest ecosystem type, reference areas must be selected to determine upper and lower bounds used as thresholds to determine the good or bad status for a particular variable in the same type of forest.

Since the exact location of the reference sites form the Maes et al. (2023) article are not public, we decided to follow the rough outline of the article to define them by ourself. Therefore, forests considered in good condition (the upper reference areas) must meet the two following criteria:

- being primary forest, alias forests where the signs of human impacts, if any, are strongly blurred due to decades without forest management or being protected areas (form before the year 2000) and highly tree-covered throughout the time series.
- should not show rapid changes or high tree-covered density loss since the year 2000.

Such criteria are observed based on the information of the following datasets:

- Primary forests from EPFD v2.0 - https://www.nature.com/articles/s41597-021-00988-7
- Protected Areas from IUCN data - https://www.protectedplanet.net/en/thematic-areas/wdpa?tab=WDPA
- Copernicus's High-Resolution Layer Tree Cover Density - https://land.copernicus.eu/en/products/high-resolution-layer-tree-cover-density
- Hansen tree cover loss: https://data.globalforestwatch.org/documents/941f17325a494ed78c4817f9bb20f33a/explore

Results are obtained by combining the inputs by using, as consistently as possible, the year 2000 as the reference year, except for the information on the Tree-cover density, whose earliest observation is in the year 2012. Whenever a forest fails to meet any of the listed criteria, it is not considered an area of reference for good condition.

Processing steps for Primary Forest selection in the PEOPLE-EA approach
Primary forests were identified by taking:

- the polygons of primary forests,
- the points of primary forests and buffer to 200m radius.

Primary forests extents match roughly with the Maes et al. (2023) figures (Supplementary Table 8) (see Figure 6):

Primary forest (ha)	Broad-leaved forest	Coniferous forest	Mixed forest	Transitional woodland and shrub	Total
Alpine	55,229	35,731	37,325	4,325	132,610
Arctic	36	0	0	0	36
Atlantic	6,305	8,728	515	676	16,224
Black Sea	6,767	0	0	0	6,767
Boreal	123,461	723,175	331,122	151,488	1329,246
Continental	36,770	4,394	11,024	987	53,175
Macaronesian	8,809	32	461	656	9,958
Mediterranean	6,073	1,132	2,521	821	10,547
Pannonian	652	0	2	3	657
Alpine (Scandinavia)	152,988	39,182	26,567	259,028	477,765
Steppic	159	0	0	0	159
Total	397,249	812,373	409,536	417,984	2,037,143

	BLF	CFF	MXF	TWS	total
ALP	47.251	44.709	35.732	4.793	132.485
ARC	36	-	-	-	36
ATL	6.247	8.956	490	646	16.339
BLS	6.811	-	48	45	6.904
BOR	100.627	1.087.285	133.233	72.972	1.394.117
CON	36.405	6.357	8.230	1.139	52.131
MAC	11.029	226	927	479	12.661
MED	6.564	2.125	3.055	1.176	12.920
PAN	747	1	10	6	764
ALS	267.333	55.767	6.677	1.026	330.803
STE	159	-	-	-	159
total	483.209	1.205.426	188.402	82.282	**1.959.319**

Figure 6: Comparison of the areas of selected primary forest sites in hectare between the Maes et al. (2023) (upper image) (also called NatCom approach) and the PEOPLE-EA approach (lower image)

Processing steps for Protected Area selection in the PEOPLE-EA approach
The Protected Areas that have been protected areas from before the year 2000 and which don't exhibit tree-cover loss over the last 20 years as well as have a minimum of 50% tree cover density were considered for this analysis.

The PA Categories used were:

1. Strict nature reserves **1a**,
2. Wilderness or wildlands **1b,** and
3. National parks **2**.

In the Maes et al. (2023) approach, depending on the bioregion analyses different categories of Protected Areas were selected compared to the PEOPLE-EA approach. The selection of the Categories 1a, 1b & 2 was the combination that matched more closely the Maes et al. (2023) figures (Supplementary Table 8).

Protected forest (ha)	Broad-leaved forest	Coniferous forest	Mixed forest	Transitional woodland and shrub	Total
Alpine	28,342	15,377	16,932	3,069	63,721
Arctic	363	0	0	0	363
Atlantic	1,060	4,086	230	86	5,462
Black Sea	62	0	15	2	79
Boreal	120,014	570,854	301,554	122,620	1,115,042
Continental	21,553	1,387	8,197	473	31,609
Macaronesian	7,905	44,512	2,047	202	54,666
Mediterranean	399,488	159,644	90,246	123,625	773,003
Pannonian	62,607	1,246	1,623	3,949	69,426
Alpine (Scandinavia)	104,896	15,259	24,696	258,715	403,566
Steppic	10,109	0	0	101	10,210
Total	756,399	812,367	445,539	512,842	2,527,147

	BLF	CFF	MXF	TWS	total
ALP	31.685	23.201	13.560	10.350	78.796
ARC	2.063	49			2.112
ATL	5.658	7.784	1.415	77	14.934
BLS	6.992		48	49	7.089
BOR	51.230	936.279	151.113	76.950	1.215.572
CON	17.081	5.259	5.024	3.541	30.905
MAC	9.660	47.767	2.048	3.213	62.688
MED	310.696	144.155	65.434	71.891	592.176
PAN	57.635	1.372	2.332	6.575	67.914
ALS	93.051	79.396	9.259	1.214	182.920
STE	10.249			105	10.354
total	596.000	1.245.262	250.233	173.965	**2.265.460**

Figure 7: Comparison of the areas of selected protected forest sites in hectare between the Maes et al. (2023) (upper image) (also called NatCom approach) and the PEOPLE-EA approach (lower image)

Finally in the PEOPLE-EA approach both datasets for healthy forest were combined, where in the NatCom approach mainly the primary forest were used, and missing areas filled with protected forest areas.
The selection of areas for the lower bounds representing the unhealthy condition are all areas not defined as reference area for the healthy condition.

2.5.3 Rescaling method

The rescaling of the forest condition variables by the upper and lower bounds of the reference dataset allows the comparison over time and space. The extraction of the upper and lower bound thresholds was done with the following method for each variable dataset:

- The upper (healthier conditions) reference threshold was set at the 98th percentile value observed in the reference healthy areas, for each type of forest, for each variable.
- The lower (worse conditions) reference threshold was set at the 2nd percentile value observed in the rest of the forest area (total forest area - healthy reference area).
- The extracted percentiles might be inverted in case the healthier conditions correspond to lower values → for example, the forest fragmentation where the higher values represent a higher fragmentation and therefore a lower health status.

Figure 8 shows the definition of the 2nd and 98th percentile of a dataset.

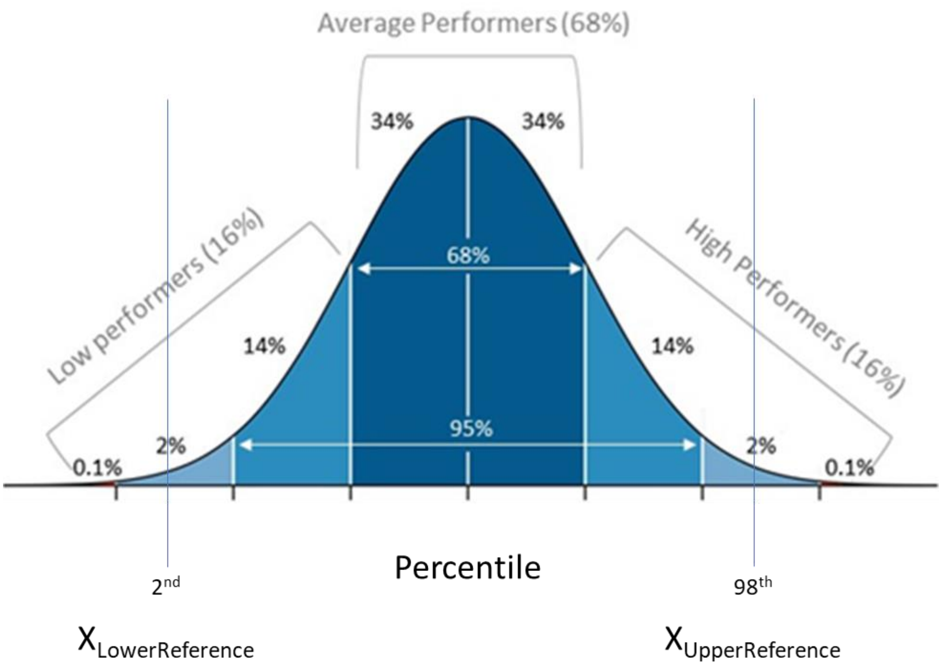

Figure 8: Definition of the lower and upper thresholds by percentiles

The rescaling of the observed variables values into indicators ranging from 0 to 1 is done by applying the following formula:

$$Xi = (X_{observed} - X_{LowerReference}) / (X_{UpperReference} - X_{LowerReference})$$

Due to the fact that the reference site selection and the definition of the upper and lower thresholds are different between the PEOPLE-EA approach and the approach implemented by Maes et al. (2023), the upper and lower boundary values for the same forest condition variable datasets vary between the both approaches. Figure 9 provides a comprehensive comparison between the two approaches for the forest condition variables used in the NatCom index.

Row Labels	birds MAES upper	birds MAES lower	birds PEOPLE upper	birds PEOPLE lower		fad MAES upper	fad MAES lower	fad PEOPLE upper	fad PEOPLE lower		lm MAES upper	lm MAES lower	lm PEOPLE upper	lm PEOPLE lower	
BLF_ALP	8.101	0.000	7.602	2.675	✗	100.000	0.000	100.000	21.000	✗	100.000	5.000	100.000	35.000	✗
BLF_ALS	7.652	0.000	5.920	2.116	✗	100.000	0.000	100.000	13.000	✗	100.000	5.000	100.000	75.000	✗
BLF_ARC	7.652	0.000	5.920	0.519	✗	100.000	3.000	100.000	5.000	✗	100.000	35.000	100.000	65.000	✗
BLF_ATL	6.753	0.000	6.266	0.393	✗	100.000	0.000	98.000	5.000	✗	100.000	5.000	100.000	5.000	✓
BLF_BLS	7.454	0.000	4.636	1.161	✗	100.000	4.000	100.000	12.000	✗	100.000	5.000	100.000	25.000	✗
BLF_BOR	8.096	0.000	8.109	3.235	✗	100.000	2.000	100.000	10.000	✗	100.000	5.000	100.000	15.000	✗
BLF_CON	7.864	0.000	7.301	1.710	✗	100.000	0.000	100.000	8.000	✗	100.000	5.000	100.000	15.000	✗
BLF_MAC	0.227	0.000	0.250	0.017	✗	100.000	3.000	98.000	6.000	✗	100.000	5.000	100.000	15.000	✗
BLF_MED	5.995	0.000	4.462	0.312	✗	100.000	0.000	100.000	7.000	✗	100.000	5.000	100.000	15.000	✗
BLF_PAN	7.454	0.000	6.951	1.862	✗	100.000	0.000	100.000	6.000	✗	100.000	5.000	100.000	15.000	✗
BLF_STE	7.454	0.000	5.477	1.404	✗	100.000	3.000	100.000	6.000	✗	100.000	5.000	100.000	15.000	✗
CFF_ALP	8.076	0.000	7.265	2.553	✗	100.000	2.000	100.000	21.000	✗	100.000	5.000	100.000	45.000	✗
CFF_ALS	8.204	1.413	6.847	2.818	✗	100.000	3.000	100.000	26.000	✗	100.000	15.000	100.000	75.000	✗
CFF_ARC	8.204	0.001	6.847	0.848	✗	100.000	5.000	100.000	4.000	✗	100.000	15.000	100.000	55.000	✗
CFF_ATL	6.753	0.000	6.125	0.404	✗	100.000	0.000	100.000	8.000	✗	100.000	5.000	100.000	15.000	✗
CFF_BLS	7.444	0.000	6.992	2.281	✗	100.000	4.000	100.000	15.000	✗	100.000	5.000	100.000	45.000	✗
CFF_BOR	8.771	0.000	7.949	3.439	✗	100.000	3.000	100.000	28.000	✗	100.000	5.000	100.000	45.000	✗
CFF_CON	7.996	0.000	7.149	2.543	✗	100.000	0.000	100.000	13.000	✗	100.000	5.000	100.000	15.000	✗
CFF_MAC	0.879	0.000	0.879	0.018	✗	100.000	5.000	100.000	10.000	✗	100.000	5.000	100.000	35.000	✗
CFF_MED	5.781	0.000	4.526	0.316	✗	100.000	0.000	100.000	9.000	✗	100.000	5.000	100.000	25.000	✗
CFF_PAN	7.444	1.305	6.992	2.579	✗	100.000	5.000	100.000	14.000	✗	100.000	5.000	100.000	25.000	✗
CFF_STE	7.444	1.350	6.992	4.359	✗	100.000	6.000	100.000	28.000	✗	100.000	5.000	100.000	35.000	✗
MXF_ALP	8.156	0.000	7.607	3.207	✗	100.000	3.000	100.000	24.000	✗	100.000	5.000	100.000	35.000	✗
MXF_ALS	7.652	1.435	6.935	2.732	✗	100.000	4.000	100.000	18.000	✗	100.000	15.000	100.000	75.000	✗
MXF_ARC	7.652	0.001	6.935	0.762	✗	100.000	5.000	100.000	4.000	✗	100.000	5.000	100.000	45.000	✗
MXF_ATL	5.630	0.000	5.855	0.313	✗	92.000	0.000	99.000	5.000	✗	100.000	5.000	100.000	5.000	✓
MXF_BLS	7.444	0.000	6.992	1.752	✗	100.000	5.000	98.000	16.000	✗	100.000	5.000	100.000	25.000	✗
MXF_BOR	8.771	0.000	8.300	3.499	✗	100.000	3.000	100.000	18.000	✗	100.000	5.000	100.000	25.000	✗
MXF_CON	7.766	0.000	7.301	2.123	✗	100.000	2.000	100.000	9.000	✗	100.000	5.000	100.000	15.000	✗
MXF_MAC	0.168	0.000	0.740	0.016	✗	95.000	5.000	91.000	8.000	✗	100.000	5.000	100.000	15.000	✗
MXF_MED	6.636	0.000	4.707	0.308	✗	100.000	2.000	100.000	10.000	✗	100.000	5.000	100.000	25.000	✗
MXF_PAN	7.444	1.399	6.992	2.112	✗	100.000	3.000	98.000	8.000	✗	100.000	5.000	100.000	15.000	✗
MXF_STE	7.444	1.623	6.992	1.623	✓	100.000	11.000	98.000	2.000	✗	100.000	15.000	100.000	5.000	✗
TWS_ALP	7.781	0.000	6.898	2.166	✗	100.000	0.000	89.000	14.000	✗	100.000	5.000	100.000	35.000	✗
TWS_ALS	8.204	1.474	6.803	3.102	✗	100.000	0.000	87.000	18.000	✗	100.000	35.000	100.000	75.000	✗
TWS_ARC	8.204	0.000	6.803	0.558	✗	100.000	4.000	87.000	3.060	✗	100.000	15.000	100.000	45.000	✗
TWS_ATL	6.753	0.000	6.454	0.330	✗	100.000	2.000	69.200	5.000	✗	100.000	5.000	100.000	15.000	✗
TWS_BLS	7.454	0.000	6.951	1.688	✗	100.000	4.000	95.000	10.000	✗	100.000	5.000	100.000	35.000	✗
TWS_BOR	8.640	0.000	8.139	3.477	✗	100.000	2.000	90.000	19.000	✗	100.000	5.000	100.000	45.000	✗
TWS_CON	7.166	0.000	6.248	1.476	✗	100.000	0.000	85.000	9.000	✗	100.000	5.000	100.000	15.000	✗
TWS_MAC	0.168	0.000	0.740	0.015	✗	98.000	4.000	74.100	5.000	✗	100.000	5.000	100.000	15.000	✗
TWS_MED	5.781	0.000	4.474	0.281	✗	100.000	0.000	86.000	6.000	✗	100.000	5.000	100.000	25.000	✗
TWS_PAN	7.454	0.000	6.951	1.613	✗	100.000	0.000	95.000	5.000	✗	100.000	5.000	100.000	5.000	✓
TWS_STE	7.454	1.060	6.951	1.353	✗	100.000	3.000	95.000	5.000	✗	100.000	5.000	100.000	5.000	✓
EU AVERAGE	6.853	0.251	6.096	1.638		99.659	2.500	96.189	11.274		100.000	7.500	100.000	29.773	

Row Labels	ndvi MAES upper	ndvi MAES lower	ndvi PEOPLE 0.000	ndvi PEOPLE 0.000		ndwi MAES upper	ndwi MAES lower	ndwi PEOPLE 0.000	ndwi PEOPLE 0.000		soc MAES upper	soc MAES lower	soc PEOPLE 0.000	soc PEOPLE 0.000		trees MAES upper	trees MAES lower	trees PEOPLE 0.000	trees PEOPLE 0.000	
BLF_ALP	0.758	0.017	0.678	0.445	✗	0.175	-0.277	0.370	0.144	✗	0.340	0.000	0.176	0.014	✗	100.000	0.000	96.000	12.000	✓
BLF_ALS	0.525	-0.193	0.613	0.388	✗	0.302	-0.388	0.355	0.230	✗	1.000	0.000	0.630	0.014	✗	88.000	0.000	67.000	0.000	✗
BLF_ARC	0.525	-0.038	0.613	0.222	✗	0.302	-0.216	0.355	0.165	✗	0.000	0.000	0.630	0.002	✗	88.000	0.000	67.000	0.000	✗
BLF_ATL	0.728	-0.192	0.680	0.438	✗	0.249	-0.460	0.373	0.157	✗	0.640	0.000	0.216	0.005	✗	96.000	0.000	85.000	0.000	✗
BLF_BLS	0.738	0.049	0.653	0.386	✗	0.059	-0.323	0.288	0.087	✗	0.000	0.000	0.052	0.012	✗	100.000	0.000	92.000	10.000	✓
BLF_BOR	0.682	-0.102	0.614	0.432	✗	0.291	-0.349	0.354	0.186	✗	1.000	0.000	0.630	0.014	✗	100.000	0.000	91.000	0.000	✓
BLF_CON	0.725	-0.110	0.659	0.421	✗	0.274	-0.332	0.313	0.129	✗	0.420	0.000	0.261	0.009	✗	100.000	0.000	97.000	3.000	✓
BLF_MAC	0.847	0.008	0.758	0.379	✗	0.167	-0.363	0.374	0.057	✗	0.000	0.000	0.000	0.000	✓	100.000	0.000	100.000	0.000	✓
BLF_MED	0.864	-0.083	0.704	0.307	✗	0.189	-0.357	0.350	-0.003	✗	0.340	0.000	0.056	0.005	✗	100.000	0.000	98.000	0.000	✓
BLF_PAN	0.738	-0.019	0.644	0.381	✗	0.059	-0.129	0.302	0.100	✗	0.420	0.000	0.116	0.011	✗	100.000	0.000	97.000	0.000	✓
BLF_STE	0.738	-0.054	0.625	0.326	✗	0.059	-0.141	0.264	0.034	✗	0.000	0.000	0.046	0.009	✗	100.000	0.000	93.000	0.000	✓
CFF_ALP	0.792	-0.030	0.644	0.375	✗	0.206	-0.298	0.426	0.213	✗	0.340	0.000	0.180	0.014	✗	100.000	0.000	95.000	3.000	✓
CFF_ALS	0.541	-0.089	0.618	0.413	✗	0.193	-0.199	0.359	0.246	✗	1.000	0.000	0.630	0.014	✗	90.000	0.000	77.000	0.000	✗
CFF_ARC	0.541	-0.028	0.618	0.141	✗	0.193	-0.217	0.359	0.147	✗	0.000	0.000	0.630	0.000	✗	90.000	0.000	77.000	0.000	✗
CFF_ATL	0.756	-0.165	0.662	0.470	✗	0.190	-0.421	0.382	0.170	✗	0.640	0.000	0.403	0.006	✗	87.000	0.000	77.000	0.000	✗
CFF_BLS	0.747	0.013	0.644	0.317	✗	0.036	-0.259	0.332	0.060	✗	0.000	0.000	0.100	0.012	✗	97.000	0.000	92.000	8.000	✓
CFF_BOR	0.895	-0.188	0.606	0.442	✗	0.321	-0.397	0.364	0.206	✗	1.000	0.000	0.630	0.014	✗	95.000	0.000	89.000	0.000	✓
CFF_CON	0.740	-0.136	0.726	0.442	✗	0.190	-0.450	0.416	0.159	✗	1.000	0.000	0.316	0.013	✗	99.000	0.000	92.000	5.000	✓
CFF_MAC	0.795	0.018	0.639	0.236	✗	0.057	-0.154	0.312	-0.062	✗	0.000	0.000	0.000	0.000	✓	100.000	0.000	93.000	0.000	✓
CFF_MED	0.848	-0.120	0.697	0.244	✗	0.431	-0.515	0.409	-0.018	✓	0.340	0.000	0.054	0.005	✗	100.000	0.000	97.000	0.000	✓
CFF_PAN	0.747	0.192	0.644	0.398	✗	0.036	-0.115	0.332	0.084	✗	0.190	0.000	0.100	0.012	✗	97.000	0.000	92.000	0.000	✓
CFF_STE	0.747	0.332	0.644	0.395	✗	0.036	-0.099	0.332	0.026	✗	0.000	0.000	0.100	0.037	✗	97.000	0.000	92.000	0.020	✓
MXF_ALP	0.769	0.032	0.672	0.429	✗	0.223	-0.307	0.391	0.186	✗	0.340	0.000	0.176	0.014	✗	100.000	0.000	97.000	13.000	✓
MXF_ALS	0.531	0.012	0.609	0.414	✗	0.177	-0.261	0.366	0.246	✗	1.000	0.000	0.630	0.014	✗	90.000	0.000	77.000	0.000	✗
MXF_ARC	0.531	-0.018	0.609	0.216	✗	0.177	-0.250	0.366	0.143	✗	0.000	0.000	0.630	0.063	✗	90.000	0.000	77.000	0.000	✗
MXF_ATL	0.718	-0.080	0.686	0.462	✗	0.163	-0.353	0.394	0.160	✗	0.220	0.000	0.216	0.006	✗	94.000	0.000	81.000	0.000	✗
MXF_BLS	0.726	0.082	0.654	0.357	✗	0.025	-0.231	0.324	0.077	✗	0.000	0.000	0.099	0.011	✗	99.000	0.000	92.000	8.000	✓
MXF_BOR	0.823	-0.190	0.612	0.440	✗	0.417	-0.264	0.360	0.199	✗	1.000	0.000	0.630	0.014	✗	100.000	0.000	91.000	2.000	✓
MXF_CON	0.740	-0.079	0.706	0.433	✗	0.167	-0.252	0.364	0.153	✗	1.000	0.000	0.185	0.011	✗	100.000	0.000	98.000	3.000	✓
MXF_MAC	0.782	0.290	0.694	0.331	✗	0.143	-0.135	0.369	0.017	✗	0.000	0.000	0.000	0.000	✓	91.000	0.000	100.000	0.000	✓
MXF_MED	0.852	-0.086	0.710	0.280	✗	0.174	-0.379	0.380	-0.011	✗	0.340	0.000	0.058	0.005	✗	100.000	0.000	98.000	0.000	✓
MXF_PAN	0.726	0.191	0.654	0.387	✗	0.025	-0.122	0.324	0.068	✗	0.420	0.000	0.099	0.011	✗	99.000	0.000	92.000	0.000	✓
MXF_STE	0.726	0.242	0.654	0.313	✗	0.025	-0.145	0.324	-0.014	✗	0.000	0.000	0.099	0.009	✗	99.000	0.000	92.000	0.000	✓
TWS_ALP	0.746	-0.029	0.622	0.345	✗	0.163	-0.320	0.399	0.042	✗	0.340	0.000	0.101	0.014	✗	98.000	0.000	89.000	0.000	✓
TWS_ALS	0.522	0.035	0.637	0.458	✗	0.232	-0.147	0.380	0.238	✗	1.000	0.000	0.630	0.014	✗	89.000	0.000	72.000	0.000	✗
TWS_ARC	0.522	-0.061	0.637	0.171	✗	0.232	-0.308	0.380	0.126	✗	0.000	0.000	0.630	0.000	✗	89.000	0.000	72.000	0.000	✗
TWS_ATL	0.671	-0.097	0.673	0.459	✗	0.147	-0.408	0.360	0.095	✗	0.640	0.000	0.403	0.006	✗	81.000	0.000	77.000	0.000	✓
TWS_BLS	0.686	-0.028	0.624	0.239	✗	0.086	-0.193	0.272	-0.031	✗	0.000	0.000	0.110	0.012	✗	100.000	0.000	88.000	0.000	✗
TWS_BOR	0.668	-0.182	0.616	0.459	✗	0.310	-0.317	0.356	0.168	✗	1.000	0.000	0.630	0.014	✗	100.000	0.000	87.000	0.000	✗
TWS_CON	0.697	-0.066	0.644	0.344	✗	0.198	-0.361	0.366	0.021	✗	1.000	0.000	0.391	0.009	✗	98.000	0.000	88.000	0.000	✗
TWS_MAC	0.812	0.038	0.761	0.182	✗	0.073	-0.271	0.288	-0.045	✗	0.000	0.000	0.000	0.000	✓	92.000	0.000	97.000	0.000	✓
TWS_MED	0.838	-0.115	0.668	0.210	✗	0.147	-0.415	0.306	-0.059	✗	0.340	0.000	0.062	0.005	✗	100.000	0.000	93.000	0.000	✓
TWS_PAN	0.686	0.013	0.624	0.352	✗	0.086	-0.144	0.272	0.015	✗	0.420	0.000	0.110	0.009	✗	100.000	0.000	88.000	0.000	✗
TWS_STE	0.686	-0.014	0.624	0.307	✗	0.086	-0.149	0.272	-0.028	✗	0.000	0.000	0.110	0.008	✗	100.000	0.000	88.000	0.000	✗
EU AVERAGE	0.715	-0.023	0.654	0.354		0.170	-0.277	0.349	0.097		0.403	0.000	0.272	0.011		96.205	0.000	88.409	1.523	

Figure 9: Comparison of the upper and lower boundary values between the PEOPLE-EA and the Maes et al. (2023) approaches for the forest condition variables used in the NatCom index

2.5.4 Overview of provided indicators

The indicator accounts compare the variable accounts in each location with their reference values for areas representing the same type of forest and bio-geographic region in 2000. When data for the year 2000 was not available, the closest temporal observation available in the time series is taken as the reference. Table 8 provides an overview which forest condition indicators accounts are available in the project and are delivered through the ARIES for PEOPLE-EA explorer.

Special Note: since the rescaling algorithm was adapted compared to the Maes et al. (2023) approach in which the minimum and the maximum threshold were used instead the 2nd and 98th percentile, the PEOPLE-EA and NatCom indicators are not directly comparable with each other. Therefore, in the ARIES for PEOPLE-EA explorer only the indicators calculated in PEOPLE-EA mode are directly accessible (viewable and download), where the indicators calculated in NatCom mode (following the Maes et al. (2023) approach) are only accessible via the generation of the NatCom index. Please consult the ARIES for PEOPLE-EA explorer manual for further details.

Table 8: Provided forest condition indicators, listed by calculation mode

Indicator	PEOPLE-EA mode: using PEOPLE-EA reference areas & rescaling method	NatCom mode: using Maes et al. (2023) reference areas & rescaling method	Note
NDWI	X	X	Available in NatCom mode only via the NatCom index generation
SOC	X	X	Available in NatCom mode only via the NatCom index generation
Threatened Forest Bird Species	X	X	Available in NatCom mode only via the NatCom index generation
AGB	X	-	
LAI	X	-	
Tree cover density	-	X	Available in NatCom mode only via the NatCom index generation
NPP	X	-	
NDVI	X	X	Available in NatCom mode only via the NatCom index generation
Forest connectivity	X	X	Available in NatCom mode only via the NatCom index generation
Landscape naturalness	-	X	Available in NatCom mode only via the NatCom index generation

2.6 Forest condition index accounts

The Forest Condition Index quantifies forest health by summarizing the information of several indicator accounts, each representing a different aspect of the forest conditions, thus is computed by considering the several dimensions represented by each metric (raw variable).
The indicators composing the index aim to represent comprehensively all the components of ecosystems (abiotic, biotic and landscape). The index is usually composed of a single indicator for each Ecosystem Typology Class (ETC) since the variables belonging to the same ETC are usually highly correlated. The indicators are selected considering their relevance, their direct relationship to forest conditions and the availability of data for their measurement.

Within the PEOPLE-EA study we adapt Maes et al. (2023) recommendation and develop a single forest condition index by combining several forest condition indicators as well as report the forest condition indicators and their trends independently to allow sensitivity analysis. Nevertheless, since the aim of the PEOPLE-EA project is the facilitation of EO in natural capital accounting, we put a high emphasis of EO variables/indicators during the assembling of the PEOPLE-EA forest condition index.

Overall, we decided to provide three different forest condition indices to allow the benchmarking of them against each other. The first index, called NatCom index, follows the original definition of Maes et al. (2023) and is based on the their original indicator definition. The second index, the PEOPLE-EA index, is based on the PEOPLE-EA definition of the indicators (reference area assignment and threshold definition). The third index, the Euclidian distance index, is mainly based on the PEOPLE-EA index but uses a geometric average instead the arithmetic average in the index generation.

Please note: the ARIES for PEOPLE-EA explorer allows not only the annual generation of the three forest condition indices accounts starting with the year 2000, but also the generation of accounts with freely choose-able time interval (e.g., three-annual, decadal).

2.6.1 PEOPLE-EA index

The index built in the PEOPLE-EA project is the result of the weighted average of these indicators:

- the Net Difference Water Index (NDWI),
- Soil Organic Carbon (SOC),
- Threatened forest bird species diversity (TFBSD),
- Above-Ground Biomass (AGB),
- Net Primary Production (NPP)
- and Forest connectivity (FC).

The index has been designed to consider one indicator for each Ecosystem Typology Class. The weights for indicator accounts are determined according to:

- their spatial resolution (i.e., the size of the smallest feature detected by a satellite sensor or displayed in a satellite image, usually expressed as a single value measuring the length of one side of a square),
- temporal resolution (i.e., the total amount of years in a dataset),
- temporal frequency (i.e., the availability of temporal observations over the same period) and
- dataset quality (referring to the proximity of the latest year to the present).

In particular, indicator accounts are ranked according to each of these categories. Larger values of these criteria are associated with a better representation of the ecological conditions and, rank in a higher position. The relative sum of the indicator accounts positions results in their index weight.

When data from more than one indicator is considered equal in one particular aspect, each indicator is attributed to the average of the positions they would represent. For example, if three indicator accounts should be ranked 7, they will be assigned 6 since it is the average of the positions these variables represent (5th, 6th and 7th). Ranking and weights attributed to indicator accounts are detailed in the Table 9.

Table 9: Scoring mechanism for the weighted arithmetic average as aggregation method to generate the PEOPLE-EA forest condition index

#	ETC class	Raw Variable	Spatial resolution	Temporal resolution	Temporal frequency	Dataset quality	Total	Final Weight
1	A1	Net Difference Water Index	5	6	6	5.5	22.5	**0.27**
2	A2	Soil Organic Carbon	2	1	1	2	6	**0.07**
3	B1	Threatened Forest Bird Species Diversity	1	3.5	3	1	8.5	**0.10**
4	B2	Above-ground Biomass	5	3.5	3	4	15.5	**0.18**
5	B3	Net Primary Production	3	5	5	5.5	18.5	**0.22**
6	C1	Forest Connectivity	5	2	3	3	13	**0.16**
Total			**21**	**21**	**21**	**21**	**84**	**1.0**

The formulation of the resulting Forest Condition Index is the following:
Forest Condition Index = (NDWI x 0.27) + (SOC x 0.07) + (TBFSD x 0.10) + (AGB x 0.18) + (NPP x 0.22) + (FC x 0.16)

For areas where Soil Organic Carbon is missing, because of dataset coverage, the index is calculated by redistributing the weights:
Forest Condition Index = (NDWI x 0.31) + (TBFSD x 0.11) + (AGB x 0.19) + (NPP x 0.24) + (FC x 0.15)

2.6.2 Euclidean distance index

The Euclidian Distance index uses the same indicators and weights to calculate the overall condition index, but it differs from the PEOPLE-EA index for using a weighted geometric average instead of the weighted arithmetic average. Euclidean distance represents the geometric distance in a between two vectors. It is a good a measure to summarize the difference in magnitude of the condition indicators of an ecosystem.

The formulation of the resulting Forest Condition Index is the following:
Forest Condition Index = sqrt((NDWI^2 x 0.27) + (SOC^2 x 0.07) + (TBFSD^2 x 0.10) + (AGB^2 x 0.18) + (NPP^2 x 0.22) + (FC^2 x 0.16))

For areas where Soil Organic Carbon is missing, because of dataset coverage, the index is calculated redistributing the weights:
Forest Condition Index = sqrt((NDWI^2 x 0.31) + (TBFSD^2 x 0.11) + (AGB^2 x 0.19) + (NPP^2 x 0.24) + (FC^2 x 0.15))

2.6.3 NatCom index

The NatCom forest condition index follows the original definition of Maes et al. (2023) and is composed of the following indicators:

- the Net Difference Water Index (NDWI),
- Soil Organic Carbon (SOC),
- Threatened forest bird species diversity (TFBSD),
- Tree cover density (TCD),
- Forest productivity (NDVI),
- Forest connectivity (FC) and
- Landscape naturalness (LN).

To obtain a unique assessment of the forest condition, the index uses the weighted average of indicator accounts. The weights for indicator accounts are assigned based on their capacity to represent the ecosystem structure (intrinsic relevance), the ecosystem services provided (instrumental relevance), the changes in forest condition derived from external factors (directionality meaning) and the anthropogenic repercussion (sensibility to human influence) as well as on their adequacy to the SEEA EA framework (framework adequacy). Indicators are ranked between 1 (lowest position) and 7 (highest position) for the five conceptual criteria proposed to the selected ecosystem condition variables. Better positioned indicators have a larger weight in the index, and the relative sum of the indicator positions results in their index weight (Maes et al., 2023). Ranking and weights attributed to indicator accounts are detailed in the Table 10.

Table 10: Scoring mechanism for the weighted arithmetic average as aggregation method to generate the NatCom forest condition index

#	ETC class	Variable	Intrinsic relevance	Instrumental relevance	Directional meaning	Sensibility to human influence	Framework conformity	Total	Final Weight
1	A1	Net Difference Water Index	1	4	1	2	3	11	**0.08**
2	A2	Soil Organic Carbon	3	5	3	1	5	17	**0.12**
3	B1	Threatened Forest Bird Species Diversity	7	3	7	7	7	31	**0.22**
4	B2	Tree Cover Density	6	6	5	6	6	29	**0.21**
5	B3	Net Difference Vegetation Index	2	7	2	3	4	18	**0.34**
6	C1	Forest Connectivity	5	2	4	5	2	18	**0.13**
7	C1	Landscape Naturalness	4	1	6	4	1	16	**0.11**
Total			**28**	**28**	**28**	**28**	**28**	**140**	**1.0**

The formulation of the resulting Forest Condition Index is the following:
Forest Condition Index = (NDWI x 0.08) + (SOC x 0.12) + (TBFSD x 0.22) + (TCD x 0.21) + (NDVI x 0.13) + (FC x 0.13) + (LN x 0.11)

For areas where Soil Organic Carbon is missing, because of dataset coverage, the index is calculated by redistributing the weights:
Forest Condition Index = (NDWI x 0.10) + (TBFSD x 0.26) + (TCD x 0.23) + (NDVI x 0.15) + (FC x 0.14) + (LN x 0.12)

2.7 ARIES for PEOPLE-EA Explorer

To ease the data access for the Early Adopters to the generated forest condition accounts, we implemented the full approach into the ARIES for PEOPLE-EA web application (explorer) (Figure 10). The ARIES for PEOPLE_EA Explorer is a web-based application built on the k.LAB Integrated Modelling Platform. The application has access to all information (data and models) available on the Integrated Modelling network and provides a dedicated user interface to allow the pilot countries to easily access and test the output of the PEOPLE-EA project, funded by the European Space Agency, and developed by the ARIES team (BC3) in collaboration with the VITO team and using the OpenEO (Open Earth Observations) platform.

Within the ARIES for PEOPLE-EA explorer the full forest condition variable accounts on Tier-level 1 and 2 are available, as well as the indicator and index accounts on Tier-1 level. As already mentioned earlier, the forest condition indicator accounts using the PEOPLE-EA mode are directly stand-alone accessible, where the indicators calculated in the NatCom mode (following the original Maes et al. (2023) methodology) are only indirect available via the generation of the NatCom forest condition index.

Please see the ARIES for PEOPLE-EA user manual for more information to generate forest condition variable, indicator and index accounts: https://confluence.integratedmodelling.org/display/AFP/ARIES+for+PEOPLE-EA+Explorer+users+guide

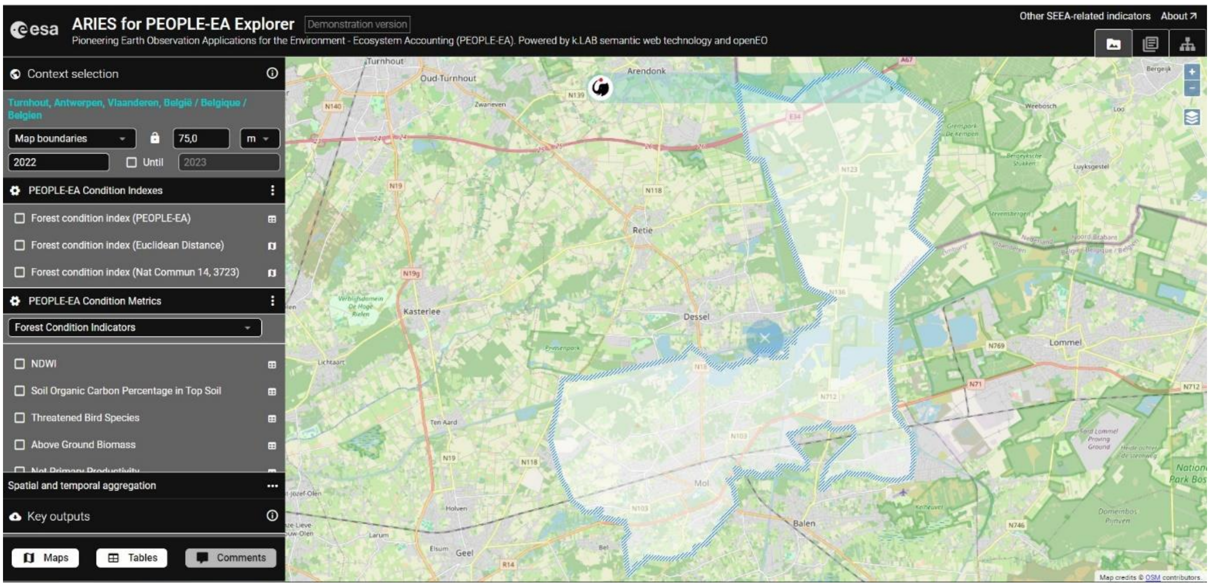

Figure 10: Screenshot of the ARIES for PEOPLE-EA Explorer interface as the main access point for forest condition account generation

2.8 Uncertainty estimation

Understanding the uncertainty in EO datasets as well as the error propagation into EO products and further into products based on EO data is highly relevant in the generation of forest condition accounts. In detail, the generation of forest condition variable, indicator and index accounts is affected by uncertainties in the RS data-to-information pipeline.
Following the principles of the Guide to expression of Uncertainties in Measurement (GUM), an uncertainty budget should always be provided for every data set (JCGM, 2008). Therefore, 1) rigorous uncertainty analysis should be applied to all steps of processing from raw sensor data to products, 2) traceability to SI international units should be guaranteed through an, ideally unbroken, chain of processes, and 3) products and their uncertainties should be validated by comparison with independent measurements that themselves include uncertainty estimates (JCGM, 2008).
Unfortunately, fully propagated uncertainty estimates are not generally available for RS instruments and their processing chains, including derived products. Therefore, a detailed uncertainty estimation for the forest condition variable, indicator and index accounts is not possible within this project. Thus, we will mainly present a brought overview to this topic and guide to more detailed quality analysis (validation reports) for the used forest condition variables. Following the request in the co-design meeting, we will present the quality assessment of the biomass datasets in more detail.

Uncertainty in the EO data and products
Randomness driven by errors in sensors and error propagation during the pre-processing of EO data may contribute to large fractions of the signal that serves as input to EO products. Sensor errors can be either systematic or random, and vary in their effects on the signal, in some cases accounting for as much as 1-2% of signal variability in the visible realm of the electromagnetic spectrum, up to >10% in the near- and shortwave infrared regions where there is less solar radiation and thus inherently lower signal-to-noise ratios (Figure 11).

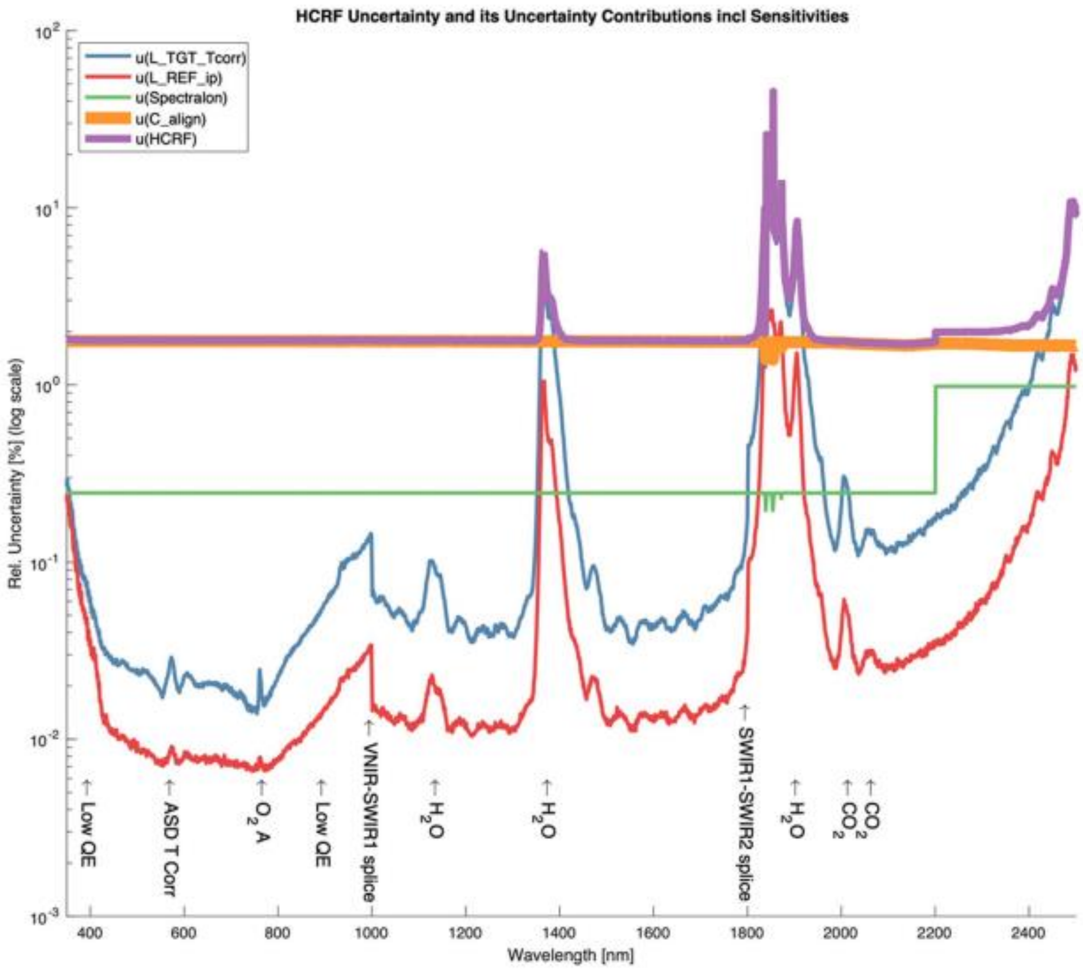

Figure 11: Uncertainty contribution in a field spectroscopy measurement to establish the hemispherical-conical reflectance factor, showing sources of uncertainty that are mostly random (red and blue spectra) or mostly systematic (green and orange spectra). Original figure by Hueni et al. (2023).

A good overview of the current state-of-the-art in uncertainty assessment in EO products can be found in Tran et al. (2023). An practical example how to set up an error propagation framework for the SENTINEL-2 NDVI variable can be found in Graf et al. (2023).

Assessment of EO products

Many of the EO-based forest condition variables used in the PEOPLE-EA project are delivered with detailed validation reports showing uncertainties estimates of the products (see Table 11).

Table 11: References to the validation reports of forest condition variables

Forest condition variable	Link to validation report
LAI	https://land.copernicus.eu/global/sites/cgls.vito.be/files/products/CGLOPS1_SQE2019_LAI1km-V1%26V2_I1.00.pdf https://land.copernicus.eu/global/sites/cgls.vito.be/files/products/CGLOPS1_QAR_LAI1km-PROBAV-V2_I1.40.pdf https://land.copernicus.eu/global/sites/cgls.vito.be/files/products/CGLOPS1_QAR_LAI300m-V1.1_I1.20.pdf
Tree cover density	https://land.copernicus.eu/en/technical-library/hrl-forest-2015-validation-report/@@download/file
NPP	https://land.copernicus.eu/global/sites/cgls.vito.be/files/products/CGLOPS1_QAR_DMP1km-V2_I1.11.pdf https://land.copernicus.eu/global/sites/cgls.vito.be/files/products/CGLOPS1_QAR_DMP-NPP300m_V1.1_I1.50.pdf
FCOVER	https://land.copernicus.eu/global/sites/cgls.vito.be/files/products/CGLOPS1_QAR_FCOVER1km-PROBAV-V2_I1.40.pdf https://land.copernicus.eu/global/sites/cgls.vito.be/files/products/GIOGL1_QAR_FCOVER1km-VGT-V2_I2.01.pdf https://land.copernicus.eu/global/sites/cgls.vito.be/files/products/CGLOPS1_QAR_FCOVER300m-V1.1_I1.20.pdf
NDVI	https://land.copernicus.eu/global/sites/cgls.vito.be/files/products/CGLOPS1_QAR_NDVI1km-V3_I1.10.pdf https://land.copernicus.eu/global/sites/cgls.vito.be/files/products/CGLOPS1_QAR_NDVI300m-V2_I1.50.pdf
PPI (Tier-2)	https://land.copernicus.eu/en/technical-library/validation-report-of-seasonal-trajectories-vpp-parameters/@@download/file
LAI, FCOVER, FAPAR, NDVI Tier-2	https://docs.terrascope.be/DataProducts/Sentinel-2/references/VITO_S2_QAR_S2_BIOPAR_inter-comparison_V200_V102.pdf

A more detailed assessment of the provided above ground biomass datasets for the biomass variables was carried out. At Tier-level 1 the ESA CCI biomass dataset in version 4 was used for which a full end-to-end ECV uncertainty budget analysis was carried out. This analysis estimated the uncertainty of the RS input data and the BIOMASAR algorithm, and outputs it as standard deviation (SD) in Mg/ha (indicating the variability of the estimate). The AGB SD datasets are available for download in the ARIES for PEOPLE-EA explorer next to the ABG variable itself (see Figure 12). More information to the generation of the SD can be found here: https://climate.esa.int/media/documents/D2.3_End_to_End_ECV_Uncertainty_Budget_V4.0_20230413.pdf

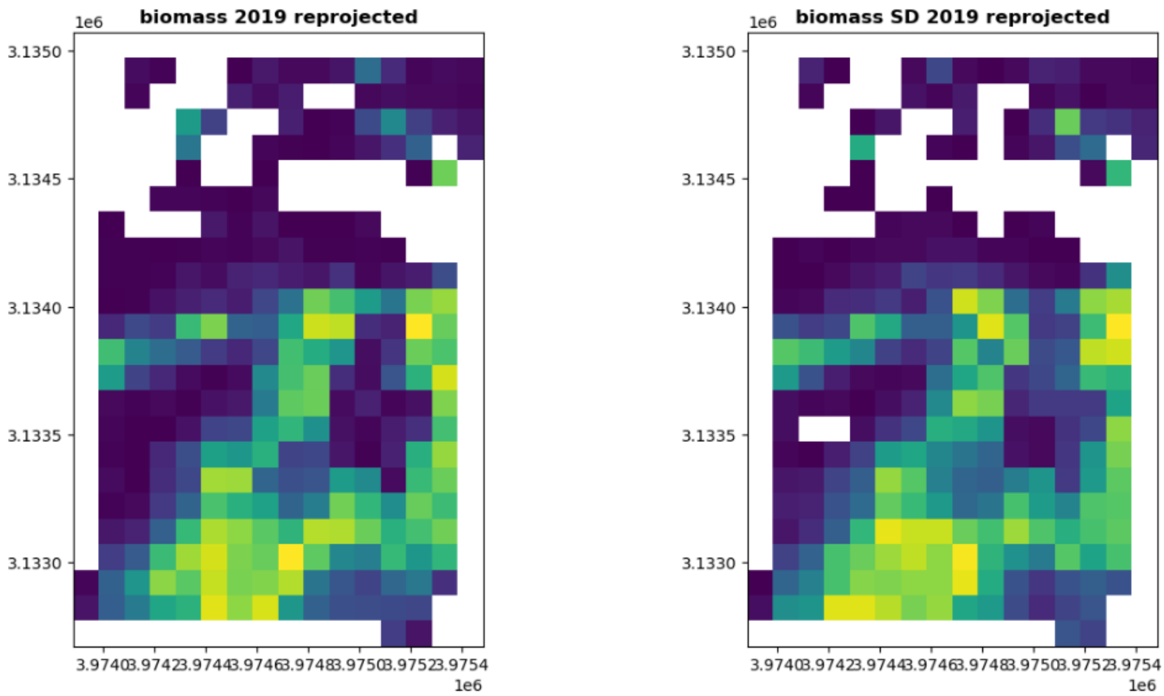

Figure 12: Example of the CCI biomass v4 dataset with its corresponding standard deviation (SD) dataset showing the uncertainty of the produced above ground biomass estimates

A more detailed analysis was carried out by Araza et al. (2022) shows that CCI biomass dataset tend to overestimate low AGB and underestimate high AGB (Figure 13). The in more detail analysis of Araza (2023) shows that the CCI lack sufficient sensitivity to measure gradual changes associated with regrowth and degradation especially in dense forests.

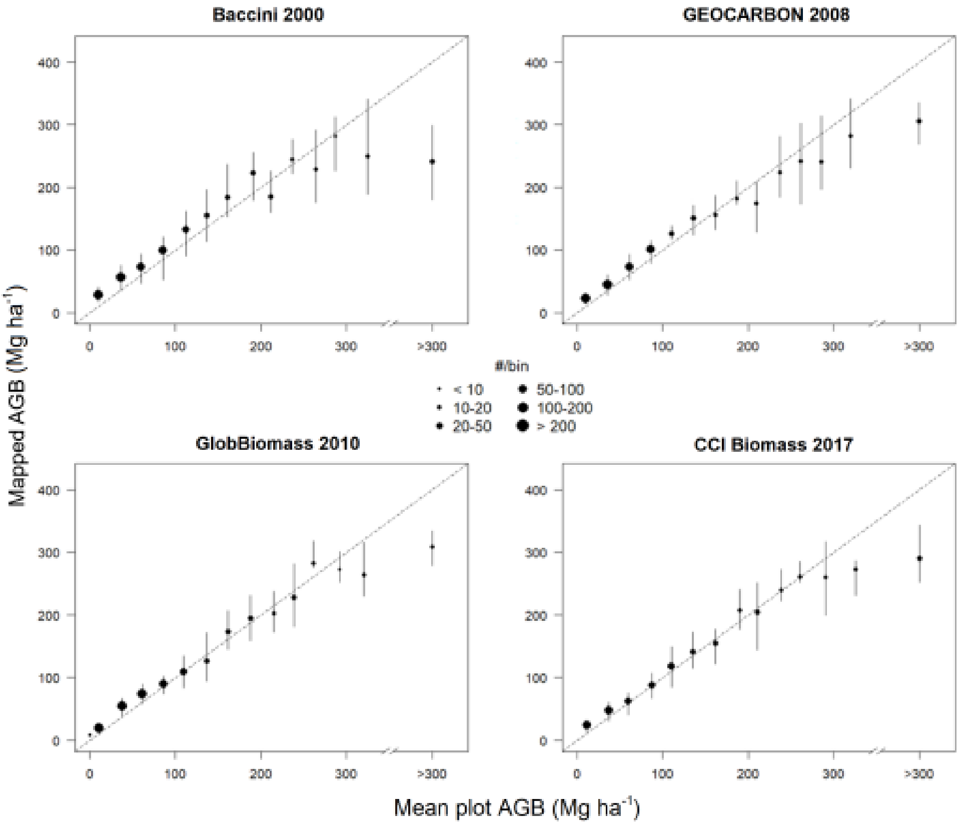

Figure 13: Accuracy assessment of several global biomass maps by Araza et al. (2022). The lower right graph represents the CCI biomass dataset.

At Tier-2 level, the ESA forest carbon monitoring dataset uses the same BIOMASAR algorithm as the ESA CCI biomass dataset but was adapted to 20m spatial resolution. This adaptation improves the spatial quality of forest variable accounts significant (Figure 14).

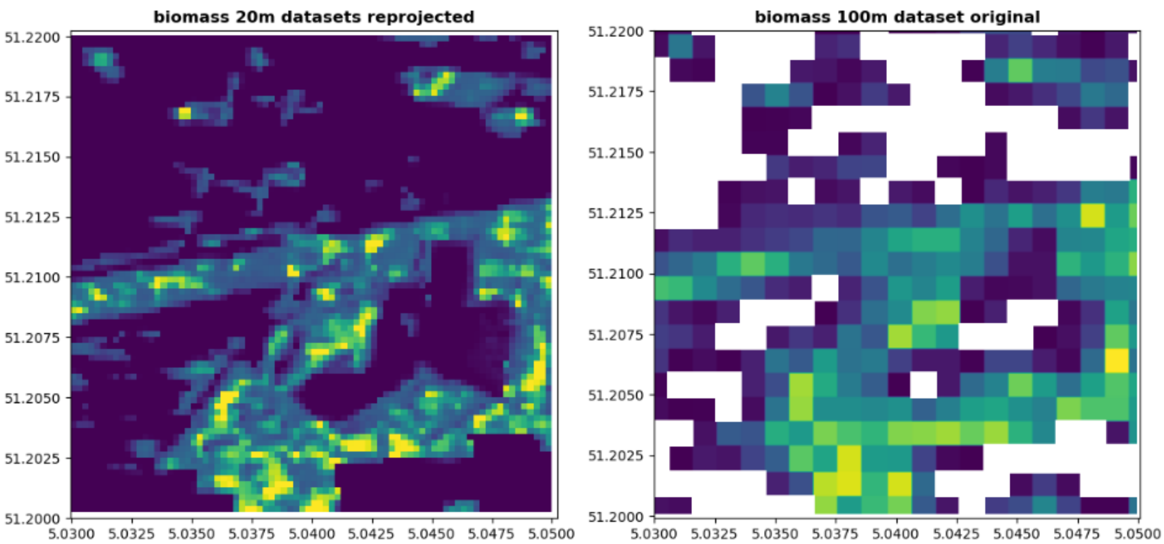

Figure 14: Visualization of the ESA forest carbon monitoring and ESA CCI biomass datasets showing the above ground biomass in Mg/ha for the year 2020.

2.9 Summary

The PEOPLE-EA implementation of Forest Condition accounts, through the integration of the ARIES and the OpenEO systems, allow to reproduce the European forest condition accounting reference publication. Due to the flexibility of the system and the openness to use Earth Observation data, forest condition accounts across entire European continent can now be generated on annual basis from 2000 onwards. More important is that new EO data is added automatically to the tool and hence also accounts for recent years can be generated once the year end is reached.

The tool provides three options to aggregate the indicators into an index, but at this stage it is not yet known which of the three options provide the best solution. The analysis from the five Early Adopters will hopefully drive a recommendation on the aggregation method.

Another important limitation is that at this stage the forest types are based on the continental dataset, while users want to be able to upload their own forest classification. The tool can support this feature only when the k.Lab modeller is installed at the user premises, which requires some specific technicalities which are mostly not available at statistical offices. Therefore, it is recommended (and already planned) to enable users to drag and drop their forest classification into the tool via a simple web interface. It should however be noted that it is advised in the future to use the forest classification from the extent account, in the detail (level 2 or 3) available.

Similarly, as integrating national forest classifications, it is recommended to further develop the tool to upload and integration national variable datasets. This is important for the more static datasets (e.g., threatened bird species).

Finally, the PEOPLE-EA provides a full solution to generate forest condition accounts at 100m spatial resolution, however there is a demand to go to 10m-20m spatial resolution. The system has included the generation of some high resolution variables but transforming them into indicators and finally an index is required as future work. Especially the method to scale variables into indicators and the large difference in spatial resolution between EO-derived and non-EO derived variables is to be further elaborated.

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Annex 1. National reference datasets

Country	Validation of:	Dataset	Source
Slovakia	Forest & Woodland condition	National Forest Inventory	Data from the National Forest Centre a on the spatial distribution of forest ecosystems. Spatial data set is covering 96% of Slovak forests (with the exception of military forests and areas not defined as forest stand) with attributes defining age, tree composition, habitat identification, etc.
Slovakia	Forest & Woodland condition	High Nature value Forests	Data from the National Forest Centre a on the spatial distribution of forest ecosystems. Spatial data set is covering 96% of Slovak forests (with the exception of military forests and areas not defined as forest stand) with attributes defining age, tree composition, habitat identification, etc. For identification of high nature value forest areas one specific parameter from data set will be used - naturalness of forest, which is calculated based on the tree composition of individual forest stands
Greece	Forest & Woodland condition	MAES_GR field protocols	LIFE-IP 4 NATURA dataset / Field survey plots at Woodland and forests
Greece	Forest & Woodland condition	Field survey of the plots on Habitat Directive monitoring projects	Ministry of Environment and Energy
Norway	Forest & Woodland condition	SR16	https://kartkatalog.geonorge.no/metadata/sr16-skogressurskart-16x16-meter/7df9ef08-faf2-4ad3-9ae2-49905f5ea808 Provides an overview of the distribution and characteristics of the country's forest resources. SR16 is divided into SR16R which is a raster map and SR16V which is a vector map. LiDAR-data https://hoydedata.no/LaserInnsyn2/
Norway	Forest & Woodland condition	'Naturebase'	'Naturebase' contains information on vegetation for selected regions. The Norwegian Environment Agency: https://geocortex01.miljodirektoratet.no/Html5Viewer/?viewer=naturbase