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Earth Observation for statistics - methodology and training

EO-4-STATISTICS

DLV 1.2 Report on process and findings

E F T A S Fernerkundung Technologietransfer GmbH

Joint tender in cooperation with:

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As sub-contractors

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Executive summary

In September 2020 Eurostat assigned the Contract ***EO 4 Statistics*** to EFTAS and its partners. The purpose of this contract is to test different methodologies to produce area statistics for different Copernicus High Resolution Layers and for the changes between different years, using different – biased and “unbiased” - statistical approaches. The reasons for any bias in statistics based on pixel counting are to be inquired and the results are to be compared with statistics derived from the LUCAS survey (Task 1). Additionally, a draft scientific paper has to be produced (Task 2) and training has to be provided (Task 3).

The partnership of EFTAS Fernerkundung Technologietransfer GmbH (Germany), consists of Prof Dr Pontus Olofsson, Prof Dr Edzer Pebesma and Prof Dr Hanna Meyer as subcontractors.

Aim of this report is the documentation of the process and findings of Task 1, the estimation of accuracy and area for Copernicus HRL forest and imperviousness and change for 2015 and 2018 for selected AOIs over Europe. Three different types of reference data are used to assess the accuracy of HRL Forest and Imperviousness layers and to demonstrate different methods for area estimation. The results are compared with the LUCAS area estimates and to the biased area estimates derived from the EO (Earth Observation) data. The applicability of the different estimators and their advantages are discussed. Given the increasing importance of remote sensing, satellite earth observation and innovative machine learning approaches for decision making and administration, this study aims to provide an overview about the widely discussed best practices of EO based area estimations and its quantitative impact on statistical significance.

Aim of this report is the documentation of the process and findings of Task 1.

- Introduction (chapter 1)
- Description of input data (chapter 2)
- Applied methods for accuracy assessment and area estimation (chapter 3)
- Results of the tests (chapter 4)
- Discussion of results and methods (chapter 5)
- Conclusive recommendation’s (chapter 6)

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List of acronyms and abbreviations

AOI	Area of interest
BIS	Bush Encroachment Information and Monitoring system for Namibia
CAP	Common Agricultural Policy
CAPI	Computer aided photo interpretation
CEOS	Committee on Earth Observation Satellites
CO	Central Office
COPERNICUS	Earth Observation Programme of the European Union
CORINE	Coordination of Information on the Environment
CRFP	Climate Risk Finance for Sustainable and Climate Resilient Rain-Fed Farming and Pastoral Systems in Sudan
CV	Coefficient of variation
CwRs	Controls with Remote Sensing in frame of the IACS subsidy controls of the CAP
DLT	HRL Dominant Leaf Type
DLTC	HRL - Dominant leaf type change product
EC	European Commission
EEA	European Environmental Agency
EO	Earth Observations
EO-4-STATISTICS	Earth Observation for statistics - methodology and training - PN5C/03/2020/E4
EQM	EFTAS quality management system ISO 9001:2015
ESA	European Space Agency
EU	European Union
Eurostat	Statistical Office of the European Commission
FAO	Food and Agriculture Organization of the United Nations
FM	Final Meeting
FTSP	GMES Fast Track Service Precursor
FTY	HRL - Forest types
GEOGLAM	Group on Earth Observations Global Agricultural Monitoring
GeoIT	Geospatial Information Technologies
GEOSS	Global Earth Observation System of Systems
GIS	Geographic Information System
GIZ	Gesellschaft für Internationale Zusammenarbeit (GIZ) GmbH
GMES	Global Monitoring for Environment and Security
GMFS	Global Monitoring For Food Security
GSARS	Global Strategy to improve Agricultural and Rural Statistics
HRL	Copernicus High Resolution Layer
IACS	Integrated Administration and Control System
IMD	HRL - Imperviousness Degree
IMCC	HRL – Imperviousness Classified Change
INSPIRE	Infrastructure for Spatial Information in the European Community
IPA	Instrument for Pre-Accession Assistance (EU)
ISTAT	Italian Institute of Statistic
JECAM	Joint Experiment for Crop Assessment and Monitoring
JRC	Joined Research Centre
LC	Land cover
LUCAS	Land Use / Cover Statistical Area Frame Survey
MARS	Monitoring Agriculture with Remote Sensing
ML	Machine Learning
MMU	Minimum Mapping Unit
MS	Member State
NDVI	Normalized Difference Vegetation Index
NUTS	Nomenclature of territorial units for statistics
OA	Overall Accuracy
PA	Producer's accuracy

PHARE	PHARE Originally: “Poland Hungary Aid for the Reconstruction of the Economy” Later: “economic aid to certain countries of Central and Eastern Europe”
PM	Project Manager / Project Management
PTS	Project tracking system
Q	Quarter (of the year)
QA	Quality Assurance
QC	Quality Control
RF	Random Forest
RO	Regional Office
RS	Remote Sensing
RSME	Root Mean Square Error
RWTÜV	Rheinisch-Westfälische Technical Surveillance Association
SAS	Statistical Analysis System – The Power to know
SE	Sweden
SIGMA	Stimulating innovation for global monitoring of agriculture
SME	Small and medium-sized enterprise
TAIEX	Technical Assistance and Information Exchange instrument of the European Commission
TCD	HRL - Tree cover density
TCCM	HRL – Tree cover change mask
ToR	Terms of Reverence
TÜV CERT	Certification of German Technical Surveillance Association (TÜV)
UA	User’s accuracy
UN	United Nations
VHR	Very High Resolution (satellite image)
VI	Vegetation Indices
WGCV	CEOS Working Group on Calibration and Validation
WP	Work package

Glossary

Bias	A property of an estimator; we say that the bias of an estimator μ^μ^ of a population parameter μμ is the difference between μμ and the expected value, μ^μ^ over all possible samples; that is, Bias(μ^)=E(μ^)−μBias(μ^)=E(μ^)−μ Casella & Berger, 2002, p. 330). Note that “…because an estimate is a number, it has no variance and no bias (Särndal et al., 1992, p. 41). The term biased [or unbiased] estimate is not recommended, although it appears occasionally in the literature.
Cartographic generalisation	Map generalization is the name of the process that simplifies the representation of geographical data to produce a map at a certain scale with a defined and readable legend. To be readable at a smaller scale, some objects are removed; others are enlarged, aggregated and displaced one to another, and all objects are simplified. During the process, the information is globally simplified but stays readable and understandable. (Ruas, 2008)
Cartographic scale	Cartographic scale is a ratio of what is displayed/measured on a map and what that measurement represents in reality.
Classification	Image classification is the process of assigning land cover classes to pixels. For example, classes include water, urban, forest, agriculture, and grassland. The 3 main types of image classification techniques in remote sensing are: Unsupervised image classification, Supervised image classification, Object-based image analysis. https://gisgeography.com/image-classification-techniques-remote-sensing/
Coefficient of variation	Measure of uncertainty of an area estimate: Coefficient of variation (CV): standard error divided by the area estimate.

Commission error	Commission error is the proportion or percentage of the area mapped as the category of interest that is erroneously predicted based on comparison to the reference classification. Commission error is the complement of user's accuracy (Olofsson et al., 2013).
Confidence interval	A 95% confidence interval for a population parameter, μμ, expresses uncertainty in the parameter estimate, μ^μ^, and is calculated using the sample data. Among the aggregate set of confidence intervals constructed using all samples that could be realized using the sampling design, 95% of such intervals are expected to include the true value of the population parameter μμ , although which intervals do and which do not include μμ is generally unknown
Estimate	The value obtained from the estimator when applied to a specific sample.
Estimator	"The rule by which an estimate of some population characteristic [i.e. parameter] μμ is calculated from the sample results" (Cochran, 1977, p. 11). In the context of this document an estimator is the formula used to calculate the estimate e.g. area.
Ground truthing	In general this term describes the collection of reference observations for an accuracy assessment. The term "truthing" implies that the reference classification provides the true ground information which would be the ideal case, but usually reference observation are also not free of errors. The suggested term is reference classification.
Map legend	A map legend defines features in a map. It simply displays the symbol followed by a text description of what that symbol represents. https://gisgeography.com/map-legend/
Margin of error	A relative measure of the uncertainty in an estimate. Note that the definitions of margin of error are not all the same. Typically, it is calculated as the ratio of the half width of a 95% confidence interval to an estimate. https://area2.readthedocs.io/en/latest/definitions.html
Nomenclature	Nomenclature is a system of names or terms, or the rules for forming these terms.
Omission error	Omission error is the proportion or percentage of area with the reference classification of the category of interest that is erroneously predicted (mapped) to be in other categories. Omission error is the complement of producer's accuracy (Olofsson et al., 2013).
Precision	In the context of estimation, Cochran (1977, p. 16) states that because "of the difficulty of ensuring that no unsuspected bias enters into estimates [sic], we will usually speak of the precision of an estimate instead of its accuracy. Accuracy refers to the size of deviations from the true mean math:*mu*, whereas precision refers to the size of deviations from the mean m obtained by repeated application of the sampling procedure." In the context of this document, we often characterize the precision of an estimate with a 95% confidence interval – the larger the interval the less the precision (and greater the uncertainty). https://area2.readthedocs.io/en/latest/definitions.html
Probability sample	A sample drawn from a population using a randomization mechanism such that "the inclusion probability for each element of the sample is known, and the inclusion probabilities are non-zero for all elements of the population." (Stehman, 1999).
Producer's accuracy	From Stehman (1997, p. 79): "Producer's accuracy for [category] *j* [is] the conditional probability that an area classified as category *j* by the reference data is classified as category *j* by the map." When expressed in terms of area, producer's accuracy is the proportion of area that has the reference classification of the category of interest that is correctly predicted (mapped) as that category.
Reference classification	The most accurate available assessment of the true condition of a population unit (example: deforestation). The result from the reference classification is the reference observation.
Reference data	Data characterizing the most accurate available assessment of the true condition at the sample location (example: fine-resolution satellite imagery).
Sampling weights	Sampling weights are used to correct for disproportionally sampling from the population. For example when selecting the same number of sample units from different large strata (subpopulations) the sampling weights correct that the sample units represent different large proportions of the entire population.
Simple random sampling	"A method for selecting n units out of the NN such that every one of [the sets of nn specified units] has an equal chance of being drawn." (Cochran 1977, p. 18).

Standard error	Measure of uncertainty of an estimate: The standard error is calculated as the square root of the variance of an estimator.
Statistical tables	No precise term. Better “estimates”
Statistics	“Statistics is the discipline that concerns the collection, organization, analysis, interpretation, and presentation of data” (Upton & Cook, 2008).
Strata	Strata are “subpopulations that are non-overlapping, and together comprise the whole population” (Cochran, 1977, p. 89)
Unbiased estimator	“An estimator µ^µ^ of µµ is unbiased if the mean value of µ^µ^, taken over all possible samples obtained using the [design], is equal to µµ” (Cochran, 1977, p. 11); or in other words, the estimator is characterized as unbiased if it produces an “estimate [that] is correct ‘on the average’” (Rice, 1995, p. 192) over all possible samples. See also bias. https://area2.readthedocs.io/en/latest/definitions.html
Uncertainty	In the context of estimation, the uncertainty of an estimate is the opposite of the precision of an estimate.
User’s accuracy	From Stehman (1997, p. 79): “User’s accuracy for [category] *i* [is] the conditional probability that an area classified as category *i* by the map is classified as category *i* by the reference data”. When expressed in terms of area, user’s accuracy is the proportion of the area that has the predicted class of the category of interest that is correctly classified as determined by comparison to the reference classification.

1 Introduction

1.1 Background

In September 2020 Eurostat assigned the Contract ***EO 4 Statistics*** to EFTAS and its partners. The purpose of this contract is to test different methodologies to produce area statistics from different Copernicus High Resolution Layers and for the changes between different years, using different – biased and “unbiased” - statistical approaches. The bias in statistics based on pixel counting are to be inquired and the results are to be compared with “unbiased” statistics and with statistics derived from the LUCAS survey (Task 1). Additionally, a draft scientific paper has to be produced (Task 2) and training has to be provided (Task3).

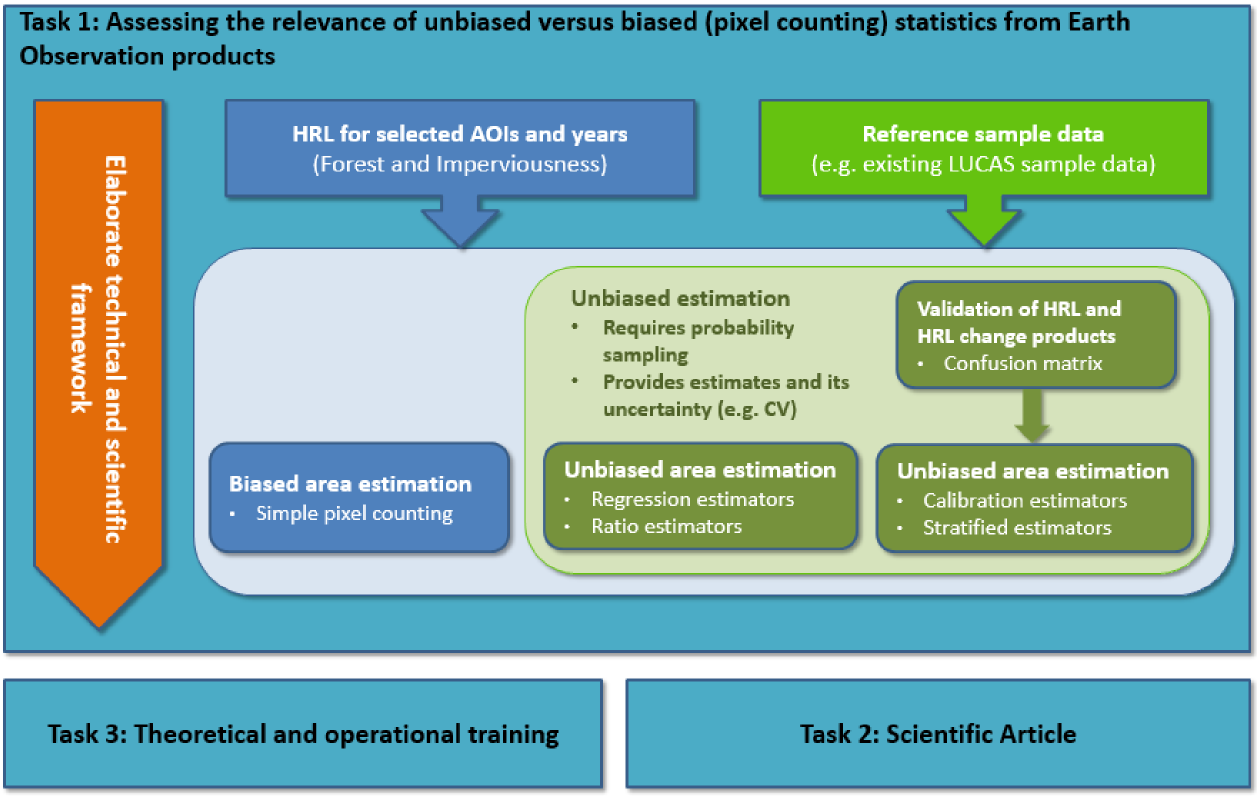

Figure 1: EO-4-Statistics Tasks and project overview

Aim of this report is the documentation of the process and findings of Task 1.

- Introduction (chapter 1)
- Description of input data (chapter 2)
- Applied methods for accuracy assessment and area estimation (chapter 3)
- Results of the tests (chapter 4)
- Discussion of results and methods (chapter 5)
- Wrap up (chapter 6)
- Conclusive recommendation’s (chapter 7)

1.2 Test protocol

In parallel to the collection of necessary input data, the next step for the execution of task 1 was the elaboration of a designated test protocol, which defined hypotheses and described the test scenarios to be applied on the selected data and AOIs. The contract covers the accuracy assessment and area estimation using different Copernicus HRL Products and the assessment of the bias using only the Copernicus HRL for area estimation. The table below shows the test protocol summarizing the different processing steps.

All processing steps of spatial data and calculation of estimates were done in QGIS, R or Excel.

Table 1: Test protocol task 1

Step	Processing	Test / check
I	**Pre-processing of the HRL layers 10/20m** and extraction of the selected AOIs for the selected years: • FTY: forest and non-forest class (2015, 2018) • TCCM: Tree Cover Change Map 2015-2018 • IMD: <30% and > =30% imperviousness (2015, 2018) • IMCC imperviousness change 2015-2018	⇨ Recode raster data to defined thresholds ⇨ The chosen 30% threshold is based on previous studies; however it was discussed to explore possibly different thresholds for imperviousness. ⇨ Comparison with other studies

II	**Creation of reference datasets** for **accuracy assessment and area estimation**
	• points and segments based on:
	  ○ LUCAS core data 2015-2018,
	  ○ LUCAS Copernicus module 2018
	• EEA validation dataset
	• Visual interpretation of VHR & Sentinel-2
		⇨ Test and benchmark of different sources that are applicable on EU 27
		⇨ Elaborate protocol for reference data collection

III	**Validation of the HRL products with the reference data:** • Outputs are confusion matrices including confidence values at class level for 22 selected NUTS2 AOIs and 4 countries	⇨ Consider sampling and response design for the existing dataset

IV	Calculation of **uncorrected area estimates** (simple pixel counting estimator)	⇨ Elaboration of protocol and workflow for area estimation using suitable estimators
		  ○ Sample design and units
		  ○ Scripts, tools, …
		⇨ Test, and execution and documentation of different estimators:
		  ○ simple pixel counting estimator
		  ○ stratified estimator
		  ○ calibration estimators
		  ○ regression estimator

V	Calculation of bias **corrected area estimates using calibration estimators / stratified estimator** and assessment of the precision of the estimate (CV).	
VI	Calculation of bias **corrected area estimates using regression estimator** and assessment of the precision of the estimate (CV).	

1.3 Selection of Area of interest (AOIs)

There are specific requirements defined in the ToR regarding spatial coverages of the tests, in order to assess the bias in different landscape settings. On basis of these minimum requirements we selected the following distribution (see Table 2 and Figure 2). The AOIs are defined by the NUTS regions available as shapefile with the reference year 2016. 4 countries (NUTS0) and 22 NUTS2 regions were selected for the assessment. For the assessment all selected HRL products were extracted to the NUTS2 or NUTS0 AOI.

Table 2: ***Area of interest***

Step	Requirement	Proposal	Assumption
A	⇨ covering min. 4 countries (or clusters of countries), each minimum 90.000 km²	⇨ Sweden 449.964 km² ⇨ Spain 504.782 km² ⇨ Germany 357.021 km² ⇨ Romania 238.391 km²	Spatially well distributed across the EU with good access to “local” knowledge & experiences
B	⇨ Selected number of NUTS2 areas levels to cover minimum 10% of EU (~ 450,000 km²)	Selected NUTS2 regions in ⇨ Germany covering 145.500 km² ⇨ Romania covering 100.000 km² ⇨ Spain covering 103.000 km² ⇨ Sweden covering 115.500 km² = 464.000 km²	The chosen NUTS2 areas will be placed within the selected countries in order to benchmark the estimates at different administrative levels
C	⇨ Different geographic regions to cover – ○ strong – low presence and ○ fragmented - non fragmented landscapes	⇨ Scandinavia ⇨ Mediterranean ⇨ Central Europe ⇨ Balkan / South East Europe	That is aimed to be covered through the selection of the above countries and regions

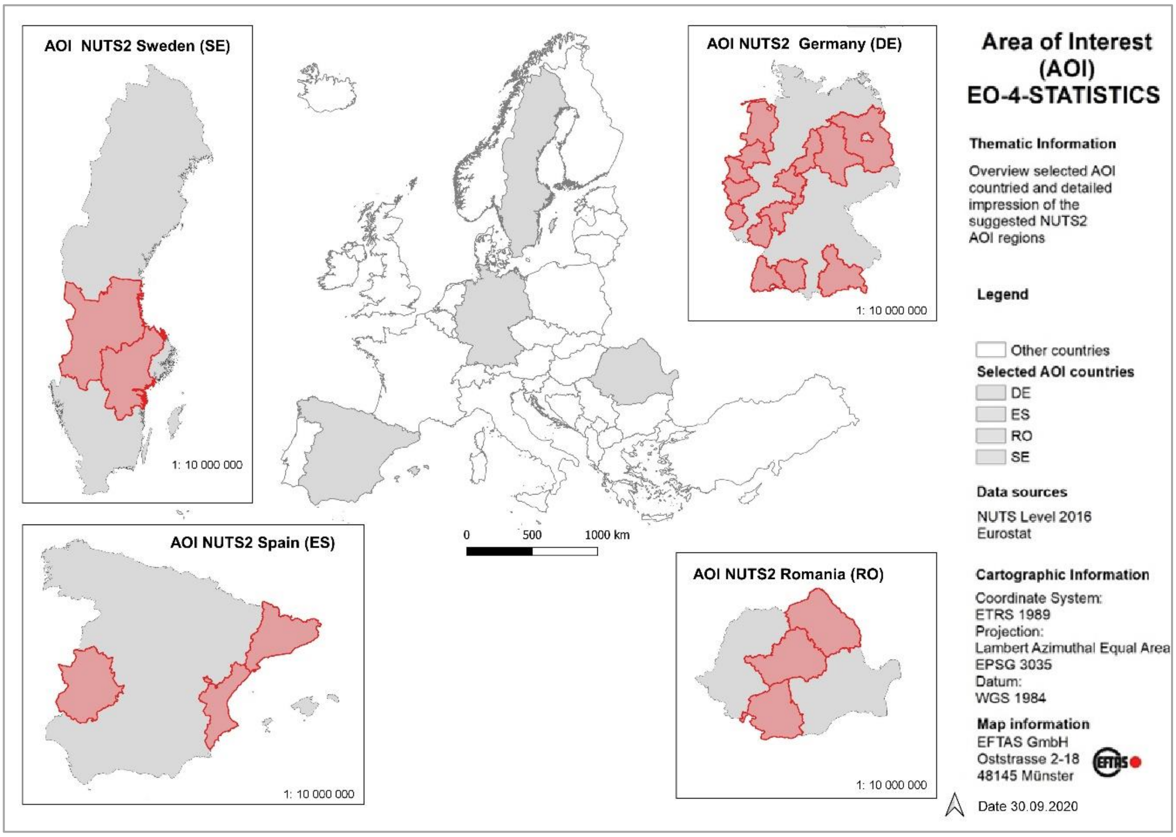

Figure 2: Selected countries and NUTS2 regions[1]

The table below contains the selected NUTS2 regions per country.

Table 3: NUTS2 regions selected as AOI

NUTS2 ID	Germany (DE)
DE13	Freiburg
DE14	Tuebingen
DE21	Oberbayern
DE40	Brandenburg
DE71	Darmstadt
DE73	Kassel
DE91	Braunschweig
DE94	Weser-Ems
DEA1	Duesseldorf
DEA2	Koeln
DEA3	Muenster
DEB2	Trier
DEB3	Rheinhessen-Pfalz
DEE0	Sachsen-Anhalt

NUTS2 ID	Spain (ES)
ES43	Extremadura
ES51	Catalunia
ES52	Comunidad Valenciana
NUTS2 ID	**Romania (RO)**
RO12	Centru
RO21	Nord-Est
RO41	Sud-Vest Oltenia
NUTS2 ID	**Sweden (SE)**
SE12	Oestra Mellansverige
SE31	Norra Mellansverige

The selection of the NUTS2 regions was based on the expected characteristics of the parameter to investigate. High presence of Forest e.g. in the NUTS regions in Sweden and the central NUTS2 region in Romania. High presence of urban areas as in the west part of Germany. The NUTS2 region "Extremadura"

[1] Administrative boundaries: © EuroGeographics

in Spain is selected because it is the main region for the traditional agroforestry management system called Dehesa. This combination of scattered trees in fields used for cultivation of crops is included in the HRL Forest product definition as forest.

2 Input data

This chapter describes the input data used for this assessment, the Copernicus HRL layers and the reference data used to validate and estimate area. Given the availability of new LUCAS components in 2018 (chapter 2.2.2) it has been agreed during the kick off meeting to shift the reference period for change assessments from initially 2012 versus 2015 towards 2015 versus 2018. The latest HRL releases (chapter 2.1) including internal validation data sets (chapter 2.2.1) had been kindly made available by the European Environment Agency (EEA).

A list of all input data including version and date of access is provided in Annex I.

2.1 EO data - Copernicus HRL layer

Task 1 of this project, the core part of this contract, is to test different methods to produce area estimates and to explore reasons and impacts for any bias in area estimates that are based solely on pixel counting. Therefore, a minimum of two **Copernicus High Resolution Layers** (HRL) on **Forest** and **Imperviousness** including its change layers are used for dedicated tests in a minimum of four selected countries and a number of selected NUTS2 regions (chapter 1.3). In the section below the HRL Imperviousness and Forest Type layers and the selected change products are described.

In detail, this assessment will be based on the following HRL products:

- Forest type 2015 & 2018
- Tree cover change mask 2015-2018
- Imperviousness degree 2015 & 2018
- Imperviousness change 2015-2018

These are part of the Copernicus Land Services and flag ship products, which stem on a number of previous releases and updates (Figure 3) that are linked to constant improvements and technical evolutions. Important improvements between 2015 and 2018 were the introduction of 10m product resolution in comparison to 20m in 2015, an increased use of Sentinel 1 and 2, and extended applications of machine learning approaches, which allow the integration of auxiliary information, such as other Copernicus layers. Important details that are relevant for this study are briefly raised in the following chapters. Full details are provided via the EEA Copernicus technical library (https://land.copernicus.eu/user-corner/technical-library).

	2012 production	**2015 production**	**2018 production**
Imperviousness	Imperviousness and imperviousness change for reference years 2006, 2009, 2012 and change products in 20m resolution	Imperviousness and imperviousness change. Full re-processing for reference years 2006, 2009, 2012 and change products, and 2015 status products in 20m resolution	Imperviousness status and change for reference year 2018 in 10 meter resolution. Addition of Impervious Built-up (IBU) and its corresponding 100 meter aggregate Share of Built-up (SBU).
Forest	Tree cover density and Forest Type products for reference year 2012 in 20m resolution	Tree cover density, dominant leaf type and forest type products + new change products for reference year 2015 in 20m resolution	Tree cover density, dominant leaf type and forest type products for reference year 2018 in 10 meter resolution.

Figure 3: Copernicus HRL product overview[2]

Beyond the significant improvements of the latest 2018 HRL product releases, it is further to be expected that ongoing innovations as well as future developments within the EO and GeoIT sector will constantly contribute to future product evolutions (Reference is made to the H2020 initiative "Evolution of Copernicus Land Services based on Sentinel data (ECoLaSS) https://www.ecolass.eu/ as well as to the extended Copernicus observation and user requirements data bases NEXTSPACE[3].

2.1.1 HRL Imperviousness Degree – IMD 2015 and 2018

The Imperviousness Degree (IMD) layer has been produced as one of the thematic HRLs. It represents an estimation of the degree of imperviousness (covered percentage of sealed surfaces) for each single 20m pixel and since 2018 in 10m pixel, semi-automatically derived from different satellite image data. In 2015 it is primarily based on the use of a calibrated vegetation index[4] (NDVI) a common way to provide information on vegetation condition. In 2018 a more advanced method and additional sensor data had been introduced into the IMD work flow that led to a new and improved generation of the product. It is expressed by EEA that this new product cannot be directly compared with 2015 or other previous versions. However, dedicated change products are explained in the next chapter.

Production 2015

3. Methodology

3.1 HRL Imperviousness 2015

The methodology applied for the production of the HRL imperviousness allows to derive the degree of imperviousness in a robust, reliable and reproducible way out of high resolution satellite images (IRS-P6/Resourcesat-2 LISS-III, SPOT 5 and Landsat 8).

The production is based on a supervised classification of built-up/non-built-up areas with subsequent visual improvement of classification results and derivation of degree of imperviousness based on continuous multi-temporal seasonal image composites (3 per year). Thus, the influences of seasonal variations of vegetation cover to the imperviousness degree was limited.

The final result is a raster dataset of built-up and non-built-up areas including the degree of imperviousness from 0-100 with a spatial resolution of 20 x 20m.

Production steps:

1. Usage of a 100 x 100 km tiles based on the EEA reference grid as production units
2. Creation of three multi-seasonal image composites (spring-summer-autumn 2014-2016) per 100 x 100 km tile
3. Derivation of biophysical variables (NDVI) per input image
4. Mosaicking of single NDVI images to maximum NDVI mosaics per 100 x 100 km tile
5. Automated derivation of classification training samples from additional reference data (CLC, HR layers)
6. Automated supervised classification of built-up and non-built-up areas

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7. Combination of classification result with the built-up masks from the HRL Imperviousness 2012 and 2006 to determine built-up changes and possible omission and commission errors
8. Visual correction and supplementation of derived built-up change candidates
9. Absolute calibration of the maximum NDVI for calculating the degree of imperviousness based on the Reference Database for absolute Calibration.

Production 2018

HRL Imperviousness 2018

The methodology applied for the production of the HRL Imperviousness allows to derive the degree of imperviousness in a robust, reliable and reproducible way out of high resolution optical (Sentinel-2) and SAR (Sentinel-1) satellite images. The production is based on a supervised classification of sealed/non-sealed areas with subsequent visual improvement of classification results and derivation of degree of imperviousness based on median composites of the reference year for all spectral bands, the 90th percentile of the NDVI as well as the median of the Sentinel-1 VV and VH backscatter. The SAR input did not always improve the result, but on the contrary, in some cases, had a negative effect on the result in some areas depending mainly on the relief and predominant land cover. For this reason, SAR data were not used for all EEA-39 tiles.

The final result is a raster dataset of sealed and non-sealed areas including the degree of imperviousness from 0-100% with a spatial resolution of 10 x 10 m.

[2] https://land.copernicus.eu/pan-european/high-resolution-layers
[3] https://www.copernicus.eu/en/documentation/studies-and-surveys/copernicus-sentinel-2-data-support-farm-management-denmarkstudies
[4] https://land.copernicus.eu/user-corner/technical-library/hrl-imperviousness-technical-document-prod-2015

	Differences from the previous version(s) HRL Imperviousness Degree 2018 compared to the historical 20m IMD products The time series of the product "High Resolution Imperviousness Degree" already started in 2006, at 20 and 100m spatial resolution of status and change layers starting for the reference period 2006-2009. Since then an update was established every three years. In the course of this time series, there have been repeated adaptations and enhancements in the technical specifications. To ensure homogeneity and continuity in the time-series of HRL Imperviousness, a reprocessing of the historical products of 2006, 2009 and 2012 took place in 2015, applying latest state of the art methodology. With the change 36 of spatial resolution from 20m to 10m in the recent production of the 2018 products, another significant methodological adaptation of the specification took place. The use of high-quality Sentinel-1 and Sentinel-2 data with its high spatial and temporal resolution enables for a significant improvement of the quality compared to the historical products. In the 2018 products, smaller structures such as minor roads or individual buildings could be detected due to the higher spatial resolution of the input data. In contrast, overestimated urban green spaces were minimized. In the density calculation, the range of density values was enlarged due to the higher resolution and thus reduced density mixing within each pixel, resulting in a more detailed density structure, especially in urban areas (see Figure 5). This improvement of better spatial differentiation between built-up and non-built-up areas, which was not possible in the previous production due to the limited quality of the input data, also means that there is a leak in the continuity of the time series between 2015 and 2018. In Figure 4 this is visualized by comparing the IMD product of 2015 in 20m resolution with the IMD product of 2018 in 10 m resolution.
EEA product specification 2015: https://land.copernicus.eu/user-corner/technical-library/hrl-imperviousness-technical-document-prod-2015	EEA User manual 2018: (https://land.copernicus.eu/user-corner/technical-library/imperviousness-2018-user-manual.pdf)

The IMD is available in a consistent times series from 2006-2009-2012 and 2015. In the new IMD 2018 product the spatial resolution changed to 10m and the processing workflow (p.32ff[2]) was changed using now Sentinel-1 and Sentinel-2 as main input data. Two types of IMD change products are also available for each of the 3-year periods between the 4 reference years (2006-2009, 2009-2012, 2012-2015 and 2015-2018):

- IMC Imperviousness change: A simple layer mapping the percentage of sealing increase or decrease for those pixels that show different reflectance indicating sealing change in the period covered. This product is available via a synthetically confectioned product grid with 20m and 100m cell size that does not directly correspond to the

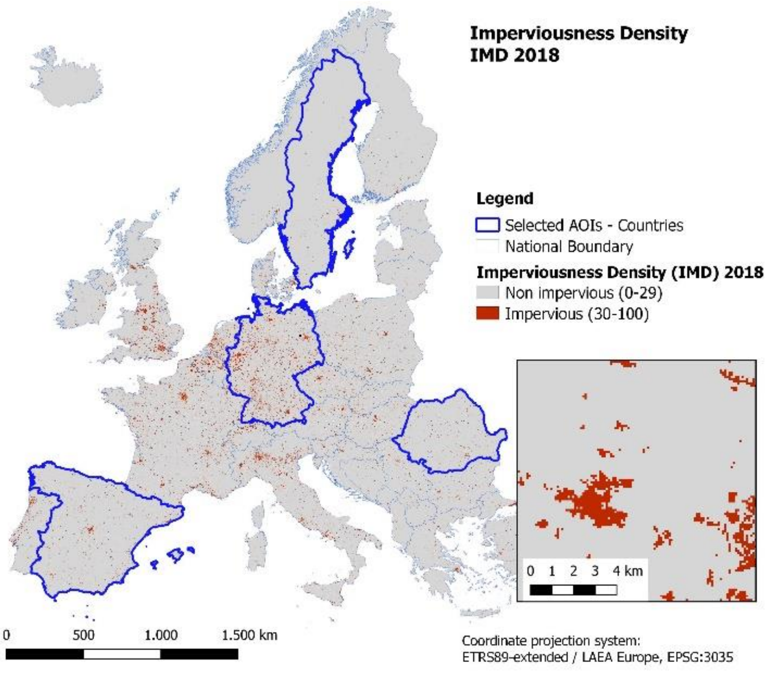


Figure 4: Copernicus HRL Imperviousness Degree and selected countries[5]

[5] Administrative boundaries: © EuroGeographics

allocation of pixels from the chosen Sentinel 1 or Sentinel 2 sensors.
- IMCC Imperviousness change classified: A classified change product that maps the most relevant categories of sealing change (unchanged no sealing, new cover, loss of cover, unchanged sealed, increased sealing, and decreased sealing). This product is available in 20m units' size only.

For the assessment the IMD 2015 and IMD 2018 and the IMCC 2015-2018 product is used.

The table below describes the definition of the IMD products compared to real land cover elements[6].

Table 4: IMD definition

ELEMENTS INCLUDED IN THE HRL IMPERVIOUSNESS 2015 and 2018
• Housing areas (even with scattered houses) • Roads • Railway tracks associated to other impervious surfaces (i.e. inside built-up area) • Industrial, commercial areas, factories, energy production and distribution facilities • Non built-up sealed surfaces, which are part of categories, such as e.g. allotment gardens, cemeteries, sport and recreation areas, camp sites, excluding green areas associated with them • Artificial grass-covered sport pitches • Construction sites with discernible evolving built-up structures. • Single (farm) houses (where possible to identify from satellite imagery) • Paved borders of water edges • Permanent greenhouses (covered through the year) (2018) • Permanent plastic covered soil (2015) • Solar panel park • Built-up traffic areas (airports, harbours, railway yards) • Non built-up traffic areas (airport runways, non-built-up harbour areas, railway yards, parking lots)
ELEMENTS EXCLUDED IN THE HRL IMPERVIOUSNESS 2015 and 2018
• Construction sites without discernible evolving • Railway tracks not associated to other impervious surfaces (i.e. outside built-up area) • Mines, quarries, peat extraction areas • Sand, sand pits • Dump sites • Natural, artificial and cultivated vegetated areas • Un-vegetated or sparsely vegetated areas • Un-vegetated agricultural fields, arable land • Vineyards, fruit plantations • Non-permanent greenhouses (temporal plastic coverage) • Grass surfaces used for sports of any kind • Glaciers, snow, water • Natural un-vegetated and sealed surfaces such as bare rocks, sand etc. are not considered as impervious
DIFFERENCES IMD DEFINITION 2015 vs 2018
• Green roofs excluded 2015 / included in 2018

Natural un-vegetated and sealed surfaces such as bare rocks, sand etc. are not considered as impervious.

[6] https://land.copernicus.eu/user-corner/technical-library/hrl-imperviousness-2018-user-manual

The imperviousness degree per pixel ranges between 0% and 100% imperviousness. As defined in the contract, a threshold of 30% imperviousness was used for the assessment of accuracy and area estimates. The IMD products was therefore classified into the two thematic classes of non-impervious (0-29%) and impervious (30-100%):

Table 5: Recoded IMD pixel values used for assessment

Description	Pixel value	Recoded value
Non-impervious	0-29	0
Impervious 30 – 100%	>=30 – 100	1
Unclassifiable	254	254
Outside area	255	255

2.1.2 HRL Imperviousness Change products – IMC and IMCC 2015-2018

The Imperviousness Change product (IMC) contains the range of detected imperviousness change; (negative change 0 to 99 %, positive change 101 to 200 %) between 2015 and 2018 in 20m spatial resolution.

Due to the technical adaptation in the product resolution from 20m in 2015 to 10m in 2018 of the IMD product the IMC change product is not directly comparable to the IMD status products.
For this assessment the classified Imperviousness Classified Change (IMCC) 2015-2018 is used, it is a classified product of the IMC with only the stable and change classes:

- stable imperviousness,
- stable non imperviousness,
- imperviousness decrease,
- imperviousness increase.

2.1.3 HRL Forest - FTY 2015 and 2018

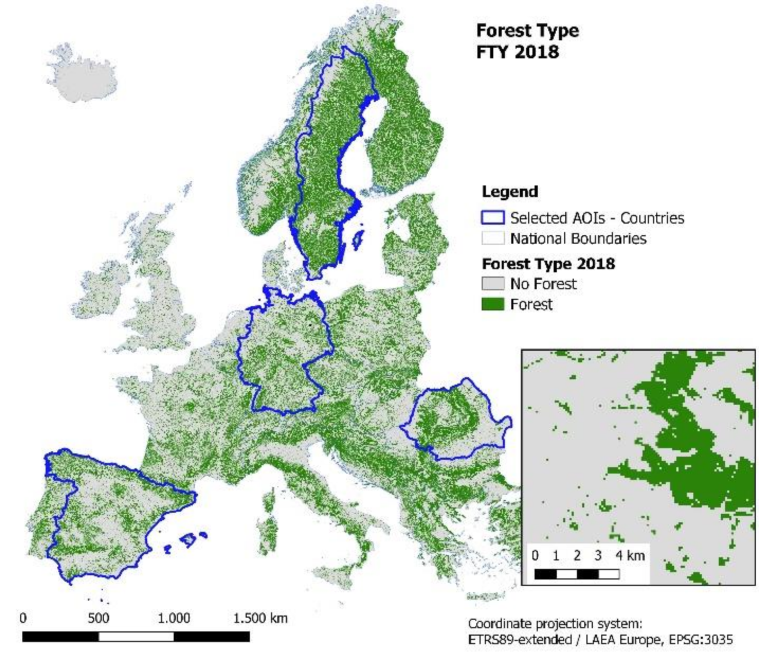


Figure 5: Copernicus HRL Forest type and selected countries[7]

Information on tree and forest characteristics is provided by the HRL Forest, being one of five Copernicus land themes represented through the pan-European High Resolution Layers (HRL) product fleet produced from 20 m and 10 m resolution satellite imagery for the reference year 2012, 2015 and 2018. Tree cover density values (TCD) are provided in a range from 0-100 %, Dominant Leaf Type (DLT) differentiating between broadleaved and coniferous trees and forest types (FTY) distinguish between broadleaved forest, coniferous forest and mixed forest based on forest definition criteria. For the TCD there is also a change product available. The Forest products are also available at aggregated 100m resolution. Contrary to the TCD product non-forest trees are excluded from the FTY product[8] and a minimum mapping unit is applied following the forest definition of the Food and Agriculture Organization (FAO).

The FTY status layer for 2015 and 2018 is used in this project. There is no FTY change product and assessment of area change is based on the differences in the status layers. To support the assessment the Tree cover change mask layer 2015-2018 was used, although it follows a different classification approach.

The FTY 2015 is available at 20m resolution the FTY 2018 is available at 10m resolution, the latter being based on Sentinel-2 data.

The forest definition follows as closely as possible the FAO Forest classification:

"Includes (FAO): forest nurseries and seed orchards that constitute an integral part of the forest; as well as forest roads, cleared tracts, firebreaks and other small open areas < 0.5 ha and/or < 20m width. Forest in national parks, nature reserves and other protected areas such as those of specific scientific, historical, cultural or spiritual interest; windbreaks and shelterbelts of trees with an area of more than 0.5 ha and width of more or equal than 20m; plantations primarily used for forestry purposes, including cork oak stands.

Excludes (FAO): land predominantly used for agricultural practices. In this sense fruit trees and olive groves are also excluded. Gardens and urban parks are also not considered as forest."

"The 20m [10m in 2018] *Forest Type products are produced applying a minimum „Forest" definition, largely following the FAO definition, whereas tree cover in traditional agroforestry systems such as Dehesa / Montado is explicitly included for EEA purposes."* Copernicus Land Monitoring Service –High Resolution Layer Forest - Product Specifications *https://land.copernicus.eu/user-corner/technical-library/hrl-forest* (24.01.2021).

The main characteristics of the FTY 2015 and 2018 product are summarised in the table below.

[7] Administrative boundaries: © EuroGeographics
[8] https://land.copernicus.eu/user-corner/technical-library/hrl-forest

Table 6: HRL FTY characteristics[9]

FTY 2015	FTY 2018
20m spatial resolution	10m spatial resolution
Tree Cover Density range of ≥10-100%	
Minimum Mapping Unit (MMU; minimum number of pixels to form a patch) of 0.52 ha (equivalent to 13 pixels)	Minimum Mapping Unit (MMU; minimum number of pixels to form a patch) of 0.5 ha (50 pixels)
MMU applicable both for tree-covered areas and for non-tree-covered areas in a 4-pixel connectivity mode. Patches within a forest not covered by >10% tree cover are kept as forest up to an area of 0.5 ha.	
Trees under agricultural use and in urban context are excluded. Dehesas / Montados are included.	
Minimum Mapping Width (MMW) of 20m	Minimum Mapping Width (MMW) of 10m[10]

The FTY raster maps differentiate between coniferous, broadleaved and mixed forest. For the assessment the FTY 2015 and 2018 is reclassified to a binary map of forest and no-forest.

Table 7: Recoded FTY pixel values

Description	Pixel value	Recoded values
All non-forest areas	0	0
Broadleaved Forest	1	1
Coniferous Forest	2	1
Unclassifiable	254	254
outside area	255	255

[9] https://land.copernicus.eu/user-corner/technical-library/forest-2018-user-manual-v1-1.pdf

[10] https://land.copernicus.eu/user-corner/technical-library/forest-2018-user-manual.pdf (Page 20)

2.1.4 HRL Tree cover change mask – TCCM 2015-2018

The Tree cover change mask TCCM is a 20 m resolution based on the DLT 2015 and 2018 status map. It consists of 2 thematic change classes (new tree cover and loss of tree cover) and 2 stable classes (tree cover / no tree cover): Similar as the FTY product it uses a minimum mapping unit. The main specifications are[11]:

- 20m spatial resolution
- TCD range of 0-100%
- Boundary filter of 1 pixel
- MMU of 1ha (25 pixels) for change classes (holes within change areas are filtered up to < 1ha MMU)

The TCCM1518 contain the following pixel values:

Table 8: Recoded TCCM pixel values

Description	Pixel value
unchanged areas with no tree cover	0
new tree cover	1
loss of tree cover	2
unchanged areas with tree cover	10
Unclassifiable	254
outside area	255

[11] https://land.copernicus.eu/user-corner/technical-library/forest-2018-user-manual.pdf

2.2 Reference data

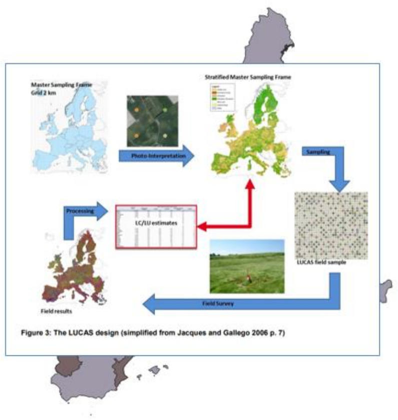
To assess the accuracy and to estimate area, the classification (map) is combined with reference data which is expected to be more precise than the information in the map (see chapter 3).

The reference data needs to fulfil a number of requirements to be used for statistical sound estimation of accuracy and area a summary is given in Haub et al. 2015:

- ⇨ The data must be selected using a **rigorous probability sampling** design.
- ⇨ The reference data must be **independent** from the data used to produce the map.
- ⇨ The data must be compatible to the map units considering **thematic, temporal, spatial** and **positional** comparability.
- ⇨ The reference data must be of a **better thematic quality** and finer geographic scale than the map, otherwise the assessment leads to completely wrong assumptions.
- ⇨ The reference data must be available for the entire area of the AOI, although it is only needed for the selected sample location.

Three different datasets are used as reference data in this assessment, the already existing internal EEA validation dataset, the LUCAS survey data and a new created reference dataset.

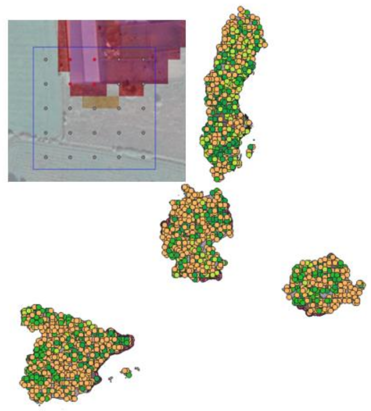
LUCAS 2015 / 2018



Sample of points with 1.5m / 20m observation radius covering Europe
(Buck et al. 2015)

Assessment for:
FTY - Country & NUTS2 level
IMD - Country & NUTS2 level

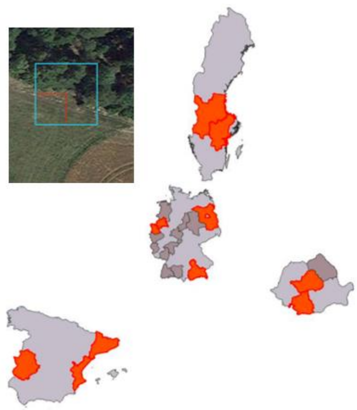
EEA validation data 2015 / 2018



Sample of 100x100m segments covering Europe
(© Validation data EEA)

Assessment for:
FTY - Country
IMD - Country

EO-4-statistics data 2015 / 2018



Sample of pixels 10m / 20m covering selected NUTS2 regions

Assessment for:
FTY – selected NUTS2
IMD – selected NUTS2
TCCM – Country & NUTS2
IMCC – NUTS2

Figure 6: Input reference data – LUCAS (2015 & 2018), EEA validation and EO-4-Statistics data[12]

2.2.1 EEA validation data (visual interpretation)

The internal validation data for the HRL layers for the FTY 2015 & 2018 and the IMD 2015 & 2018 was provided by EEA for this contract. In this report this datasets are referred to as “EEA validation data”.

The HRL products are provided as raster data in an artificially aggregated product grid (note: grid units (pixels) of the HRL products are different than the input satellite pixels). The spatial resolution of the HRL products is mostly 20x20m and 10x10m, additionally aggregated products with 100x100m pixel resolution

[12] Administrative boundaries: © EuroGeographics

are provided. The EEA internal validation of the HRL products was based on these aggregated 100x100m resolution products.

The sample units are square segments of 100x100m covering exactly 1 artificial product unit (pixel) of the aggregated HRL layers. The sample units were selected using the LUCAS Master Frame Grid as sampling frame. The sampling frame was stratified into strata using countries or group of countries and different dedicated sampling strata based on the classes of the HRL layers and additional data sources (see below). From each stratum a defined number of sample units were selected using a systematic approach. The sample units were interpreted visually on base of different Satellite and Orthophotos.

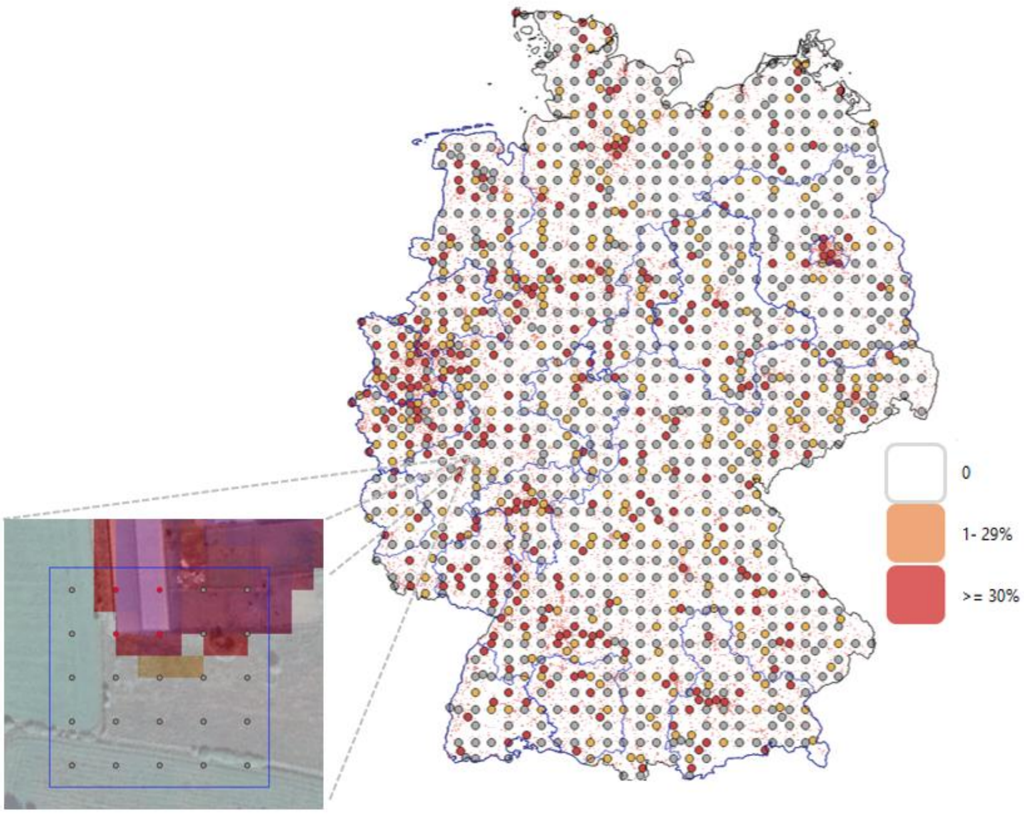
To guide the interpretation for the imperviousness degree, secondary sample units consisting of a grid of 5x5 points were used. Each point it was interpreted whether it falls on sealed surface or not. The proportion of sealed points from the total of 25 points within the 100x100 sample unit provides the reference value of imperviousness degree (see Figure 7 and Figure 8). A shifting rule was applied in case the point is located on a border, so that about half of the border points are classified as sealed. A detailed description and the results of the validation are available in the product validation reports[13] which are online available on the Copernicus website.

Primary sample unit (PSU) 100x100m segment and Secondary sampling units (SSU) points of 5x5 points. Red points are recorded as imperviousness from the interpreters. Left shows the sample unit with Google Earth as background, right shows the HRL IMD 2018 with 100m resolution as background.

Google Earth Pro © Maxar Technologies 2021
© Validation data EEA

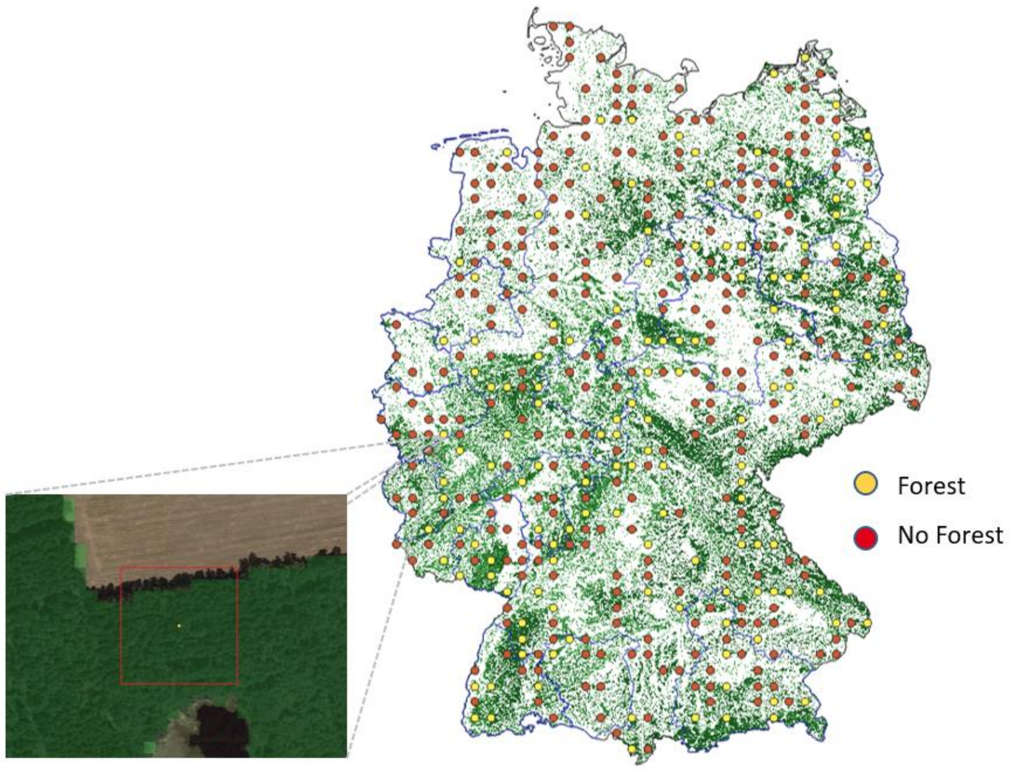
Figure 7: EEA 100x100m sample segment and 5x5 sample points

[13] https://land.copernicus.eu/user-corner/technical-library/hrl-forest-2015-final-validation-report
https://land.copernicus.eu/user-corner/technical-library/clms_hrl_imd_validation_report_sc04_1_3.pdf
https://land.copernicus.eu/user-corner/technical-library/hrl-imperviousness-2015-validation-report



©: Digital Orthophoto North Rhine Westphalia - Geobasis NRW, Validation data EEA, Administrative boundaries: © EuroGeographics

Figure 8: EEA validation data for IMD18 – 100x100m sample units and sample points and distribution of the sample over Germany



©: Digital Orthophoto North Rhine Westphalia - Geobasis NRW, Validation data EEA, Administrative boundaries: © EuroGeographics

Figure 9: EEA validation data for FTY18 – 100x100m sample unit and distribution of the sample over Germany

For the validation of the forest layers, the presence or absence of forest in the sample units was recorded.

According to the report the interpretation was done using a blind approach were the interpreter was unaware about the map class in the unit and a “plausibility interpretation” were the map class is confirmed or not. In this assessment the results from the “plausibility interpretation” was used to estimate area on country level using stratified estimator for the FTY 2015 & 2018 and a regression estimator for the IMD 2015 & 2018. The number of sample units per product and country is described in Table 9.The data was provided as a shapefile for each product and for each year and containing for each sample unit the relevant information on:

- the result from the blind interpretation
- the result from the plausibility control
- the value of the corresponding HRL pixel
- the sample strata, point ID and country (zone) and sample weight

Further details are described in the metadata in DLV1.3.

For the application of the area estimators the proportion of each stratum used for the selection of the sample units is required. This information was not available for the selected countries and had to be calculated based on the strata descriptions in the validation reports. This is further described in chapter 3.2.3 and chapter 3.2.4.

To be mentioned here is that the description of the sampling strata used for the validation of the impervious products 2015 and 2018 was not entirely clear:

- The strata used for the selection of the validation sample for the Imperviousness change product (IMCC) 2015-2018 are based on a combination of several previous IMD status and change layers. Due to the complexity of the sampling strata and the fact that we could not entirely comprehend how the strata were created, the EEA validation data for the IMD change products was not used in our assessment.
- The strata for the selection of the validation sample for the IMD 2015 and 2018 status products include the combination of Corine land cover data and Open street map (OSM) paved road data. Corine land cover data could be readily extracted. The OSM data which was used in the creation of the strata is not clearly described in the validation report of the products. In our assessment the data used from OSM had to be approximated by us using all road types which we assumed to be paved.

For the forest type products 2015 and 2018 the tree cover density layer from 2015 was used to create strata for the selection of the sample units. Two strata were used: Tree cover= 0 and Tree cover >0. Therefore the strata and their proportions could be extracted for the selected countries.

The systematic approach to select the samples for the IMD and FTY using a stratified approach were not fully comprehensible to us, in our assessment the sampling design is treated as a stratified sample, we make no differentiation between systematic stratified or random stratified.

Table 9: Number of sample units for the different HRL products in the AOI Countries

	FTY15	FTY18	IMD15	IMD18	IMC1518	TCCM1518
Germany	939	439	1,304	1,304	922	Not available
Spain	1,305	625	1,473	1,473	774	Not available
Romania	600	274	735	735	341	Not available
Sweden	1,166	567	1,213	1,213	551	Not available

The Copernicus HRL products have been internally validated by EEA on country level and using the above described EEA validation dataset. The validation was done on the aggregated 100m products. The validation results have been published on the Copernicus website[14]. In this contract it is therefore not foreseen to repeat the same assessment with the same data, but validate the products with different reference data and on different geographic extents while using the high resolution products on 20m and 10m basis.

2.2.2 LUCAS field data 2015 & 2018

2.2.2.1 LUCAS statistical concept

The Land Use/Cover Area frame Survey (LUCAS) is an EU wide area frame field survey using points as sampling units. It is conducted three-annual on behalf of Eurostat (Eurostat, 2016). The LUCAS survey data provides a unique pan-European dataset. Since the LUCAS 2006 campaign the sample of the survey is selected using a two phase sampling design with stratification.

In the first phase a systematic and regular 2 km grid of points was overlaid on the whole EU territory. This grid of points is the master grid or frame where each point represents a proportion of the total population (area of the EU). The LUCAS points are defined with a radius of 1.5 m around the point.

For stratification each point from the master frame was photo-interpreted and assigned to a land cover class:

- arable land
- permanent crops
- grassland
- wooded areas and shrub land
- bare land
- artificial land
- water

The interpretation of the master frame was done using mainly aerial images or best available satellite images with coarser resolutions (Gallego and Delincé 2010). The first interpretation of the master frame was done in 2005 and repeated for the 2018 campaign. In the updated stratification “shrub land” and “transitional water” were added as individual classes[15]. For new member states the master frame was extended using the same method.

In the second phase a subsample of points is selected **via a rigorous sampling scheme** from the stratified master frame to be visited in the field. The selection of the points, number and allocation, is based on the assigned land cover class (**defined weights per class**) and specific **target precision estimates**. The allocation of the sample is further optimised using specific rules to improve the spatial distribution of the sample points and to minimize cases were sample points fall close to each other and provide redundant information (see Gallego and Delincé 2010, Jacques and Gallego 2006 and Ballin et al. 2018)). The selection process in the second phase was revised for the campaign 2018, see Ballin et al. 2018.

The selected sample of points is then observed by surveyors in the field and recorded using the full LUCAS land cover / land use nomenclature. The survey takes place between March and September, earlier in the southern countries and later in the northern countries, thus providing data from the same vegetation season within the same year. The information collected from the field survey is used to generate the

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[14] https://land.copernicus.eu/user-corner/technical-library/hrl-forest-2015-final-validation-report

https://land.copernicus.eu/user-corner/technical-library/clms_hrl_imd_validation_report_sc04_1_3.pdf

[15] https://ec.europa.eu/eurostat/documents/205002/7329820/LUCAS2018_S1-StratificationGuidelines_20160523.pdf

statistics for the different land cover and land use parameters on different NUTS level and for the entire EU. The calculation of estimates, e.g. the surface of a specific crop, is straightforward using the known proportions of points classified as a specific crop within a stratum and the weight of the stratum (see Gallego and Delincé 2010, Jacques and Gallego 2006 and Ballin et al. 2018)). The proportions can be extrapolated to the entire population of the master frame or different NUTS level and transferred to absolute acreage.

An overview of the general survey design is given in the figure below.

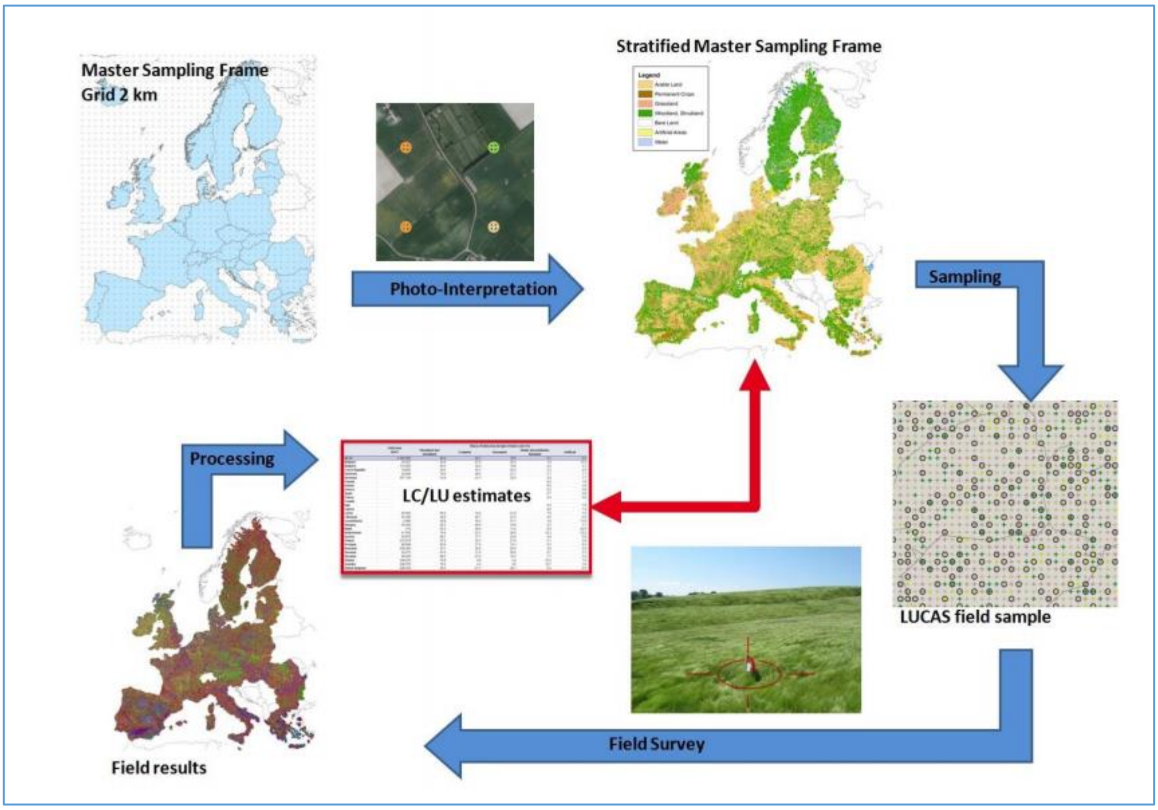


Figure 10: LUCAS sampling design (Buck et al. 2015)

The LUCAS survey is executed in 3 years cycle and has been executed in 2006, 2009, 2012, 2015 and 2018.

The core LUCAS parameters are the recording of Land cover and Land use at the plot where the LUCAS point is located. The LUCAS point is defined with a radius of 1.5m around the point coordinate and the observation takes place within this radius. For heterogeneous land cover such as grassland, woodland, wetland and bare areas the observation radius is extended to 20 meter radius around the point (extended window of observation), but only within the same land cover plot where the LUCAS point is located, the so called homogenous plot. Figure 11 shows the concept of the homogenous plot, the observation takes place only for the area within the blue line.

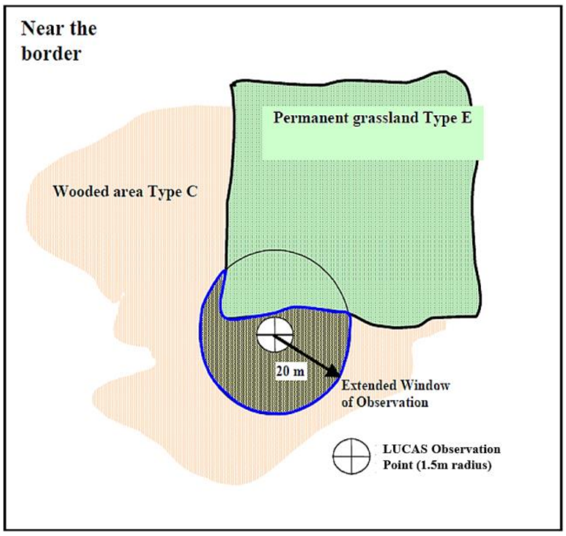


Figure 11: LUCAS 1.5 m observation radius, extended window of observation (20m) and the concept of homogenous plot [16]

In addition to the core parameters further components have been included in the survey setup. Some of the components are only captured at certain points, e. g. based on the land cover or at a subsample of the points (see 2.2.2.2).

Geotagged photos are taken at each point in the cardinal directions of the position of the LUCAS point and the land cover or crop. Further photos are taken to document observed parameters (e.g. soil horizon) or special circumstances of the survey (photo documenting the reason why the point could not be reached). The photos are further used for the quality control of the LUCAS survey data.

In 2018 the LUCAS data model consisted of various specific modules that are captured beyond the core land cover and land use information (Figure 12). Those are of relevance in order to create a thematic 1:1 match between the assessed data (see chapter 4.2).

[16] https://ec.europa.eu/eurostat/web/lucas/methodology

2.2.2.2 LUCAS data model

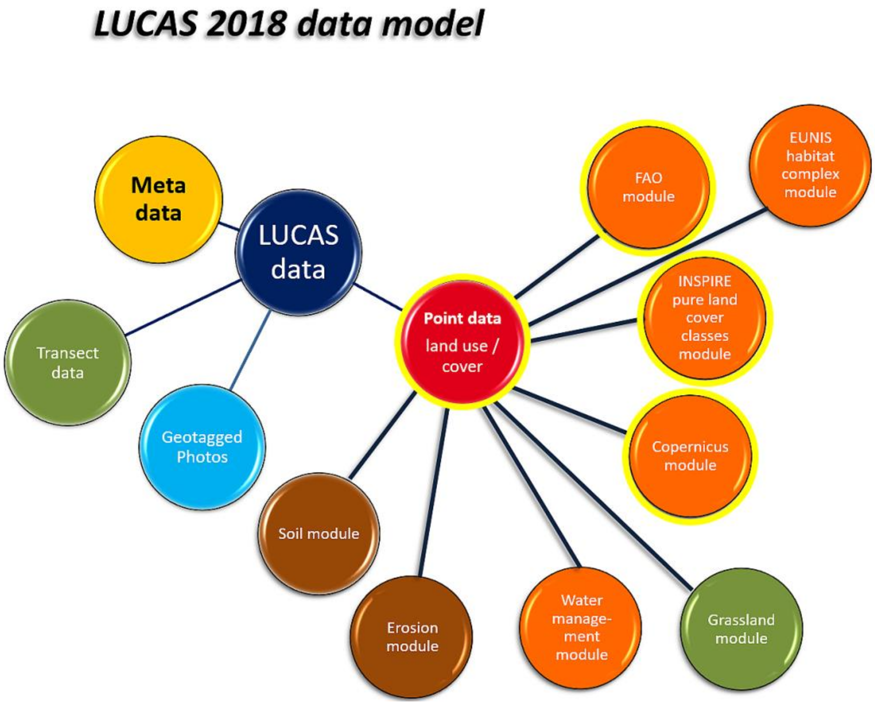


Figure 12: LUCAS 2018 data model

The LUCAS data model for 2018 illustrates the different modules captured in the LUCAS survey campaign. Detailed description of the different modules, parameters and how they are recorded is provided in the LUCAS Technical reference document C1 – Instruction for Surveyors for 2015 and 2018:

- *LUCAS 2018 Technical reference document C1 – Instruction for Surveyors* [17] and
- *LUCAS 2015 Technical reference document C1 – Instruction for Surveyors* [18]

And the LUCAS Nomenclature:

- *LUCAS 2018 Technical reference document C3 - Classification (Land cover & Land use)*[19]
- *LUCAS 2018 Technical reference document C3 - Classification (Land cover & Land use)*[20]

For the assessment within this project the following modules and parameters have been relevant to create a 1:1 relation with the HRL Copernicus product Forest type and Imperviousness.

Point data land use / land cover: For each LUCAS point the information on land cover and land use are recorded at the time of the survey. As described above, land cover and land use are observed within a certain radius around the point, but only within the same "homogenous" plot. Usually one land cover and one land use code is recorded and only in certain cases two land cover codes and or two land use codes can be assigned to describe the condition at the ground. The relevant land cover classes for this assessment have been artificial (A) and wooded area s with >10% tree cover (C).

Along with land cover and land use, the area of the parcel, area of the same land cover and land use, is recorded. This parameter is relevant since the forest definition includes a minimum mapping size of 0.5 ha for wooded areas.

[17] https://ec.europa.eu/eurostat/documents/205002/8072634/LUCAS2018-C1-Instructions.pdf

[18] https://ec.europa.eu/eurostat/documents/205002/6786255/LUCAS2015-C1-Instructions-20150227.pdf

[19] https://ec.europa.eu/eurostat/documents/205002/8072634/LUCAS2018-C3-Classification.pdf

[20] https://ec.europa.eu/eurostat/documents/205002/6786255/LUCAS2015_C3-Classification_20160729.pdf

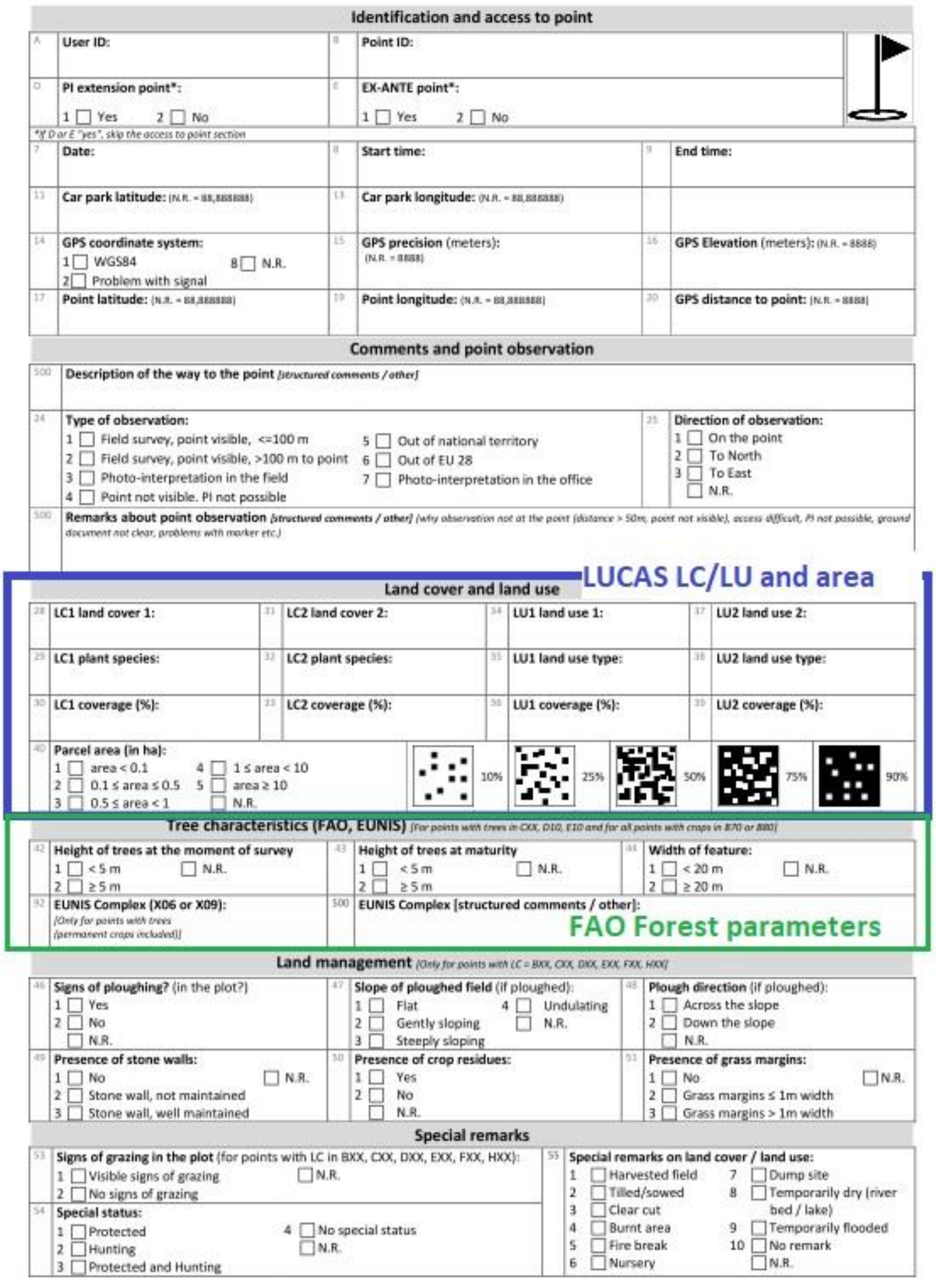
FAO module: In the FAO module information on characteristics of wooded land covers are recorded: Width of the wooded land cover feature (> 20m or not) and height of trees at maturity (>5m or not). These parameters allow defining if woodland at the point is forest or not in compliance with the FAO forest definition. These parameters along with the land cover and land use, allowed to classify the LUCAS points into an aggregated forest / no forest class, which is in compliance with the HRL Forest type definition. In the 2018 survey campaign it was further recorded if the wooded land is used under certain traditional agroforestry systems, such as Dehesa. This is relevant since the HRL Forest type definition, contrary to the FAO definition, includes Dehesas in the forest definition.

Inspire pure land cover module: In the Inspire pure land cover components module, the proportions of main land cover classes are recorded within the homogenous plot in a 20m radius using bird's eye view. This information was only recorded for land cover not belonging to artificial, agriculture and water. This module was not used in the assessment since it is not available for all LUCAS points and the spatial extent of the observation unit (homogenous plot) is unknown.

Copernicus module: The Copernicus module was introduced in 2018 survey campaign for a subsample of points. The aim of this module is to support the integration of LUCAS data for the Copernicus Earth observation products. The extent of the main land cover class is recorded in the cardinal directions up to 51m. Different to the other parameters, the Copernicus information is recorded at the position of the surveyor which is not necessarily the position of the point. A further component of this module is the recording of the breadth of the next land cover type as visible in landscape photos taken in the cardinal directions. The number of artificial points with Copernicus module is very low and the sampling design (sampling weights) have not been available for this assessment. The available Copernicus data was only used to support the creation of a spatial link between the LUCAS point and the HRL pixels.

LUCAS imperviousness component 2018: Is another component which was specifically introduced into the LUCAS survey for a comparison with the HRL Imperviousness layer. With a focus to the recent IMD 2015 definition the proportion of non-vegetated area in a fixed radius of 20m around the LUCAS points were observed in 2018. However, with the newly applied production workflow (see chapter 2.1.1 above) this does not adequately cover the latest IMD 2018 definition. For future LUCAS campaigns the observation rules should be adapted to the latest HRL definitions for a better harmonisation (see recommendations in chapter7).

Meta data on survey: For each point information on the survey itself is recorded. This meta data contains date and time of the survey as well as information on whether the theoretical LUCAS point was reached by the surveyor and if its precise position could be allocated in the field or if the point was photo interpreted from a distance. Recorded are the position and distance from which the surveyor observed the point, in an ideal case it is the same position as the LUCAS point, and whether the point is located on a land cover border. In that case a shifting rule is applied. In case a point is not reached and not visible, the surveyor uses the ground document to interpret the parameters. The ground document includes most recent VHR imagery of the point position. In case the point has been observed in a previous campaign, the main parameters and photos from the previous campaign are also printed on the document to support the interpretation.



Identification and access to point

A User ID:
B Point ID:
D PI extension point*: 1 Yes 2 No
E EX-ANTE point*: 1 Yes 2 No
*If D or E "yes", skip the access to point section
7 Date:
8 Start time:
9 End time:
11 Car park latitude: (N.R. = 88,888888)
13 Car park longitude: (N.R. = 88,888888)
14 GPS coordinate system: 1 WGS84 8 N.R. 2 Problem with signal
15 GPS precision (meters): (N.R. = 8888)
16 GPS Elevation (meters): (N.R. = 8888)
17 Point latitude: (N.R. = 88,888888)
19 Point longitude: (N.R. = 88,888888)
20 GPS distance to point: (N.R. = 8888)

Comments and point observation

500 Description of the way to the point (structured comments / other)
24 Type of observation:
1 Field survey, point visible, <=100 m
2 Field survey, point visible, >100 m to point
3 Photo-interpretation in the field
4 Point not visible. PI not possible
5 Out of national territory
6 Out of EU 28
7 Photo-interpretation in the office
25 Direction of observation:
1 On the point
2 To North
3 To East
N.R.
500 Remarks about point observation (structured comments / other) (why observation not at the point (distance > 50m, point not visible), access difficult, PI not possible, ground document not clear, problems with marker etc.)

Land cover and land use

LUCAS LC/LU and area

28 LC1 land cover 1:
31 LC2 land cover 2:
34 LU1 land use 1:
37 LU2 land use 2:
29 LC1 plant species:
32 LC2 plant species:
35 LU1 land use type:
38 LU2 land use type:
30 LC1 coverage (%):
33 LC2 coverage (%):
36 LU1 coverage (%):
39 LU2 coverage (%):
40 Parcel area (in ha):
1 area < 0.1
2 0.1 ≤ area ≤ 0.5
3 0.5 ≤ area < 1
4 1 ≤ area < 10
5 area ≥ 10
N.R.
10% 25% 50% 75% 90%

Tree characteristics (FAO, EUNIS) (For points with trees in CXX, D10, E10 and for all points with crops in B70 or B80)

42 Height of trees at the moment of survey: 1 < 5 m 2 ≥ 5 m N.R.
43 Height of trees at maturity: 1 < 5 m 2 ≥ 5 m N.R.
44 Width of feature: 1 < 20 m 2 ≥ 20 m N.R.
52 EUNIS Complex (X06 or X09): (Only for points with trees (permanent crops included))
500 EUNIS Complex [structured comments / other]:

FAO Forest parameters

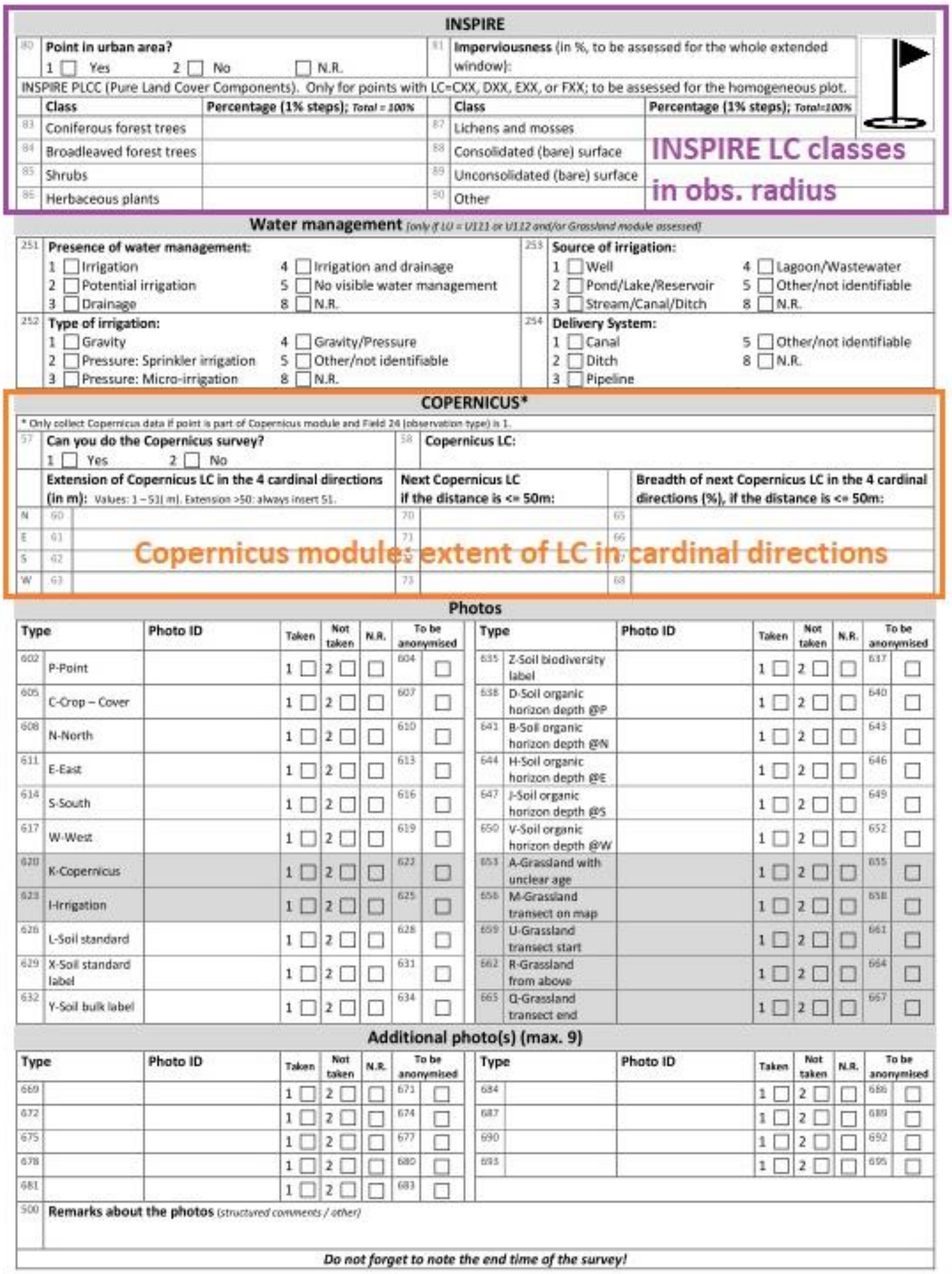
Land management (Only for points with LC = BXX, CXX, DXX, EXX, FXX, HXX)

46 Signs of ploughing? (in the plot?) 1 Yes 2 No N.R.
47 Slope of ploughed field (if ploughed): 1 Flat 2 Gently sloping 3 Steeply sloping 4 Undulating N.R.
48 Plough direction (if ploughed): 1 Across the slope 2 Down the slope N.R.
49 Presence of stone walls: 1 No 2 Stone wall, not maintained 3 Stone wall, well maintained N.R.
50 Presence of crop residues: 1 Yes 2 No N.R.
51 Presence of grass margins: 1 No 2 Grass margins ≤ 1m width 3 Grass margins > 1m width N.R.

Special remarks

53 Signs of grazing in the plot (for points with LC in BXX, CXX, DXX, EXX, FXX, HXX): 1 Visible signs of grazing 2 No signs of grazing N.R.
54 Special status: 1 Protected 2 Hunting 3 Protected and Hunting 4 No special status N.R.
55 Special remarks on land cover / land use:
1 Harvested field
2 Tilled/sowed
3 Clear cut
4 Burnt area
5 Fire break
6 Nursery
7 Dump site
8 Temporarily dry (river bed / lake)
9 Temporarily flooded
10 No remark
N.R.

Figure 13a: LUCAS C2 Field Form 2018 and relevant survey modules



INSPIRE

80	**Point in urban area?** 1 ☐ Yes 2 ☐ No ☐ N.R.	81	**Imperviousness** (in %, to be assessed for the whole extended window):	

INSPIRE PLCC (Pure Land Cover Components). Only for points with LC=CXX, DXX, EXX, or FXX; to be assessed for the homogeneous plot.

	Class	Percentage (1% steps); *Total = 100%*		Class	Percentage (1% steps); *Total=100%*
83	Coniferous forest trees		87	Lichens and mosses	
84	Broadleaved forest trees		88	Consolidated (bare) surface	
85	Shrubs		89	Unconsolidated (bare) surface	
86	Herbaceous plants		90	Other	

Water management *(only if LU = U111 or U112 and/or Grassland module assessed)*

251 **Presence of water management:** 1 ☐ Irrigation; 2 ☐ Potential irrigation; 3 ☐ Drainage; 4 ☐ Irrigation and drainage; 5 ☐ No visible water management; 8 ☐ N.R.

253 **Source of irrigation:** 1 ☐ Well; 2 ☐ Pond/Lake/Reservoir; 3 ☐ Stream/Canal/Ditch; 4 ☐ Lagoon/Wastewater; 5 ☐ Other/not identifiable; 8 ☐ N.R.

252 **Type of irrigation:** 1 ☐ Gravity; 2 ☐ Pressure: Sprinkler irrigation; 3 ☐ Pressure: Micro-irrigation; 4 ☐ Gravity/Pressure; 5 ☐ Other/not identifiable; 8 ☐ N.R.

254 **Delivery System:** 1 ☐ Canal; 2 ☐ Ditch; 3 ☐ Pipeline; 5 ☐ Other/not identifiable; 8 ☐ N.R.

COPERNICUS*

* Only collect Copernicus data if point is part of Copernicus module and Field 24 (observation type) is 1.

57 **Can you do the Copernicus survey?** 1 ☐ Yes 2 ☐ No

58 **Copernicus LC:**

		Extension of Copernicus LC in the 4 cardinal directions (in m): Values: 1 – 51(m). Extension >50: always insert 51.		Next Copernicus LC if the distance is <= 50m:		Breadth of next Copernicus LC in the 4 cardinal directions (%), if the distance is <= 50m:
N	60		70		65	
E	61		71		66	
S	62		72		67	
W	63		73		68	

Photos

	Type	Photo ID	Taken	Not taken	N.R.		To be anonymised		Type	Photo ID	Taken	Not taken	N.R.		To be anonymised
602	P-Point		1 ☐	2 ☐	☐	604	☐	635	Z-Soil biodiversity label		1 ☐	2 ☐	☐	637	☐
605	C-Crop – Cover		1 ☐	2 ☐	☐	607	☐	638	D-Soil organic horizon depth @P		1 ☐	2 ☐	☐	640	☐
608	N-North		1 ☐	2 ☐	☐	610	☐	641	B-Soil organic horizon depth @N		1 ☐	2 ☐	☐	643	☐
611	E-East		1 ☐	2 ☐	☐	613	☐	644	H-Soil organic horizon depth @E		1 ☐	2 ☐	☐	646	☐
614	S-South		1 ☐	2 ☐	☐	616	☐	647	J-Soil organic horizon depth @S		1 ☐	2 ☐	☐	649	☐
617	W-West		1 ☐	2 ☐	☐	619	☐	650	V-Soil organic horizon depth @W		1 ☐	2 ☐	☐	652	☐
620	K-Copernicus		1 ☐	2 ☐	☐	622	☐	653	A-Grassland with unclear age		1 ☐	2 ☐	☐	655	☐
623	I-Irrigation		1 ☐	2 ☐	☐	625	☐	656	M-Grassland transect on map		1 ☐	2 ☐	☐	658	☐
626	L-Soil standard		1 ☐	2 ☐	☐	628	☐	659	U-Grassland transect start		1 ☐	2 ☐	☐	661	☐
629	X-Soil standard label		1 ☐	2 ☐	☐	631	☐	662	R-Grassland from above		1 ☐	2 ☐	☐	664	☐
632	Y-Soil bulk label		1 ☐	2 ☐	☐	634	☐	665	Q-Grassland transect end		1 ☐	2 ☐	☐	667	☐

Additional photo(s) (max. 9)

	Type	Photo ID	Taken	Not taken	N.R.		To be anonymised		Type	Photo ID	Taken	Not taken	N.R.		To be anonymised
669			1 ☐	2 ☐	☐	671	☐	684			1 ☐	2 ☐	☐	686	☐
672			1 ☐	2 ☐	☐	674	☐	687			1 ☐	2 ☐	☐	689	☐
675			1 ☐	2 ☐	☐	677	☐	690			1 ☐	2 ☐	☐	692	☐
678			1 ☐	2 ☐	☐	680	☐	693			1 ☐	2 ☐	☐	695	☐
681			1 ☐	2 ☐	☐	683	☐								

500 **Remarks about the photos** *(structured comments / other)*

Do not forget to note the end time of the survey!

Figure 14b: LUCAS C2 Field Form 2018 and relevant survey modules

The LUCAS 2018 Copernicus polygons contain the automatically generated polygons based on the new LUCAS Copernicus module introduced in the 2018 survey. It contains information on the extent of Level 1 land cover in the cardinal directions and up to 50m from the position of the surveyor. Important to note is that the position of the Copernicus point may differ from the LUCAS point position and therefore other LUCAS parameters may not be applicable to the Copernicus point. This was considered in the construction of the Copernicus polygons (LUCAS point inside the polygon or not) and the attribute data of the polygons provide the information if the LUCAS parameters are applicable to the polygon or not (see d'Andrimont et al. 2020). The Copernicus polygons were used in the assessment of the IMD thresholds and for the verification of the LUCAS land cover extent, see chapter 4.2.1.3. The dataset has been provided by JRC.

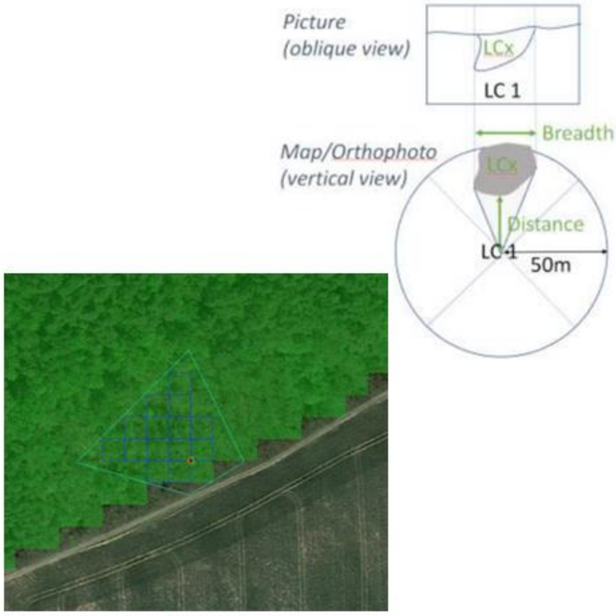


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Figure 15: LUCAS 2018 schematic Copernicus module

The LUCAS primary data is available as csv download from the LUCAS homepage. https://ec.europa.eu/eurostat/web/lucas/data/primary-data. For this assessment the data from the campaigns in 2015 and 2018 for the selected countries (Germany, Spain, Romania and Sweden) was downloaded.

In addition to the LUCAS primary data, the following additional LUCAS dataset were used.

- LUCAS grid master sampling frame containing the information from the stratification used for the sample selection for 2015 and 2018 survey campaign. This data was downloaded as csv from the LUCAS homepage. https://ec.europa.eu/eurostat/web/lucas/data/lucas-grid
- LUCAS sampling weights for the survey 2015 and 2018 campaign. The data contain for each point the area proportion it represents from the total area considering the sampling design. The data was provided by Eurostat in frame of this project.
- LUCAS Copernicus polygons for 2018. The data is a shapefile with polygons representing the extent of the land cover in the cardinal directions. This data was created from the Copernicus Module integrated in 2018 survey. More details are provided in chapter 4.2.1. The different LUCAS datasets were linked to the LUCAS primary data based on the unique LUCAS point-ID and extracted for the selected countries.

Further details on the data are described in the Meta data in DLV1.3.

Chapter 4.2.1 describes how the LUCAS survey data was prepared for the assessment with the HRL products.

2.2.2.3 LUCAS data flow and non-sampling error quality control

LUCAS is per design a “statistical” survey that strictly follows a quality control protocol (Eurostat, 2018) aiming it ensuring highest quality of the sampled micro information and to prevent non-sampling errors. In order to systematically identify and trace inconsistencies and their correction measures, a quasi “tamper-proof” digital data collection environment including several obligatory individual control steps have been developed and established (Figure 16).

Figure 16: LUCAS 2015 visual quality control (Eurostat, 2009a)

Starting from an extended preparation that involves the qualification of surveyors, the preparation of intensive trainings, as well as carefully organisation of the survey logistics, the observation of a LUCAS point starts with the collected information from the previous campaign. Therefore each point is supplied with an individualized ground document, which contains the observed land cover codes, the taken LUCAS photos, together with the GPS track on a as recent as possible digital orthophoto (DOP) of that point (Figure 17). This ensures a proper localisation of the sample units within the required observation window of less than 1.5m radius. In case of insufficient GPS signals or limited resolution of DOPs, the surveyors are refereeing to the observation position that is indicated with a point marker or kept in the centre within the LUCAS point photo.

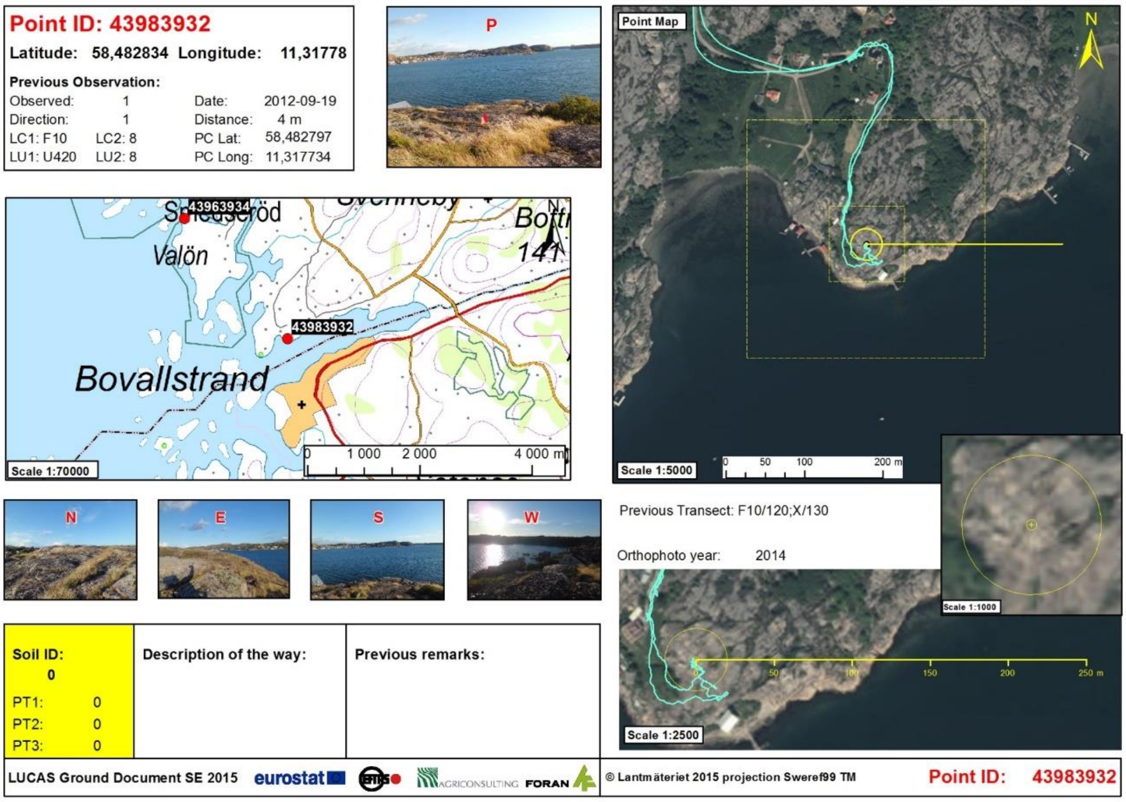


Figure 17: Ground documents (LUCAS FI 2015 including extra marks for SOIL POINT)

Data entry is then captured via a dedicated LUCAS Data Management Tool (DMT) that keeps track of any change or adaptation of the data entries across all levels within the data flow. Once having entered and uploaded to a central server, any single point of the collected surveyor data are controlled by the service contractors through visual inspections of the taken photos, the recorded GPS track and the available DOPs (Figure 18). Simultaneously interactive plausibility controls are employed along the entire digital data entry from the surveyor level up to the final control step at the Commission. As an additional LUCAS specific quality control measure a systematic simple wise external quality control is executed by an independent service contractor.

This approach allows full transparency of each observation and the possibility to measure data consistency. An investigation of the 2009 campaign explored an overall range of 0.3% inconsistencies across all member states (Eurostat, 2009b). To summarise, the, LUCAS data flow and quality control regime forms a comprehensive solution to track, monitor and reduce non-sampling errors and can be considered as high quality reference data.

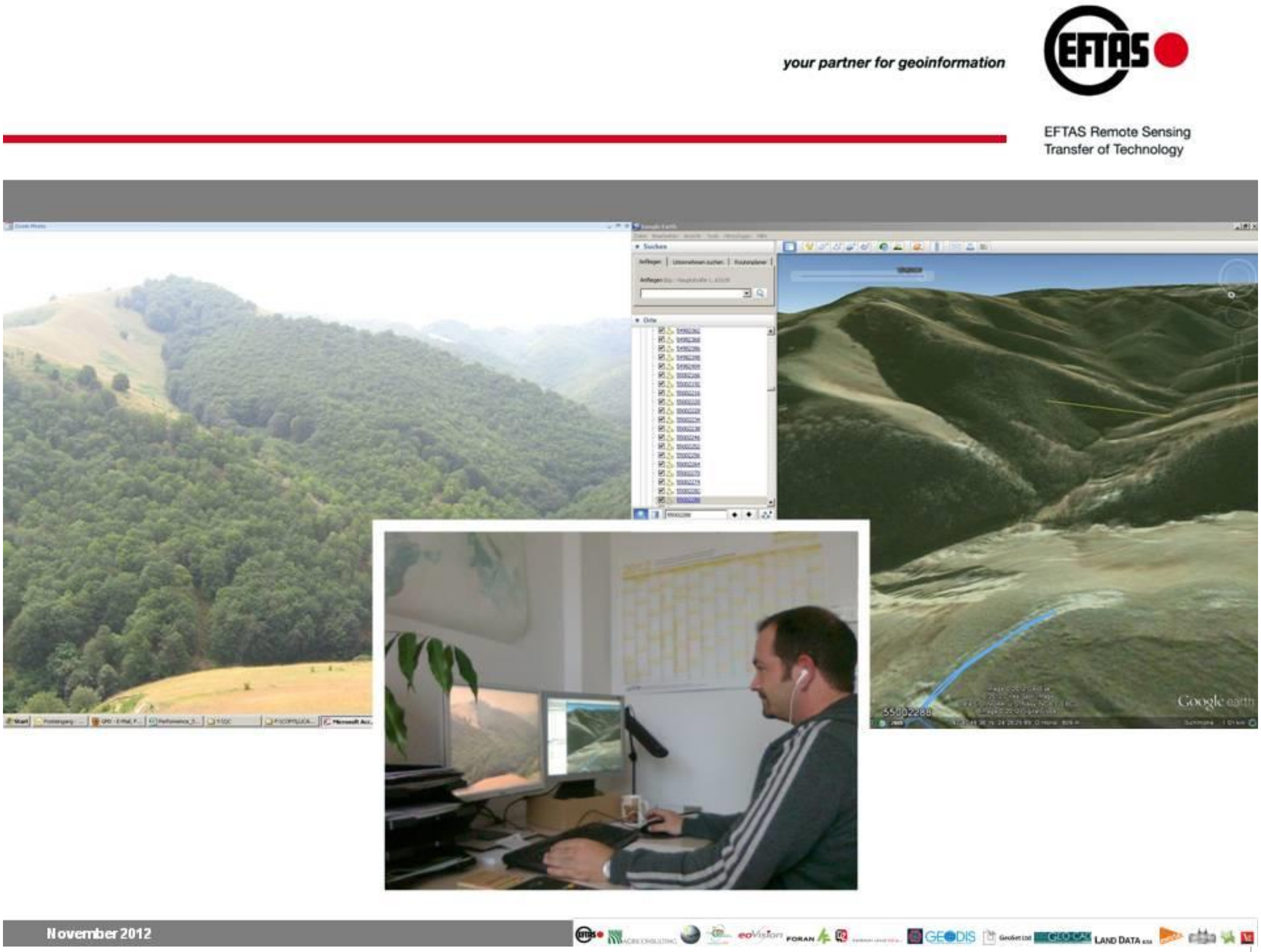


Figure 18: LUCAS 2015 visual quality control

2.2.2.4 Identified synergies and applicability for EO

The LUCAS data from 2015 and 2018 survey is tested for estimation of accuracy for the FTY 2015 and 2018 and for the IMD 2015 and 2018. The data is aggregated to thematically correspond to the Copernicus HRL Forest and Imperviousness product definition. All survey points from the 4 selected countries for 2015 and 2018 were converted to point shapefiles and thematically aggregated to correspond with the required classes. This is further described in chapter 4.2.

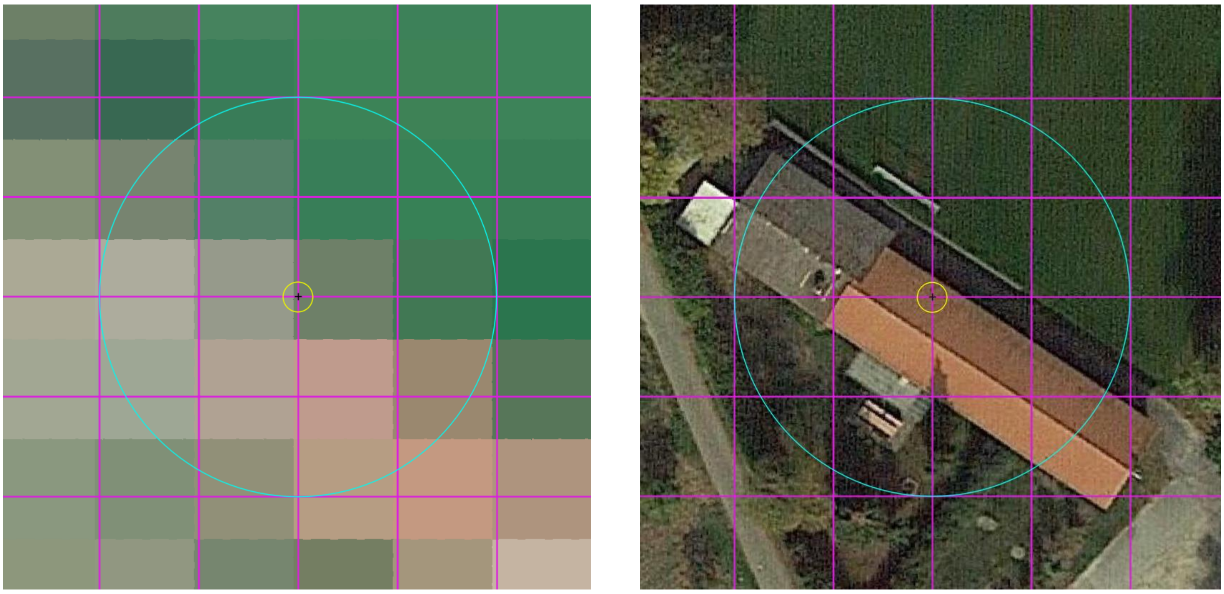
Advantages for using LUCAS survey data as reference data for EO assessment:

- Harmonised survey methodology
- Consistent quality control that verifies each single point via contractors in order to trace non-sampling errors.
- Thematic compatibility, parameters for forest definition according to FAO and suitable land cover classes to compare with HRL IMD product.
- Independent from the HRL products, LUCAS data was not used in the production of the HRL products (Buck et al. 2015)
- LUCAS points are selected on NUTS2 level and provide a high number of points and a sampling design at this geographic level
- Temporal compliance with HRL products 2015 and 2018
- Data is free available and transparent

Limitations for using LUCAS as reference data for HRL Forest and Imperviousness products (see also recommendations in chapter 7.

- Complicated sampling design when targeting aggregated classes such as forest
- LUCAS points are located at the grid cell intersection of the HRL product grid and are only directly comparable when the applied LUCAS observation radius certainly exceeds the product resolution (Nyquist-Shannon sampling theorem) Figure 19 shows the LUCAS observation radius compared to Sentinel-2 pixel location and the HRL grid.
- LUCAS extended observation radius is not fixed, but applies only within the homogenous plot were the point is located. The extent of the land cover is only known when the "homogeneous plot" exceeds the applied observation radius – which is not recorded

At this point it shall be also referred to a detailed study on the compatibility between LUCAS and HRL data that was elaborated on behalf of the EEA (Buck et al. 2015).



©: Sentinel 2 – ESA, *©: Digital Orthophoto North Rhine Westphalia - Geobasis NRW*

Figure 19: LUCAS observation radius and HRL European grid (purple) compared to Sentinel-2 pixels (left) and digital Orthophoto (right)

2.2.3 EO-4-statistics- reference data (visual interpretation)

In addition to the LUCAS and EEA validation data a dataset was created within this project for a selected number of AOIs in order to benchmark the EEA data and the LUCAS reference data with a dedicated reference dataset that allows to:

- Fill the gap to provide accuracy and area estimates of the IMD change and TCCM change layers at NUTS2 level, both is not covered by the other datasets.
- Apply and demonstrate an "easy" applicable sampling approach and showcase the stratified estimator for area estimation on a selected number of NUTS2 AOIs.

Reference data was created for the following products and AOIs:

- FTY 15 & 18 on selected NUTS2
- IMD 15 & 18 on selected NUTS2
- TCCM1518 on all NUTS2
- IMCC1518 on all NUTS2

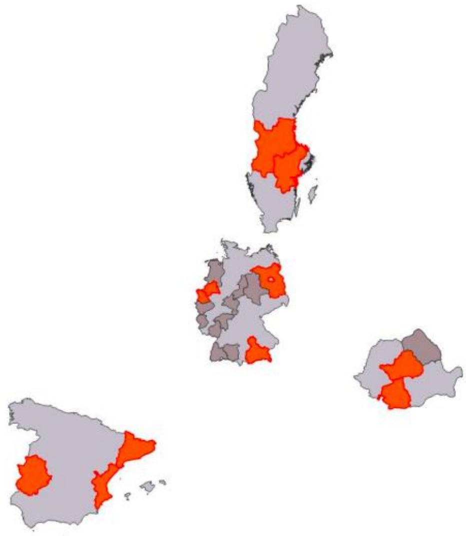
Sample units are the map pixels / HRL units, either 10x10m or 20x20m and using simple random sampling and stratified random sampling.

The sample units are interpreted using visual interpretation of different available pan European image data. Further details are described in chapter 4.3.

FTY 2015: Forest Reference: Forest 0.5	FTY 2018: no-forest Reference: no-forest	Sample units for 2015 20x20 and 2018 10x10

© Digital Orthophoto North Rhine Westphalia - Geobasis NRW (right)

Figure 20: Creation of a new Eo-4-Statistics reference data set (visual interpretation)



Administrative boundaries: © EuroGeographics

Figure 21: Allocation of a new EO-4-Statistics reference data set (visual interpretation)

2.3 Statistical benchmark - LUCAS estimates

Besides the micro data Eurostat publishes validated estimates from NUTS2 through EU level for all observed LUCAS land cover (LC) classes in i) square kilometre, ii) percentage, and iii) coefficient of variations, including comprehensive explanatory notes and Metadata documentations[21] . The LUCAS statistics are available from the Eurostat website https://ec.europa.eu/eurostat/web/lucas/data/database (see Figure 23). Figure 22 shows the statistical time series for forest area for EU and selected countries. This interactive data base allows the selection and download of chosen LC classes and administrative levels for a comparable statistical change assessment that adequately considers the individual **sampling intensities** and applied **weight factors** over different LUCAS campaigns (see below Figure 22 and Figure 24). In principle, land cover changes can be considered only as statistically significant, when the observed change is bigger than the applied CVs. In order to prevent misinterpretation, the published CVs are flagged with:

'b' break in time series
‘e’ estimated
‘p’ provisional
‘u’ low reliability
‘c’ confidential
‘f’ forecast
‘r’ revised
‘z’ not applicable
‘d’ definition differs, see metadata
‘s’ Eurostat estimate
‘:’ not available

Extracted from Eurostat https://ec.europa.eu/eurostat/web/lucas/data/database

	2018			2015			2012			2009		
Forest FAO	[KM²]	[%]	[CV*]	[KM²]	[%]	[CV*]	[KM²]	[%]	[CV*]	[KM²]	[%]	[CV*]
EU (aggregated according to the context)	1.464.197	37	0,3	1.432.500	36,2	0,2	1.393.116	35,2	0,2	1.366.850	34,6	0,2
EU 27 (from 2020)	1.592.024	38,6	0,3	1.559.407	37,8	0,2	:	:	:	:	:	:
Germany	113.270	31,7	0,9	113.153	31,6	0,6	109.454	30,5	0,7	108.745	30,3	0,7
Spain	139.364	28	1,3	134.779	27	0,6	124.469	25	0,6	122.433	24,6	0,7
Romania	79.470	33,3	1,1	78.141	32,7	0,8	74.281	31,1	0,8	:	:	:
Sweden	273.463	61,1	2	277.628	61,7	0,4	276.015	61,4	0,4	272.295	60,5	0,4

*) CV for absolute value

Figure 22: LUCAS statistical database - Forest area statistics for EU and selected countries

Given that during the time of writing this report, not all LUCAS estimates for 2018 were yet published at NUTS2 level, and related to the fact, that some Copernicus class definitions do not precisely match with the available LUCAS forest and artificial classes, **“aggregated” LUCAS estimates**, which are extracted from the entire list of LUCAS parameters, had been created for this report (see chapter 4) in order to allow adequate benchmarking of the outcomes (see chapter 5). These are only intermediate unofficial figures and are not to be misunderstood as official estimates.

[21] https://ec.europa.eu/eurostat/cache/metadata/en/lan_esms.htm

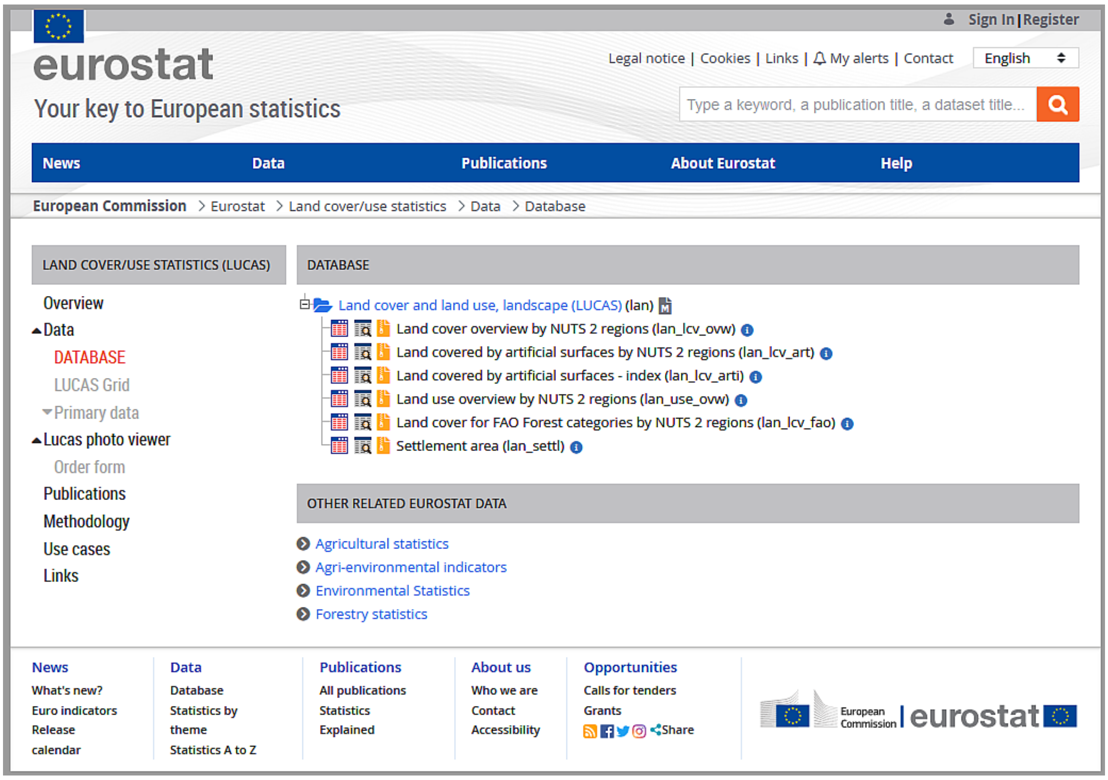


Figure 23: LUCAS website and access to database

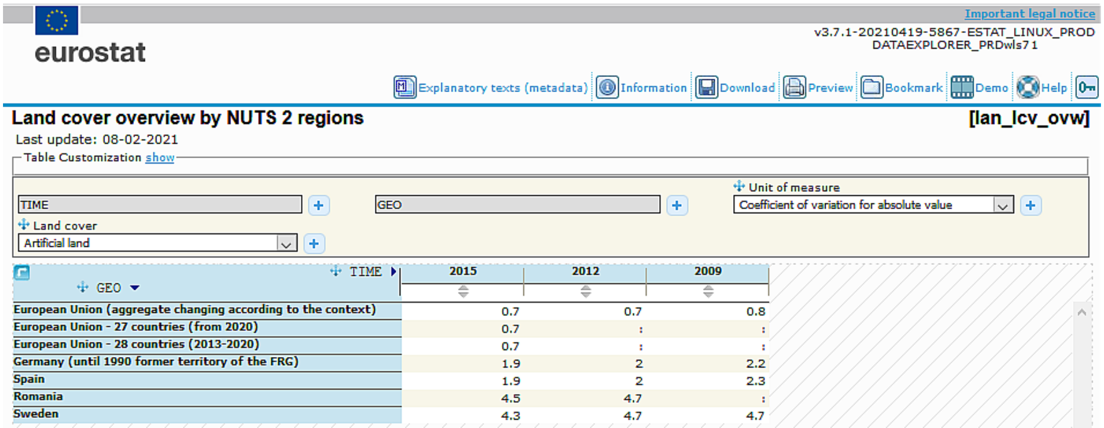


Figure 24: LUCAS interactive database

3 Using EO classifications for area estimation

There are several approaches to use an EO classification (a map) to generate area estimates (Benedetti et al. 2010, Carfagna & Gallego 2005, Gallego 2010, GSARS 2017, and GEOSS 2009). EO classification and map are used synonymously in this document.

There are three general approaches in which remote sensing based EO classification (a map) can contribute to generating area statistics for land cover (GEOSS 2009, Gallego 2004).

1. EO is the main source of data
2. EO is combined with accurate information on a sample of reference data
3. EO is used as tool to improve the sample frame e.g. for delineation of sample units or stratification

Using a map as the sole data for estimation areas of land cover or land cover change is so called "**pixel counting**". The area of a land cover is estimated by counting the number of pixels of a land cover classification.

Simple pixel counting will produce erroneous results because of classification errors present in the map (GFOI 2016). This approach can therefore be considered as "biased" because it makes no provision for errors in the classified map product. To assess the bias of a map, a validation approach is required which provides accuracies and quantifies the classification errors for the map classes.

Simple pixel counting is applied to the HRL products to provide biased area estimates for all AOIs.
⇨ **An example calculation for the biased pixel counting estimator is described in chapter 3.1.**

The remote sensing community has recognized the issues associated with "pixel counting" and map accuracies; scholarly work in the remote sensing literature is recommending sampling based approaches for assessing the accuracy of maps and for estimating areas (e.g. Gallego 2004; Olofsson et al. 2014).

Such an approach combines the map with a sample of accurate reference data and will yield an estimate, i.e. a number, of the area or accuracy of a land cover class of interest and a measure how reliable the estimate is.

The overall concept is that the reference data provides the "true" land cover information, but only for a sample and not the entire map. Therefore the reference sample has to be selected using a probability sampling design which allows to extrapolate from the sample to the entire map.

Due to the fact that the calculated area or accuracy is based on a sample and not the entire map (that would be a census), there is an uncertainty due to the sampling process. This uncertainty of the estimate can be quantified (usually from the variance of the sample) and is expressed as, for example standard error, coefficient of variation (CV), margin of error or confidence intervals (see Glossary for definition). The "uncertainty" of an estimate is the opposite of the "precision" of an estimate, for consistency we will use the term "uncertainty" in this document.

These estimation approaches are considered as "unbiased", because they are based on the unbiased ("true") land cover information from the reference data (e.g. from a field survey) and compensate for the uncertainty from the sampling process by providing a measure of uncertainty.

Combination of the EO map with reference data has the purpose of comparing the land cover in the reference with the land cover in the map over the sample to check for agreement (for validation or calibration of area) or explore the relation between the proportion of land cover in reference and map (using regression).

A further main role of the map in sampling based approaches is to use the map for a more efficient allocation of the sample of reference data by using stratification. The aim of stratification is in general to reduce the uncertainty in the estimates by creating more "homogenous" strata and to allocate the sample units more efficiently. If the land cover of interest is a small proportion of the study area, an efficient map based stratification is often essential to allocate samples in that land cover (Olofsson et al. 2014).

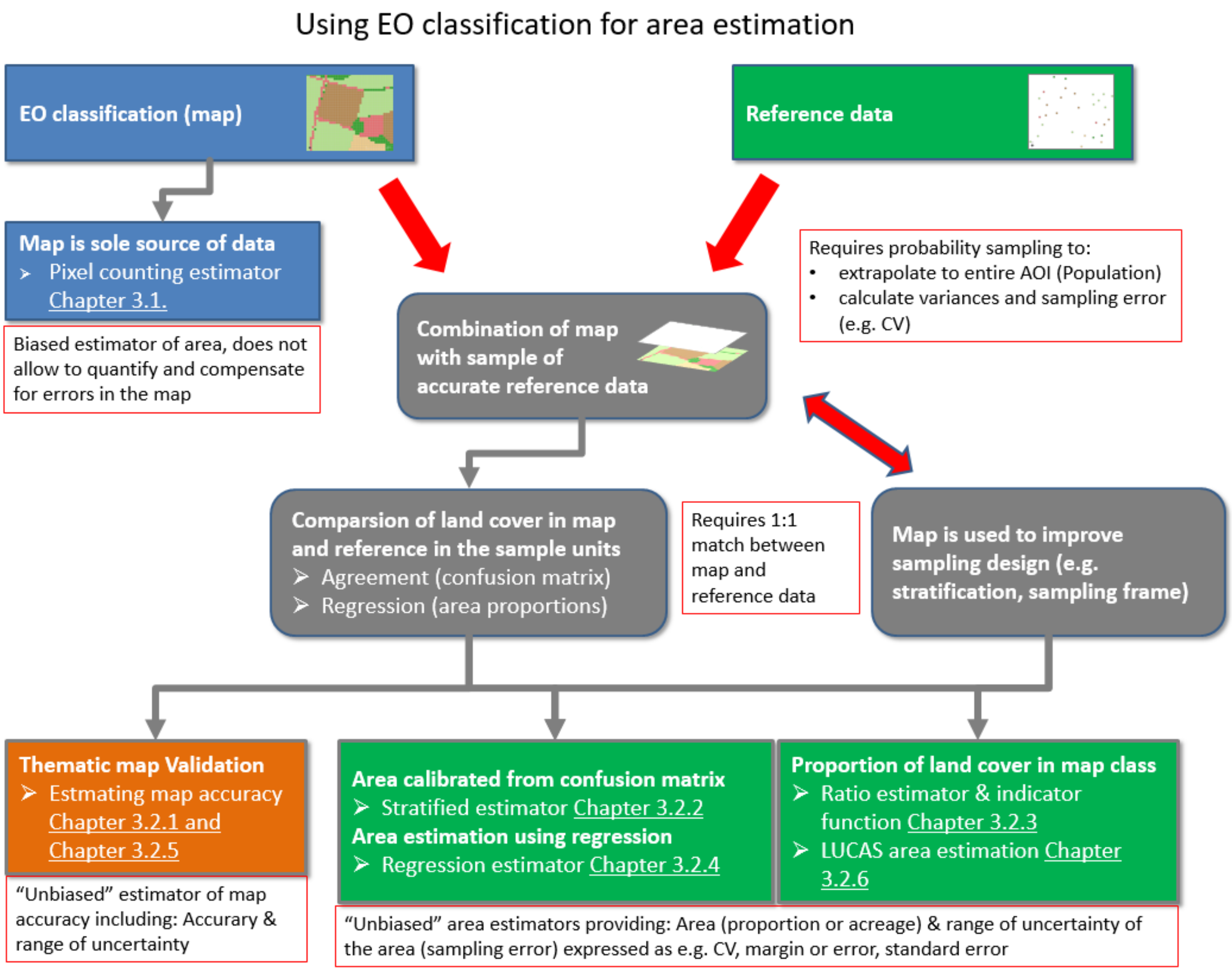


Figure 25: Schematic overview of approaches to use EO for area estimation and applied estimators in this assessment

An overview on the general concepts to estimate area or accuracy by combining a sample of reference data and an EO classification is provided in Figure 26. The Figure also shows in which chapter the application of the specific approach is described in detail using the HRL and reference data.

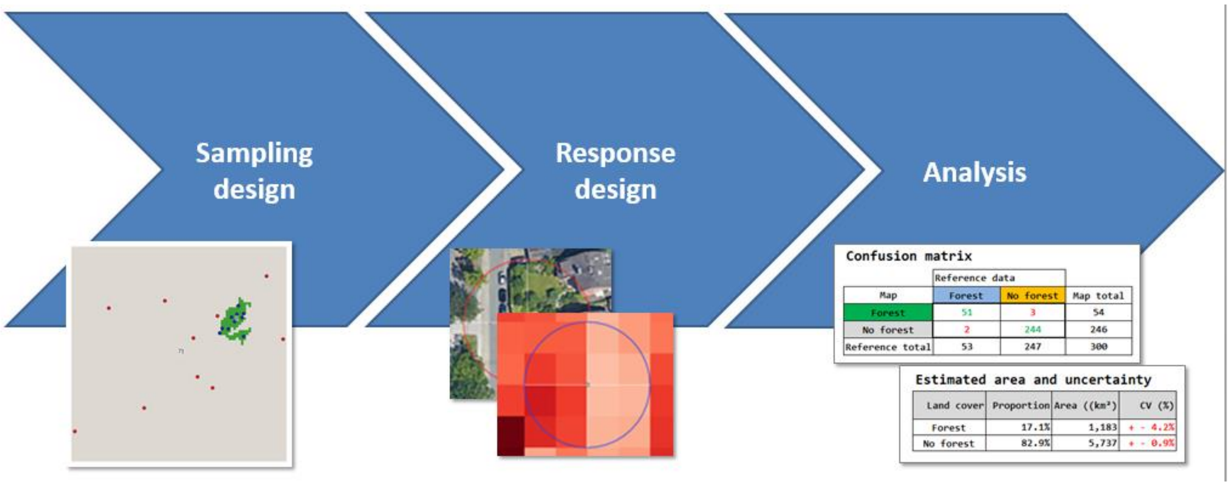


Figure 26: Overall approach for "unbiased" estimation

The process of estimating area or accuracy of a map using a sample of reference data includes three fundamental components.

(i) The **sampling design** is the protocol by which the sample units are selected from the area of interest. This includes the decision on number of sample units as well as the strategy to select them. The sample has to be selected following a probability approach, which provides that each area unit in the AOI had the chance of being selected and that this probability can be calculated. Often applied probability sampling designs are simple random sampling, systematic sampling and random stratified and systematic stratified sampling, each with some advantage or disadvantages. In general the choice comes down to whether to use stratification or not and whether to use random or systematic sampling. Stratification means dividing the area of interest into different strata (sub populations) based on one (or more) variable. The samples are then selected from each stratum, e.g. randomly or systematic. An obvious decision is to use the map classes from an EO classification as strata. Stratification has some advantages as it provides control on how many sample units are allocated in each stratum (map class) and to ensure that rare classes receive sufficient sample units. Deciding the number of sample units is a difficult task, as usually the total number is limited by available resources for the reference interpretation. In general the more sample units are available, the lower the uncertainty of the estimates. An example for the considerations on sample design is provided in chapter 4.3.1.

(ii) The **response design** encompasses all steps to collect reference data at the sample units and combine it with the map data. This includes the decision on the type of sample unit (point, pixel, etc.), nomenclature and rules for reference data classification as well as the data collection itself and quality control measures. The response design therefore includes all relevant steps to create the required thematic, spatial and temporal match between reference and map data.

(iii) The **analysis** is the actual calculation of the estimate (accuracy or area) and its uncertainty. It includes the selection of appropriate estimators considering the sampling design and response design. Since the estimation is based on a sample and not on the entire population (AOI), the results have a sampling error. The sampling error is the uncertainty of the estimate and is usually calculated from the variance of the sample. Therefore the analysis includes the choice of an estimator (formula) to calculate the estimate (area or accuracy) and an estimator to calculate the uncertainty of that estimate.

The three components contain the key information to understand reference data and applied estimation processes. If existing reference data is used, the documentation and understanding of the applied sampling and response design to create the reference data is crucial in order to choose the appropriate estimators for “unbiased estimation”.

The following section describes the general concept for accuracy assessment and concepts of common “unbiased” area estimators. Chapter 3.2 describes how this estimation approaches are applied to the HRL products using reference data.

Thematic map validation or better called “estimating thematic accuracy” of a map has the aim to assess the quality of a map and to quantify accuracy and mapping errors and its classes. This is an obligatory step in map production and is done by comparing the image classification with reference data which is expected to be more accurate than the classification. Since not the entire map can be compared, a sample of reference data is used. For each reference sample the map pixel information is compared to the information from the reference data. The result of the comparison between the map and the reference for all sample units is summarised in a confusion matrix. If the sample was selected following a rigorous sampling via a probability design like random or systematic it is representative for the entire map and accuracy parameters can be calculated for the entire map.

If a different sampling approach was used such as a stratified sampling, the confusing matrix has to be weighted with the selection probabilities per stratum to account for different selection probabilities. The resulting matrix is a so called **“**weighted matrix” or “error matrix”.

In the classical and most simple approach the map classes are used as strata for the sampling and the sampling weights can be derived from the proportion of each map class.

If a non-probability sampling was used for the selection of the sample or if the sampling design and selection probabilities of the sample are unknown, the accuracy assessment becomes difficult (or impossible) and can lead to a high bias (see for example Gallego 2017b, Stehman & Foody 2019 and Olofsson et al. 2014).

A confusion matrix requires a 1:1 comparison of the class from the reference sample unit (e.g. a point) and the map unit (e.g. a pixel).

Note, "… *although map accuracy indices can inform issues of systematic errors and precision, they do not directly produce the information necessary to construct confidence intervals."* (GFOI, 2016). Errors in a map classification are inevitable and an accuracy of the map classification of 100% can be considered as impossible. Therefore errors are present in a map and an “unbiased” approach to estimate areas is required in addition to the accuracy assessment.

⇨ **Chapter 3.2.1 shows how the confusion matrix is created and how to calculate the accuracy parameters when the map class are used for sampling – using EO-4-Statistics reference data and all selected HRL products.**

⇨ **Chapter 3.2.5 shows how to calculate the accuracy parameters of the HRL forest and imperviousness layers using LUCAS sample data**.

For **estimating area** there are different suitable estimators described in the literature that combine EO based image classification (a map) with samples of reference data (Gallego 2017b, GEOSS 2009, Olofsson et. al 2014):

- Stratified and simple random estimators
- Calibration estimators
- Regression estimators
- Ratio estimators

These estimators use the combination of accurate and possibly unbiased reference data (e.g. from a field survey) with exhaustive but less accurate information from a co-variable, e.g. EO classification. The estimators use the unbiased information from the reference data and thus do not inherit the bias from the EO classification (Gallego et al. 2010, see also Deville & Särndal 1992, Olofsson et al. 2014).

The family of **Calibration estimators** use the content of the confusion matrix to correct the bias of the pixel counting estimates. The probabilities of pixels being correctly classified in the unbiased sample and the probabilities of pixels been wrongly classified are used to estimate the true proportion of the land cover classes (Gallego 2004). The confusion matrix is the central element of this estimators. Precondition is that the sample design is correctly considered when building the confusion matrix and strata weights are correctly applied, otherwise it can lead to completely wrong results. An example on the effects of neglecting the sample probability is given by Gallego et al. 2010.

Simple random and **stratified estimators** (the former also referred to as simple expansion estimators; Cochran 1977) are frequently used in the literature together with simple random, systematic and stratified designs because of their efficiency and simplicity of implementation. Stratified estimator can be estimated directly from the confusion matrix when the map classes are also the strata (Stehman 2013). The approach can then be considered as a form of calibration estimator and will lead to similar results.

When the map strata used for the sampling are different than the classes to be estimated, the estimators have to be adjusted using an indicator function (Stehman 2014). A **ratio estimator** can be applied using the proportion (ratio) of reference samples from a certain land cover in a map strata to estimate the total area of the land cover in the entire AOI.

- ⇨ **Chapter 3.2.2 describes how the stratified estimator is applied when the map classes are used for sampling – EO-4- Statistics reference data.**
- ⇨ **Chapter 3.2.3 describes how the area estimation is applied when a different strata than the map is used using a ratio estimator and indicator function – EEA validation data for Forest.**

Regression estimators use a linear relationship (regression) between the proportion of the land cover in the reference sample unit and the proportion of the land cover in the classified image. This linear relationship allows to correct the bias of the classified image. Regression estimators are usually applied using segments and the proportion of a land cover in the segment and in the pixels. Due to the larger sample units, regression estimators are less affected by positional inaccuracy than points. Also the effect of mixed pixels is reduced because proportions of a land cover and pixel values are recorded in the sample unit (Gallego 2018).

- ⇨ **Chapter 3.2.4 describes how the regression estimator is applied to estimate impervious area using the EEA validation data and HRL IMD product.**

In the following chapters the different methods are described with examples from the input data.

<u>Practical considerations: Sample design of existing data</u>

For area estimation as well as accuracy assessment the foundation is the probabilistic sampling design by which the reference data is collected. Only with the understanding of the design by which reference data was collected the correct estimators can be applied. In case already existing data is used, as it is the case with the LUCAS Survey data and the EEA validation data, understanding the sampling design is crucial.

- ⇨ A considerable effort was necessary to understand the sampling design of the EEA validation data. The critical aspect was the reproducibility of the strata which were used for the sampling. In case of the IMD an “artificial” stratum consisting of Corine land cover classes and Open Street map (OSM) data was used. This was not clearly defined in the report and could not be exactly reproduced for this assessment.
- ⇨ Understanding the LUCAS sampling design and how it can be applied for the estimation of area and accuracy with the HRL layers was possibly the most challenging part of this

assessment. A simplification of the sampling design would support the use of the data for EO applications

Using existing reference data which has been produced without using the map in the sampling design, complicates the selection of an appropriate estimator for area and accuracy and requires usually support from a statistician that knows the sampling design of the existing data...

The table below provides an overview which data was used with which method and on which geographical level.

Table 10: Overview on the methods applied to the different HRL products and geographic entity

	AOI level	LUCAS aggregated class 15 & 18	EEA validation data	EO-4-Statistics reference data
FTY18 & 15	Country		Indicator function and ratio estimator	
	NUTS2	Validation		Validation & Stratified area estimator (selected NUTS2)
IMD15 & 18	Country	Validation	Regression estimator	
	NUTS2	Validation		Validation & Stratified area estimator (selected NUTS2)
IMCC15-18	Country			Not executed due to reported quality issues
	NUTS2			Validation & Stratified area estimator
TCCM15-18	Country			Validation & Stratified area estimator
	NUTS2			Validation & Stratified area estimator

3.1 Biased area estimation - Simple pixel counting estimator

Simple pixel counting estimator is applied on the different AOIs by simply counting the number of pixels N_{c+} of the target class dividing by the total pixels N_{++} and multiplying with the area A of the AOI.

$$\text{Simple pixel counting estimator (Naïve estimator): } A_c = \left({}^{N_{c+}}/_{N_{++}} \right) * A$$

(Gallego 2004)

The calculation is straightforward and software such as QGIS can be used to extract the number of unique pixels in a raster dataset and the total number of pixels.

An alternative way for pixel counting is multiplying the number of pixels of a target class with the area of a pixel in the map. This results in slightly different area totals when maps with different pixel resolution are compared. In this assessment, to allow better comparability between different raster resolutions of the HRL products, 10m in 2018, 20m in 2015 and 100m on country level, the first method is used.

Pixel counting as described above requires that the pixel values are hard coded into classes of land cover.

The FTY and the classified change layers TCCM and IMCC are hard coded into land cover classes. All pixels are assigned to a certain class and counting the pixels per class is straightforward in software such as QGIS or R.

For continuous data such as the IMD where the pixel values are proportions of imperviousness ranging from 0% to 100%, hard coding into classes would be required in order to apply pixel counting as described above. In case of the IMD a threshold of >=30% is used to classify each pixel to the class “impervious” or “non-impervious”. .An alternative approach to extract impervious area from is to calculate:

$$\tilde{A} = \sum_i m_i$$

where each pixel i represents a proportion m_i of imperviousness, and the total proportion of imperviousness is the sum from all pixels in the AOI. That would provide the area proportion with 100% imperviousness in the AOI. An example for this calculation without using a threshold is provided in the table below.

The IMD pixel values range from 0-100 therefore the sum of the IMD in the area is divided by 100 to get proportions. Unclassified pixels (value 254) are considered as no–data and excluded. The example below uses the aggregated 100m IMD products where each pixel is 100x100m (0.01 km²).

Table 11: Calculation of impervious area from simple pixel counting using the sum of imperviousness degree.

Germany	Total pixels (100x100m) in AOI	Sum of imperviousness degree from all pixels in AOI	Proportion of imperviousness in AOI	Impervious area in km² in AOI
IMD 2015	35,765,228	1,546,338	0.0432	15,463
IMD 2018	35,766,004	1,850,521	0.0517	18,505

The results of the biased pixel counting areas for the HRL are in the ANNEX II and are used for the comparison with the results from the area estimation in chapter 5.

Practical considerations: Biased pixel counting

Simple pixel counting is a straightforward method to calculate area from the Copernicus layers, but the calculated area is biased and this bias is not known unless an accuracy assessment is done.

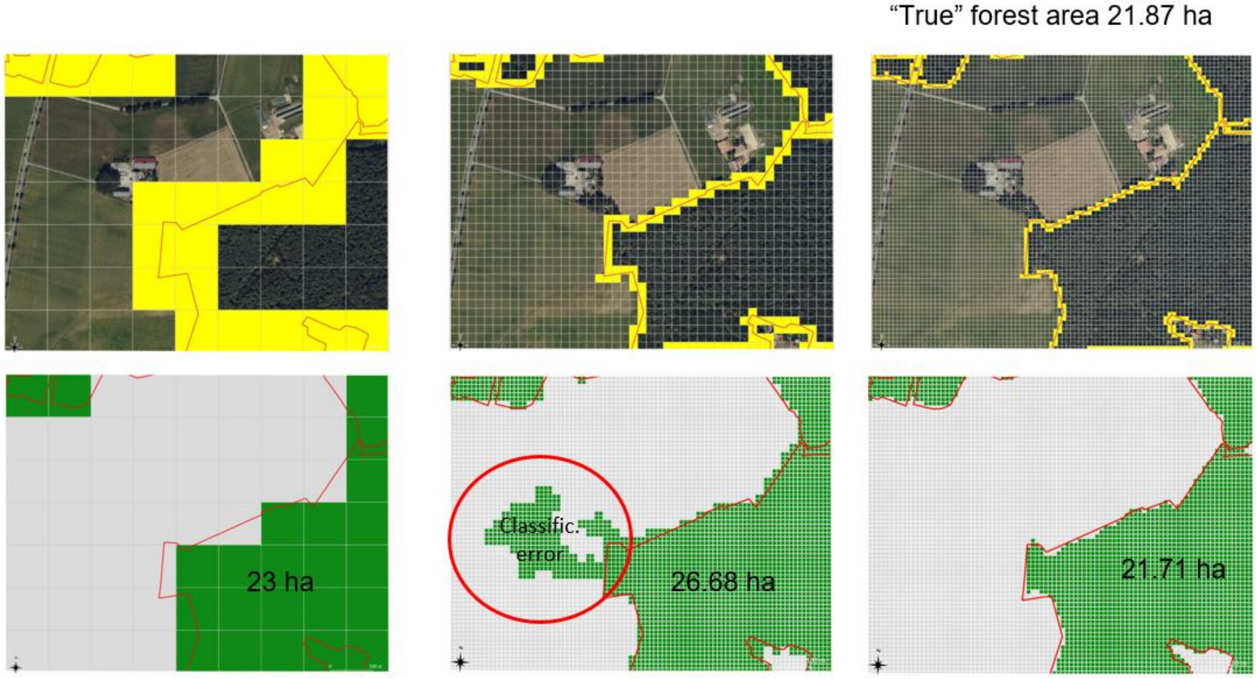
Also marginal, there is a difference if the area if calculated by (i) multiplying the number of pixels from a land cover class with the pixel area or by (ii) using the proportion of pixels from a class from the total pixel with total are of the AOI defined by the NUTS shapefile.

3.1.1 Sources of bias in the map

Simple pixel counting has no sampling error, the classification covers the entire AOI (not considering minor gaps due to unclassified pixels). The bias of a land cover area obtained from pixel counting is the difference to the "true" area of the land cover in the AOI.

It is therefore not only determined by the thematic accuracy of a map classification (e. g. derived from a validation), since the classification errors for a particular class can outbalance each other. This makes it more difficult to assess the bias and its sources since even maps with low thematic accuracies could provide acceptable area estimates. In general the major sources of bias come from the classification process itself and pixels wrongly classified to a land cover class. Another source of bias are the presence of mixed pixels in the classification. Mixed pixels are pixels which cover more than one land cover class, but have been classified to only one class in the classification, due to the classification algorithm of the map, as it is the case for the Forest product which is based on a hard classification of tree cover and MMU rules. If the proportion of the other land cover class is not represented in the map pixel it can lead to a bias and an over or under representation of a land cover class. An example is provided in *© Digital Orthophoto North Rhine Westphalia - Geobasis NRW*

Figure 27, it shows the HRL Forest type (green) at 100m resolution in 2018, at 20m resolution in 2015 and at 10m resolution in 2018, for each example the area from pixel counting is extracted.



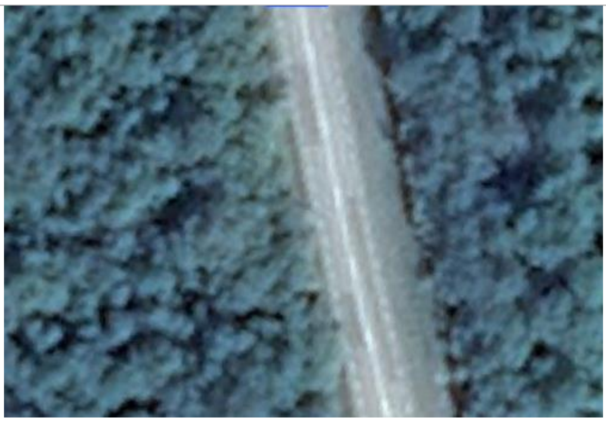
© Digital Orthophoto North Rhine Westphalia - Geobasis NRW

Figure 27: Example for possible sources of error from pixel counting, due to possible mixed pixels at land cover borders (yellow) and classification errors.

The number of mixed pixels and its effect on the area estimate depends among other on the size of the pixel (spatial resolution) and the landscape. The more fragmented the landscape or the target land cover the higher the rate of mixed pixels. For example classifying forest in the Mediterranean landscape with shrub land, with scattered trees, tree plantation (olive, citrus, cork oaks …) and agroforestry systems such as the Dehesas, a high rate of mixed pixels is expected.

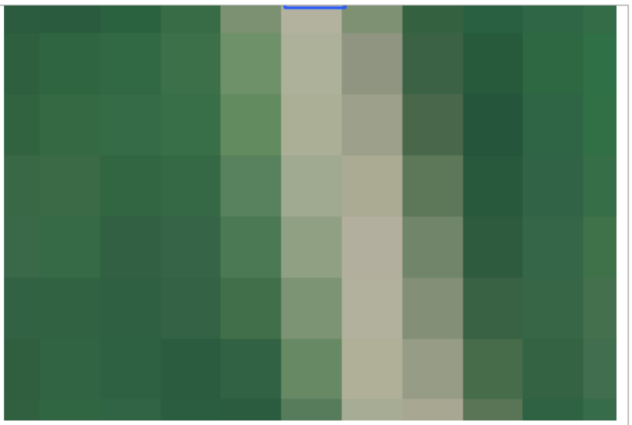
Artificial surfaces are a very fragmented land cover and a high rate of mixed pixels can be expected in particular in areas with a more fragmented settlement structure. An effect which increases the problem of mixed pixels is overexposure of bright surfaces, such as roads. The example of a road in Sweden in Figure 28, shows the effect of overexposure of the bright surface of the road to the darker forest area in the Sentinel-2 image. This effect can lead to an overestimation of specific land cover classes.

In case of the HRL Imperviousness product the pixels are not hard coded and sub pixel proportions of impervious area are provided.



Background: Google Earth

Google Earth Pro © CNES/Airbus 2021



Background: Sentinel-2 2018.

Copernicus Sentinel data 2018 processed by ESA

Figure 28: Example for "mixed pixels" increased by the effect of overexposure of the surface of a road

A possible approach to compensate the effect of mixed pixels in reference data classification is described in chapter 4.2.1 and 4.3.2.

3.2 "Unbiased" estimation approaches

3.2.1 Thematic map validation

The thematic accuracy of the HRL is assessed by comparing HRL layers information with reference data, which is assumed to be more accurate than the information in the HRL image product. The comparison of the information of the image classification and the reference data is usually summarised in a confusion matrix. From the confusion matrix the traditional accuracy parameters can be calculated to quantify the thematic bias of the image classification; **user's accuracy**, **producer's accuracy**, **overall accuracy** and the **uncertainty of the accuracy** expressed as **margins of error**. Precondition to extrapolate the accuracy obtained from the sample is that the sample was selected using a **probability sampling design**. That means each pixel of the map had a chance of being selected for the validation and that this selection probability is known. The most common sampling designs are simple random, systematic or stratified random or stratified systematic.

The calculation of the confusion matrix and accuracy parameters for the HRL products follows the approach described in Olofsson et al. 2014 (see also Congalton & Green 2008, Gallego 2017, Congalton 1991, Foody 2002, Strahler et al. 2006, Stehman & Foody 2019).

The approach described below uses formulas and estimators when a systematic or simple random sampling design was used or a stratified design where the map classes are also the sampling strata.

Accuracy assessment of the HRL using the LUCAS data requires different estimators and is described in chapter 4.2.

For the accuracy assessment the reference data are intersected with the HRL products at the extent of the related classified sample units in order to construct a 1:1 relation between reference and HRL pixel data.

The resulting table contains the class value from the map and the corresponding value from the reference data.

Table 12: Comparison table map - reference used as input for the confusion matrix

Map value	Reference value
Forest	Forest
No-Forest	Forest
…	…

The confusion matrix summarizes the comparison from reference data class and map class. The reference data is usually provided in the columns and the map classes in the rows. The diagonal of the confusion matrix contains the counts from the sample units where reference and pixel have an agreement. The off-diagonal cells contain number of sample units with disagreement. If the sample design follows a probability sampling the confusion matrix should be weighted considering the sampling probabilities and strata weights.The example below shows the accuracy assessment of FTY2018 using the EO-4-Statistics reference data for the NUTS2 DE40 (Brandenburg). The sample units have been selected using the map class (forest / no forest) as strata. This is the recommended approach, as it simplifies the assessment of accuracy parameters. The proportion of the sample strata (map class) from the entire area provides the strata weight.

Confusion matrix with counts

	FTY18 DE40	Reference data		
		Forest	No-forest	Total
FTY18	Forest	262	11	273
	No-forest	16	411	427
	Total	278	422	700

Map proportion from pixel counting	
Class	Proportion
Forest	0.3834
No-Forest	0.6166
Total	1

To contribute to different sample probabilities each cell of the confusion matrix is weighed using the weight of the strata and the ratio of the sample count from the total sample in the map class.

For the Forest – Forest cell this is: 0.3834 * (262/ 273) = 0.3680

For the Forest - No-forest cell it is: 0.3834 * (11/273) = 0.0155

Confusion matrix with proportions

		Reference				
		Forest	No-forest	Total	User's accuracy	margin of error 95% CI
FTY18	Forest	0.3680	0.0155	0.3834	95.97%	+ - 2.3%
	No-forest	0.0231	0.5935	0.6166	96.25%	+ - 1.8%
	Total	0.3911	0.6089			
	Producer's Accuracy	94.09%	97.46%			
	margin of error 95% CI	+ - 2.7%	+ - 1.4%			

Overall accuracy	margin of error 95% CI
96.14%	+ - 1.4%

The resulting matrix is an estimate of the proportions of correct and incorrect classified pixels in the map. The accuracy estimators can be directly calculated from the matrix and following the formulas provided in Olofsson et al. 2014 Equitation 1-3).

User accuracy (UA) of class *C* – if you print the map and go to a location mapped as *C*, user's accuracy tells you the probability that the location is *C* in reality.

It is calculated as the proportion of map classified as C and having also reference C.

For the forest class: 0.3680 / 0.3834 = 0.9567

The complement of the user's accuracy is the **Commission error,** for the forest class: 1 - 0.9567= 0.0433

Producer's accuracy (PA) of class *C* – if *C* is present at a certain location on the ground, prod.'s accuracy tells you the probability that the location is classified as *C* in the map

It is calculated as the proportion of reference class C that has been classified as C.

For the Forest class: 0.3680 / 0.3911 = 0.9409

The complement of the producer's accuracy is the **Omission error,** for the forest class: 1 - 0.9409= 0.0591

Overall map accuracy (OA) - probability that a random map unit is correctly classified.

It is calculated as the proportion of map class correctly classified. In the example it is the diagonal of the error matrix.0.3680 + 0.5935 = 0.9614

The bias of a pixel counting estimate is the difference between Commission and Omission error. For the forest class -0.0158. How to use the information from confusion matrix to correct the bias and provide the relevant uncertainties is explored in chapter 3.2.2.

Any accuracy assessment should be accompanied by an estimate of the uncertainty of the accuracy parameters. In other words an estimate on how reliable the calculated accuracy parameter is. This in general depends on the number of sample units used for the assessment and the accuracy of the map. Uncertainty of the accuracy parameters can be expressed as **margin of error** or standard error which is the half-width of the confidence interval of the estimate. It describes the possible +/- range of the estimate and is usually expressed as a proportion.

The Equitation 5, 6 and 7 in Olofsson et al. 2014, are used to calculate the variance for the Overall, User's and Producer's accuracy. The square root of the **variance** is the **standard error** of the parameters. Multiplying the standard error by 1.96 provides a margin of error on a 95% confidence level.

The overall accuracy of 96.14% with a margin of error of +/-1.4% on a 95% confidence level means: If we repeat the sampling process over and over again, the results will be in 95% of cases within 94.74 and 97.54.

The R script used for the calculation of accuracy is provided in DLV 1.4 *R script Accuracy Assessment with EO-4-Statistics reference data.*

Applicable script / template
⇨ **DLV1_4_R_script_Accuracy_Assessment_with_EO-4-Statistics_reference_data_v1.R** ⇨ **DLV1_4_R_script_Accuracy_Assessment_with_EO-4-Statistics_reference_data_v1.txt**

<u>Practical considerations: Confusion matrix</u>

Building a confusion matrix requires a hard coding of the pixel values and reference data in order to build a 1:1 comparison of the values.

A practical guideline for the accuracy assessment of thematic maps is provided in the SIGMA Protocol for land cover validation (Haub et al. 2015)[22].

For continuous data such as the HRL imperviousness degree the assessment of accuracy requires that hard classes are defined to build an agreement between map and reference data. Alternative approaches for the assessment of the accuracy of imperviousness degree are for example described in Gallego et al. 2016 or Pennec et al. 2019 (see below extract).

For the comparison of the sample units as vector shapefile with the pixel values of the HRL raster dataset, simple intersection processes are used as available in QGIS. For example the QGIS "Point sampling tool" plugin or the Zonal statistics.

3.2.1.1 Threshold for assessment of impervious area (continuous data)

The above explained concept to verify mapping accuracies via a confusion matrix, requires distinct classes that are to be observed. The validation of continuous data that are provided within a defined range per pixel is not feasible via confusion matrices. A suitable solution is to group the continuous values into "hard classes". I.e., for the assessment of the HRL Imperviousness products a threshold of 30% was defined. Assessments with similar thresholds on the IMD products have been undertaken by Gallego et al. (2016) and Pennec et al. (2019). The table below shows a comparison between the IMD pixel average values derived at LUCAS survey points from 2018 with artificial and non-artificial land cover. The analysis seems to support the 30% threshold, at least when comparing the IMD values with LUCAS artificial classes, all average values and the median are above the 30% threshold at LUCAS points with artificial land cover. The standard deviation of the IMD average values is high, which is probably due to mixed pixel effects. The LUCAS point information applies to a 1.5 m radius whereas the IMD value is the average from 4 pixels with an area of 20x20m. LUCAS points on linear features, such as roads, have therefore been excluded as the corresponding IMD pixels might contain a considerable large part of non-artificial area.

Table 13: IMD values compared to LUCAS „non-artificial surface" points

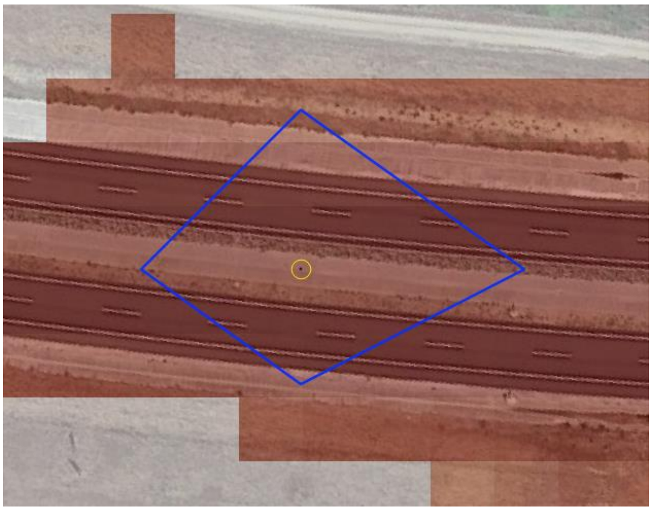
LUCAS non artificial	IMD 2018 average value (%) from in 4 pixels intersecting with the LUCAS point			
	DE	ES	RO	SE
N	23,776	42,175	15,542	25,077
MEAN	1.17	0.41	0.55	0.31
MEDIAN	0	0	0	0
Stand. Dev.	7.26	4.42	4.43	3.48
av. max	1.80	0.69	0.85	0.56
av. min	0.63	0.18	0.30	0.13

[22] https://www.eftas.de/upload/15356999-SIGMA-D33-2-Protocol-for-land-cover-validation-v2.0-2015-06-22vprint.pdf

Table 14: IMD values compared to LUCAS "artificial surface" points

LUCAS artificial excl. Roads (A22)	IMD 2018 average value (%) from in 4 pixels intersecting with the LUCAS point			
	DE	ES	RO	SE
N	1,038	1,059	375	381
MEAN	70.08	56.07	44.03	47.06
MEDIAN	75.62	64.26	43.24	44.25
Stand. dev.	28.69	28.36	38.18	37.04
av. max	81.58	64.3673	54.05	56.78
av. min	57.89	47.37	34.09	36.78

In a further assessment, the LUCAS 2018 Copernicus polygons (see chapter 2.2.2) have been used to extract the IMD value of the HRL pixels falling in the polygon. The LUCAS Copernicus polygons provide the extent of the land cover observed at the position of the surveyor towards the cardinal directions up to 50m. Figure 9 shows an example of a Copernicus polygon (blue) around the LUCAS point (yellow) and the IMD18 in the background (transparent red). The average value of the pixels inside the polygon is extracted.



Google Earth Pro © Maxar Technologies 2021

Figure 29: LUCAS Copernicus polygon at a wide road in Spain, background IMD18 and Google Earth

The table below shows the mean values of the IMD 2018 average values from each LUCAS 2018 Copernicus Component polygon for artificial classes and non-artificial classes over DE, ES, RO, and SE. Unfortunately there are only 71 artificial Copernicus observations in the entire 4 countries.

The average mean value is at 60 and the Min value at 50 which is well above the threshold of 30.

Table 15: Mean IMD18 values inside LUCAS Copernicus Component polygons

LUCAS LC	N	MEAN	MEDIAN	MAX	MIN
artificial	71	59.88	81	65.48	50.21
non-artificial	20954	0.38	0	0.61	0.25

3.2.2 Estimating area using the confusion matrix – Stratified estimator

The content from the confusion matrix can be used to quantify and adjust for the bias of a classification, provided a rigorous sample design uses the map classes as strata or when a simple random sampling was applied. The information from the classified image is used as a co-variable to reduce the error of the estimate from the reference data. As described in Olofsson et al. (2014) the stratified estimators can be calculated directly from the validation sample using the appropriate formulas for the applied sampling plan (stratified); the standard error to estimate the CV of the estimates will be calculated from the confusion matrix. This formulas are the correct estimators for simple random, stratified and systematic sampling when the strata are the map classes to be assessed.

Stratified estimator: Equitation 9 in Olofsson et al. 2014:

$$\hat{p}_{\cdot k} = \sum_{i=1}^{q} W_i \frac{n_{ik}}{n_{i\cdot}}$$

Standard error of the area estimate: Equitation 10 in Olofsson et al. 2014

$$S(\hat{p}_{\cdot k}) = \sqrt{\sum_i W_i^2 \frac{\frac{n_{ik}}{n_{i\cdot}}\left(1-\frac{n_{ik}}{n_{i\cdot}}\right)}{n_{i\cdot}-1}} = \sqrt{\sum_i \frac{W_i\hat{p}_{ik}-\hat{p}_{ik}^2}{n_{i\cdot}-1}}$$

Where n_{ik} is the sample count at cell (i, k) in the confusion matrix, $W_i$is the area proportion of map class i and$p_{ik} = {}^{W_i n_{ik}}/_{n_{i.}}$ and the summation is over the q classes.
The stratified estimator of the area proportions is the column sum of the error matrix. It is the proportion of forest correctly classified as forest (forest, forest) and the proportion of forest incorrectly classified (forest, no-forest).
In the example above the adjusted proportion of forest is 0.3680 + 0.02311 = 0.3911.
For the no-forest class the corrected area proportion is 0.6089.

The adjusted proportion of forest is multiplied with the total Area of the AOI to get the area estimate of forest. Since the adjusted area is an estimate the standard error is calculated to provide the uncertainty of the estimate. The standard error is the measure of uncertainty of the estimate and multiplied with the total area of the AOI it provides the error as an area. To provide the uncertainty on a confidence level of 95% the standard error is multiplied with 1.96. In the example this is 216 * 1.96 = 424 km². This means the bias corrected area of forest is 11,600 km² with a possible error of +/- 424 km².
The error is often expressed as coefficient of variation (CV), the proportion of the standard error on the adjusted area expressed as a percentage. In the example 216 / 11,600 *100 = 1.9%.

Table 16: Example: Area estimation using stratified estimator

Class	Area from pixel counting			Adjusted area estimate		Standard error		Margin of Error 95% CI	CV
	Pixel counts	km²	%	prop.	Km²	prop.	km²	+/- km²	+/- %
Forest	1,137,300	11,373	38%	0.3911	11,600	0.0073	216	424	1.9%
No-forest	1,828,700	18,287	62%	0.6089	18,060	0.0073	216	424	1.2%

The correction of the bias from the pixel counting using the validation sample is used for the HRL products on NUTS2 level using the EO-4-statistics reference data in chapter 4.3.3.

The correction of the bias and adjustment of the area estimate is done using R script and excel.

<u>Practical considerations: Stratified estimator</u>

The stratified estimator is an easy to apply method to estimate area using a classified image and reference data.

The estimation of area and its uncertainty can be done directly from the confusion matrix of the accuracy assessment. The stratified estimator is therefore an easy and logical step from accuracy assessment to area estimation. The critical aspect when using the stratified estimator is that appropriate reference data has to be used and that the sampling design and sample weight are known. Only with this information the correct sample and strata weights can be calculated. The above described estimators can be applied to simple random, systematic or stratified sampling when the map classes are used as strata.

A stratum is a defined part of the map from which a sample was selected with the same probability. In the recommended approach the map classes are used as strata. E.g. the forest and non- forest area from the FTY. The strata weights are the proportion of a stratum from the total area of the map derived from the pixel counting. If the strata weights are unknown or wrong the extrapolation to the entire map is wrong and the area estimates are wrong.

- ⇨ The recommended approach is to use the map classes as strata for the sample selection, as demonstrated in chapter 4.3.
- ⇨ In case strata different than the map classes have been used, the stratified estimator has to be adjusted using an indicator function and ratio estimator (see Stehman 2014).

The sampling approach and the results from the estimation of accuracy and area for the selected NUTS2 regions the different HRL products is described in chapter 4.3.

The R script used for the estimation of accuracy (see chapter above) also provides the area estimates using the stratified estimator

Applicable script / template

- ⇨ **DLV1_4_R_script_Accuracy_Assessment_with_EO-4-Statistics_reference_data_v1.R**
- ⇨ **DLV1_4_R_script_Accuracy_Assessment_with_EO-4-Statistics_reference_data_v1.txt**

3.2.3 Estimating area when the map classes are not the strata used for sampling – Ratio estimator and indicator function

In case of the EEA validation data for FTY15 and FTY18 the sample were selected using different strata then the map. The TCD15 (tree cover density 2015) HRL was used as strata to select the sample for the FTY 2015 and 2018 validation data. In this case an indicator function and a ratio estimator is used which estimates the proportion of correctly classified forest in the sample, for each strata defined by the tree cover layer.

It is not entirely clear to us how the sampling strata for the EEA validation data was constructed, therefore the strata weights are calculated from the TCD15 100m layer, this should be close to the original used strata weights.

Two strata were defined: stratum 1 with a TCD15 = 0 (i.e. no tree cover present), and stratum 2 with a TCD15 > 0 (i.e. tree cover present). The presence of forest was observed at each sample unit; a reference label of 0 indicates no presence of forest, and a reference label of 1 indicates the presence of forest in the sample unit. The recoded Copernicus HRL of forest type in 2015 and 2018 (FTY15 and FTY18) have map labels that correspond to the reference labels (0: non-forest, 1: forest). The use of this map is likely to reduce the standard errors of area estimates of forest and non-forest compared to using the sample alone.

The problem is that the traditional stratified estimators (Cochran, 1977), as described above, are biased estimators when the map classes (FTY in our case) do not correspond to the strata used to select the sample (TCD15); different estimators must be constructed (Stehman, 2014). "Unbiased" estimators are easily constructed by expressing the area and map accuracy parameters using **simple indicator observations** denoted as y_u and x_u, respectively, where these observations obtained for pixel u have just two possible values, 0 or 1.

To estimate area, let's first define:

$$y_u = \begin{cases} 1 & \text{if unit } u \text{ is observed as forest} \\ 0 & \text{if unit } u \text{ is not observed as forest} \end{cases} \tag{1}$$

The area of forest is then calculated as (Stehman 2014, Eq. 15)

$$\bar{Y} = \sum_{u=1}^{N} \frac{y_u}{N} \tag{2}$$

and an unbiased estimator of $\bar{Y}$ is (Stehman 2014, p. 4930)

$$\hat{\bar{Y}} = \sum_{h=1}^{H} \frac{N_h^* \bar{y}_h}{N}; \bar{y}_h = \sum_{u \in h} \frac{y_u}{n_h^*} \tag{3}$$

where N_h^* and n_h^* are the numbers of population and sample units in stratum h. A variance estimator of $\hat{\bar{Y}}$ is (Stehman, 2014, Eq. 25)

$$\hat{V}(\hat{\bar{Y}}) = \frac{1}{N^2} \sum_{h=1}^{H} N_h^{*2} \left(1 - \frac{n_h^*}{N_h^*}\right) \frac{s_{yh}^2}{n_h^*} \tag{4}$$

where the sample variance of the y_u values from stratum h is

$$s_{yh}^2 = \sum_{u \in h} \frac{(y_u - \bar{y}_h)^2}{n_h^* - 1} \tag{5}$$

The results from estimation of forest area using the EEA validation data and the FTY 2015 and 2018 for the 4 selected countries is provided in chapter 4.1.1.

A template and description how to estimate forest area using the EEA validation data is provided in the *DLV1_4_ Indicator_Function_estimator_EEA_sample_data.*:

Applicable script / template
⇨ ***DLV1_4_Indicator_Function_estimator_EEA_sample_data_v1.pdf***   ⇨ ***DLV1_4_Indicator_Function_estimator_EEA_sample_data_v1.xlsx***

3.2.4 Estimating area using proportions - Regression estimator

For the estimation of impervious area using the HRL IMD and the EEA validation data a regression estimator is used, see Cochran 1977 (chapter 7.1) and Gallego 2004 and Gallego 2017b:

$$\hat{y}_{reg} = \bar{r} + b\,(\bar{M} - \bar{m})$$

$\bar{r}$ (r for reference) is the mean proportion of the target land cover in the sample units of the reference data, $\bar{m}$ and $\bar{M}$ (m for map) are the mean proportions of the target land cover in the image classification in the sample units and in the entire AOI and b is the slope of a linear regression between reference *($\bar{r}$)* and map *($\bar{m}$)*.

The variance of the regression estimator is approximated by

$$Var(\hat{y}_{reg}) = Var(\bar{r})(1 - \rho^2)$$

where $Var(\bar{r})$ = $S_{\bar{r}}^2/n$ is the variance of the imperviousness mean value in the reference sample, ρ is the linear correlation between the $\bar{r}$ and $\bar{m}$ in the sampling units. The variance formula shows that the variance of the regression estimator is always lower than the variance from the estimate when using only the reference data unless the correlation is 0. Higher correlation between reference value and map value results in higher precision.

Since 3 different sampling strata were used for the validation of the IMD 2015 and 2018, the regression estimator is calculated for each stratum h separately (Gallego 2017b).

$$\hat{y}_h = \bar{r}_h + b_h(\bar{M}_h - \bar{m}_h)$$

The result is multiplied with the total area of the stratum to obtain acreage. The results from the strata are aggregated for the entire AOI.

For the calculation of the variance of the area estimate for the entire AOI we use a formula for separate variance estimation under stratified sampling Cochran 1977 (Equitation 7.51):

$$V(\hat{y}_{reg}) = \sum_h \frac{W_h^2}{n_h} \quad (S_{\bar{r}h}^2 - 2b_h S_{\overline{rm}h} + b_h^2 S_{\bar{m}h}^2)$$

where for each stratum h: $S_{\bar{r}h}^2$ and $S_{\bar{m}h}^2$ are the variance of the imperviousness value in the reference data and in the map (pixel) for the sample units, $S_{\overline{rm}h}$ is the covariance between $\bar{r}$ and $\bar{m}$, b_h is the slope of the regression and n_h are the number of sample units. W_h is the proportion (weight) of the stratum *h* from the total AOI.

The strata are derived mainly from the 100m aggregated IMD product from 2015:

- Strata 10: all pixels IMD > 0 in
- Strata 30: all pixels IMD =0 but intersecting with an artificial layer consisting of Corine land cover 2012 artificial classes and Open Street map (OSM) data.
- Strata 40: all other pixels with IMD =0

The regression estimator cannot be calculated when the strata are also the map classes. The calculation requires variation within the pixel values in a stratum and this is not the case when the pixels in the strata have the same value (see Stehman 2013). This is the case for the stratum 30 and 40 in 2015, the linear regression and the slope are both 0 and applying the regression estimator does not provide any improvement of the area estimate or precision. In both strata the proportion of IMD in the pixels of the sample ($\bar{m}_h$) and in the entire strata ($\bar{M}_h$) are 0. The area and the uncertainty in this strata is therefore calculated as the sample mean of the impervious value of the reference data and its variance. Area estimate and variance are weighted with the strata weights and aggregated to the total AOI. For 2018 this is not the case because the strata are based on the 2015 IMD product, thus there are pixels with IMD value >0 in stratum 30 and 40 and the regression estimator is applied

The estimation in a stratified sampling design requires information from each stratum separately, therefore the sampling strata had to be created in order to extract the required values. As described in chapter 2.2.1 the complete strata information was not available for this assessment. Strata 30 was approximated from available CLC and OSM data (see further details in chapter 4.1.2). The resulting strata might not be the same as the strata used for the sample selection and this might introduce a bias. Nevertheless the data is used to showcase the method.

In the example below the regression estimator is calculated using the IMD 2018 for Spain.

In the first step the information available from the 256 sample units of the validation data and from the HRL raster data is derived.

D_h is the total area of the stratum. For stratum 10 this is 2,311,076 pixels of 1 ha area, 23,111 km².

$\bar{r}_h$ is the mean proportion of IMD from the reference interpretation of all sample units in stratum 10: 0.3608

$\bar{m}_h$ is the mean proportion of IMD from the classification of all sample units in stratum 10: 0.30512

$\bar{M}_h$ is the mean proportion of IMD of all pixels in stratum 10, the population mean: 0.3224

In the second step the IMD value from the raster in the sample units is compared to the IMD value within the reference sample units for the 256 sample units in the stratum using a linear regression. The correlation parameter R² (ρ^2 in the equitation) shows a good correlation of 0.8295, the linear slope (b_h in the equitation) is 1.0218.

The linear slope is used to adjust the area from the image classification.

Regression estimator for stratum 10:

0.3608 + 1.0218*(0.3224-0.30512) = **0.38**

This results in 23,111 * 0.38 ≈ **8,746 km²**

The same is repeated for the strata 30 and 40 and the results are aggregated to a total area estimate of 14,782 km² for Spain.

For the calculation of the variance of the estimate for the entire AOI a weighted variance is calculated for each stratum separately and aggregated for the entire AOI. For stratum 10 the required values are:

W_h = 23,111 / 505,939 = 0.046
$S^2_{\bar{r}h}$ = 0.092
$S_{\overline{rm}h}$ = 0.075
$S^2_{\bar{m}h}$ = 0.073

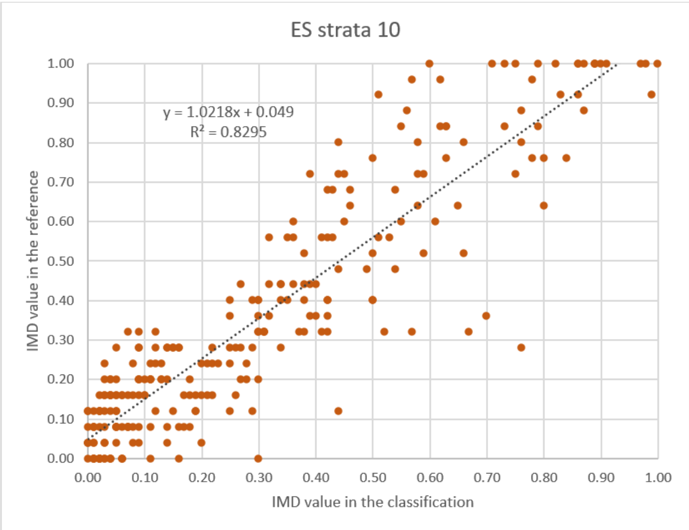


Figure 30: Regression between IMD proportion in the IMD2018 and in the reference data for the 256 samples in stratum 10.

The calculation is: $Var(\bar{r}_{h\ str}) =$ 0.046²/256*(0.092- 2*1.02*0.075² + 0.073 = 0.00000012
This calculation is repeated for the other strata and summarised for all strata to get the variance for the stratified regression estimator for the entire AOI. From the variance the standard error and the CV is calculated.

The table below shows the area estimates for the 3 different strata used for sampling in Spain in 2018 and compares the area from pixel counting and regression estimator.

Table 17: Results of area estimation using EEA validation data and regression estimator - (Spain 2018)

Strata	Area of strata km²	IMD 2015 (pixel mean) 100m product	Regression estimator	CV %
Strata 10	23,111	7,451	8,746	2.8
Strata 30	17,416	220	1,656	15.8
Strata 40	465,412	277	4,380	9.6
Total	505,939	7,948	14,782	**3.4**

The results from area estimation using the EEA validation data and the IMD 2015 and 2018 for the 4 selected countries are provided in chapter 4.1.2.

A template to calculate the area of Imperviousness for the selected countries using regression estimator is provided in deliverable *DLV1_4_RegressionEstimator_IMD_with_EEA_sample_data_v1.xlsx.*

Applicable script / template
⇨ ***DLV1_4_RegressionEstimator_IMD_with_EEA_sample_data_v1.xlsx***

3.2.5 Estimating accuracy and area using LUCAS data – Ratio estimator and indicator function

As described in chapter 2.2.2, the LUCAS sample results were collected under two-phase sampling. See also Ballin et al. (2019) for detailed description of the design. Two-phase sampling, or double sampling, involves selecting a first phase sample that is treated as a population from which a second phase sample is selected. Such designs are (Lohr 1999) "useful when the variable of interest *y* is relatively expensive to measure, but a correlated variable *x* can be measured fairly easily and used to improve the precision of the estimator of ty" (ty = population total of y). Using the symbols in Cochran (1977), the LUCAS sample consists of a first phase sample of n' > 1,100,000 which are the centre points of all 2 x 2 km grid cells that make up EU territory. Reference conditions on the land surface at the locations of the n' sample units were observed in aerial photo and satellite data. In the second phase, a sample was selected from the first phase sample under stratified random sampling. The second phase sampling was designed to optimize the stratification, sample size, and allocation such as to "vary according to the specificity of the country and NUTS2 territories".
To use the LUCAS sample results for estimating parameters such as map accuracy, we need to construct an estimator that corresponds to the sampling design. Of importance is the very large sample size selected in the first phase – from the standpoint of the variance of any estimate, the sample size of the first phase makes the design nearly equivalent to having stratified the entire population.
Because the LUCAS sample results were collected using a stratification different than the HRLs, we cannot apply the conventional stratified estimators in Cochran (1977) as those are biased when the rows of the population error matrix do not correspond to the strata used to select the sample. Instead, (similar as for the estimation of forest in chapter 3.2.3) we need to construct different estimators using **indicator functions** and a **ratio estimator** (Stehman 2014). In the case of LUCAS, we have different strata. **Seven strata in 2015** and **ten strata in 2018** (Gallego et al. 2015, Ballin et al. 2018).

LUCAS strata 2018:	LUCAS Strata 2015:
h = 1 Arable land h = 2 Permanent crops h = 3 Grass h = 4 Wooded areas h = 6 Shrubs h = 7 Bare surface, rare or low vegetation h = 8 Artificial, construction and sealed areas h = 9 Inland water h = 10 Transitional and coastal waters	h = 1. Arable land h = 2. Permanent crops h = 3. Grassland h = 4. Woodland and shrubland h = 5. Bareland h = 6 Artificial h = 7 Water and wetlands

The sample weight for each LUCAS point is provided in the LUCAS data, the weight is the area each point represents in the NUTS2 region. It is usually the same for all sample units in one stratum and NUTS2 region and allows to extrapolate to the entire NUTS2 region.
The approach allows to estimate accuracy of the HRL forest and imperviousness layers on NUTS2 level using the aggregated LUCAS reference data. Margin of error are not calculated for the accuracy parameters, the elaboration of a suitable variance estimator was not finally clarified within this project. The preparation of the LUCAS data for thematic and spatial compliance with the HRL data and the results from the accuracy assessment are described in chapter 4.2.1.

- ⇨ An unsolved issue of using the LUCAS data is an adequate variance estimator for the accuracy parameters which would allow to calculate margin of error. Despite a lot of effort put into solving this issue no suitable variance estimator could be elaborated. The same applies to using the HRL map as strata to reduce the variance of the LUCAS area estimates (see recommendation in chapter 7).

A template to calculate the accuracy of the HRL imperviousness (IMD) and forest (FTY) using the LUCAS survey and a detailed explanation of the applied estimators is provided in *DLV1_4_Accuracy_Assessment_of_IMD_FTY_with_LUCAS_SurveyData.*

Applicable script / template
⇨ **DLV1_4_Accuracy_Assessment_of_IMD_FTY_with_LUCAS_SurveyData.pdf**
⇨ **DLV1_4_Accuracy_Assessment_of_IMD_FTY_with_LUCAS_SurveyData.xlsx**

3.2.6 Estimating area for benchmarking from LUCAS data

The provided sample weights from the LUCAS data allow calculating area estimates from the LUCAS data including CV. This allows to benchmark the results from the different tests against the LUCAS derived area estimates. For the calculation of the area estimates and CV from the LUCAS data an R script was provided by GOPA. The script uses the software REGENESEES (R evolved generalized software for sampling estimates and errors in surveys). Documentation and download are available at https://www.istat.it/en/methods-and-tools/methods-and-it-tools/process/processing-tools/regenesees.

Area estimates and CVs are calculated for the “aggregated” LUCAS classes (see chapter 4.2.1) and used for the benchmark with the results from the different estimators for the 22 selected NUTS2 regions and 4 countries.Another option would be to benchmark the achieved area estimates against the LUCAS derived estimates including CV ranges at different NUTS regions as provided via the LUCAS web site: https://ec.europa.eu/eurostat/web/lucas/data/database.

4 Applied tests and results

The following chapter describes the applied tests and outcomes of the assessments. Beside the focus on the achieved results, extra attention is to be drawn on the necessary data preparation steps, which are necessary in order to ensure an adequate 1:1 match between the above described EO input and reference data (chapter 2). The results from the assessments are provided in this chapter applying the concepts described in chapter 3. Figure 31 and Figure 32 illustrate the different methods and datasets applied for accuracy assessment and area estimation using the HRL Forest and Imperviousness layers in 22 NUTS2 regions and 4 countries.

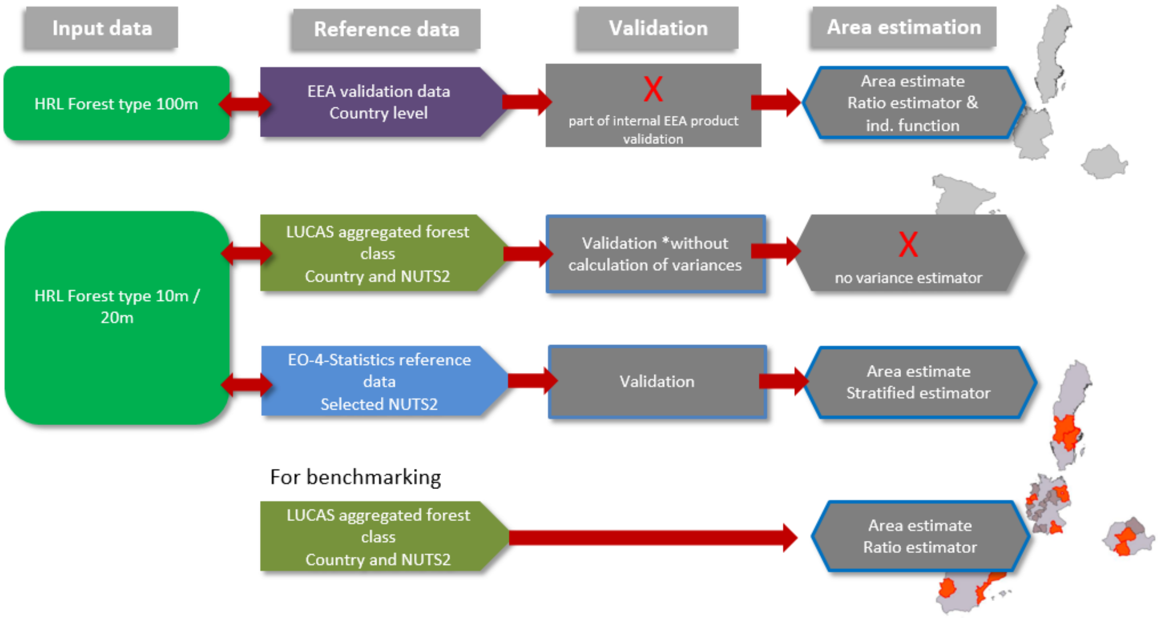


Figure 31: Applied methods for accuracy assessment and area estimation on country and NUTS2 level - using HRL Forest type layer 2015 and 2018 (*Administrative boundaries: © EuroGeographics)*

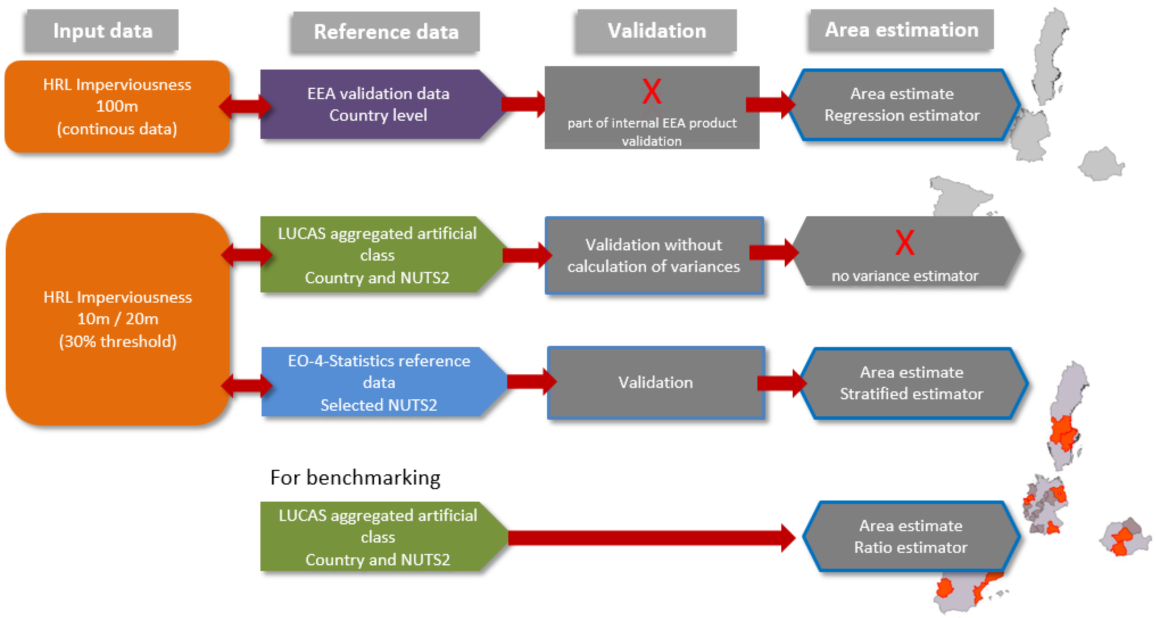


Figure 32: Applied methods for accuracy assessment and area estimation on country and NUTS2 level - using HRL Imperviousness density layer 2015 and 2018 (*Administrative boundaries: © EuroGeographics)*

4.1 Area estimation using EEA validation data

4.1.1 Forest area - Stratified estimator and indicator function

In this test the EEA validation data for the Forest type (FTY) product was used to estimate area of forest using a stratified estimator and indicator function.

As described in chapter 3.2.3, the sampling design of the EEA validation data for the forest product used the HRL Tree cover density (TCD15) product from 2015 as strata to allocate the sample units in areas with tree cover and areas with no tree cover.

Each sample unit was then visually interpreted and classified as forest or no forest. This means the strata used for sampling (Tree cover) are different than the class to be estimated (Forest). In the calculation of the area estimates using the stratified estimator this was considered by using a simple indicator function.

The application of the estimator for the forest area is straightforward, the EEA validation data provides the information if the sample unit is forest or not according to the visual interpretation and if the corresponding pixel of the HRL FTY product is classified as forest or not. This provides the required 1:1 comparability between map and reference data to build a confusion matrix. The weights to adjust for unequal sampling are extracted from the HRL Tree cover density layer 2015 (TCD15) and the number of sample units selected in each stratum.

The table below compares the proportion of forest area from simple pixel counting and the results of the forest area estimation using the EEA validation data. For this assessment the 100m aggregated FTY products were used. The coefficient of variation (CV) describes the uncertainty of the estimate, it is the +/- percentage of error from the estimated area.

Except for Sweden the difference between the pixel counts and the estimates is higher in 2015 than in 2018.

Table 18: Stratified estimator using TCD15 (100m) and EEA validation data to estimate Forest area in 2015 and 2018

	Pixel counts 100m 2015	EEA validation data - stratified estimator 2015			Pixel counts 100m 2018	EEA validation data - stratified estimator 2018		
	%	km²	%	CV	%	km²	%	CV
DE	33.5%	121,821	34.1%	6.3%	33.1%	118,717	33.2%	9.8%
ES	32.9%	159,217	31.9%	5.9%	31.8%	161,812	32.5%	8.5%
RO	34.2%	83,471	35.0%	7.6%	35.2%	82,941	34.8%	11.9%
SE	60.2%	267,729	59.5%	2.4%	59.3%	255,437	56.8%	3.7%

The CV for the estimates in 2018 is slightly higher, possibly due to less sample units used for the validation for the 2018 product (see Table 9). In general the CVs are quiet high for the forest class except for Sweden.

4.1.2 Impervious area - Regression estimator

The application of the regression estimator using the IMD 100m products and the EEA validation data could be realised for all countries and both years. The EEA validation data provided the required information on degree of imperviousness from the visual interpretation and degree of imperviousness from the corresponding 100x100 pixel of the IMD products. In this test no threshold is applied to the continuous data of the HRL IMD product.

As mentioned in chapter 2.2.1 the major difficulty was the understanding of the sampling design of the validation data and the reproduction of the sampling strata in order to extract the required parameters to calculate the regression estimator for each stratum.

According to the validation report the following strata were used for the sampling of the validation data for the individual countries:

- Strata 10: all pixels IMD > 0 in 2015
- Strata 30: all pixels IMD =0 2015 but intersecting with an artificial layer consisting of Corine land cover 2012 artificial classes and Open Street map (OSM) data.
- Strata 40: all other pixels with IMD =0 in 2015

The strata 10 and 40 are based on the IMD 2015 and could be readily extracted. Strata 30 was constructed based on the description in the validation report:

"For both status and change layers, CLC artificial classes and Open Street Map road network are used and converted to a pseudo artificial layer. Relevant OSM road types are selected and rasterized to 100m (for example, abandoned, construction, cycleway, path, planned, trail, track… are removed) to obtain the artificial areas. Using a relevant selection of OSM road types tend to lead to a better spatialization of artificial and impervious areas.

CLC impervious classes are defined as follows based on CLC2012:
1.1.1 = continuous urban fabric
1.1.2 = discontinuous urban fabric
1.2.1 = industrial, commercial areas
1.2.3 = ports
1.2.4 = airports"

HRL IMPERVIOUSNESS DEGREE 2018 VALIDATION REPORT (https://land.copernicus.eu/user-corner/technical-library/clms_hrl_imd_validation_report_sc04_1_3.pdf)

The applied steps to recreate the strata 30 included the following steps:

a. Downloading OSM and Corine Land cover vector data for the selected countries
b. Extraction of the different OSM paved roads types as indicated in the EEA validation report. Extraction of the relevant Corine land cover classes
c. Combining and rasterizing the CLC and OSM vector data to the 100m grid of the HRL
d. Intersection with the strata 10 and 40 to extract the strata 30 and strata 40

Downloading, extracting and merging the OSM and CLC data on the geographic level of the different countries required a considerable effort. For the selection of the OSM road data it was not clear which road types are included or not and which version of the OSM data was used. Therefore the strata used in this assessment might not be the same as used for the sampling of the validation data.

Further, some aspects in the approach to select the samples from each strata was not fully comprehensible to us and we made the following assumptions:

- The sample units of the EEA validation data have been selected using the LUCAS master as sample frame, a stratification based on different criteria and a systematic selection method.
    - ⇨ In our assessment the sampling design is treated as a stratified sample, we make no differentiation between systematic stratified or random stratified.
- The visual interpretation of the impervious value was not done on the entire 100x100m sample unit. A secondary subsample of 25 points was used to interpret and derive the impervious value for each sample unit (see chapter 2.2.1).
    - ⇨ In our assessment we make no provision for the uncertainty due to the sub-sampling.

The table below shows the results of the regression estimator for impervious area in the 4 countries for each stratum and aggregated to the total per country. The coefficient of variation (CV) is the sampling error (uncertainty) of the estimates expressed as a proportion of the estimated area. The table further includes the area estimates and CV using only the validation data and extrapolating to the entire stratum.

Comparing the results from the biased pixel counting of impervious area (pixel mean) with the estimates from the reference data and from the regression estimator, the later show considerably higher areas in all countries. This indicates the bias related to pixel counting in this case.

Table 19: Comparison of impervious area proportion from pixel counting, stratified estimator and regression estimator using EEA validation data - 2015

Country 2015	Strata	Proportion of strata	IMD (pixel mean) 100m	Extrapolated from EEA validation data			EEA validation data - Regression estimator		
			area prop.	km²	area prop.	CV %	km²	area prop.	CV %
DE	Strata 10	14.0%	4.3%	19,297	5.4%	3.5	19,321	5.4%	2.0
	Strata 30	6.3%	0.0%	1,881	0.5%	13.0	1,881	0.5%	13.0
	Strata 40	79.7%	0.0%	3,002	0.8%	14.0	3,002	0.8%	14.0
	Total	**100%**	**4.3%**	24,180	**6.8%**	**3.4**	24,204	**6.8%**	**2.3**
ES	Strata 10	4.6%	1.2%	8,038	1.6%	5.4	8,673	1.7%	3.3
	Strata 30	3.4%	0.0%	1,894	0.4%	13.7	1,894	0.4%	13.7
	Strata 40	92.0%	0.0%	4,144	0.8%	9.9	4,144	0.8%	9.9
	Total	**100%**	**1.2%**	14,077	**2.8%**	**4.6**	14,712	**2.9%**	**3.6**
RO	Strata 10	4.8%	0.9%	3,192	1.3%	8.1	3,298	1.4%	5.3
	Strata 30	4.1%	0.0%	734	0.3%	13.3	734	0.3%	13.3
	Strata 40	91.1%	0.0%	933	0.4%	21.4	933	0.4%	21.4
	Total	**100%**	**0.9%**	4,860	**2.0%**	**7.0**	4,966	**2.1%**	**5.2**
SE	Strata 10	2.9%	0.4%	2,558	0.6%	9.4	2,820	0.6%	5.0
	Strata 30	1.9%	0.0%	785	0.2%	17.2	785	0.2%	17.2
	Strata 40	95.2%	0.0%	3,190	0.7%	13.5	3,190	0.7%	13.5
	Total	**100%**	**0.4%**	6,533	**1.5%**	**7.8**	6,795	**1.5%**	**6.8**

Table 20: Comparison of impervious area proportion from pixel counting, stratified estimator and regression estimator using EEA validation data - 2018

Country 2018	Strata	Proportion of strata	IMD (pixel mean) 100m	Extrapolated from EEA validation data			EEA validation data - Regression estimator		
			area prop.	km²	area prop.	CV %	km²	area prop.	CV %
DE	Strata 10	14.0%	4.9%	20,073	5.6%	3.4	20,155	5.6%	1.8
	Strata 30	6.3%	0.1%	1,891	0.5%	14.5	1,718	0.5%	12.3
	Strata 40	79.7%	0.1%	3,111	0.9%	14.1	2,872	0.8%	14.4
	Total	**100%**	**5.2%**	25,075	**7.0%**	**3.4**	24,745	**6.9%**	**1.9**
ES	Strata 10	4.6%	1.5%	8,338	1.6%	5.3	8,746	1.7%	2.8
	Strata 30	3.4%	0.0%	1,907	0.4%	14.1	1,656	0.3%	15.8
	Strata 40	92.0%	0.1%	4,192	0.8%	10.1	4,380	0.9%	9.6
	Total	**100%**	**1.6%**	14,437	**2.9%**	**4.6**	14,782	**2.9%**	**3.5**
RO	Strata 10	4.8%	1.1%	3,439	1.4%	7.3	3,668	1.5%	4.0
	Strata 30	4.1%	0.1%	813	0.3%	13.9	923	0.4%	12.0
	Strata 40	91.1%	0.0%	997	0.4%	22.4	1033	0.4%	20.6
	Total	**100%**	**1.1%**	5,249	**2.2%**	**7.0**	5,623	**2.4%**	**4.2**
SE	Strata 10	2.9%	0.5%	2,663	0.6%	9.0	3,005	0.7%	4.8
	Strata 30	1.9%	0.0%	850	0.2%	17.5	762	0.2%	19.4
	Strata 40	95.2%	0.0%	3,174	0.7%	13.9	2,932	0.7%	14.8
	Total	**100%**	**0.5%**	6,686	**1.5%**	**7.8**	6,700	**1.5%**	**6.6**

The difference between the impervious area extrapolated directly from the validation data compared to the regression estimator is quiet low. This is due to the fact that in both methods the same reference data is used and the main contribution to the estimation process comes from the stratification into large non impervious strata and a small impervious stratum which contains the major part of the "true" impervious area.

Comparing the CVs of both estimators shows that the regression estimator provides in all cases better results (lower CV). When comparing the CVs of the different strata from the reference data and from the regression estimator the highest reduction in the CVs is in strata 10 where the vast majority of artificial area is located. For strata 30 and 40 in 2015 the results from the extrapolation of the reference data and the regression estimator are the same. This due to the fact that the pixels value in this strata are 0 and thus the regression estimator does not provide any improvement of area or variance estimation.

In general the test and the differences in the results show that the area extracted only from the IMD products by extracting the pixel mean, do not provide reliable area results for imperviousness in the tested countries. The regression estimator can be applied using the EEA validation data and is a suitable method for area estimation using the continuous impervious density degree pixel data. No threshold has to be applied for the imperviousness density degree. In the applied tests the major contribution for the area estimates comes from the stratification using mainly the IMD product itself, applying the regression estimator could further reduce the CV for the estimates.

4.2 Accuracy estimation using LUCAS survey data

4.2.1 LUCAS data preparation

Two steps were used to prepare the LUCAS survey data to be used as reference data for the FTY and IMD products:

- Thematic aggregation of the LUCAS parameters to match with Forest and Imperviousness definition of the HRL products.
- Spatial intersection of the LUCAS sample unit and the HRL pixels and verification of the extent of land cover for points located on borders

4.2.1.1 LUCAS Forest class

To be compliant with the forest definition of the HRL Forest layer the LUCAS parameters from the core land cover observation as well as the FAO forest parameters are used to select all surveyed points where:

- Land cover class belong to Wooded area (tree cover > 10%)
- Trees are not primary used for agricultural purposes (fruit trees, olive …)
- Minimum width of the plot is >20m
- Minimum plot area is > 0.5 ha, this is recorded for each point located in wooded area
- Height of tress at maturity is >5m
- Traditional agroforestry systems (Dehesa) are included

The LUCAS land cover class Cxx includes areas with tree canopy >10% and with trees not primarily used for agricultural production. Trees used for agricultural production (which are excluded in the Forest definition) such as fruit trees and olives are recorded as permanent crops in the Bxx class. Dehesas which are included in the HRL forest definition are in the LUCAS nomenclature recorded as woodland (Cxx) with a second land cover of typically grassland (Exx) or crops (Bxx). In the 2018 LUCAS survey the EUNIS habitat information was included to explicitly record those types of traditional agroforestry. The below table shows the relevant LUCAS parameters for the aggregation into a forest and no-forest class which is compliant with the HRL forest definition. The output is an aggregated forest class (Forest_Ref) which classifies each LUCAS sample point into “forest” and “no forest”.

Table 21: LUCAS parameter for FTY forest definition

HRL Forest type definition		LUCAS survey parameters	
Parameter	Defined value	Parameter	Relevant values / thresholds
Canopy Cover	> 10 %	Land cover	All areas covered by trees with a canopy of > 10 % are defined as Woodland: LC = CXX
Area size	> 0,5 ha	Parcel area (ha)	Area size 0.5 ≤ area < 1 or higher
Width of feature	> 20 m In 2018 this is changed to 10m (1 pixel)	Width of feature	≥ 20m
Min. height of trees at maturity	> 5m	Height of trees at maturity	≥ 5m
Traditional Agroforestry	included (e.g. Dehesa / Montado)	Second land cover (supported by EUNIS Complex in 2018)	LC2 = Bx is not excluded
Agricultural use (olive trees, fruit plantations, …)	excluded	Land cover	Only Cx class, Bx classes are exclude
Areas <0.5 ha without tree cover inside forest area (firebreaks, roads, temporal clearings,..)	Included in forest	Not applicable	
All points with Land Cover 2 = Cx (Woodland) are removed as only occurring in special cases with superimposing structures such as powerlines, bridges, viaducts, etc.			

The table below shows the total number of LUCAS points classified to the aggregated forest class per country and for the reference year 2015 and 2018.

Table 22: Number of LUCAS points aggregated to forest and no-forest class for 2015 and 2018

	2015		2018	
LUCAS 2015	no forest	forest	no forest	forest
DE	19,019	7,570	19,478	7,290
ES	33,783	16,492	29,972	15,329
RO	11,165	5,554	13,168	3,554
SE	9,774	16,864	12,981	13,706

Further details are provided in the DLV1.4_EO_4_Statistics_Estimation_Routines_Scripts and DLV1.3 Meta data description.

The LUCAS parameter allows to easily create a thematic match following the definition of the HRL forest product. An unsolved difference is in the minimum mapping unit. The HRL Forest product uses a minimum mapping unit of 0.5 ha for areas inside a forest. This means that areas inside a forest without tree cover are included to the forest as long as they are smaller than 0.5ha. In the LUCAS survey, land cover and land use are recorded if the area is larger than 3x3 meters. It is therefore possible that a LUCAS point located on a plot of e.g. grassland < 0.5 ha and surrounded by forest is classified as forest in the HRL. The example in Figure 33 shows a LUCAS point located on a patch of grassland which is classified as forest in the HRL FTY layer. How many of these cases exist is not known.

Google Earth Pro © CNES/Airbus 2021

Figure 33: Example for LUCAS point located in a small grassland inside a forest, which is included in the HRL FTY as forest

4.2.1.2 LUCAS aggregated artificial class

To be compliant with the HRL IMD product the LUCAS parameters are aggregated to an "aggregated artificial class" which follows the definition of imperviousness in the IMD definition. The assumption is that this aggregated artificial class reflect an IMD threshold of >=30%. The definition of impervious area from the IMD shown in Table 4 is compared to the LUCAS nomenclature.

In general all artificial land cover classes from the LUCAS survey are considered as impervious with the following exceptions:

- LUCAS points on roads with non-sealed surface such as sand or dirt tracks are considered as non-impervious. For example sandy forest roads in Sweden.
- Railway tracks outside of urban area are considered as non-impervious following the definition of the IMD.
- Dump sites are considered as non-impervious
- Points under a superimposed structure, such as electrical lines, bridges, etc. are excluded if the second land cover belongs to non-artificial LUCAS class

The definition of the IMD does not provide further information on what kind of roads are included in the impervious definition and if roads with non-sealed surfaces are excluded or not. An analysis of the 779 artificial non-built up (A21 & A22) LUCAS points 2018 from Sweden showed that 292 have a second non artificial land cover. Most of them are roads or parking areas with non-sealed surfaces such as sand, bare soil or grass and belong to the forest track network. An initial comparison with the corresponding IMD 2018 pixel values showed that out of the 292 cases 250 are classified as non-impervious and 21 as impervious in the IMD 2018. In 21 cases the corresponding pixels were impervious and non-impervious. This supported the decision to exclude roads with un-sealed surface from the aggregated artificial class, in favour of the validation of the IMD products.

The table below shows the total number of available LUCAS points aggregated to the artificial classes per country and for the reference 2015 and 2018.

Table 23: Number of LUCAS points aggregated to impervious and non-impervious artificial classes for 2015 and 2018

	2015		2018	
LUCAS	impervious	non-impervious	impervious	non-impervious
DE	1,701	24,802	1,910	24,848
ES	1,231	46,618	1,947	43,350
RO	312	16,407	631	16,082
SE	353	26,280	767	25,920

The output is an aggregated artificial class (IMD_Ref) which classifies each LUCAS sample point into “artificial” and “non artificial” in compliance with the HRL IMD definition.

Further details are provided in the DLV1.4_EO_4_Statistics_Estimation_Routines_Scripts and DLV1.3 Meta data description.

4.2.1.3 Verification of LUCAS land cover extent

The HRL products use the same European grid as synthetically confectioned product cells as the LUCAS sampling frame. These product cells do not necessarily correspond to the actual pixel location of the employed satellite sensors, e.g. Sentinel 1 or 2. The theoretical LUCAS point is located at the corner of these HRL product cells, see Figure 34 and Figure 35. The 1.5m radius of the theoretical LUCAS point intersects with 4 HRL pixel-cells, not considering any positional inaccuracies of the HRL or the LUCAS observation.

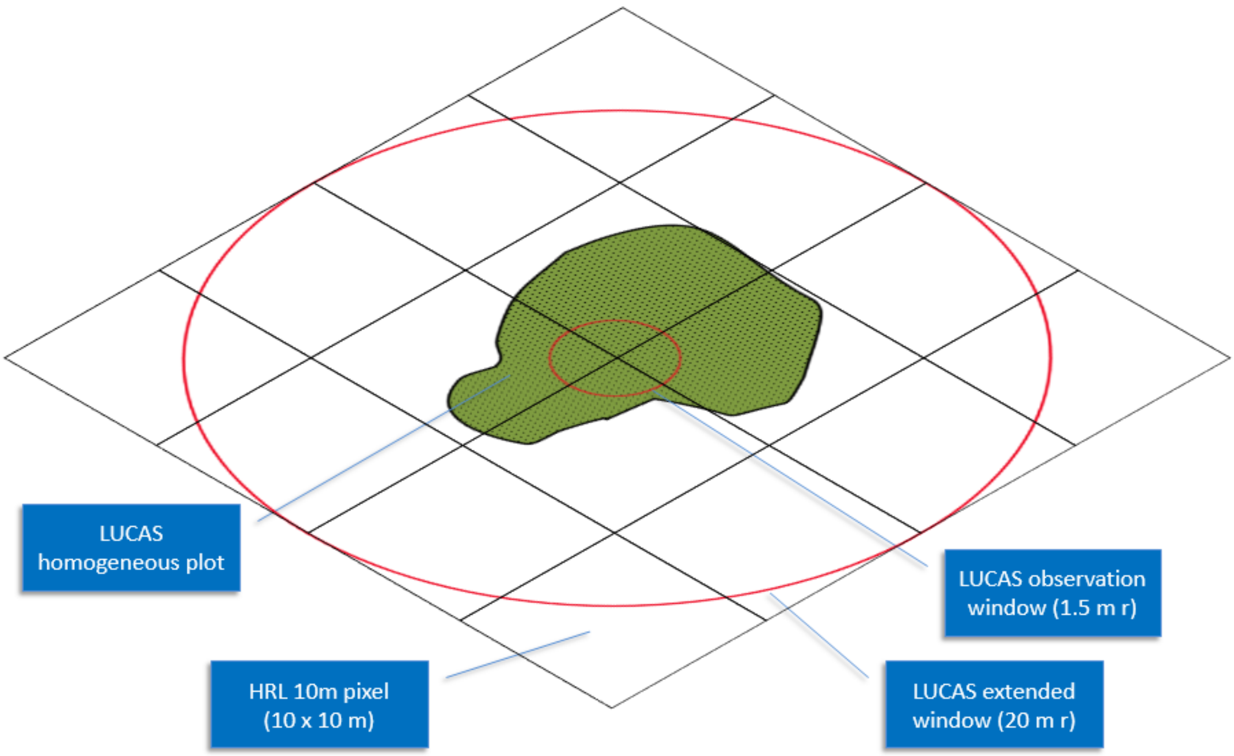


Figure 34: LUCAS observation radius, extended window of observation and HRL pixel grid

The LUCAS observation radius of 1.5m is extended to 20 meter when the land cover at the point is heterogeneous, but only within the plot where the point is located (homogenous plot), see Figure 11.

Figure 35 shows an example of a LUCAS point close to the border between woodland and agricultural field. The LUCAS observation will only cover the land cover of the plot where the point is located, in the example, the agricultural field.

Three cases are possible:

1. The LUCAS point is located inside a land cover plot and the same land cover extents in all directions over the extended observation radius of 20m and covering the HRL pixel cells.

2. The LUCAS point is located close to a land cover border and the 20m radius extents over the land cover border, in this case the LUCAS observation will only cover the land cover of the homogenous plot. The distance to the next land cover border from the LUCAS point position is not recorded as a standard parameter.

3. The LUCAS point is directly located on a border or element with minimum width < 3m, in this case the observation is shifted following a fixed rule (look to the north and look to the east in case of north-south direction of the border/linear element), in this cases the information of the plot north or east of the LUCAS point is recorded. The direction (north or east) in which the observation is shifted is recorded in the meta data of the point.

Case 2 and 3 can create a mismatch between the LUCAS point information and the corresponding pixels of the 10m or 20m HRL products when the LUCAS point is on or close to a land cover border.

An automated analysis of the LUCAS landscape photos to detect change in a certain distance could possibly support the applicability of the LUCAS data for EO applications.

The new Copernicus Module records the extent of the land cover in the cardinal directions which addresses exactly these cases. It was introduced in 2018, but only on a subsample of LUCAS points and only if certain survey conditions applied, LUCAS point had to be visible, and the land cover had to extent for a minimum of 5 meters in each direction. Further, the information was recorded at the position of the surveyor and might not apply to the same land cover characteristics as on the point. This further reduced the number of observation in particular for artificial land cover which are usually very fragmented (see d'Andrimont et al. 2020). For the selected 4 countries out of the around 115.000 surveyed points, on about 21,413 Copernicus observations were done, but only 91 in artificial area. For future LUCAS campaigns this component should be extended (see recommendations in chapter 7).

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Figure 35: LUCAS point (1.5m) and 20m observation radius compared to the HRL 10m pixels of the HRL forest product.

In order to find a practical solution to improve the spatial applicability of the LUCAS data for the use with the HRL, a verification process is suggested, guided by the following practical assumptions:

- LUCAS points intersecting with 4 pixels from the same HRL class (e.g. forest) are assumed to be spatially comparable and no action is required. The value from the 4 pixels is compared to the LUCAS aggregated class to build the confusion matrix.
- The LUCAS Copernicus polygons, wherever available, are used to verify the land cover extent at the LUCAS points and to build a 1:1 relation between reference information and pixel value.
- LUCAS points recorded as being on a land cover border or linear element are marked as "to be verified".

- All LUCAS points intersecting with more than one HRL Map class value are marked as "unclear".in the corresponding Map value. In the analysis a weight of 0.5 is assigned to this sample units to consider that about half of the pixels match with the reference data.

The example in Figure 36 illustrates the verification process using the Copernicus polygons. It shows the extent of the land cover derived from the Copernicus polygon around the position of the surveyor (red). The HRL pixels falling completely within the Copernicus polygon are highlighted in blue. For the assessment only the pixels (marked with green x) which fall completely in the Copernicus polygon and are within 10m to the position of the surveyor (Copernicus point) are used. In case no HRL pixel falls completely within the Copernicus polygon, only those pixels are selected where the centroid of the pixel falls inside the polygon.

The pixel values of the selected pixels provide the Map value to be compared with the aggregated reference class.

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Figure 36: Example for the verification process using Copernicus polygons and HRL Forest map.

In case the selected pixels in the Copernicus polygon have different values (e.g. "forest" and "no forest") the map value is set to "unclear".

In 1,412 cases out of 21,413 the LUCAS Copernicus observation was done on a different land cover than the LUCAS core observation and /or the LUCAS point is not located within the Copernicus polygon. In those cases the LUCAS parameters do not apply to the Copernicus polygon and only the main land cover class recorded at the Copernicus point is recorded (see d'Andrimont et al. 2020). Those polygons have not been used since the full thematic comparability with the HRL definition could not be applied (see recommendations in chapter 7).

A verification process was applied to the LUCAS points in the 22 NUTS2 regions for 2015 using a rapid assessment approach based on visual interpretation. An assessment of the remaining points and for 2018 was not realised. In the verification process it is recorded if the land cover (forest, artificial or other) of the aggregated LUCAS point extents over the pixel position of the HRL. The land cover class of the LUCAS point remains unchanged. The output is the information which of the 4 HRL pixel cells units is located in the same land cover as the LUCAS point. For imperviousness the 30% threshold (proportion of artificial surface in the pixel is used) and for forest the definition and minimum mapping units are considered. The interpretation is based on free available Sentinel-2 data from 2015 / 2016, ESA VHR 2015 imagery provided within this project and open accessible map service Google Earth as main reference and other open accessible map services such as Bing maps and Esri Imagery as supportive data. The AcATaMa - QGIS plugin for Accuracy Assessment of Thematic Maps[23] was used for this assessment.

[23] https://smbyc.github.io/AcATaMa/

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Figure 37: LUCAS land cover extent rapid verification approach using QGIS plugin.

The example above shows a LUCAS point classified as cropland and located close to the border of forest. In the verification process the southern HRL units are marked as belonging to the same land cover class and will be used for the comparison with the HRL units.

In the 22 selected NUTS2 regions for a total of 4,179 points the extent of the land cover has been verified, for 337 points the extent could not be verified.

This verification is suggested for the entire dataset, but was not realised in this project. The table below shows the number of points where the LUCAS point intersects with more than one different pixel value.

Table 24: Number of LUCAS points intersecting with different HRL pixel values

	2015		2018	
	Different HRL pixel values	Total	Different HRL pixel values	Total
DE	1,835	26,589	782	26,768
ES	4,080	50,275	2,545	45,301
RO	800	16,719	497	16,722
SE	2,614	26,638	1,812	26,687

The LUCAS points where no 1:1 relation between point and pixel value could be established, are marked as “unclear”. These points are assigned a weight factor of 0.5 for the accuracy assessment. They contribute with half their weight to the correct and half weight to the error. This can create a bias in the estimates but was considered a better option than excluding these sample units. In particular for 2015 the comparison of the LUCAS point (minimum 3m in diameter) with 4 pixels from the HRL (in total 40x40m) can create a bias. How far this affects the estimates of accuracy particular for heterogeneous landscapes remains unclear. As already mentioned, LUCAS survey modules which record land cover or land cover proportions within a fixed or clearly defined spatial unit and a clear sampling design should be extended in future survey campaigns (see recommendations in chapter 7).

4.2.2 Accuracy estimation - Indicator function and ratio estimator

4.2.2.1 Forest 2015 and 2018

This chapter describes the results from the accuracy estimation by means of indicator functions of LUCAS survey data 2015 and 2018 using the method described in chapter 3.2.5. Please note that although we calculated confusion matrices and accuracy parameters between the chosen HRL maps and the LUCAS data these are not aimed to be a product validation (which is provided by EEA only). The assessment aims to explore the applicability of the LUCAS data for HRL validation and demonstrate the workflow. Limitations of this approach are discussed in chapter 5.4.1.

The result from the accuracy assessment for the countries is provided in Table 25.

Table 25: Accuracy assessment of HRL forest type FTY 2015 and 2018 using LUCAS survey data

AOI	**2015**	**Number LUCAS points**		**FTY forest**		**FTY no forest**		**Overall accuracy**
NUTS ID	NUTS Name	Total	Forest	UA	PA	UA	PA	OA
DE	Germany	26,589	7,531	82.8%	95.6%	97.9%	91.3%	92.6%
ES	Spain	50,275	15,512	67.8%	80.5%	91.0%	83.7%	82.7%
RO	Romania	16,719	5,554	87.6%	94.8%	97.4%	93.6%	94.0%
SE	Sweden	26,638	16,864	89.0%	86.5%	79.9%	83.4%	85.3%

AOI	**2018**	**Number LUCAS points**		**FTY forest**		**FTY no forest**		**Overall accuracy**
NUTS ID	NUTS Name	Total	Forest	UA	PA	UA	PA	OA
DE	Germany	26,768	7,279	90.7%	95.6%	97.9%	95.4%	95.5%
ES	Spain	45,301	15,285	81.1%	78.2%	89.6%	91.1%	86.9%
RO	Romania	16,722	3,500	89.6%	94.9%	97.4%	94.6%	94.7%
SE	Sweden	26,687	13,694	93.8%	88.8%	83.4%	90.6%	89.5%

In general the accuracy is higher in 2018 than in 2015, possibly due to the higher FTY resolution of 10m in 2018 and improved input data situation with Sentinel-2 data. The lowest accuracies are in both years in Spain. In 2015, except for Sweden, the user's accuracy (UA) is lower than the producer's accuracy (PA) indicating an over estimation of forest area in the map.

The results from the accuracy assessment of the HRL Forest type 2015 and 2018 using LUCAS aggregated forest class for the 22 selected NUTS2 regions are provided in Table 26 and Table 27.

Table 26: Accuracy assessment of FTY2015 using aggregated LUCAS survey data

AOI	2015	Total area	FTY 2015 - pixel counts	Number LUCAS sample units		FTY - forest		FTY - no forest		Overall accuracy
NUTS ID	NUTS Name	km²	prop	Total	Forest	UA	PA	UA	PA	OA
DE13	Freiburg	9,402	0.48	600	199	87.9%	95.3%	96.2%	90.0%	92.3%
DE14	Tuebingen	9,136	0.34	644	161	87.7%	97.2%	98.5%	93.0%	94.4%
DE21	Oberbayern	17,531	0.38	1,426	494	84.1%	96.0%	98.0%	91.3%	92.8%
DE40	Brandenburg	29,654	0.38	2,379	939	90.8%	96.5%	97.9%	94.3%	95.1%
DE71	Darmstadt	7,444	0.44	539	220	87.0%	98.7%	98.9%	89.2%	93.2%
DE73	Kassel	8,290	0.45	566	197	85.2%	98.6%	98.9%	87.9%	92.3%
DE91	Braunschweig	8,122	0.36	610	212	88.0%	99.1%	99.5%	92.3%	94.8%
DE94	Weser-Ems	14,987	0.16	1,156	163	79.8%	90.5%	98.3%	96.1%	95.2%
DEA1	Duesseldorf	5,293	0.18	384	51	53.6%	98.2%	99.6%	85.7%	87.5%
DEA2	Koeln	7,366	0.33	506	105	72.2%	96.6%	98.4%	84.9%	88.3%
DEA3	Muenster	6,920	0.17	520	101	83.5%	89.3%	97.9%	96.6%	95.4%
DEB2	Trier	4,928	0.49	336	112	73.2%	98.3%	98.7%	78.2%	85.8%
DEB3	Rheinhessen-Pfalz	6,851	0.40	476	132	87.7%	99.0%	99.4%	91.8%	94.5%
DEE0	Sachsen-Anhalt	20,553	0.24	1,606	395	84.6%	94.8%	98.3%	94.5%	94.6%
ES43	Extremadura	41,631	0.39	3,941	1,163	67.5%	78.4%	88.6%	81.6%	80.6%
ES51	Catalunia	32,113	0.48	3,282	1,391	76.7%	90.2%	91.6%	79.8%	84.2%
ES52	Comunidad Valenciana	23,261	0.30	2,055	548	53.4%	78.4%	89.4%	72.7%	74.3%
RO12	Centru	34,107	0.49	2,422	1,075	89.8%	95.3%	96.0%	91.3%	93.1%
RO21	Nord-Est	36,851	0.37	2,619	950	91.2%	95.7%	97.7%	95.1%	95.4%
RO41	Sud-Vest Oltenia	29,207	0.35	2,044	689	86.4%	95.8%	97.8%	92.6%	93.7%
SE12	Oestra Mellansverige	43,298	0.57	3,047	1,827	92.1%	91.1%	88.1%	89.4%	90.4%
SE31	Norra Mellansverige	72,023	0.66	4,747	3,472	93.1%	87.6%	74.3%	84.6%	86.7%

The lowest results are in Spain and in the western NUTS2 regions in Germany. In most AOIs the forest class has a lower accuracy than the no-forest class, an exception is Sweden. The user's accuracy of forest is in all AOIs lower than the producer's accuracy, which indicates and over estimation of forest area in the HRL map. As mentioned in chapter 4.2.1.3 there are limitations in the spatial compatibility of the LUCAS sample unit with the HRL pixels, which might create an unknown bias in the assessment.

Table 27: Accuracy assessment of FTY 2018 using aggregated LUCAS survey data

AOI	2018	Total area	FTY 2018 - pixel counts	Number LUCAS sample units		FTY - forest		FTY - no forest		Overall accuracy
NUTS ID	NUTS Name	km²	prop	Total	Forest	UA	PA	UA	PA	OA
DE13	Freiburg	9,402	0.49	457	151	95.0%	98.1%	98.4%	95.8%	96.8%
DE14	Tuebingen	9,136	0.37	589	162	92.7%	94.4%	97.2%	96.3%	95.6%
DE21	Oberbayern	17,531	0.39	993	228	89.0%	94.4%	96.7%	93.4%	93.7%
DE40	Brandenburg	29,654	0.39	2,171	597	93.1%	94.3%	96.6%	95.9%	95.3%
DE71	Darmstadt	7,444	0.48	517	231	94.9%	94.6%	95.8%	96.1%	95.4%
DE73	Kassel	8,290	0.47	663	282	91.1%	96.7%	97.5%	93.1%	94.6%
DE91	Braunschweig	8,122	0.39	704	191	94.2%	95.3%	96.9%	96.2%	95.8%
DE94	Weser-Ems	14,987	0.16	1,274	192	84.9%	92.7%	98.7%	97.0%	96.4%
DEA1	Duesseldorf	5,293	0.26	430	90	83.9%	84.2%	96.6%	96.5%	94.3%
DEA2	Koeln	7,366	0.37	522	154	84.8%	94.4%	97.6%	93.2%	93.5%
DEA3	Muenster	6,920	0.22	718	101	83.5%	89.3%	97.9%	96.6%	95.4%
DEB2	Trier	4,928	0.49	309	117	86.3%	98.1%	98.5%	88.9%	92.7%
DEB3	Rheinhessen-Pfalz	6,851	0.41	390	180	94.6%	99.5%	99.7%	96.6%	97.7%
DEE0	Sachsen-Anhalt	20,553	0.26	1,769	337	90.4%	93.0%	97.8%	97.0%	96.1%
ES43	Extremadura	41,631	0.41	3,454	1,359	77.5%	81.6%	88.5%	85.6%	84.1%
ES51	Catalunia	32,113	0.52	2,338	820	86.3%	88.6%	89.3%	87.2%	87.9%
ES52	Comunidad Valenciana	23,261	0.41	2,163	823	72.8%	66.6%	83.7%	87.4%	80.4%
RO12	Centru	34,107	0.47	3,007	787	90.4%	95.7%	96.0%	91.0%	93.2%
RO21	Nord-Est	36,851	0.36	2,820	532	87.5%	96.7%	98.3%	93.1%	94.3%
RO41	Sud-Vest Oltenia	29,207	0.37	2,256	470	92.8%	93.3%	96.5%	96.2%	95.2%
SE12	Oestra Mellansverige	43,298	0.56	3,506	1,818	93.9%	92.9%	90.5%	91.8%	92.4%
SE31	Norra Mellansverige	72,023	0.66	5,538	4,033	95.5%	89.4%	76.9%	89.3%	89.4%

In 2018 the accuracy is in all AOIs higher than in 2015, possibly related to the input of Sentinel-2 data and the higher resolution of 10m. As in 2015 the lowest accuracies are reached in Spain. In general the difference between user's and producer's accuracy is lower than in 2015. This indicates that the bias of the area from pixel counting is lower in 2018 than in 2015. Equal producer's and user's accuracy implies that the proportion of forest classified as no forest is the same as the proportion of no forest classified as forest and the errors in both classes are outbalancing each other. This is explored further in chapter 5.

4.2.2.2 Imperviousness 2015 and 2018

The result from the accuracy assessment of the IMD 2015 and 2018 using LUCAS survey data for the countries is provided in Table 28.

Table 28: Accuracy assessment of the HRL Imperviousness density (IMD) 2015 and 2018 for the selected countries

2015	Number LUCAS sample units		IMD - impervious (>=30%)		IMD - non-impervious (<30%)		Overall accuracy
AOI	Total	artificial	UA	PA	UA	PA	OA
Germany	26,589	1,700	62.94%	63.74%	97.57%	97.48%	95.36%
Spain	50,275	1,231	75.68%	45.58%	98.39%	99.56%	97.99%
Romania	16,719	312	56.84%	46.19%	98.97%	99.33%	98.33%
Sweden	26,638	353	62.25%	30.85%	99.24%	99.79%	99.04%

2018	Number LUCAS sample units		IMD - impervious (>=30%)		IMD non-impervious (<30%)		Overall accuracy
AOI	Total	artificial	UA	PA	UA	PA	OA
Germany	26,768	1,910	68.9%	71.0%	97.9%	97.7%	95.9%
Spain	45,301	1,947	74.1%	47.4%	98.4%	99.5%	97.9%
Romania	16,722	631	63.1%	57.7%	99.1%	99.3%	98.4%
Sweden	26,687	767	61.1%	45.3%	99.4%	99.7%	99.1%

The results show a very low accuracy for the impervious class in 2015 and 2018. No accuracy value is above 80 %. The low accuracy values are confirmed in the assessment using the EO-4-Statatistics reference data (see chapter 4.3.3). The results from the accuracy assessment of the HRL Imperviousness density 2015 and 2018 using LUCAS artificial class for the 22 selected NUTS2 regions are provided in Table 29 and Table 30.

Table 29: Accuracy assessment HRL Impervious density (IMD) 2015 using LUCAS survey data

AOI	2015	Total area	IMD 2015 - pixel counts	Number LUCAS sample units		IMD impervious (>=30%)		IMD non-impervious		Overall accuracy
NUTS ID	NUTS Name	km²	prop.	Total	agg. artificial	UA	PA	UA	PA	OA
DE13	Freiburg	9,402	0.06	600	42	61.8%	64.4%	97.9%	97.7%	95.8%
DE14	Tuebingen	9,136	0.06	644	50	65.0%	59.2%	97.0%	97.7%	95.0%
DE21	Oberbayern	17,531	0.06	1,426	84	71.2%	69.3%	97.9%	98.1%	96.2%
DE40	Brandenburg	29,654	0.04	2,379	68	49.6%	59.4%	98.6%	98.0%	96.7%
DE71	Darmstadt	7,444	0.11	539	51	73.0%	79.6%	97.8%	96.8%	95.2%
DE73	Kassel	8,290	4.9%	566	39	79.1%	53.4%	96.9%	99.0%	96.2%
DE91	Braunschweig	8,122	6.3%	610	43	78.7%	62.4%	97.0%	98.6%	95.9%
DE94	Weser-Ems	14,987	6.2%	1,156	65	64.4%	64.5%	97.6%	97.6%	95.5%
DEA1	Duesseldorf	5,293	0.20	384	78	75.4%	82.6%	95.9%	93.8%	91.7%
DEA2	Koeln	7,366	0.12	506	65	68.3%	65.3%	95.5%	96.1%	92.6%
DEA3	Muenster	6,920	0.10	520	55	68.0%	60.4%	95.5%	96.7%	92.9%
DEB2	Trier	4,928	0.04	336	20	71.7%	43.9%	96.7%	99.0%	95.9%
DEB3	Rheinhessen-Pfalz	6,851	0.08	476	45	67.5%	65.0%	97.0%	97.3%	94.7%
DEE0	Sachsen-Anhalt	20,553	0.05	1,606	66	56.4%	63.8%	98.3%	97.8%	96.3%
ES43	Extremadura	41,631	0.01	3,941	53	70.7%	38.0%	99.1%	99.8%	98.9%
ES51	Catalunia	32,113	0.03	3,282	160	85.2%	48.4%	96.9%	99.5%	96.6%
ES52	Comunidad Valenciana	23,261	0.04	2,055	115	78.3%	44.5%	96.7%	99.2%	96.0%
RO12	Centru	34,107	0.01	2,422	37	58.2%	45.9%	99.2%	99.5%	98.7%
RO21	Nord-Est	36,851	0.02	2,619	46	56.9%	47.2%	99.0%	99.3%	98.3%
RO41	Sud-Vest Oltenia	29,207	0.02	2,044	36	55.4%	47.4%	99.1%	99.3%	98.4%
SE12	Oestra Mellansverige	43,298	0.01	3,046	64	75.2%	31.8%	98.6%	99.8%	98.4%
SE31	Norra Mellansverige	72,023	0.01	4,747	51	73.4%	35.5%	99.4%	99.9%	99.3%

The accuracy assessment shows a quite low accuracy for the 2015 IMD map, in some AOIs below 50%. Again this might be partly related to the different spatial units when comparing the HRL units with LUCAS point information. The accuracy improves in 2018 in all AOIs, but is still low in particular for the producer's accuracy. Highest accuracies are reached in both years in Germany, probably related to less fragmented artificial areas and in general a higher proportion of artificial area.

Table 30: Accuracy assessment HRL Imperviousness density (IMD) 2018 using LUCAS survey data

AOI	2018	Total area	IMD 2018 - pixel counts	Number LUCAS sample units		IMD impervious (>=30%)		IMD non-impervious		Overall accuracy
NUTS ID	NUTS Name	km²	prop.	total	agg. artificial	UA	PA	UA	PA	OA
DE13	Freiburg	9,402	0.07	457	39	53.3%	82.6%	99.1%	96.2%	95.6%
DE14	Tuebingen	9,136	0.07	589	53	68.6%	69.9%	98.1%	98.0%	96.3%
DE21	Oberbayern	17,531	0.07	993	98	73.4%	70.3%	97.8%	98.1%	96.2%
DE40	Brandenburg	29,654	0.04	2,171	85	58.9%	68.6%	98.7%	98.1%	97.0%
DE71	Darmstadt	7,444	0.12	517	59	79.5%	85.1%	98.3%	97.5%	96.2%
DE73	Kassel	8,290	0.05	663	36	77.1%	71.8%	98.4%	98.8%	97.4%
DE91	Braunschweig	8,122	0.06	704	50	85.9%	77.1%	98.4%	99.1%	97.7%
DE94	Weser-Ems	14,987	0.07	1,274	85	71.2%	74.7%	97.9%	97.6%	95.8%
DEA1	Duesseldorf	5,293	0.20	430	79	67.3%	82.7%	95.2%	89.5%	88.1%
DEA2	Koeln	7,366	0.13	522	70	65.2%	72.1%	96.0%	94.5%	91.8%
DEA3	Muenster	6,920	0.11	718	67	74.2%	61.6%	93.7%	96.4%	91.3%
DEB2	Trier	4,928	0.04	309	16	59.8%	49.2%	97.7%	98.5%	96.3%
DEB3	Rheinhessen-Pfalz	6,851	0.09	390	50	84.0%	66.9%	95.8%	98.4%	94.8%
DEE0	Sachsen-Anhalt	20,553	0.05	1,769	81	64.4%	69.6%	98.6%	98.2%	97.0%
ES43	Extremadura	41,631	0.01	3,454	85	85.1%	43.9%	99.1%	99.9%	99.0%
ES51	Catalunia	32,113	0.04	2,338	193	76.1%	52.7%	97.5%	99.1%	96.7%
ES52	Comunidad Valenciana	23,261	0.04	2,163	160	81.7%	50.6%	96.7%	99.2%	96.1%
RO12	Centru	34,107	0.02	3,007	97	75.2%	56.8%	99.0%	99.6%	98.6%
RO21	Nord-Est	36,851	0.02	2,820	79	56.2%	54.9%	99.1%	99.2%	98.4%
RO41	Sud-Vest Oltenia	29,207	0.02	2,256	86	58.0%	64.8%	99.3%	99.1%	98.5%
SE12	Oestra Mellansverige	43,298	0.01	3,506	128	54.0%	41.4%	98.8%	99.3%	98.1%
SE31	Norra Mellansverige	72,023	0.01	5,538	91	56.9%	41.8%	99.4%	99.7%	99.1%

The overall accuracy is in both years very high, but this is related to the high proportion of correct classified non-impervious area in the AOIs. For the assessment of the accuracy of the IMD, the overall accuracy is not a suitable measure.

LUCAS artificial point in 2015 and 2018 and IMD 2015 (left) and IMD 2018 (right) with threshold 30% (red colours) scale 1:1000 *Google Earth © CNES/Airbus 2021 (Image date 18.09.2018)*

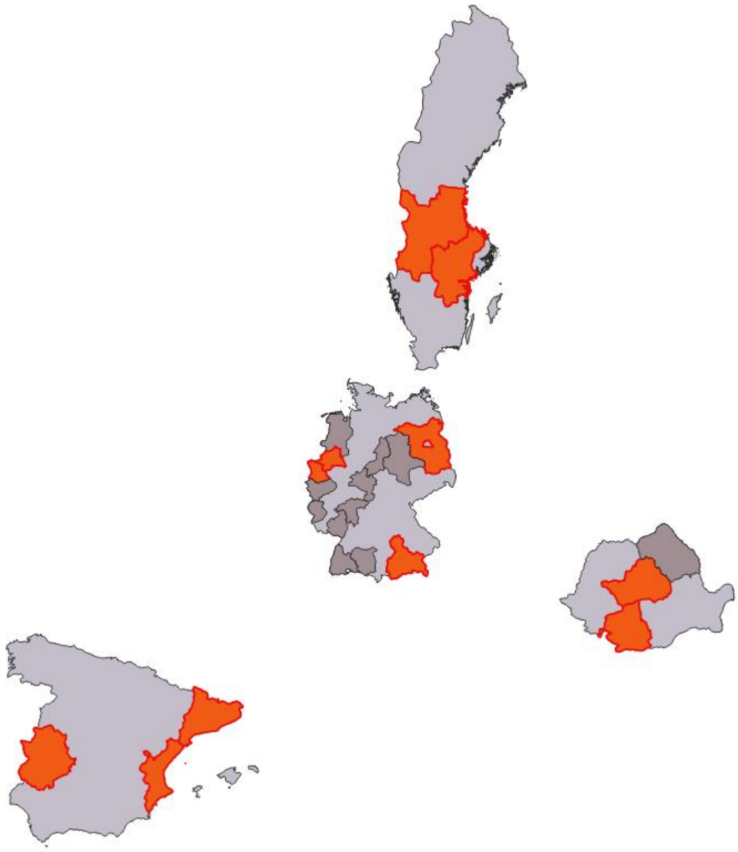
Figure 38: LUCAS artificial point and imperviousness density 2015 and 2018

The example in Figure 38 shows a LUCAS point classified as artificial in 2015 and 2018 and the IMD 2015 and 2018 with a 30% threshold (red colours). The LUCAS point is located on a house, in the IMD 2015 it is classified as non-impervious and in 2018 as impervious >30%.

4.3 Accuracy and area estimation using EO-4-Statistics reference data

New reference data was created for the TCCM1518 and IMC1518 on NUTS2 level as this is not covered by the other reference datasets.

In addition it was agreed to create new reference data to estimate accuracy and area for selected AOIs for FTY 2015 and 2018 and IMD 2015 / 2018 in order to demonstrate a different sampling and estimation approach. Out of the 22 NUTS2 regions 11 were selected to create an independent assessment with new reference data. The NUTS2 regions were selected based on the following considerations: at least two from each country, considering different landscapes and proportions of the maps classes in the AOIs, different sizes of the AOIs and available resources for the interpretation of reference data.



DE21	Oberbayern
DE40	Brandenburg
DEA1	Duesseldorf
DEA3	Muenster
ES43	Extremadura
ES51	Catalunia
ES52	Comunidad Valenciana
RO12	Centru
RO41	Sud-Vest Oltenia
SE12	Oestra Mellansverige
SE31	Norra Mellansverige

Administrative boundaries: © EuroGeographics

Figure 39: NUTS2 regions (in red) selected for assessment with new reference data.

4.3.1 Sample design considerations

For the creation of the sampling design different options where considered:

Using the LUCAS Frame as sampling frame in a systematic stratified approach. The advantage would have been to use already available ground information from the survey 2015 and 2018 for possibly a considerable part of the selected sample units. This was discarded since both other reference datasets use a systematic approach linked to the LUCAS data.

Since the HRL products shared the same European grid, it was considered to combine the HRL maps from Forest and Imperviousness and the Change maps to create a single dataset e.g. for Imperviousness 2015 and 2018 and change. The idea behind is to reduce the number of strata to be sampled and thus reducing the number of needed sample units. Due to the product definition and the change of the resolution from

Status maps from 20m in 2015 to 10m in 2018 this was not realised. The different HRL map classes are not exclusive. The same pixel classified as forest in the FTY can be Imperviousness in the IMD product. Similar to the change in the IMC1518 product, a pixel classified as non-impervious in 2015 corresponds to 4 pixels in the 2018 product. Due to the higher resolution e.g. linear objects such as roads are more likely captured as impervious. Thus a new approach was considered.

The sampling design was selected using the following considerations:

- simple random sampling without stratification is preferred as it is allows to use the same sample units for different map products
- stratified random sampling with the map class as strata to allocate sufficient sample units in rare classes
- sampling design suitable to use stratified estimators for area estimation
- a minimum number of 30 sample units per class for accuracy assessment
- sample units are the map pixels either 20m or 10m
- visual interpretation to create the reference data
- and available resources for the collection of reference observations.

Simple random sampling has the advantage that the sample can be used for all map products of the same NUTS2 AOI. The weights of the sample are proportional to the strata (map classes) and the design allows to add more sample units to improve the estimates if required.

For area estimation, proportional sampling such as simple random sampling provides the better results but requires a higher number of sample units. Equal allocation of sample units per map class is more suitable for targeting the user's accuracy (Olofsson et al. 2014).

The disadvantage of simple random sampling is that rare classes such as change classes or Imperviousness will not be covered with sufficient sample units unless the total number of sample units is very high. In those cases a stratified approach using the map classes as strata to identify the rare classes is more suitable.

There is no difference in the approach when estimating parameters for a small or a large AOI, the difference is more related to the proportion of the different map classes and presence of rare classes, such as change classes, which cover only a marginal part of the AOI. In a design based sampling approach each sample unit represents a proportion of the map class it is selected from. This is expressed in the sample weight which is a function of the proportion of the class from the AOI and the number of sample units selected from that class.

In a stratified sampling design all sample units selected from the same stratum have the same weight, represent the same map proportion. The higher the number of sample units in a class the lower the individual weight of a sample unit. The larger the map class the higher the individual sample weight. This means few sample units selected from a large map class (stratum) will have a much higher sample weight than the same number of sample units selected from a small map class. This can create a problem in case a sample unit selected from the large class, actually belongs to the rare class and the large weight of the sample unit is transferred to the estimate of the rare class. This can cause a considerable overestimation of the rare class caused by one single sample unit. Therefore it is very difficult to reliably estimate the area or accuracy of rare classes with a reasonable number of sample units. The same problem applies to the estimation of area of rare classes with too few sample units. For a reliable estimate the uncertainty (standard error) of the estimated area must be considerably smaller than the estimated area itself. An area estimate showing 500 km² of artificial area but with a standard error of +/-500km² has no meaningful output. Reducing the standard error can be achieved by either adding more sample units (to all classes) or by using better strata. I. e. better map classification. It is therefore the aim of the sampling design to find a balance between number of sample units and an acceptable uncertainty of the expected estimates.

For the TCCM1518 and IMC1518 with change classes covering in some AOIs <1% of the area a stratified random sampling with an equal number of 30 sample units per class was applied. This targets the accuracy assessment of the map classes. The minimum number of sample units per class was estimated using the formula for standard error of the user's accuracy provided in Olofsson et al. 2014. It allows to calculate the number of sample units required to reach a defined precision of the User's accuracy. It requires that the user's accuracy of the map classes are anticipated. For simplicity we assumed a user's accuracy of 90% for all classes in the change map and define the margin of error for the user's accuracy to be around +/- 10% under a 95% confidence level. This results in about 30 sample units per map class per AOI. The sample size was calculated using the SIGMA thematic map validation – QGIS plugin (see Haub et al. 2018).

For in total 22 NUTS2 regions, two change maps with each 4 classes a total of about 5,300 sample units were required.

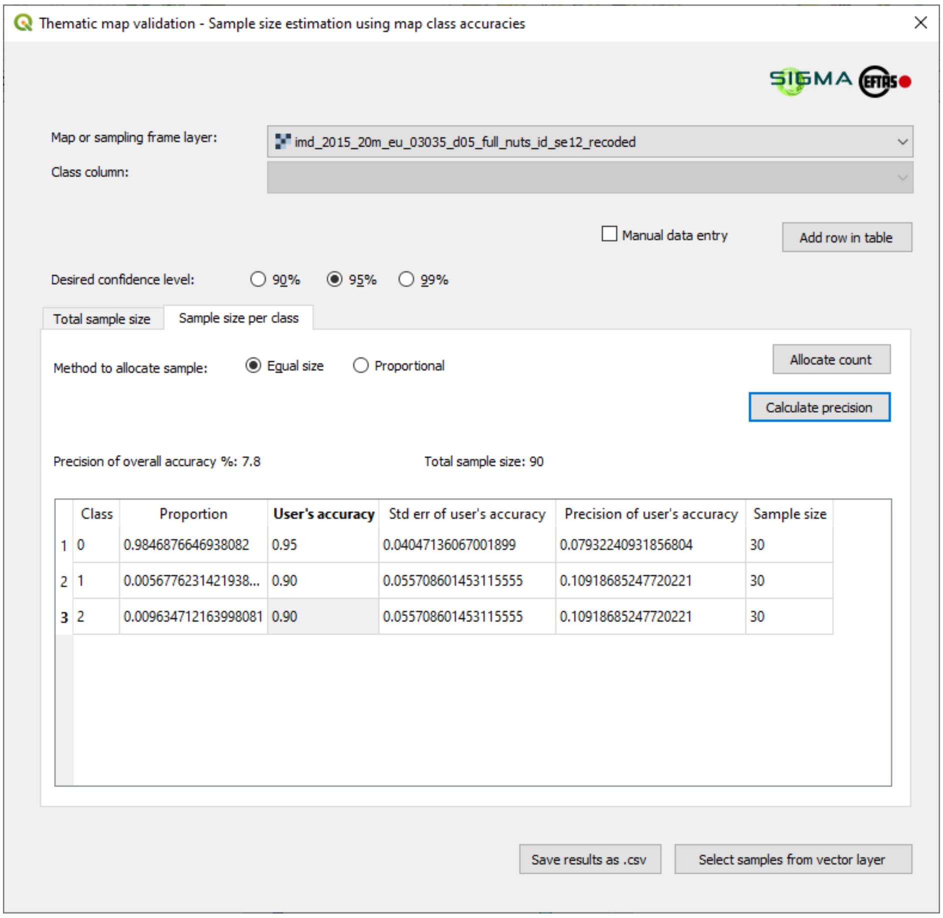


Figure 40: Estimating sample size for defined precision of UA using the SIGMA - Thematic map validation plugin for QGIS

For the Forest and Imperviousness map a simple random sampling design was applied. With the advantage that the same sample units can be used for the two reference years and for both maps.

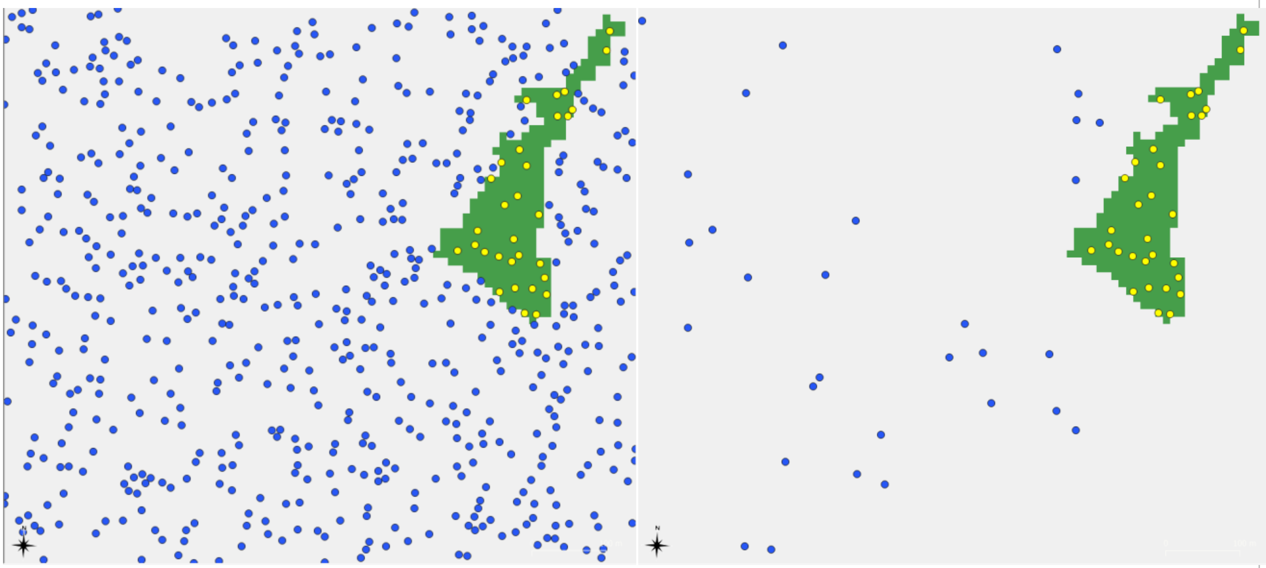
To estimate the number of required sample units again a minimum of 30 sample was defined per class to ensure reliable accuracy assessment (see above).

Random sampling means selecting randomly pixels in the AOI. The number of sample units per map class is therefore automatically proportional to the proportion of each map class in the AOI. That means to select 30 pixels from a map class which covers 10% of the AOI, about 300 random allocated pixels have to be selected from the entire map. In case a map class covers only 1%, a total of 3,000 sample units is required.

Based on this logic, it was decided for each HRL layer based on the proportion of the rarest class if a random sampling or a stratified sampling approach is applied.

The example in Figure 41 illustrates the concept of random sampling and stratified sampling when targeting rare classes.

In a simple random sampling each sample unit represents the same proportion of the map, but much more sample units are required to allocate 30 sample units in the rare class. In the stratified sampling design with equal number of sample units per strata, only 60 sample units are required to cover both classes with 30 sample units. In this approach the individual sample units in the rare class represent a smaller proportion of the map than the sample units in the large strata. Therefore the weight of the sample units in the large class are much higher. This can have a huge impact on the estimation results in case the reference interpretation reveals that a sample from the huge class belongs in fact to the rare class. An example is described in chapter 4.3.3.3.



Example: Random sampling, 700 sample units are required to allocate 30 sample units in the rare class.

Example: Stratified random sampling, the map classes are used as strata to allocate 30 sample units in each class (stratum).

Figure 41: Simple random sampling and stratified sampling

In addition to the minimum number of sample units per class, the selection of the number of sample units was guided to reach a target CV of the Forest area estimates to be comparable to the CV from the LUCAS estimates for forest and no-forest classes.

To calculate the required number of sample units to reach a defined target CV of forest area under a random sampling (SRS) equitation Eq 4.2 in Cochran (1977) is used:

$$n = \frac{p(1-p)}{{SE_p}^2}$$

where p is the proportion of forest in the AOI, SE_p is target standard error of the forest area estimate. The CV is the ratio of the standard error to the proportion of estimated forest area.

Table 31: Calculation of sample size under simple random sampling

NUTS ID	NUTS Name	Total area km²	Target CV forest area (%)	FTY 2018 forest area km²	FTY 2018 forest area proportion (p)	Target SE (forest) in km²	Target SE (forest) as proportion from total area	Sample size n under SRS
SE31	Norra Mellansverige	72,023	5.0%	47,850	0.664	2,393	0.033	205

The table provides an example how to calculate the required sample units to reach a target CV of 5% for a NUTS2 region with a high proportion of forest.

In the first step the target CV of the area estimate is calculated as a proportion of the forest area known from the FTY map. For SE31 in the example 47,850 *0.05 = 2,393 km²

The results are calculated as a proportion from the total area of the AOI: 2,393 / 72,023 = 0.033

To calculate the number of sample units required to reach this estimate under a simple random sampling design the above formula is used: $0.664 * (1-0.664) / 0.033^2 = 205$ sample units.

The sample units can be used to estimate area and accuracy for all HRL and map classes in the AOI and will meet a CV of 5% if the proportion of the map class is 0.66 or higher.

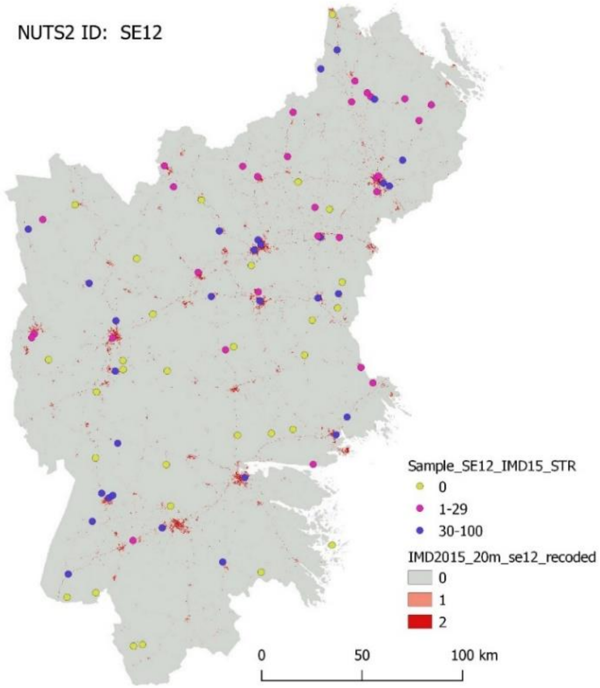
Table 32: Sample design applied to the AOIs

HRL product	Sampling design	AOIs
TCCM1518	Stratified sampling with 30 sample units per map class	22 NUTS2 regions
IMCC1518	Stratified sampling with 30 sample units per map class	22 NUTS2 regions
FTY 2015 & 2018	Simple random with minimum target CV of area estimate	11 NUTS regions
IMD 2015 & 2018	Simple random with minimum 30 sample units per class	DE21, DE40, DEA1, DEA3, ES51, ES52, RO41
IMD 2015 & 2018	stratified random with 30 sample units per map class (IMD-0, IMD1-29, IMD30-100)	ES43, RO12, SE12, SE31

The table below shows the number of sample units for the selected NUTS2 regions. The rows highlighted in green shared the same sample locations due to simple random sampling design.

Table 33: Number of sample units for Forest and Imperviousness accuracy and area assessment.

NUTS ID	AOI	FTY15	FTY18	IMD15	IMD18
DE21	Oberbayern	475	475	475	475
DE40	Brandenburg	700	700	700	700
DEA1	Duesseldorf	200	200	200	200
DEA3	Muenster	300	300	300	300
ES43	Extremadura	210	210	90 (STR)	90 (STR)
ES51	Catalunia	901	901	901	901
ES52	Comunidad Valenciana	815	815	815	815
RO12	Centru	210	210	90 (STR)	90 (STR)
RO41	Sud-Vest Oltenia	1880	1880	1880	1880
SE12	Oestra Mellansverige	211	211	90 (STR)	90 (STR)
SE31	Norra Mellansverige	210	210	90 (STR)	90 (STR)



Administrative boundaries: © EuroGeographics

Figure 42: Stratified random sample for IMD 2015 in AOI SE12

Using the map pixels as sample unit has some advantages:

- sample can be directly selected from the map and represents the resolution of the map
- size of the sample unit to be interpreted is small and interpretation is fast
- a direct 1:1 comparison to the pixel value is established for building the confusion matrix
- the sample size of 20x20m or 10x10m is suitable to record impervious surface as a proportion

Disadvantages of the pixel as sample unit are:

- If the imagery available for the interpretation is of poor quality or low resolution the interpretation of land cover proportions becomes difficult at this scale. VHR reference data in particular for capturing impervious area is required.
- Errors due to geolocation of the background imagery are likely at this scale. The imagery used to interpret the sample can be shifted compared to the HRL map. A positional error of +/- 0.5 -1 pixel is expected in the HRL products, this can lead to a positional shift of up to 10-20m. Care has to be taken and if possible different sources of imagery used, to identify shift and adjust accordingly. To reduce the effect of positional inaccuracy a larger sample unit should be selected. The Nyquist-Shannon sampling theorem provides guidance on the required size of a sample unit to adequately consider the resolution of the input signal (pixel resolution).

4.3.2 Reference data interpretation

The selected pixels were interpreted based on visual interpretation using free available Sentinel-2 data from 2018 and 2015 and 2016, ESA VHR 2015 imagery provided within this project and the open accessible map service Google Earth (including historical imagery) as main reference. Other open access map services such as Bing maps and Esri Imagery were displayed as supporting information.

Uncertainties in the acquisition dates of the open available VHR sources such as Google satellites were addressed by comparing with Sentinel-2 data with known acquisition dates and the “historical imagery function” in the Google Earth desktop application.

For the sample units where simple random sample was used, the parameters for HRL products are selected at the same location in the corresponding 10x10 or 20x20m segment.

For each segment the interpreter selected the confidence of his decision using a classification of “high”, “moderate”, “low”.

After the blind interpretation of the sample units a quality control of random selected points and plausibility checks was applied including all segments with confidence not “high” and all mismatches between interpretation and map. In case of errors the reference value was corrected.

To provide comparable estimates for area and for accuracy the definitions of the HRL was applied during the reference data interpretation. For the interpretation of samples for forest, this means that areas without tree cover surrounded by forest and smaller than 0.5 ha or with less than 20m width are classified as forest.

Forest 2015 and 2018 reference value: In the visual interpretation the sample unit is classified into “forest” or “no forest”, considering the HRL forest definition and 0.5ha MMU. To consider cases where a clear forest border is visible and only a part of the sample unit belongs to the forest class, the sample unit is classified based on the proportion of forest using three classes:

- 0-40% –> No Forest
- 41-59% -> Forest 0.5 (sample weight will be 0.5 for forest area estimation)
- 60-100% -> Forest

The class 41-59% is for cases where the forest covers about half of the sample unit with no clearly visible majority for either the forest or the no forest class. For those mixed pixel cases a weight of 0.5 is applied in the analysis to consider that about half of the sample unit actually belongs to the other class.

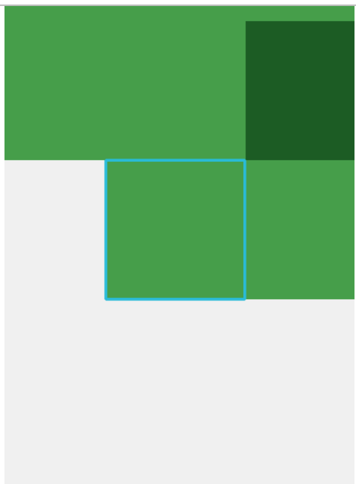
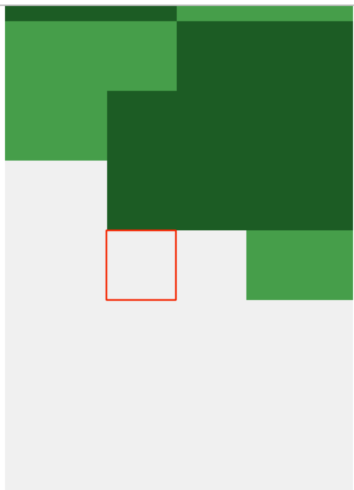
		
Sample units for 2015 20x20 and 2018 10x10 *© Digital Orthophoto North Rhine Westphalia - Geobasis NRW*	FTY 2015: Forest Reference: Forest 0.5	FTY 2018: no-forest Reference: no-forest

Figure 43: Sample units for forest assessment

Difficulties in the interpretation of forest and no-forest were in particular reported for:

Spain:

- Difficult to differentiate between forest , Macchia and agricultural used trees such as olives and citrus
- Difficult to follow and define the threshold of 10% tree cover canopy in areas with scattered trees and poor image quality
- Difficult to differentiate between Dehesas and other agricultural used trees

Sweden:

- Difficult to define if patches with scattered trees inside a forest belong to the forest or not following the MMU and threshold of >10% canopy cover
- High forestry activities which made it very important to consider the acquisition dates of the reference images

Germany:

- Difficult to define if trees in and between urban areas belong to the forest class or not.

Romania:

- High construction activities which made it very important to consider the acquisition dates of the reference images

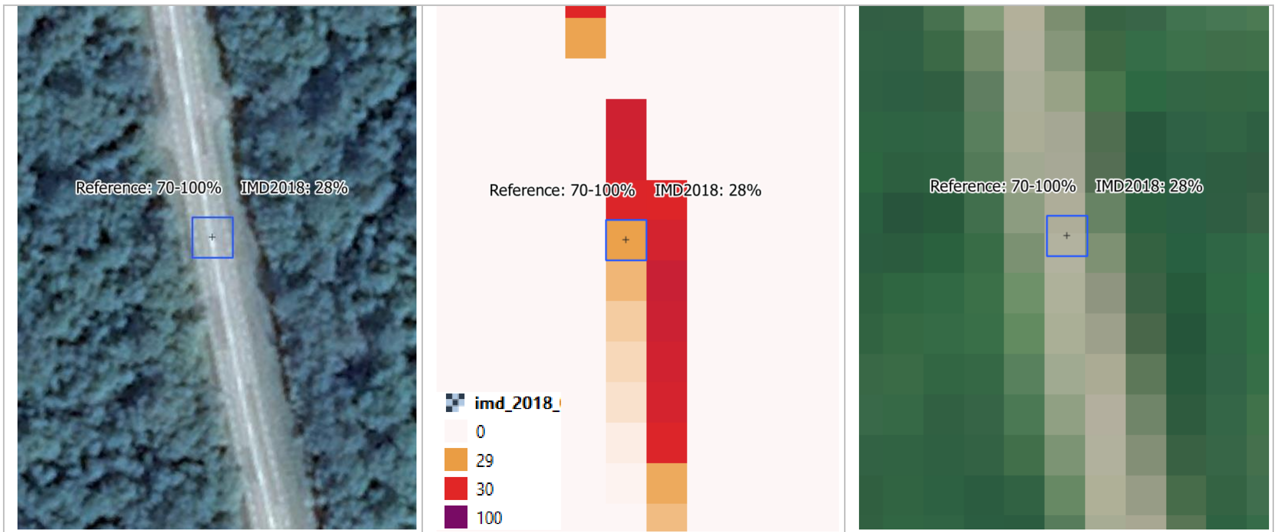
- **Imperviousness 2015 and 2018:** In the visual interpretation the proportion of artificial surface (sealed) is recorded for the sample units. The proportion of artificial surface is recorded as percentage using six different classes. 0% -> Non Impervious
- 1-19% -> Non impervious
- 20-29% -> Non impervious
- 30-39% -> impervious
- 40-69% -> impervious
- 70-100% -> impervious

The classes have been defined in order to be comparable with the 30% HRL imperviousness threshold, providing three classes below and three classes above the 30 % threshold.

The finer discrimination into six classes was chosen in order to:

- allow for a possible finer level of analysis
- create narrow "tolerance" classes below and above the 30% threshold, in order to filter for cases where the reference classification is close to the 30% threshold

For the analysis the classes were collapsed to the three classes 0%, 1-29% and >30%.



Background: Google Earth | Background: IMD 2018. | Background: Sentinel-2 2018.

Example from Sweden showing a 10x10m sample pixel located on a road and classified as >30% impervious in the interpretation and classified as <30% in the map.

Google Earth Pro © CNES/Airbus 2021 (left), Copernicus Sentinel data 2018 processed by ESA (right)

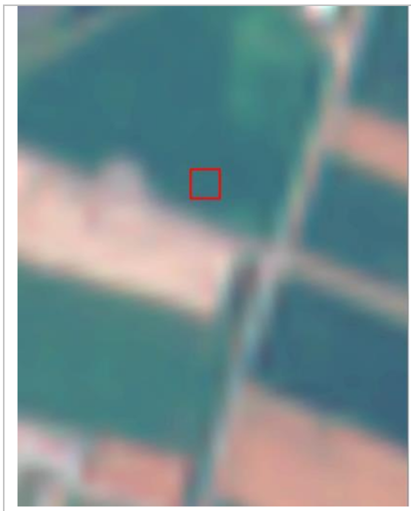
Figure 44: Interpretation of sample units for IMD assessment

Difficulties in the interpretation of artificial area were in particular reported for areas where the available imagery used for the interpretation was of poor quality.

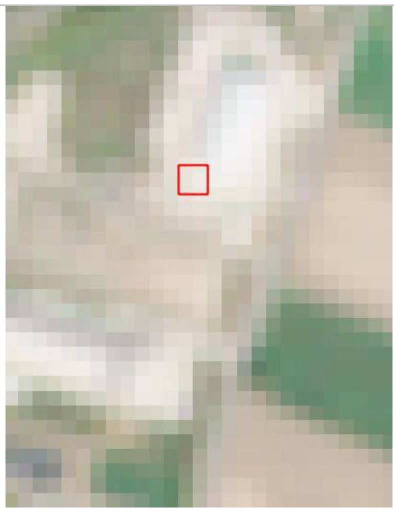
For the HRL change layers the reference data was collected using a plausibility approach based on the aggregated change classes.

For the IMCC1518 the comparison of the 2015 and 2018 artificial surface was translated to:

- Artificial surface in both years
- No Artificial surface in both years
- Increase in artificial surface from 2015 to 2018
- Decrease in artificial surface from 2015 to 2018



Background: Sentinel-2 2015-2016 (1:2500)



Background: Sentinel-2 2018 (1:2500)

Background: Google Earth 2020 (1:2500)

Imperviousness change - IMCC 2015-2018 (1:2500)

Example from Germany showing a 20x20m sample pixel classified as IMD-increase and the corresponding Sentinel-2, IMCC1518 classification and Google Earth imagery.

Google Earth Pro © CNES/Airbus 2021, Copernicus Sentinel data 2015 / 2018 processed by ESA

Figure 45: Interpretation process of Impervious change in the reference data

For the interpretation of tree cover change a plausibility approach was used were the interpreter is aware of the result of the image classification. Due to different image quality as well as seasonal changes in the canopy cover a precise interpretation of the canopy cover in a 20x20m segment is difficult. Further the 1ha minimum mapping unit and boundary rule of the TCCM1518 was considered during the interpretation. As guidance, the threshold of <10%, >10% and >30% canopy cover in the 20x20m segment were used. Seasonal differences in the tree cover were considered.

4.3.3 Accuracy and area estimation – Stratified estimator

The reference data and the corresponding pixel values were used for the accuracy assessment and area estimation using the stratified estimator as described in chapter 3.2 and 3.2.2. The complete results including the error matrix is provided in the ANNEX III. In chapter 5 the aggregated results are also compared to the LUCAS aggregated estimates for artificial and forest.

4.3.3.1 Forest 2015 and 2018

The tables below summarize the accuracy and area estimates of the FTY 2015 and FTY 2018.

Table 34: Forest type (FTY) 2015 - accuracy and area estimates using EO-4-Statistics reference data and stratified estimator

Forest type 2015		FTY 2015 - pixel counts	User's accuracy and MoE CI95%		Producer's accuracy and MoE CI95%		Stratified estimator - adjusted area estimate		
AOI		prop.	UA	+/-	PA	+/-	km²	%	CV %
de21	Oberbayern	0.391	90.4	4.4	98.3	1.9	6,315	36.0	2.6%
de40	Brandenburg	0.387	96.7	2.1	95.9	2.3	11,600	39.1	1.6%
dea1	Duesseldorf	0.26	67.4	13.7	94.8	6.9	980	18.5	10.5%
dea3	Muenster	0.222	69.3	10.5	97.8	4.2	1,087	15.7	7.9%
es43	Extremadura	0.41	80.4	7.6	81.6	7.6	16,828	40.4	6.2%
es51	Catalunia	0.52	79.1	3.7	91.3	2.5	14,452	45.0	2.6%
es52	Comunidad Valenciana	0.41	56.2	5.4	86.4	4.1	6,169	26.5	4.9%
ro12	Centru	0.47	98.9	2.1	90.2	5.0	17,571	51.5	3.0%
ro41	Sud-Vest Oltenia	0.37	93.6	1.9	94.4	1.6	10,606	36.3	1.3%
se12	Oestra Mellansverige	0.56	90.2	5.5	91.3	4.5	24,124	55.7	3.8%
se31	Norra Mellansverige	0.66	97.9	2.4	94.1	3.6	51,933	68.5	2.3%

For all AOIs except Duesseldorf and Muenster the accuracy could be estimated with a margin of error below 10% and for most below 5%. In general the accuracy is better in 2018 than in 2015. For most AOIs the accuracy is above 90%. As expected the accuracy is lower in the Spanish NUTS in both years.

Area estimation for the forest class could be achieved for most AOIs with a CV below 5%, highest CVs are for 2015 in Duesseldorf related to the lower accuracy.

Table 35: Forest type (FTY) 2018 - accuracy and area estimates using EO-4-Statistics reference data and stratified estimator

Forest type 2018		FTY 2018 - pixel counts	User's accuracy and MoE CI95%		Producer's accuracy and MoE CI95%		Stratified estimator - adjusted area estimate		
AOI		prop.	UA	+/-	PA	+/-	km²	%	CV %
de21	Oberbayern	0.38	92.6	3.9	98.3	1.9	6,295	35.9	2.3
de40	Brandenburg	0.38	96.0	2.3	94.1	2.7	11,597	39.1	1.9
dea1	Duesseldorf	0.18	93.9	8.3	94.6	7.1	958	18.1	5.7
dea3	Muenster	0.17	94.4	6.2	96.1	5.2	1,184	17.1	4.2
es43	Extremadura	0.39	85.4	6.9	82.6	7.7	16,546	39.7	5.8
es51	Catalunia	0.48	87.1	3.2	89.0	2.7	14,935	46.5	2.2
es52	Comunidad Valenciana	0.30	76.7	5.5	84.2	4.2	6,368	27.4	4.0
ro12	Centru	0.49	97.0	3.4	92.7	4.5	17,363	50.9	3.0
ro41	Sud-Vest Oltenia	0.35	94.8	1.7	91.5	2.0	10,516	36.0	1.4
se12	Oestra Mellansverige	0.57	92.9	4.8	93.9	3.8	24,601	56.8	3.2
se31	Norra Mellansverige	0.66	97.1	2.8	93.7	5.7	50,107	70.0	2.5

The lowest accuracy is in both years in Spain possibly due to the misclassification of olive, citrus, etc. plantations and “macchia” as forest. Both are difficult to differentiate from forest according to the FAO definition. In Spain errors in the reference data might be a factor as it is difficult to follow the FTY forest definition in this landscape in particular for the interpretation of 2015 images. In Germany bigger differences are in the smaller more urban NUTS2 region in the west part of Germany. Here a possible source for the higher forest area is due to the misclassification of urban trees as forest. In Muenster the typical landscape with small forest patches might have an effect on the classification.

4.3.3.2 Impervious area 2015 and 2018

The tables below summarize the accuracy and area estimates of the IMD 2015 and IMD 2018 using the 30% threshold and the EO-4-Statistics reference data.

Table 36: Impervious density (IMD) 2015 - accuracy and area estimates using EO-4-Statistics reference data and stratified estimator

Imperviousness density degree 2015		IMD 2015 pixel counts	User's accuracy and MoE CI95%		Producer's accuracy and MoE CI95%		Stratified estimator - adjusted area estimate		
AOI		prop.	UA	+/-	PA	+/-	km²	%	CV %
de21	Oberbayern	0.063	86.1	11.5	76.0	12.8	1,255	7.2	9.9
de40	Brandenburg	0.041	84.6	14.1	71.1	13.1	1,456	4.9	10.9
dea1	Duesseldorf	0.197	93.0	7.7	70.8	10.1	1,370	25.9	7.8
dea3	Muenster	0.1	93.9	8.3	69.9	11.5	934	13.5	8.9
es43	Extremadura	0.008	76.7	15.4	96.7	2.7	250	0.6	10.7
es51	Catalunia	0.033	84.2	16.8	66.3	12.9	1,359	4.2	11.5
es52	Comunidad Valenciana	0.037	90.6	10.3	53.0	10.1	1,463	6.3	9.8
ro12	Centru	0.012	93.3	9.1	86.7	6.0	444	1.3	5.5
ro41	Sud-Vest Oltenia	0.016	91.4	9.4	65.5	11.1	650	2.2	9.1
se12	Oestra Mellansverige	0.01	76.7	15.4	86.7	8.7	390	0.9	9.6
se31	Norra Mellansverige	0.005	76.7	15.4	80.2	12.0	360	0.5	10.2

For the Impervious area the accuracy is lower in 2015 than in 2018. The margin of error is for most estimates close to the targeted 10%. In most AOIs the PA is lower than the UA which indicates an underestimation of the impervious area. An exception are the NUTS2 regions from Sweden with a lower user's accuracy than producer's accuracy indicating and underestimation of the impervious area.

The stratified sampling approach using the IMD class of 1-29 as an additional stratum proofed to increase the precision of the estimates considerably. Nevertheless the estimation of area for rare classes which cover only a small part of the total area is difficult. The sampling weight of the non-target class is so huge that one wrongly classified sample leads to a huge change in the area.

An example for the problem of using equal number of sample units per class for the estimation of area is visible in the AOI se12 in 2018. One out of the 30 sample units in the non-impervious class was classified in the interpretation as impervious. Due to the very large sample weight of the non-impervious class the impervious area is increased by more than 1,000 km².

Table 37: Impervious density (IMD) 2015 - accuracy and area estimates using EO-4-Statistics reference data and stratified estimator

Imperviousness density degree 2018		IMD 2018 pixel counts	User's accuracy and MoE CI95%		Producer's accuracy and MoE CI95%		Stratified estimator - adjusted area estimate		
AOI		prop	UA	+/-	PA	+/-	km²	%	CV %
de21	Oberbayern	0.069	96.9	6.1	80.4	10.8	1,456	8.3	7.3
de40	Brandenburg	0.041	72.4	16.6	77.9	14.3	1,137	3.8	12.8
dea1	Duesseldorf	0.203	92.2	7.5	81.9	10.2	1,211	22.9	7.1
dea3	Muenster	0.114	87.5	11.6	76.9	10.4	895	12.9	8.5
es43	Extremadura	0.01	86.7	12.4	98.0	1.9	333	0.8	7.6
es51	Catalunia	0.039	76.9	16.5	71.6	13.6	1,333	4.2	12.0
es52	Comunidad Valenciana	0.042	86.1	11.5	55.9	9.6	1,499	6.4	9.0
ro12	Centru	0.015	86.7	12.4	92.2	5.3	478	1.4	7.4
ro41	Sud-Vest Oltenia	0.019	76.6	12.2	66.7	11.7	651	2.2	10.2
se12	Oestra Mellansverige	0.013	90.0	10.9	26.2	37.0	1,968	4.5	72.0
se31	Norra Mellansverige	0.005	80.0	14.6	80.7	9.8	360	0.5	10.1

4.3.3.3 Tree cover change 2015 - 2018

The tree cover change layer was analysed in support to the assessment of change of the forest type map. The table below summarize the accuracy and area estimates of the TCCM1518 change classes.

There are hardly any changes in tree cover classified in this HRL product. Only in the two NUTS2 regions in Sweden a loss of more than 1% area is classified. Important to note again is that the TCCM has a minimum mapping unit of 1 ha, this means only patches of tree cover loss or gain of 1 ha or larger are recorded. Pixels with new tree cover are also very few and in some NUTS2 regions none are recorded.

The effect of the very small proportion of tree cover change and a MMU of 1 ha is that in some cases the 30 sample units per class are selected from the same patch of loss or new tree cover. In case the patch was correctly classified most of the sample units are correct or wrong in case the classification was wrong. This effect is visible in the Producer' accuracy, which is often very high or very low.

The sampling strategy using stratified sampling with fixed 30 sample units per map class results in a strong imbalance of the sample weights. The 60 sample units in the no-change classes represent in most AOIs close to 99% of the area. The weight of a single sample unit in the no-change class is therefore much bigger than the weight of a sample in the change classes. A single sample unit classified as no-change in the map but classified as change in the reference will therefore strongly decrease the producer's accuracy for the no-change class.

Table 38: TCCM1518 change classes –accuracy and area estimates using EO-4-Statistics reference data and stratified estimator – NUTS2 regions

TCCM1518		TCCM Change class	TCCM 2015-2018 pixel counts	User's accuracy and MoE CI95%		Producer's accuracy and MoE CI95%		Stratified estimator - adjusted area estimate		
NUTS ID	NUTS Name		prop.	UA	+/-	PA	+/-	km²	%	CV %
DE13	Freiburg	tc_loss	0.0010	86.7	12.4	100	0.0	9	0.1	3.9
		tc_new	NA	NA	NA	NA	NA	NA	NA	NA
DE14	Tuebingen	tc_loss	0.0020	82.8	14.0	100	0.0	14	0.2	8.6
		tc_new	NA	NA	NA	NA	NA	NA	NA	NA
DE21	Oberbayern	tc_loss	0.0010	86.7	12.4	5.8	10.8	249	1.4	94.2
		tc_new	0.0000	93.3	9.1	100	0.0	0.175	0.0	5.6
DE40	Brandenburg	tc_loss	0.0010	90.0	10.9	100	0.0	26	0.1	6.2
		tc_new	0.0001	90.0	10.9	100	0.0	2	0.0	6.2
DE71	Darmstadt	tc_loss	0.0010	90.0	10.9	4.7	8.7	122	1.6	95.4
		tc_new	NA	NA	NA	NA	NA	NA	NA	NA
DE73	Kassel	tc_loss	0.0020	83.3	13.6	10.3	18.2	145	1.7	89.7
		tc_new	0.0000	93.3	9.1	100	0.0	0.166	0.0	4.3
DE91	Braunschweig	tc_loss	0.0040	86.7	12.4	100	0.0	30	0.4	7.3
		tc_new	0.0001	90.0	10.9	100	0.0	0.406	0.0	6.8
DE94	Weser-Ems	tc_loss	0.0010	83.3	13.6	100	0.0	8	0.1	8.3
		tc_new	0.0000	100	0.0	100	0.0	0.150	0.0	0.0
DEA1	Duesseldorf	tc_loss	0.0010	76.7	15.4	100	0.0	3	0.1	10.3
		tc_new	0.0000	100	0.0	100	0.0	0.106	0.0	0.0
DEA2	Koeln	tc_loss	0.0010	90.0	10.9	6.4	11.8	99	1.3	93.6
		tc_new	0.0000	100	0.0	0.0	0.0	92	1.3	99.9
DEA3	Muenster	tc_loss	0.0010	76.7	15.4	9.6	17.0	54	0.8	90.4
		tc_new	NA	NA	NA	NA	NA	NA	NA	NA
DEB2	Trier	tc_loss	0.0010	76.7	15.4	2.9	5.5	84	1.7	97.1
		tc_new	0.0000	100	0.0	41.9	47.7	0.197	0.0	53.4
DEB3	Rheinhessen-Pfalz	tc_loss	0.0000	76.7	15.4	100	0.0	0.206	0.0	10.9
		tc_new	NA	NA	NA	NA	NA	NA	NA	NA
DEE0	Sachsen-Anhalt	tc_loss	0.0020	86.7	12.4	100	0.0	33	0.2	7.3
		tc_new	0.0000	0.0	0.0	NA	0.0	0.000	0.0	NA
ES43	Extremadura	tc_loss	0.0001	20.0	16.0	100	0.0	0.416	0.0	40.0
		tc_new	0.0005	66.7	17.2	2.2	4.3	578	1.4	97.8
ES51	Catalunia	tc_loss	0.0010	76.7	15.4	100	0.0	14	0.0	10.2
		tc_new	0.0000	95.2	9.3	0.0	0.0	2,914	9.1	39.5
ES52	Comunidad Valenciana	tc_loss	0.0010	56.7	18.0	100	0.0	12	0.1	16.3
		tc_new	0.0002	60.0	17.8	76.8	35.3	3	0.0	25.1
RO12	Centru	tc_loss	0.0010	83.3	13.6	100	0.0	33	0.1	8.3
		tc_new	0.0000	46.7	18.2	0.0	0.1	566	1.7	100.0
RO21	Nord-Est	tc_loss	0.0010	90.0	10.9	100	0.0	32	0.1	6.2
		tc_new	0.0000	80.0	14.6	0.2	0.4	479	1.3	99.8
RO41	Sud-Vest Oltenia	tc_loss	0.0010	66.7	17.2	100	0.0	11	0.0	13.2
		tc_new	0.0001	93.3	9.1	100	0.0	1	0.0	4.9
SE12	Oestra Mellansverige	tc_loss	0.0140	83.3	13.6	46.3	48.9	1,063	2.5	53.8
		tc_new	0.0010	30.0	16.7	100	0.0	11	0.0	28.1
SE31	Norra Mellansverige	tc_loss	0.0140	90.0	10.9	99.9	0.1	912	1.3	6.2
		tc_new	0.0002	43.3	18.0	0.4	0.8	1,636	2.3	99.6

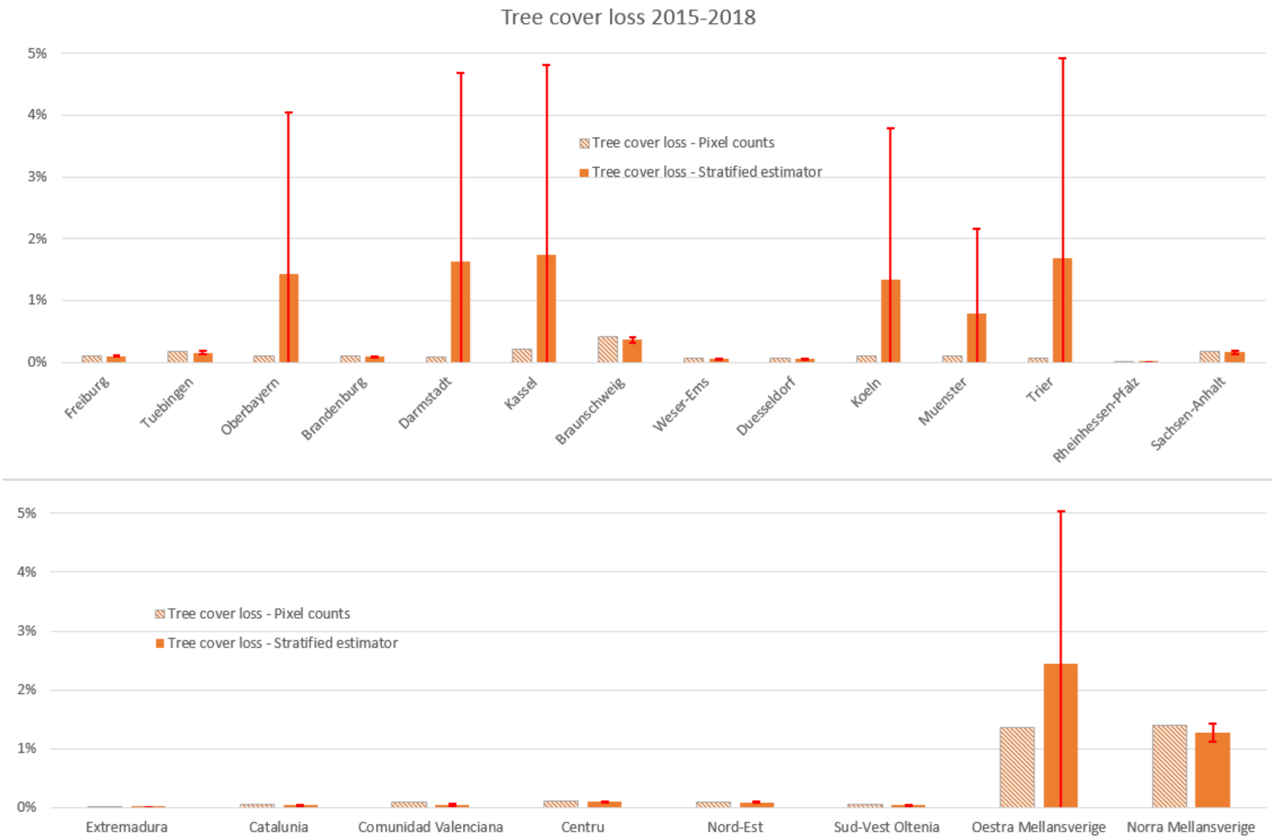


Figure 46: Area estimates of tree cover loss for selected NUTS2 - unreliable

The same effects from the accuracy assessment are visible when the data is used for area estimation using a stratified estimator (see Figure 46). The big differences between mapped area and adjusted area for some of the NUTS2 regions are caused by sample units which are classified as “tree cover loss” in the reference data interpretation and classified as “no tree cover” or “stable tree cover” in the map. The high CV shows the uncertainty caused by the small number of sample units and unequal sampling weights.

Table 39: TCCM1518 - accuracy and area estimates using EO-4-Statistics reference data and stratified estimator - Countries

Tree cover change mask 2015 - 2018		TCCM Change class	TCCM 2015-2018 pixel counts	User's accuracy and MoE CI95%		Producer's accuracy and MoE CI95%		Stratified estimator - adjusted area estimate		
NUTS ID	NUTS Name	class	prop.	UA	+/-	PA	+/-	km²	%	CV %
		tc_loss	0.0010	100	0.0	100	0.0	343	0.1	0.0
		tc_new	0.0000	80.0	14.6	100	0.0	11	0.0	8.5
		no_tc	0.6340	86.7	12.4	100	0.0	196,456	54.9	7.3
DE	Germany	tc	0.3650	100	0.0	81.2	14.2	160,910	45.0	8.9
		tc_loss	0.0010	90.0	10.9	100	0.0	521	0.1	6.2
		tc_new	0.0000	80.0	14.6	100	0.0	167	0.0	9.2
		no_tc	0.6060	66.7	17.2	96.5	6.6	211,912	41.9	13.2
ES	Spain	tc	0.3920	96.3	7.3	65.1	11.8	293,465	58.0	9.5
		tc_loss	0.0010	80.0	14.6	100	0.0	143	0.1	9.2
		tc_new	0.0001	90.0	10.9	100	0.0	14.303	0.0	6.6
		no_tc	0.6270	76.7	15.4	100	0.0	114,630	48.1	10.3
RO	Romania	tc	0.3720	100	0.0	71.7	13.4	123,598	51.8	9.5
		tc_loss	0.0100	100	0.0	100	0.0	4,611	1.0	0.0
		tc_new	0.0009	86.7	12.4	100	0.0	351	0.1	7.2
		no_tc	0.3920	93.3	9.1	100	0.0	164,468	36.6	4.9
SE	Sweden	tc	0.5970	100	0.0	95.8	5.5	280,384	62.3	2.9

The Tree cover change on country level shows accuracies above 80% for UA and PA for most of the classes in the countries. The highest accuracy is reached in Sweden and the lowest results in Spain. 30 sample units were interpreted for each class per country. The aim was to reach a margin of error for the UA of about +/-10%, this was reached in most classes. **Equal number of sample units per class support estimating user's accuracy. For area estimation proportional sampling is preferable.** The CV of the estimated area is in most cases below 10% but this estimates are based on few sample units.

4.3.3.4 Imperviousness change 2015 - 2018

The IMCC1518 change product is not directly comparable to the corresponding status layers due to the change in the resolution from 20m to 10m. It was therefore not possible to combine the status layers from IMD15 and IMD18 to a map with stable and change classes. The IMCC1518 has been therefore treated as an independent product. It was analysed for all 22 selected NUTS2 regions using a stratified sampling approach. The results are provided in ANNEX III: Results from the accuracy assessment and area estimation with EO-4-Statistics reference data and show overall very low accuracies which is confirmed for country level by the internal validation report. Huge differences between UA and PA lead to very high CV and unreliable estimates of accuracy and area. In general the accuracy is very low. User's accuracy is in no case above 60% and Producer's accuracy is either 100% for some AOIs or close to 0. The low thematic quality is also confirmed by the internal IMC1518 validation report[24] and on the Copernicus HRL Imperviousness website related to the change of the production method. The assessment of the Imperviousness change product was not further continued and the results not used:

Note on the Copernicus HRL Imperviousness website:

[24] https://land.copernicus.eu/user-corner/technical-library/clms_hrl_imd_validation_report_sc04_1_3.pdf

"IMPORTANT: *Please be aware that we are currently investigating the reliability of the magnitude of imperviousness increase that was mapped for the 2015-2018 period. The change products (as mapped) show a significant increase of the speed to soil sealing/imperviousness as compared to the previous periods for which we have change data (2006-2009, 2009-2012 and 2012-2015). We are confident that the trend and the spatial pattern of the trend reflects reality, but the magnitude of the increase needs to be further investigated."* *https://land.copernicus.eu/pan-european/high-resolution-layers/imperviousness/change-maps/2015-2018* (*accessed* 15.05.2021).

5 Discussion - comparison of different methods and reference data

This chapter highlights the findings of the task 1 activities and compares the outcomes and impacts from the different estimators. It reflects the results of the applied “biased” and “unbiased” area estimation methods (chapter 4) in the light of the underlying concepts (chapter 3) and the available input data, which are then benchmarked against estimates from the LUCAS data (see chapter 2).

5.1 The meaning of “biased” versus “unbiased” estimates in the context of EO

Errors in satellite Earth Observation (EO) products are inevitable, given the technical specifications of satellite sensor systems, the process to convert observed spectral reflectance’s of the earth into digital signals and the complexity to aggregate these signals into cartographically generalized image classifications (chapter 3.1). As widely discussed, and explained in scholar this inevitable error in EO is the commonly accepted source for a bias in EO data when used as sole source for statistics. The approach to assess the error related bias through **validation measures** does not change the quality of the maps, but allows to quantify the range of mapping errors and is a step towards the generation of “corrected” or “unbiased” area estimation.

As described in chapter 3, the difference in the calculation of estimates using “unbiased” estimators is that they account for the bias by provision of statistical descriptors that quantify the range of uncertainty. Although the term “unbiased” estimates seems to be somehow unfavourable, this is what is meant within this contract – correcting or adjusting biased area from pixel counting and **calculating the uncertainty of the area estimate (possible range of error)**, i.e. the area estimates corrected however are still biased, but with a quantified known range of error.

Essential for sound validations and “unbiased” area estimation are adequate and independent **reference data**. As a first conclusion within this contract, we experienced an increasing availability of standardized validation efforts and in particular within the Copernicus HRL framework, which partly uses LUCAS data already.

There is an increasing awareness and availability of adequate and independent reference data for EO mapping products at EU level.

5.2 From map validation to “unbiased” area estimation

The above introduced thematic map validation informs about accuracy of the map and its classes, but unless accuracy is 100% classification errors are present and an “unbiased” estimator to estimate areas is required in addition to the accuracy assessment. Key element for accuracy and area estimation is the combination of the EO classification with reference data over a sample. This allows the extraction of accuracy or area estimates and their related **variances.** The variances quantify the uncertainty of the sample based estimates and allow exploring the statistical significance of achieved accuracy or area estimates and its changes in a given time. Precondition is that the following three obligatory aspects are ensured:

- an adequate match between the EO map and the reference data, that is based on
- a rigorous probability sampling of the reference data, in order to
- apply the appropriate “unbiased” estimator including the calculation of variances.

The various assessments (chapter 4) were systematically explored through the test protocol within the task 1 of this contract (chapter 1.2).

5.2.1 Adequate data match

Key for a sound validation of EO classifications is an adequate **response design** that ensures an **EO compliant 1:1 match** between the EO input data and the reference data. Therefore, three criteria are crucial:

1) Spatial match

The spatial dimension of the reference data observation must match with the specification of the employed satellite data. At a minimum the spatial ground resolution (or pixel size) has to be covered including a certain buffer, here it is referred to the Nyquist–Shannon sampling theorem, in order to prevent misclassifications of mixed pixels and support spatial co-registration.

The aggregated Copernicus product grid and the underlying LUCAS master grid are created on the same geographical basis. Although there are various spatial Copernicus product resolutions, it is a great advantage that there is a common reference. Nevertheless further assessment is needed in order to improve the spatial match of both data sets.

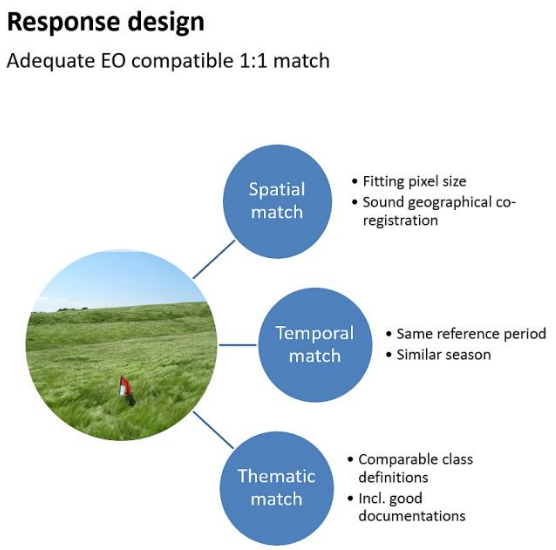


Figure 47: EO compatible response designs

2) Temporal match

To provide doubtless comparisons, both observations are crucially to be gathered on basis of the same reference period. If difficult, criteria shall be aggregated to stable land cover classes that are unlikely to change within a possible time span between EO data and reference observation. Such can be forest, artificial or other overall land cover types, such as crop land, rather than individual crop classes, in order to prevent errors between “real changes” or “wrong observations”. Problematic are cases, where no information about image acquisition or observation date are registered. That creates a certain source of non-sampling errors.

The employed three-year Copernicus image acquisition windows are since 2009 well matched with the LUCAS field data collection campaigns. Uncertainties appear in case of image interpretations of sources with unknown acquisition date, such as for instance Google Earth, which was the case for the EO-4-statistics reference data.

3) Thematic match

A precondition to ensure reliable comparison of class categories is to ensure a 1:1 thematic relation between reference data and EO classifications. Therefor precise and systematic class descriptions are crucial and if necessary classes are to be aggregated or indicators are to be created.

With the employed data different approaches where used to reach the needed thematic compliance. The visual interpretations through the EEA validation data and the EO-4-statistics interpretation showed limitations and uncertainties in the thematic level of details of the classes, whereas detailed HRL forest classes could be extracted through dedicated data base queries from the full LUCAS data base.

5.2.1 Rigorous sampling design

In opposition to cartographic mapping, which basically aims to generalize a given area to “simplified” mapping units (e.g. pixels), area estimates are the statistical extrapolation of a limited sample towards an entire population. In that sense, each mistake will be multiplied by the factor of the sampling weight. Only with the known distribution, the total number and weight of the selected number of sample units per class, a sound quantification of mistakes within the different classes and thus a sound extrapolation is possible. For this study, three different reference data sets had been used with different sampling designs at different administrative levels. Extensive assessments were made to explore the applicability as well as the limitations of the given reference data sets for "unbiased" estimation.

Although there is an increasing awareness and availability of adequate and independent reference data for EO mapping products and prominent projects at EU level, there is still a lack of specifically designed independent reference data sets, which allow multiple use for statistical EO assessments.

5.2.1 "Unbiased" estimator

The final processing step towards "unbiased estimates" is more or less a straight forward data analysis step by using the appropriate estimator (formula), provided the above preconditions: i) adequate 1:1 match and ii) a rigorous probability sampling are fulfilled, which is then properly expressed in the presentation and discussion of the results through a comprehensive documentation of the extracted CVs. This will be demonstrated in following chapter by means of the performed assessments and achieved estimates.

5.3 Achieved benchmarks

The following assessments are aiming to compare the outcomes of the different estimators of task 1. In the next chapters the results from the different estimators are benchmarked against the area estimates calculated for the aggregated LUCAS classes of forest and artificial (see chapter 4.2.1.1 see 4.2.1.2). An assessment of area change between 2015 and 2018 is based on the comparison of the area estimates from 2015 and 2018, because Change products for forest are not available and the impervious change product is reported to be unreliable.

For the purpose of benchmarking, the results from the thematic accuracy of the HRL products assessed within Task 1 are compared with the results from the internal EEA product validation. Although, we calculated confusion matrices and accuracy parameters between the chosen HRL maps and the different reference data sets, these are not aimed to be a product validation. The assessments are:

- intermediate calculations in a statistical workflow
- aim to explore the applicability of the reference datasets for HRL validation
- aim to showcase the workflow.

Official product validations at the relevant administrative scales are available for Copernicus products from EEA.

5.3.1 Forest area and change

The accuracy of forest area was assessed on country and NUTS2 level using LUCAS survey data and the EO-4-Statistics reference data. The internal EEA validation report for the FTY products provides accuracy assessment only on country and bio-geographic region. It is provided at the Copernicus website. The table below shows the results from the blind and plausibility analysis for the 4 selected countries for 2015.the FTY 100 product 2015. The validation report for the 2018 product was not available at the time of writing.

Table 40: Results of the EEA internal validation: Thematic accuracy of HRL FTY forest type 100 m product, for the blind interpretation and plausibility analysis - HLR FOREST 2015 - Final validation report[25]

2015	Number sample units	Forest - Blind interpretation				Forest – Plausibility Analysis			
NUTS Name	Total	UA	CI 95%	PA	CI 95%	UA	CI 95%	PA	CI 95%
Germany	939	96.1%	0.9%	91.5%	1.3%	97.7%	0.7%	92.8%	1.2%
Spain	1,305	82.7%	1.5%	82.9%	1.5%	85.7%	1.4%	88.8%	1.3%
Romania	600	97.0%	0.9%	92.8%	1.5%	97.5%	0.9%	93.8%	1.4%
Sweden	1,166	93.5%	1.2%	96.3%	0.9%	93.9%	1.2%	96.7%	0.9%

Compared to the results from the accuracy assessment of the 20m product using the LUCAS data on country level, the accuracy is in general higher. In both assessments the lowest results are obtained in Spain. The margins of error on a 95% confidence level for the LUCAS accuracy estimates have not been calculated but it can be expected that they are very low, considering the number of available LUCAS points.

Table 41: Accuracy assessment of HRL forest type 10m FTY 2015 using LUCAS aggregated forest class

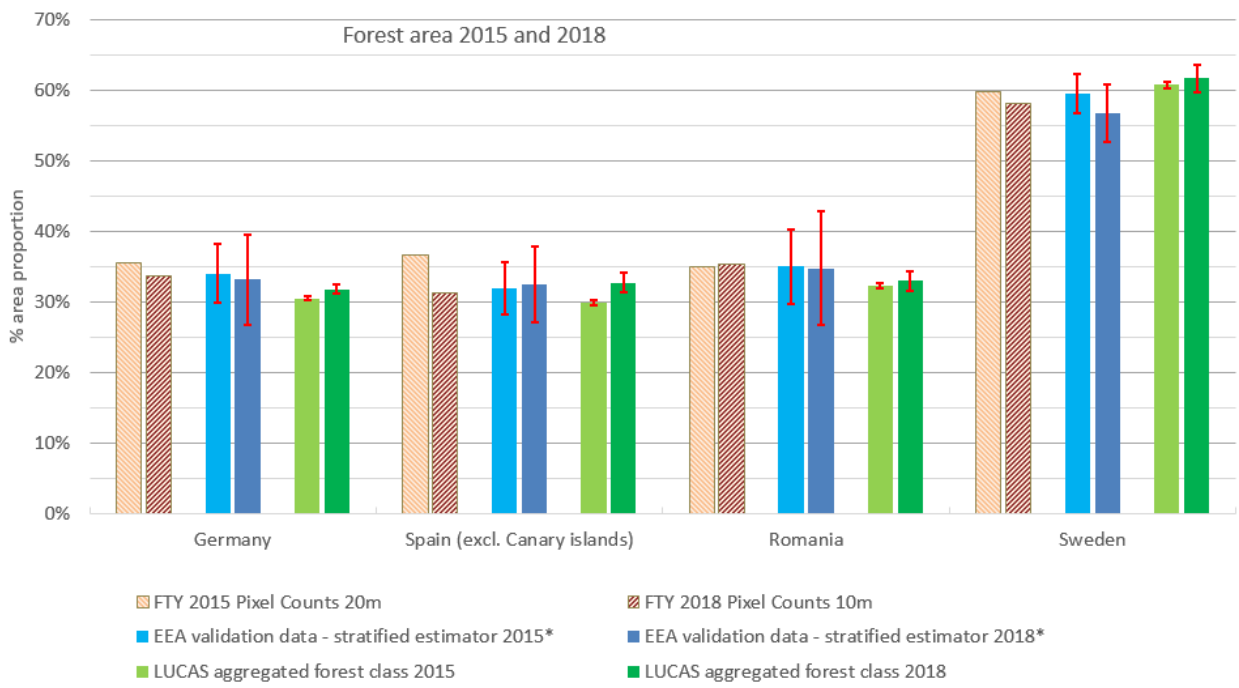
2015	Number of LUCAS points		FTY forest	
NUTS Name	Total	Aggregated Forest class	UA	PA
Germany	26,589	7,570	82.8%	95.6%
Spain	50,275	16,492	67.8%	80.5%
Romania	16,719	5,554	87.6%	94.8%
Sweden	26,638	16,864	89.0%	86.5%

In this project the area of forest has been estimated on country level for 2015 and 2018 using biased pixel counting from the HRL FTY15 in 20m resolution and HRL FTY18 in 10m resolution (see chapter 3.1).

“Unbiased estimates” of forest were calculated using the EEA validation data of the aggregated 100m FTY product and using a stratified estimator with a simple indicator function. The indicator function was required because the sampling of the validation data used the HRL Tree cover density layer 2015 as strata and not the HRL Forest product layers, see chapter 3.2.3 and 4.1.1. Both estimates are compared to the “unbiased estimates” from the LUCAS aggregated forest class (see chapter 3.2.6 and 4.2.1.1). The results are summarized in Figure 48Figure 48 and Table 42.

All area estimates calculated with EEA validation data reach CVs of below 10% in both years, except in Romania in 2018 (11.9%). CVs below 5% are only reached in Sweden in both years. Compared to the CVs reached by the estimates using the LUCAS data these CVs are quiet high, see for example in Germany in 2018 where the CV from the EEA validation data estimate is 9.8% compared to the CV of 1.1% from the LUCAS data estimate.

[25] Source: https://land.copernicus.eu/user-corner/technical-library/hrl-forest-2015-final-validation-report



(* estimates include Canary Islands approx. 1,400 km² forest area). The error indication shows the upper and lower 95% confidence interval of the estimates

Figure 48: Forest area proportion from biased pixel counts and "unbiased" estimates - 2015 and 2018 per country.

Table 42: Forest area from biased pixel counts compared to "unbiased" estimates - 2015 and 2018 per country.

FTY	FTY Pixel counts 2015 (20m) and 2018 (10m)*	EEA validation data - stratified estimator 100m			LUCAS aggregated Forest class*		
2015	%	Km²	%	CV	Km²	%	CV
Germany	35.6%	121,821	34.1%	6.3%	109,211	30.5%	0.6%
Spain	36.6%	159,217	31.9%	5.9%	149,263	29.9%	0.6%
Romania	35.0%	83,471	35.0%	7.6%	77,091	32.3%	0.6%
Sweden	59.9%	267,729	59.5%	2.4%	272,019	60.5%	0.4%
2018	%	Km²		CV	Km²	%	CV
Germany	33.6%	118,717	33.2%	9.8%	113,636	31.8%	1.1%
Spain	31.3%	161,812	32.5%	8.5%	163,158	32.7%	2.2%
Romania	35.3%	82,941	34.8%	11.9%	78,730	33.0%	2.1%
Sweden	58.3%	255,437	56.8%	3.7%	276,151	61.4%	1.6%

* Estimates exclude Canary Islands approx.1,400 km² forest area

Compared to the area extracted from pixel counting using the 100m FTY product, the area estimated from the EEA validation data is not very different, except for Spain in 2015.

The areas estimated from the LUCAS aggregated Forest class are in all countries the lowest except in Sweden and Spain (only 2018). The biggest differences are in Spain, this might be linked to the landscape where it is difficult to define forest and due to the inclusion of Dehesas in the FTY definition. The effect of mixed pixels is expected to be high for this areas as well as for areas in northern Sweden where the density of tree cover is close to the 10% threshold.

In the interpretation of the EEA forest validation data a sample unit was assigned to forest when the majority of the area inside belonged to the forest class. This has probably an effect on the estimation since the area not belonging to the forest in the sample unit is ignored in the assessment. A sampling approach where the proportion of the land cover classes in the sample unit are considered is preferable. For example, by adding a weight of 0.5 to the sample unit when it is only half covered with the land cover class. An example how this can be realised is provided in chapter 4.3.2.

An assessment of forest area change from 2015 to 2018 is provided in the Figure 49 below, it shows the difference in forest area from the same data source. For the estimates the difference between the lower 95% confidence interval in 2015 and the upper 95% confidence interval in 2018 is included in order to consider the uncertainty of the estimates in both years.

Looking at change in forest area from 2015 to 2018 the pixel counting results show a decrease in forest area except for Romania. The change is in a range that this could be possibly due to the change in the production method of the HRL Forest product (making full use of the Sentinel 2 data) and a higher spatial resolution in 2018. The low change area indicated in the assessment of the Tree cover change area in chapter 4.3.3.3 also supports that high changes in forest area are unlikely.

From the applied estimator only the LUCAS data indicates a change in forest area for Germany and Spain. In both cases the change in area proportion is larger than the range between the upper confidence interval in 2015 and the lower interval in 2018.

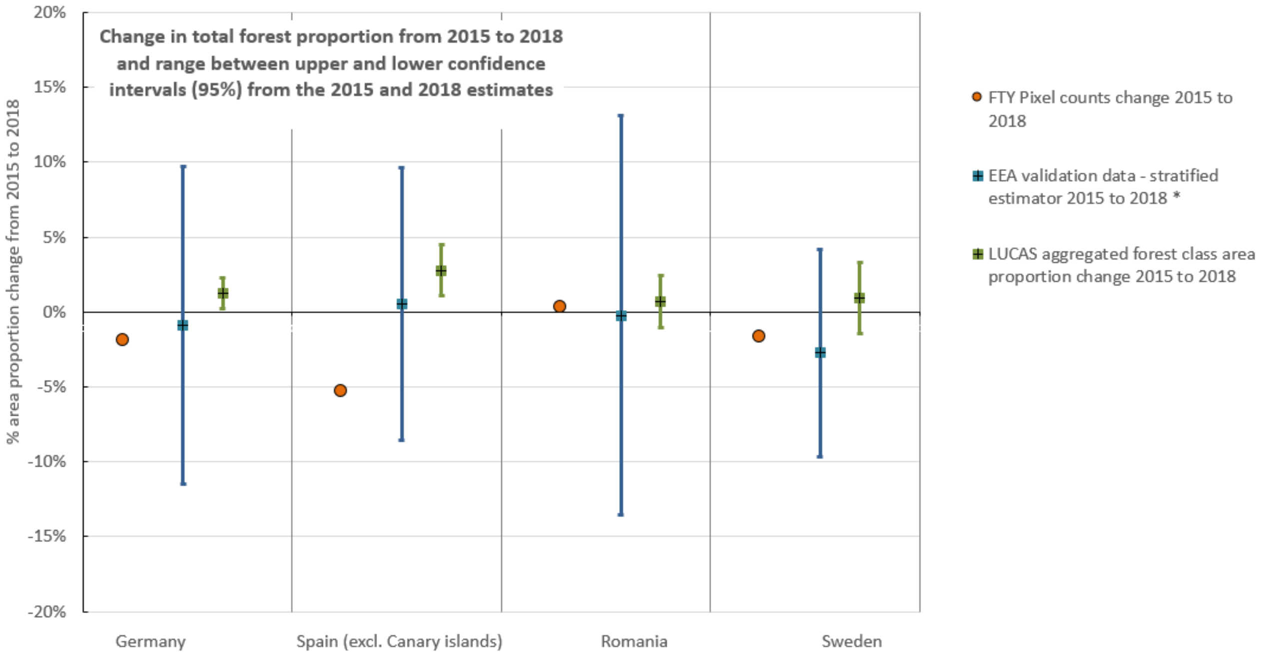


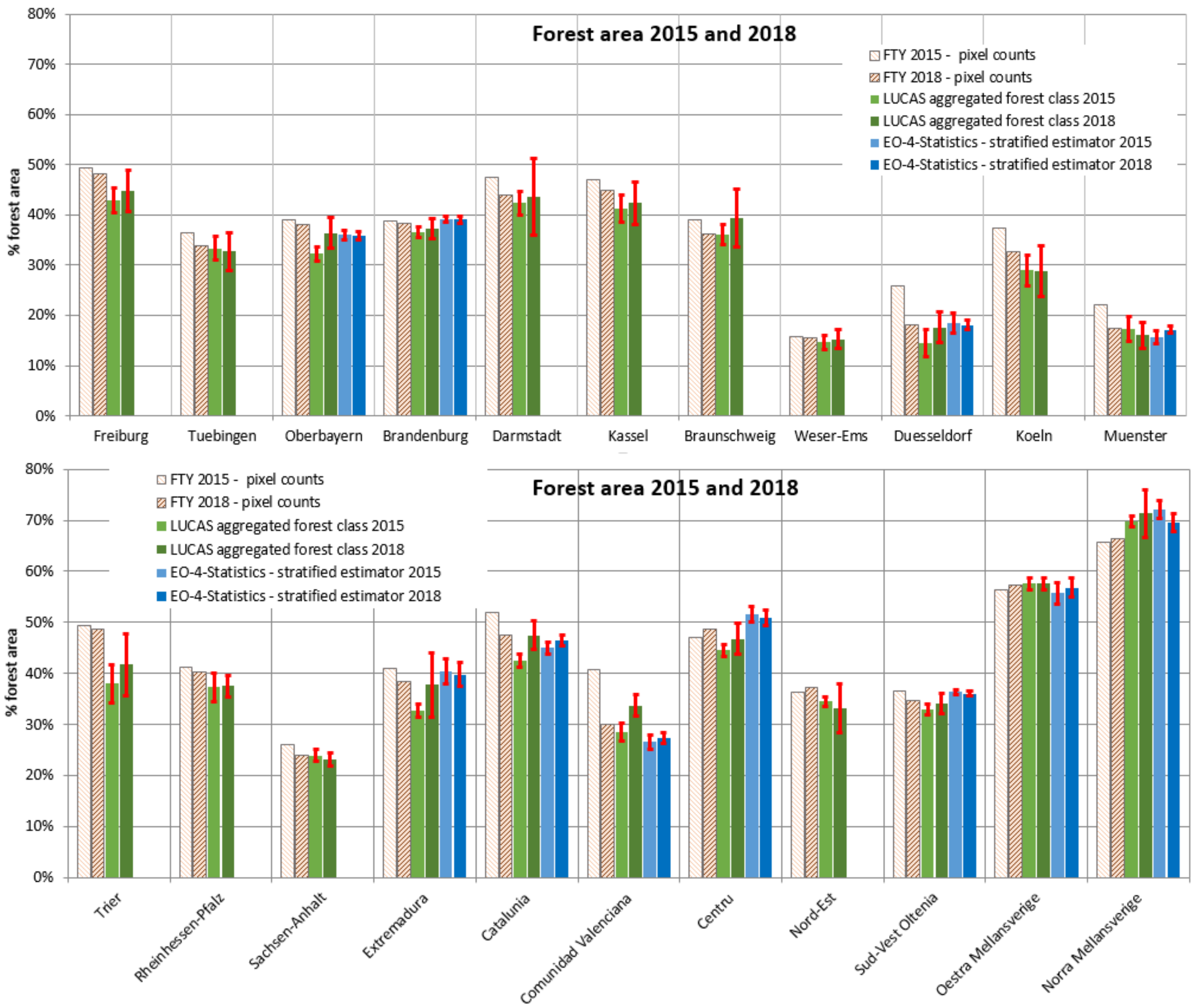
Figure 49: Change of forest area proportion from 2015 to 2018 and range between upper and lower 95% confidence intervals from 2015 and 2018 area estimates (* includes Canary Islands)

The comparison of the change rates shows that the area estimates from the EEA validation data does not allow providing forest area estimates in a sufficient precision to identify and quantify forest area change on country level within a 3 years interval. The uncertainty in the estimates is too high to identify possible changes.

The assessment of the accuracy and area estimation on the selected NUTS2 level (see chapter 4.3.3) using EO-4-Statistics reference data followed a simple random sampling approach using the pixel of the 2015 and 2018 Forest type layer as sample units. Simple random is a suitable approach for accuracy and area estimation of forest as it provides a sample proportional to the land cover classes. Adding a weight of 0.5 to sample units which are only half covered by forest reduced the effect of mixed pixels. This was in general only practical when a clear forest border was visible. Due to the small sample units of 1 pixel and possible positional inaccuracies at this scale the effect might be low, but it simplified the decision for the interpreters.

The accuracy of the FTY products in the selected NUTS2 regions is high (>90%) except for Spain and two NUTS2 in Germany. In Spain errors in the reference data can be expected due to the difficult landscape. In Germany the differentiation between "forest like" patches in urban areas seem to be a source of error in the map classification as well as in the reference data interpretation. Further the minimum mapping unit of 0.5 ha has to be considered when comparing the FTY estimate with LUCAS. Non-forest patches within a forest are added to the forest area and would be excluded in the LUCAS observation.

Area is estimated directly from the confusion matrix using stratified estimator and following the approach described in Olofsson et al. 2014. The sampling design with a quite high number of sample units proportionally allocated to the map classes is suitable for area estimation. The CV of the area estimates of the forest area is, except for one AOI, below 10% and for most below 5%. The results are close to the LUCAS aggregated estimates except for some cases already discussed in chapter 4.3.3. Figure 50 compares the area estimates with the area extracted from the pixel counting and the LUCAS aggregated forest estimates.



The error indication shows the upper and lower 95% confidence interval of the estimate.

Figure 50: Forest area proportion from biased pixel counts and "unbiased" estimators - 2015 and 2018 selected NUTS2 regions

An assessment of forest area change from 2015 to 2018 is provided in the Figure 51 below, it shows the difference in forest area from the same data source. For the estimates the difference between the lower

95% confidence interval in 2015 and the upper 95% confidence interval is included in order to consider the error range of the estimates in both years. It shows that only in two NUTS regions in Spain an increase in forest area is indicated by the estimates from the LUCAS aggregated forest class.

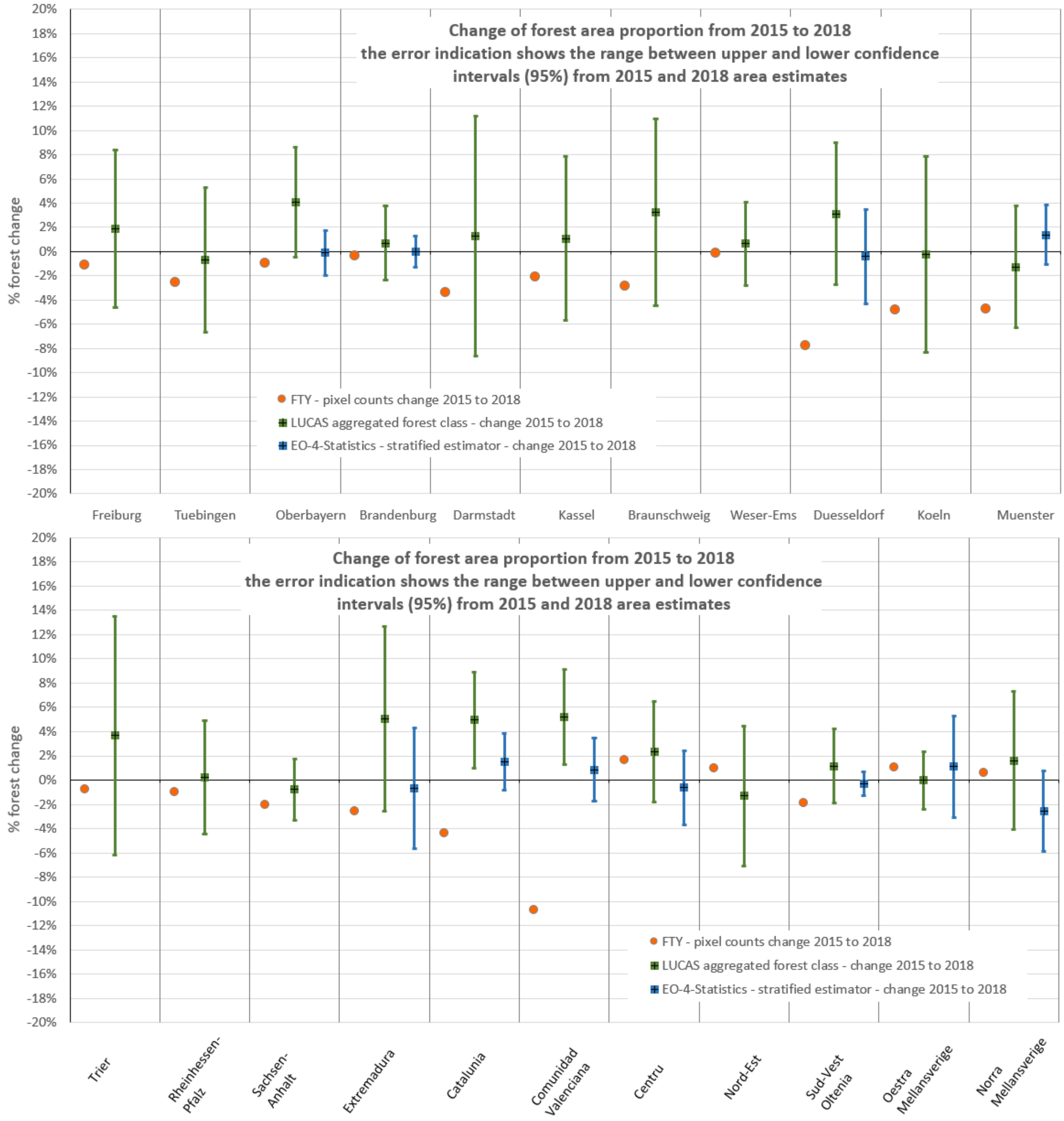


Figure 51: Change of forest area proportion from 2015 to 2018 and range between upper and lower 95% confidence intervals from 2015 and 2018 area estimates for selected NUTS2 regions

Tree cover change was analysed using the EO-4-Statistics reference data with a stratified sampling approach and 30 sample units per class and AOI. As discussed in chapter 4.3.3.3 Tree cover change has a strong regionalisation. In some AOIs a single patch of tree cover change existed and all sample units of the change class where, due to the selection process, placed in the same patch resulting in a strong correlation. In general estimating accuracy or area of rare classes is difficult since the difference between the weights of the strata is very huge and any misclassification has a huge impact on the result.

5.3.2 Impervious area and change

The accuracy of HRL imperviousness products was assessed using LUCAS survey data and the EO-4-Statistics reference data in the selected NUTS2 AOIs. The results showed an overall moderate-high agreement and higher agreement for 2018 than for 2015 and lowest agreement in Romania. Both assessments used the 10m and 20m impervious product from 2015 and 2018.

is the results are confirmed by the internal EEA validation (Table 43) of the aggregated 100m product which showed low producer's accuracy values for Romania. In general, the producer's accuracy is considerably lower than the user's accuracy which implies an underestimation of the impervious area.

Table 43: EEA internal validation results for the IMD 2015 and 2018 100m product imperviousness class (30% threshold) for blind interpretation and plausibility correspondence [26]

		2015				2018			
Blind interpretation									
AOI		**UA**	**CI95%**	**PA**	**CI95%**	**UA**	**CI95%**	**PA**	**CI95%**
DE	Germany	93.66%	0.11%	63.78%	0.35%	94.45%	0.10%	79.17%	0.29%
ES	Spain	88.89%	0.04%	50.46%	0.39%	89.47%	0.04%	80.32%	0.05%
RO	Romania	100%	0.00%	35.82%	0.08%	96.77%	0.03%	45.91%	0.40%
SE	Sweden	100%	0.00%	29.36%	0.64%	95.32%	0.02%	49.58%	0.68%
Plausibility correspondence									
AOI		**UA**	**+/-**	**PA**	**+/-**	**UA**	**+/-**	**PA**	**+/-**
DE	Germany	95.12%	0.09%	83.57%	0.25%	97.62%	0.07%	94.86%	0.20%
ES	Spain	93.83%	0.03%	71.70%	0.06%	95.61%	0.03%	91.60%	0.04%
RO	Romania	100%	0.00%	96.00%	0.03%	100%	0.00%	79.49%	0.06%
SE	Sweden	100%	0.00%	62.65%	0.66%	100%	0.00%	91.43%	0.03%

Source: GMES Initial Operations / Copernicus Land monitoring services – Validation of products: HRL IMPERVIOUSNESS DEGREE 2018 VALIDATION REPORT. available at https://land.copernicus.eu/user-corner/technical-library/clms_hrl_imd_validation_report_sc04_1_3.pdf (2021-02-11)

Biased area estimates on country level were calculated using simple pixel counting of the hard coded imperviousness pixel values and aggregation of the IMD products Unbiased area estimates were calculated combining the HRL products and the EEA validation data aby using an regression estimator. The resulting impervious area estimate was in all cases higher than from the pixel counts and closer to the LUCAS aggregated artificial area estimates. Figure 52 compares the results from the different estimates with the area extracted from pixel counting.

[26] https://land.copernicus.eu/user-corner/technical-library/clms_hrl_imd_validation_report_sc04_1_3.pdf

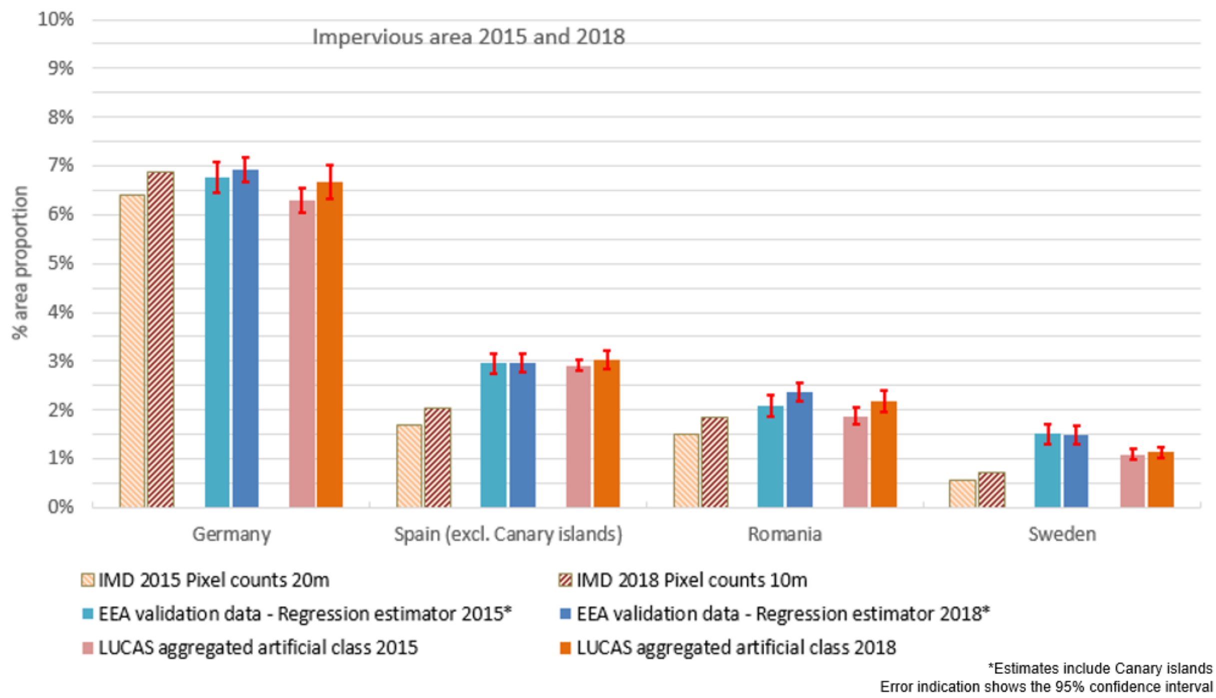


Figure 52: Impervious area proportion from biased pixel counts and "unbiased" estimates - 2015 and 2018 per country

The application of the regression estimator required the reproduction of the sample strata which were used by the internal EEA validation. One stratum (Strata 30) had to be approximated as it is not based on the HRL layer to be analysed, but on an intersection with Corine land cover and Open street map data. This may lead to a bias in the area estimation.

Table 44: Impervious area estimates from biased pixel counts compared to "unbiased" estimators – 2015 and 2018 per country

IMD	IMD Pixel counts (30% threshold)	IMD Pixel mean 100m (no threshold	Regression estimator 100m			LUCAS aggregated artificial class *		
2015	IMD15 (20m) area proportion %	area proportion%	Km²	%	CV	Km²	%	CV
Germany	6.4%	4.3%	24,204	6.8%	2.3%	22,463	6.3%	2.1%
Spain	1.7%	1.2%	14,712	3.0%	3.6%	14,527	2.9%	2.1%
Romania	1.5%	0.9%	4,966	2.1%	5.2%	4,483	1.9%	4.9%
Sweden	0.6%	0.8%	6,795	1.5%	6.8%	4,883	1.1%	5.1%
2018	IMD18 (10m) Km²	Km²	Km²		CV	Km²	%	CV
Germany	6.9%	5.2%	24,745	6.9%	1.9%	23,745	6.6%	2.6%
Spain	2.0%*	1.6%	14,782	3.0%	3.4%	15,028	3.0%	3.1%
Romania	1.8%	0.9%	5,623	2.4%	4.2%	5,062	2.1%	5.10%
Sweden	0.7%	0.5%	6,700	1.5%	6.6%	5,081	1.1%	5.2%

* estimates exclude Canary Islands

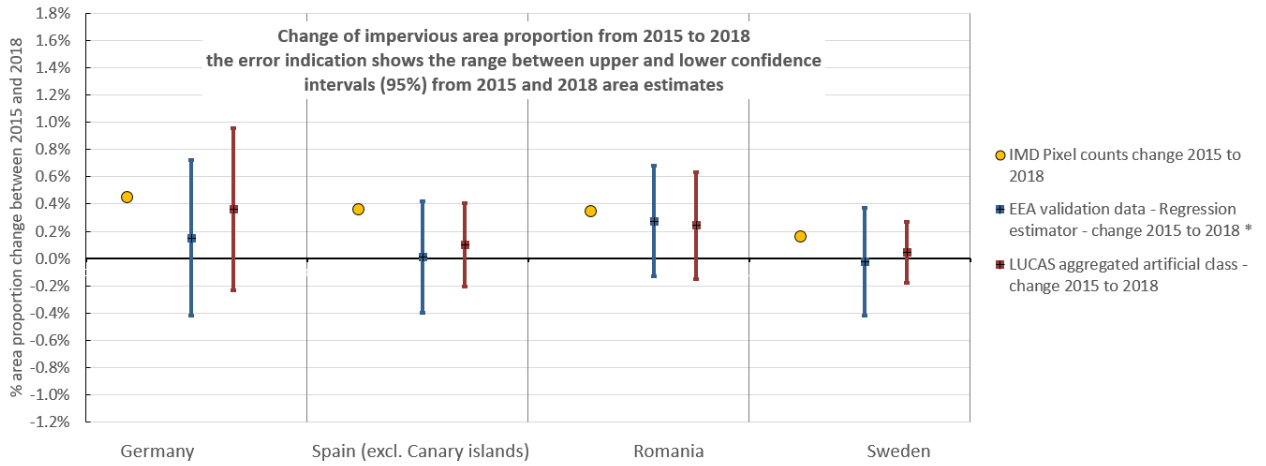
Table 44 provides the biased pixel counts from the imperviousness product IMD15 and IMD18 on 20m and 10m with a threshold of >=30%, the impervious area derived from the sum of imperviousness degree from the IMD 100m products, the estimates from the regression estimator and the estimates from the LUCAS aggregated artificial class. The results from the regression estimator are close to the estimates from the LUCAS aggregated class whereas the impervious area from the pixel counting is much lower. The CV of the regression estimator is apart from Sweden and Romania in 2015 below 5%. In Germany in 2015 and 2018 and Romania in 2018 the CV of the regression estimator is lower than the CV of the estimate from the aggregated LUCAS class.

Higher CV s in the estimates from the LUCAS aggregated class are partly due to the fact that during the aggregation of the LUCAS data, points belonging to the artificial stratum have been reclassified as non-artificial because the secondary land cover belongs to a non-impervious land cover. For example in Sweden 309 artificial LUCAS points out of the 1076 points in the artificial stratum have been reclassified as non-artificial in the aggregated class. Those points are mainly located on roads and parking lots consisting of unconsolidated material such as sand, bare soil or grass and electrical lines, they have been considered as non-impervious (see chapter 4.2.1.2). As a result the variance in the artificial stratum and thus the CV of the LUCAS aggregated artificial estimates is increased.

An assessment of impervious area change from 2015 to 2018 is provided in the Figure 53 below, it shows the difference in impervious area from 2015 to 2018 using the same data source. For the estimates the difference between the lower 95% confidence interval in 2015 and the upper 95% confidence interval is included in order to consider the uncertainty of the estimates in both years.

Looking at change in impervious area from 2015 to 2018 the pixel counting result shows an increase of impervious area in all tested countries. The change rate is in a range that this is expected to be due to the change in the resolution and input data in the production of the IMD 2018. This is further described in the assessment of the impervious change product (IMCC15-18) in chapter 4.3.3.4.

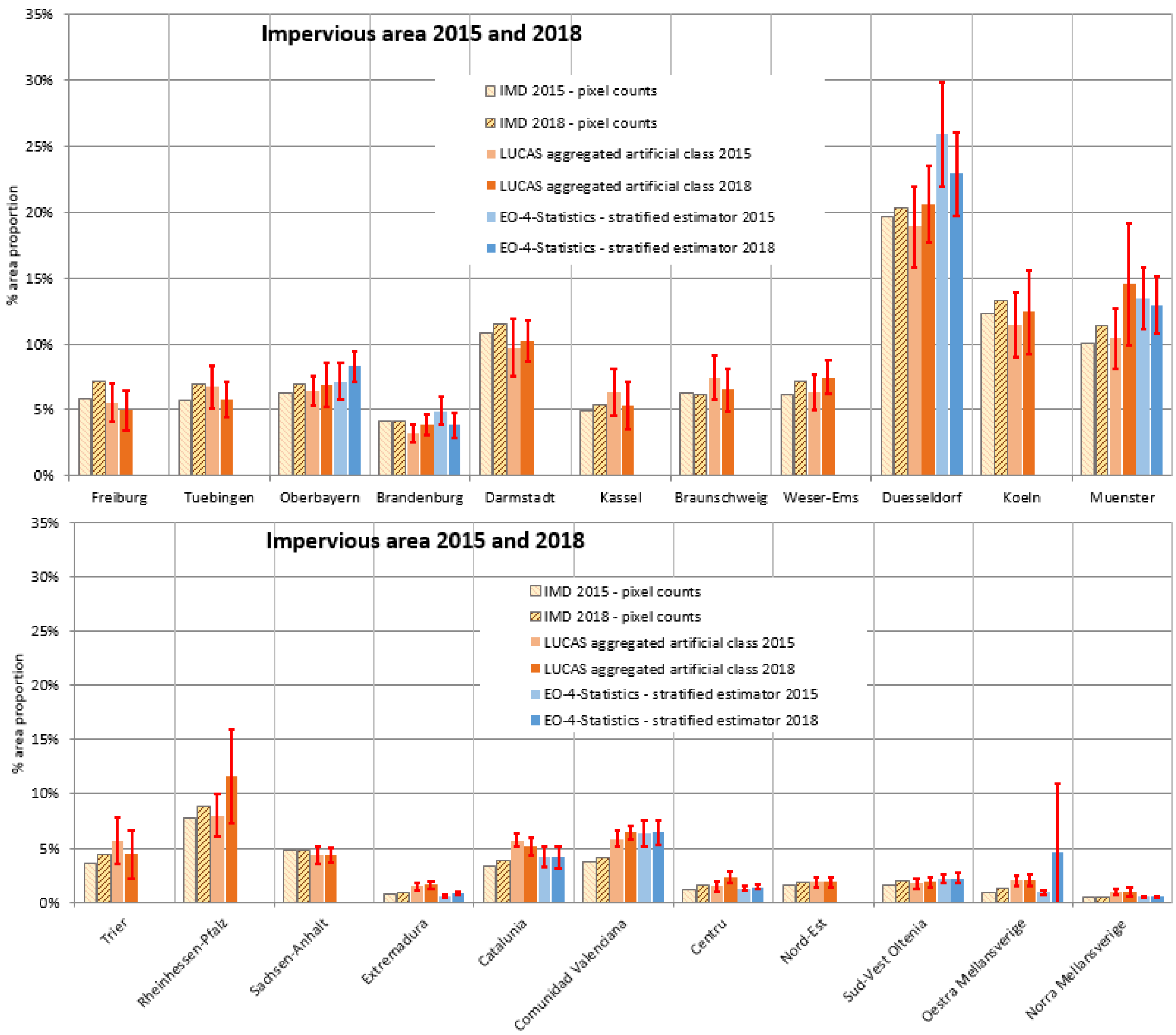
The change in impervious area from the regression estimator in 2015 and 2018 is low for all countries. An exception is Romania where the results indicate an increase in impervious area from 2015 to 2018 although the uncertainty of the change is higher than the change rate itself.



(* includes Canary Islands)

Figure 53: Change of impervious area proportion from 2015 to 2018 and range between upper and lower 95% confidence intervals from 2015 and 2018 area estimates

The assessment of the accuracy and area estimation on the selected NUTS2 level (see chapter 4.3.3) using EO-4-Statistics reference data and the 20m and 10m IMD products confirmed the indication of an underestimation of the impervious area. In fact, the producer's accuracy is for most AOIs lower than the user's accuracy. Apart from few NUTS2 regions the impervious area extracted by pixel counting from the HRL products is lower, than the area estimated from the LUCAS aggregated artificial class.



The error indication shows the upper and lower 95% confidence interval of the estimate.

Figure 54: Impervious area estimates from biased pixel counts compared to “unbiased” estimators – 2015 and 2018 selected NUTS2 regions

The stratified sampling approach with only 30 sample units per map class which was applied in some of the selected NUTS2 regions allowed to considerably reduce the number of sample units. In some cases this sampling approach resulted in high uncertainty of the area estimate, for example in Oestra Mellansverige. The sampling weight of the non-target class is so huge that one wrongly classified sample leads to a huge change in the estimated area. This is further described in chapter 4.3.3. Nevertheless it shows that the estimation of area for rare classes which cover only a small part of the total area is difficult.

An assessment of imperviousness area change from 2015 to 2018 on NUTS2 level is provided in Figure 55 below, it shows the difference in imperviousness area using the same estimator. For the estimates the difference between the lower 95% confidence interval in 2015 and the upper 95% confidence interval is included in order to consider the uncertainty of the estimates in both years. In all cases the range of the 95% confidence interval between the estimates in 2015 and 2018 is overlapping with 0%. This indicates that there is no clear indication of a change in area. This means that either there is no change or the change is so small that it cannot be estimated with the applied estimators and data at this administrative level within a time frame of 3 years.

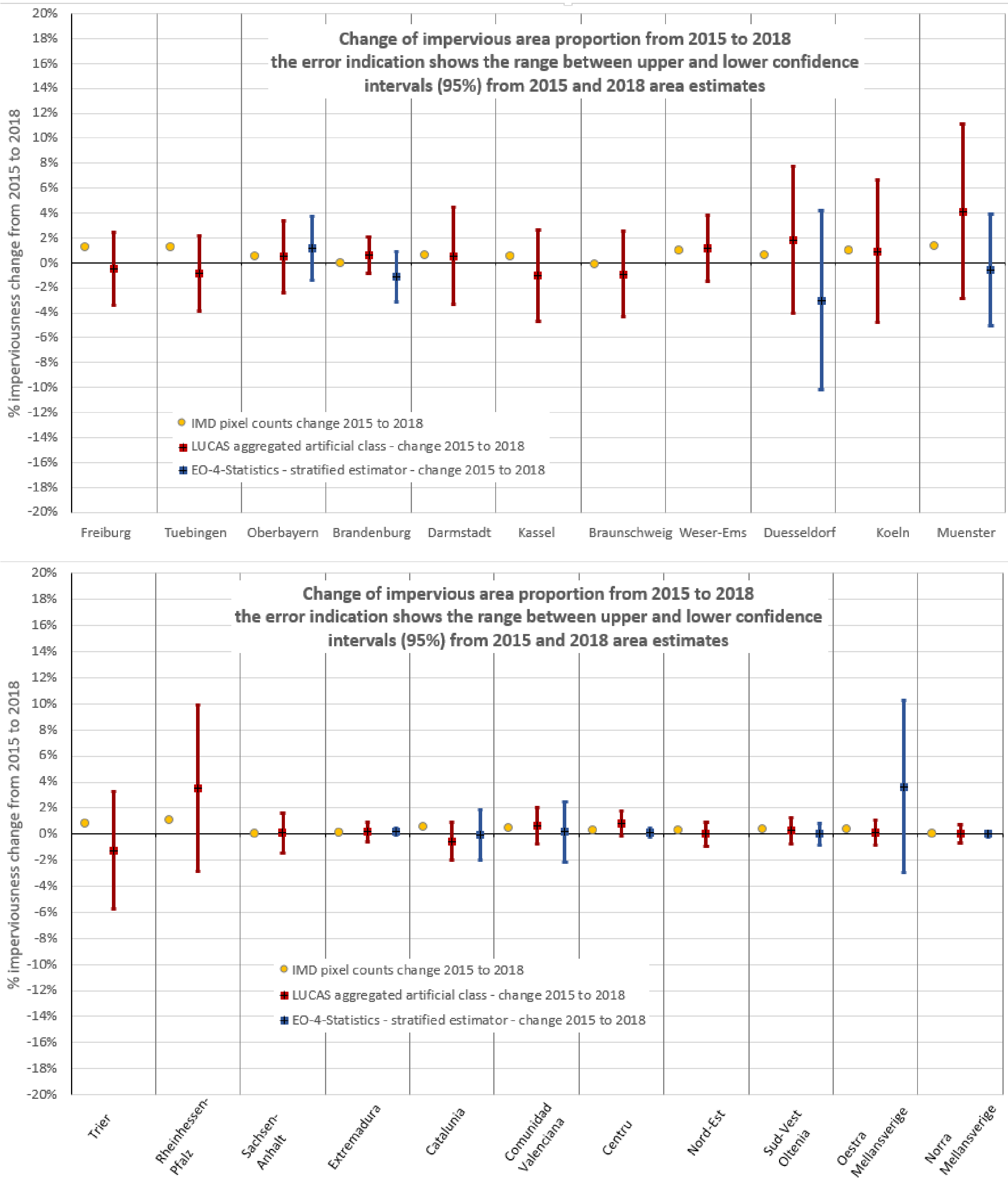


Figure 55: Change of impervious area proportion from 2015 to 2018 and range between upper and lower 95% confidence intervals from 2015 and 2018 area estimates - NUTS 2 regions

5.4 Statistical impact

The above visualisation of the various results allows to focus on the key criteria of "unbiased" area estimation in the light of change assessments. Of relevance is the question: if and how far are the explored changes meaningful, i.e., statistically significant? As expressed above, rarely the individually tested "unbiased" AOI estimation showed a statistically significant change, except some of the benchmarked forest changes that were calculated on basis of aggregated LUCAS observations. Only when the range of area change exceeds the quantified CVs a statistical significance would be proven. In many cases the assessed land cover changes are relatively small, which are "surpassed" through possible sources of errors in the area estimation approach.

5.4.1 Sources of error in the area estimates

There are two types of errors in the estimates for area and accuracy. The error or uncertainty from the sampling design, the so-called **sampling error**. It quantifies the uncertainty of the estimate, which is caused by the fact that a sample is used to estimate a parameter for the entire AOI. The sampling error for area estimates is often expressed as the **coefficient of variation** (CV) or standard error. For accuracy estimates the **margin of error on a certain confidence level** is used. The sampling error can be calculated knowing the sampling design (sampling probabilities) and choosing the appropriate estimator (see chapter 3). The lower the sampling error the more precise is the estimate. To increase the reliability of the estimate (reduce the sampling error) in a design based approach there are in general two options, increase the number of sample units or make the sampling design more efficient, e.g. by using a more accurate map to allocate the sample units to the target classes (stratification).

An example for the possible effect of the chosen sampling design on the sampling error is provided in chapter 4.3.3.2. Using equally 30 sample units per class for area estimation of the rare class "impervious" in the NUTS2 region Oestra Mellansverige resulted in a high CV of 72%. This reveals the disadvantage of the chosen sampling approach "equal proportion" in this scenario as it results in unequal "sampling weights". Conversely, "equal weights" would have considerably increased the number of sample units in "unequal proportions".

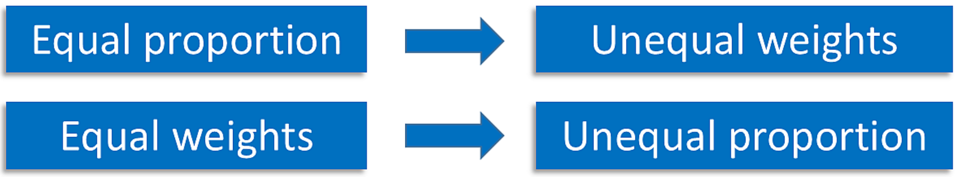


Figure 56: Impact of sampling strategies

All other remaining errors are so called **non-sampling errors**, which include all error sources not related to the sampling design, for example classification or positional errors in the reference data, mixed signatures, observation mistakes, and others. Non-sampling errors are important but difficult to quantify and can have a huge impact on the estimates. Below possible sources of non-sampling errors are discussed.

5.4.1.1 Compatibility between EO classification and reference data

Thematic compatibility between map and reference data and clear definition of classes is essential. Small differences in the definition of a land cover class and how the class definition is applied during the collection of the reference data can have a significant impact on the estimation results. A 1:1 thematic relation between reference data and classified image is an essential requirement.

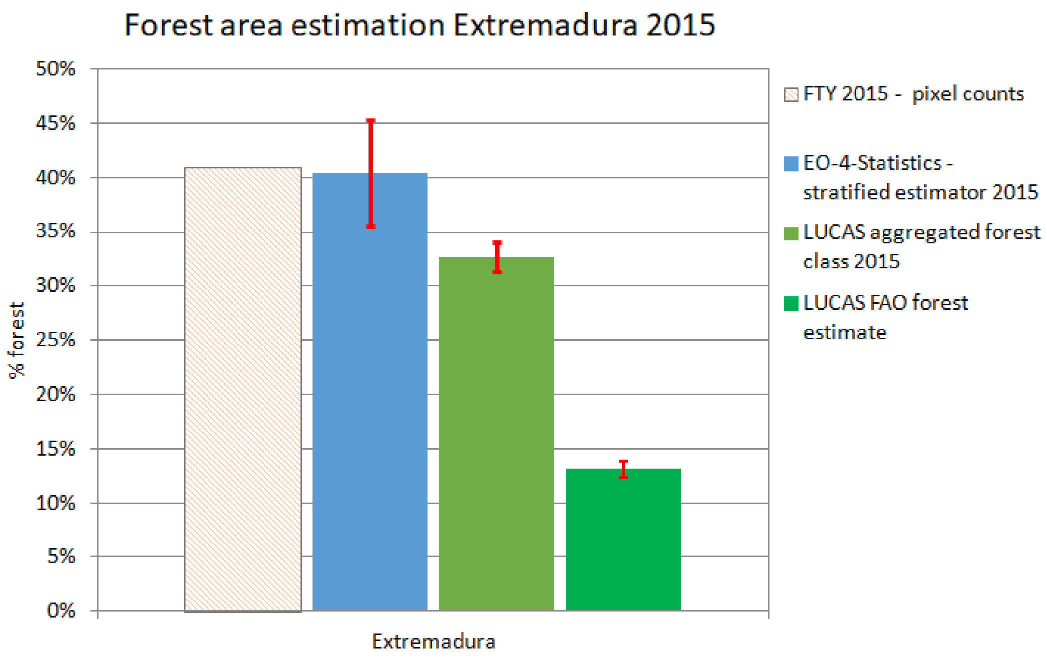
Explored examples:

- ⇨ The definition of forest includes components which are related to the land use and go beyond a pure land cover definition such as tree cover, for example exclusion of trees in urban context. Since "urban areas" or "urban context" is difficult to be defined from a remote sensing perspective as well as for the collection of reference data, this can lead to different interpretations of the same patch of tree between reference data and image classification.

The forest definition which is used for the FTY product follows mainly the FAO definition, but it explicitly includes Dehesas and Montados, an agroforestry system typical for some regions of Spain and Portugal. In the LUCAS FAO forest statistics Dehesas are excluded. The huge difference in the estimates becomes obvious when the "forest" area estimates are compared for the Extremadura, a Spanish region where Dehesas are very common. The full LUCAS database contains parameters that allow to include Dehesas in the LUCAS estimates via an aggregation using different LUCAS components to get aggregated forest classes (chapter 4.2.1). This provides a better thematic comparison with the HRL forest definition.

The error indication shows the 95% confidence interval of the estimate.

- ⇨ Figure 57 illustrates the difference in the forest definition when including Dehesas (light green) or excluding Dehesas (dark green) for the region Extremadura.



The error indication shows the 95% confidence interval of the estimate.

Figure 57: Comparison of forest area estimates with LUCAS data including and excluding Dehesas for Extremadura.

⇨ In case of Imperviousness the definition is clearer, but sources of errors do possibly appear during the interpretation of the reference data (see below). Misinterpretations can appear similarly as compared to image classification, such as in the given example it can be expected for:

- unpaved roads (e.g. forest roads in Sweden) or unpaved parking areas
- construction sites
- dump sites
- mining areas
- temporary greenhouses or fields covered with plastic cover
- artificial surfaces which are partly or completely covered by tree canopy

Figure 58: Examples of "roads" with different surfaces from the LUCAS survey (LUCAS photo viewer)

For example in the LUCAS nomenclatures roads are classified as an artificial land cover 'A', but in case the road is unpaved a second land cover is recorded to specify the material of the road, e.g. bare soil or sand. Figure 58 shows examples of different types of "roads", the examples on the right have been recorded with a second land cover specifying the surface (sand, gravel, soil, grass, …). This allows to better differentiating between the actual land cover and the land use (road) towards an EO based definition of imperviousness or artificial surfaces. In this assessment LUCAS points belonging to the artificial class, but with a pervious surface have been considered as non-impervious.

In the EEA validation data the secondary subsample points are classified into artificial "sealed" or "unsealed" to derive the reference impervious density value in the sample unit. It is not further specified if for example roads consisting of unconsolidated material, such as gravel are considered as sealed or unsealed.

Spatial compatibility between the map units and the sample units from the reference data are required to compare the same part of the surface of the earth. In case different areas are compared it leads to errors which are not related to the classification of the image or the classification of the reference data. This type of errors are more eminent in fragmented landscapes or when the target land cover is very fragmented, as it is the case with impervious surfaces.

Explored examples:

⇨ Due to the location of the LUCAS point at the corner of the aggregated HRL grid, the reference information from the LUCAS core observation is compared to 4 pixels from the HRL map. In theory:

  - The LUCAS point has a diameter of 3m (approx. 7 m²), when the extended window of observation of 20m is applied, the observed area is 1.257 m².
  - 4 HRL pixels in 2015 cover an area of 40x40m (1600 m²)
  - 4 HRL pixels in 2018 cover an area of 20x20m (400 m²).

This can create a possible error when for example the land cover information observed at 7m² is compared to a theoretical pixel area of 1600m². An additional issue is that the extended window of observation in not fixed for the core LUCAS parameter, but extents only to the homogenous plot (see chapter 2.2.2). Some additional preparation steps have been applied to the LUCAS data to increase the spatial compatibility with the HRL pixels, see chapter 4.2.1.3. Modules such as the Copernicus observations introduced in 2018 can improve the spatial compatibility. See further recommendations in chapter 7.

The HRL forest product uses a minimum mapping unit of 0.5 ha (see chapter 2.1.3) for non-forest area within a forest. The LUCAS minimum mapping unit are land cover objects of 3x3m. This will create a mismatch in cases when the LUCAS point falls on such areas, for example a road in a forest. See chapter 4.2.1.1.

- ⇨ Issues in the spatial co-registration of background imagery used for visual interpretation of sample units. Positional errors either in the classification or in the reference imagery can lead to errors simply due to the fact that the sample unit overlaid in a GIS, appears to be in a different location than in the HRL map. For the collection of EO-4-statistics reference data single pixels were used as sample unit, this increased the risk that the actual position in the reference imagery is different than the position in the HRL map. Using larger sample units reduces the risk of positional errors, but then the map has to be aggregated and accuracy cannot be assessed on individual pixel level in full resolution.
- ⇨ Superimposed features can create an error in particular when the reference data is collected in the field. For example a LUCAS point falling on a road is classified as road, regardless if the road is covered by tree canopy and would be interpreted as tree cover from bird's eye view. In the EEA validation data and in the EO-4-Statistics reference data bird's eye view is used to classify the reference samples.

Temporal compatibility between the map and the reference data are required to compare the same time period. In case the same area is compared at different time periods it can result in different land covers in reference and map but not due to an error in the map. This is in particular relevant for land covers with a high change rate.

Explored examples:

- ⇨ Forestry activity is high in Sweden and often large areas of forest are completely cut (clear cut). In the selection of reference imagery for the interpretation of the EO-4-Statistics reference data care had to be taken to select and check for the correct time period of image sources. Whereas visual interpretation usually allows to use multiple image sources from multiple dates, the LUCAS land cover observation is taken at a single date, the date of the survey. In case of land cover changes shortly before or after the survey date differences between map and reference data may appear.

5.4.1.2 Issues related to reference data

A common approach to create the reference observation is based on visual interpretation of very high resolution remote sensing data for example open accessible satellite image sources such as Google Maps or Bing Maps data or official sources, such as public aerial images. Depending on the quality of the image data, the appropriateness of the acquisition dates, as well as the training and experiences of the remote sensing interpreters, errors and inconsistencies in the image interpretation may happen and have an impact on the estimates. Measures to minimise errors in the reference data due to interpretation mistakes include proper training and interpretation protocol (data collection manual), using experienced operators and a thorough quality control procedure and possibly a double blind approach for the visual interpretation of reference data.

Explored examples:

- ⇨ Two of the three employed reference data sets were based on visual interpretation. This approach is a widely accepted and effective way to create remotely sensed reference data. Contrary to remote sensing based classification, validation of remotely sensed reference information is rarely applied. Conversely, handling and understanding of visually interpreted reference data as “ground truthing” may mislead the interpretation of the results. Particularly through the fact, that the core information in “unbiased” approaches comes from the reference sample, it is crucial to ensure sound quality control, access to micro data and to quantify non-sampling-errors.
- ⇨ The lower thematic accuracies of the forest product in Spain may partly be further affected by higher error rates in the reference data. Forest is not a clear distinguishable land cover class and according to the Forest definition and applied MMU, the forest class may include areas which belong to different land cover classes e.g. areas with tree cover and without tree cover. In areas where the natural woodland is close to the defined 10% tree cover threshold for forest definition, transition between forest and other woodland is often not clearly detectable. This increases the error rate in the reference data. In the applied examples this is the case for northern Sweden and Spain. Measures like an additional plausibility control of samples units as applied in the EEA validation may be helpful to reduce arguable differences between map and reference data, but may also lead to an overestimation of map accuracy.

5.4.1.3 Issues related to EO classification

- ⇨ Besides the above explored inevitable technical mapping error in remote sensing (chapter 5.1) the degree of fragmentation of the observed landscape or land cover class impacts. The more fragmented landscapes or parameters such as artificial surfaces are, the bigger is the impact of misclassifications caused by the spectral reflectance within a pixel, or in “mixed pixels” along borders. For the reference data collection there are different ways to deal with those cases.

  - Applying a shifting rule to the observation point in case it is located on a border or linear element. In LUCAS survey a look to the north or east rule is applied when the 1.5m radius around the point is located on a border or linear element. Shifting rules require a clear definition of this cases and rigorous implementation through the interpreters or surveyors. For a direct spatial comparison with the HRL pixels this creates a possible mismatch and source of error, since the original LUCAS point observation has been shifted.
  - Applying a weight to the sample unit in case only half of it is covered by the land cover. This reduces the bias which is introduced when ignoring the proportion of a land cover or when excluding the sample unit. This method was applied during the interpretation of the EO-4-Statistics reference data. When a segment was covered between 40 and 60% by forest a weight of 0.5 was applied in the accuracy assessment and area estimation.
    In the EEA validation data for forest a 100x100m segment is classified as forest when the majority of area belongs to the forest class. This creates the same issue as mixed pixels in the map: an unknown proportion of the land cover class in the sample units is not considered and creates a bias in the estimation of area or accuracy.
  - Using a larger sample unit and recording proportions of land cover is properly the best approach to avoid or minimise the effect of mixed pixels in map and in reference data. Observing proportions in a sample is more time consuming, but allows to deal with complex land cover scenarios without introducing a bias in the sample unit. If the map provides proportions (like the IMD) or if the sample unit covers a sufficient number of pixels to calculate proportions a regression estimator can be used for the assessment of the area. This is an advantage from a statistical viewpoint.

⇨ Furthermore, additional sources for errors in area estimation are related to the use of different satellite or sensor systems or a change in the image classification procedure, even if the class definitions remain unchanged (see chapter 2.1 above). Although technical evolutions and constant processing improvements are essential characteristics of modern EO and GeoIT, the caused range of error can significantly exceed the actually identified increase or decrease of area estimates. Attention is required in order to explore the potential usability of Copernicus data for area estimations, given that future evolutions are very likely. A possible prospectus is elaborated via the H2020 study ECoLaSS[27].

5.4.2 Target scale and expected CV

The EO-4-Statistics project proofed the general feasibility to calculate "unbiased" area estimates by means of Copernicus HRL data with different reference data sets, across selected member states and NUTS2 regions (about 10% of EU 27 territory). Whereby on country level, with the exception of impervious area in Germany in 2018, none of the areas or area changes derived from simple pixel counting were confirmed with statistical representativeness through the independent "unbiased" approaches. Conversely, a benchmark with LUCAS estimates that was available via the Eurostat website including CVs[28] shows trends with statistical significance (Figure 59). This leads to an important lesson that shall be considered carefully. As a common principle, sound statistical assessments start with investigations on the expected scale and level of detail of the subjected parameter, whether area or area of change. The range of errors or uncertainty of the area estimate has to be considerably smaller than the area of the parameter to be observed. This impacts the appropriateness of selected observation means in view to possibly expected error sources and uncertainties related to the sample design. As such, it is crucial to clarify in advance of the implementation of area estimations with whatever means are employed to:

- Define the expected subject, scale and level of detail ahead of the exercise
- Define accepted margin of errors (CV)
- Plan resources / appreciate related costs for reference data collection
- Be clear about the scope of the exercise: area estimation / change monitoring / decision making / or just product validation.
- Don´t mix purposes and mandates.

Eurostat		2015			2012			2009	
	[km²]	[%]	[CV*]	[km²]	[%]	[CV*]	[km²]	[%]	[CV*]
Axx - Artificial land									
European Union (aggregate changing according to the context)	173.295	4,4	0,7	166.733	4,2	0,7	160.770	4,1	0,8
European Union - 27 countries (from 2020)	167.119	4,1	0,7	:	:	:	:	:	:
European Union - 28 countries (2013-2020)	183.122	4,2	0,7	:	:	:	:	:	:
A11 - Buildings with 1 to 3 floors									
European Union (aggregate changing according to the context)	48.909	1,2	1,4	48.127	1,2	1,5	46.066	1,2	1,7
European Union - 27 countries (from 2020)	46.835	1,1	1,4	:	:	:	:	:	:
European Union - 28 countries (2013-2020)	52.267	1,2	1,4	:	:	:	:	:	:
A12 - Buildings with more than 3 floors									
European Union (aggregate changing according to the context)	4.292	0,1	5,1	3.951	0,1	5,7	3.537	0,1	6,3
European Union - 27 countries (from 2020)	4.184	0,1	5	:	:	:	:	:	:
European Union - 28 countries (2013-2020)	4.434	0,1	5	:	:	:	:	:	:

*) CV for absolute value

Figure 59: LUCAS estimates that are available via the Eurostat website including CVs

[27] https://6c1e2b9b-e840-4757-9a09-97d14ddbfe72.filesusr.com/ugd/c90769_5a431f06039141a6b4db4d6b4596d272.pdf
[28] https://ec.europa.eu/eurostat/web/lucas/data/database

6 Wrap up

The use of remote sensing data for area estimation has been widely discussed over decades. Although, scientific literature well documented the key notions on how remote sensing has to be properly employed for area estimations since the late 1970s, evidences of inappropriate adaptions and unquestioned use by decision makers of related outcomes were found (Foody, 2002). Ongoing efforts and an ongoing discourse since then lead to an increased awareness and constantly improving exploitations of remote sensing techniques for statistically representative area estimations (Gallego et al. 2016). Actually, related advices are formulated by prominent intergovernmental organisations, such as the **Group on Earth Observation** (GFOI, 2016), or the United Nations Food and Agriculture Organisations "**Global Strategy to improve Agricultural and Rural Statistics**" (GSARS, 2017). There are increasing examples on how to adequately link EO validation and possible area estimation with adequate reference data (e.g. "COPERNICUS support to Group on Earth Observations Global Agricultural Monitoring (GEOGLAM) "(n°: JRC/IPR/2020/OP/0303). However, there seems to remain a prevailing uncertainty on how to adequately employ remote sensing for statistical purposes on one hand side, and how to ensure the benefits of the increasing opportunities of freely available remote sensing data and processing algorithms, on the other hand side. The questions for decision makers and stakeholders are:

- ⇨ **How to ensure highest efficiency of scientifically sound statistical approaches while fully employing the power of contemporary remote sensing and earth observation methods?**
- ⇨ **How to prevent repeating past mistakes or stepping into traps?**

In order to provide effective guidance on how to best ***integrate remote sensing into area estimation approaches*** and how to prevent possible insufficiencies in the application of statistical procedures in the use of remote sensing, it is recommended to wrap up the relevant key underlying concepts.

Through latest developments of Satellite Earth Observation technologies, including recent approaches such as machine learning algorithms or artificial intelligence, the increasing availability of advanced open processing libraries, as well as the increasing accessibility of EO data and services, such as the Copernicus program, there is a tremendous potential and growing demand to use EO data for spatial assessments and monitoring in administration and decision making. This evolution also attracts "new" approaches for statistical assessments and area estimation, whereas the underlying principles of Satellite Earth Observation and remote sensing concepts are not new. It is crucial to understand EO classifications as a cartographic generalization of the desired land surface that contains inevitable omission and commission errors. EO mapping is an aggregation of the real situation following cartographic principles (minimum mapping unit, cartographic scale, pixel resolution …). In simple terms, it is a simplification of the landscape's complexity (Figure 60).

Errors in an EO classification are inevitable and extracting areas directly from an EO classification through "simple pixel counting" will produce erroneous results. Simple pixel counting is a biased approach because it makes no provision for errors in the EO classification map product.

©: Digital Orthophoto North Rhine Westphalia - [Geobasis NRW](https://www.bezreg-koeln.nrw.de) (left), Sentinel 2 – ESA (center)

Figure 60: Sources of errors in remote sensing, e.g. varying classifications of shadow

As widely discussed, and explained in scholar, the approach to assess and correct the error related bias in EO classifications is through using independent and adequate reference data in a sample based approach.

Validation measures compare the map with the reference data over a sample and allow to assess the thematic quality of the entire map by means of confusion matrix (Figure 61). Although this does not change the quality of the maps, it is obligatory to quantify the range of mapping errors and the bias in the area.

To "correct" the bias in the area from EO classifications, there are different estimation approaches which combine precise reference data with EO classification to provide "unbiased" area estimates. The "unbiased" reference data, available only for a sample, is used to correct the "bias" in the EO classification, available for the entire area. These estimators produce "corrected" or "unbiased" area estimates and also provide statistical descriptors to quantify the range of uncertainty due to the fact that the estimate is based on a sample.

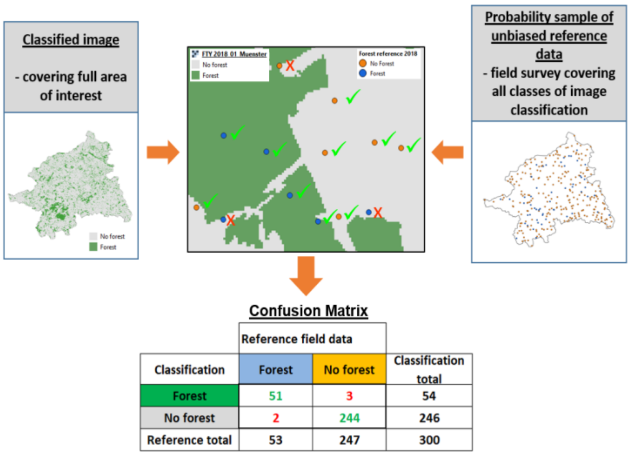


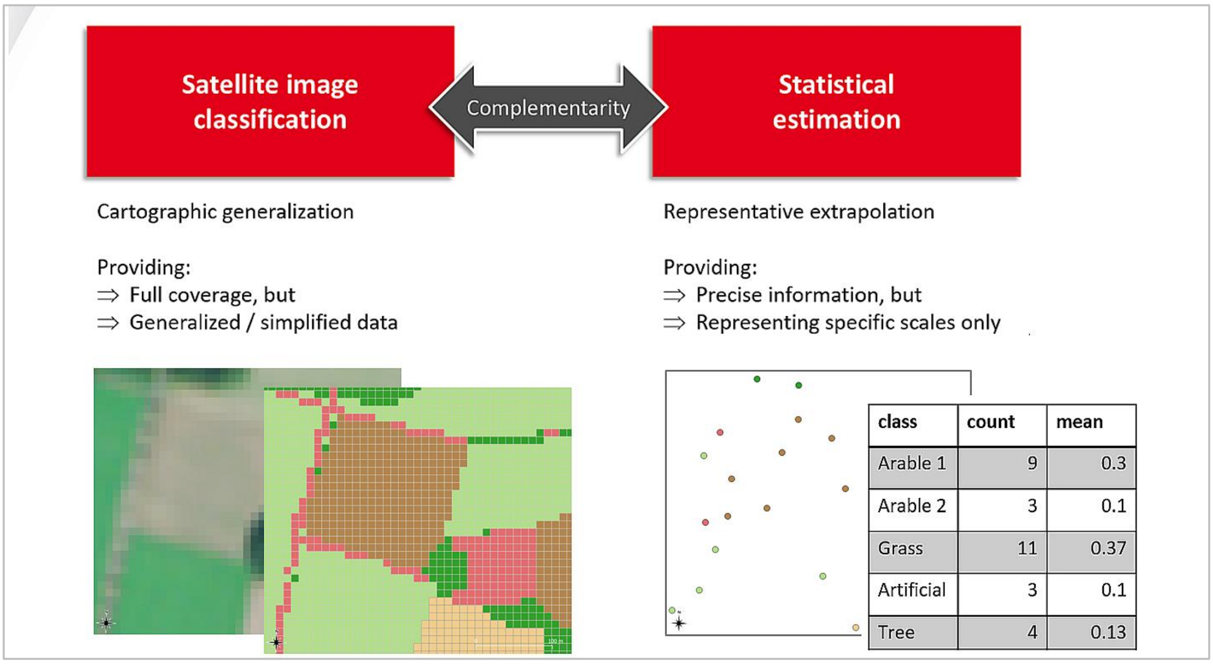
Figure 61: Overall approach for thematic map validation[29].

The difference between "biased" versus "unbiased" estimation is to compensate for the errors in the EO classification and the provision of statistical descriptors that quantify the range of uncertainty of the estimation process, such as the Coefficient of Variations (CV) at a given Confidence Interval (CI). Although the term "unbiased" estimates seems to be somehow unfavourable, this is what is meant within this contract – correcting or adjusting biased area from pixel counting and calculating the uncertainty of the area estimate (range of error), i.e. the area estimates corrected however still have a uncertainty, but with a known range of error.

In this context "*biased*" estimation or "*simple pixel counting*" is lacking:

- ⇨ **Consideration and compensation of inevitable mapping errors, i. e. the map accuracy**
- ⇨ **Measurements on the precision of the extracted areas, i.e. the range of error of the estimate must be smaller than the estimated area**

[29] *Administrative boundaries: © EuroGeographics*



©:Sentinel 2 – ESA

Figure 62: Complementarity between remote sensing based EO classification and sample based statistical estimation approaches

Conversely, estimates based on sample of reference data are an extrapolation of precise observations based on selected sample units towards an entire population. Errors due to the sampling or errors in the reference data created in the data collection process are multiplied towards the entire outcomes (Figure 63) which is why error tracing (sampling / non-sampling errors) and its quantification require crucial attention.

This study systematically calculated area estimates using "biased" and "unbiased" estimation approaches by means of Copernicus High Resolution Layers (Forest and Imperviousness, chapter 2.1) and using three different reference data sets (LUCAS, EEA validation and EO-4-Statistics data, chapter 2.2) over selected administrative levels, which covered about 10% of the EU27 territory (chapter 1.3).

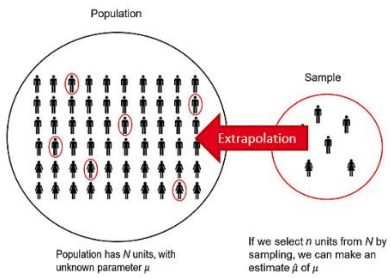


Figure 63: Extrapolation of precise observations

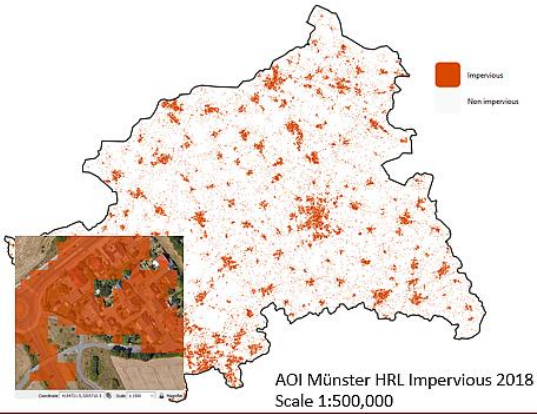
6.1 *Findings*

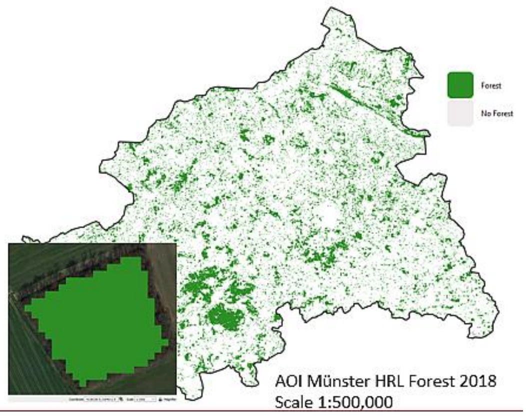
In a first step biased pixel counts for the selected EO input data had been extracted from the maps (Figure 64 a). In the next step the reference data sets had been used for thematic map validations. Therefore, the sampling and response designs had been carefully crosschecked and in case if necessary adapted (Figure 64 b). In the final step different "unbiased" estimators had been calculated for the suitable administrative levels, either at country or NUTS2 level (Figure 64 c). The below example provides an impression of the assessments for the NUTS2 AOI "Münster".

a) Simple pixel counting to extract biased area proportion of forest and impervious surface

	Impervious pixels	Non impervious pixels
Pixel counts	7,868,611	61,362,648
Proportion	0.114	0.886

	Forest pixels	No forest pixels
Pixel counts	12,044,185	57,187,074
Proportion	0.174	0.826



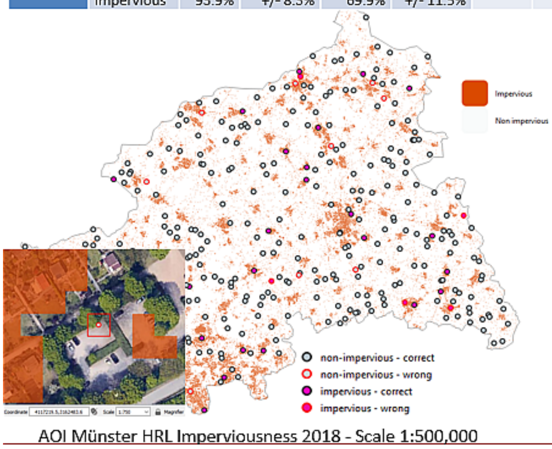


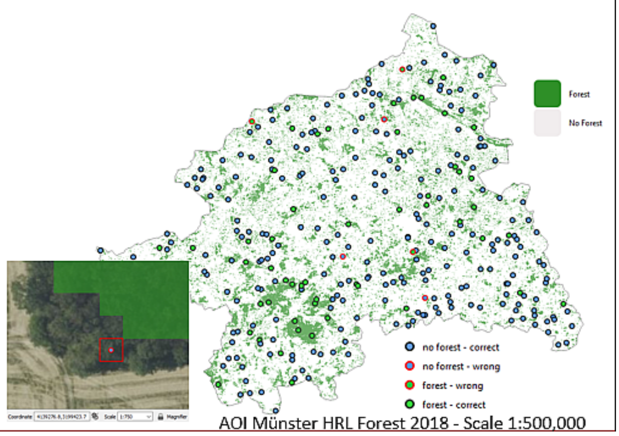
Administrative boundaries: © [EuroGeographics]

b) Accuracy assessment (map validation) of the HRL Forest and Imperviousness layer by comparing with reference data

HRL Imperviousness 2018		UA and margin of error CI95		PA and margin of error CI95		OA and margin of error CI95	
AOI	strata						
Münster	Non impervious	92.4%	+/- 3.2%	98.4%	+/- 1.4%	91.3%	+/- 3.0%
	impervious	93.9%	+/- 8.3%	69.9%	+/- 11.5%		

HRL Forest 2018		UA and margin of error CI95		PA and margin of error CI95		OA and margin of error CI95	
AOI	strata						
Münster	Forest	94.4%	+/- 6.2%	96.1%	+/- 5.2%	98.4%	+/- 1.4%
	No forest	99.2%	+/- 1.1%	98.8%	+/- 1.3%		





Administrative boundaries: © [EuroGeographics]

c) Estimation of Forest and Impervious surface by using the reference data and applying different "unbiased" area estimators

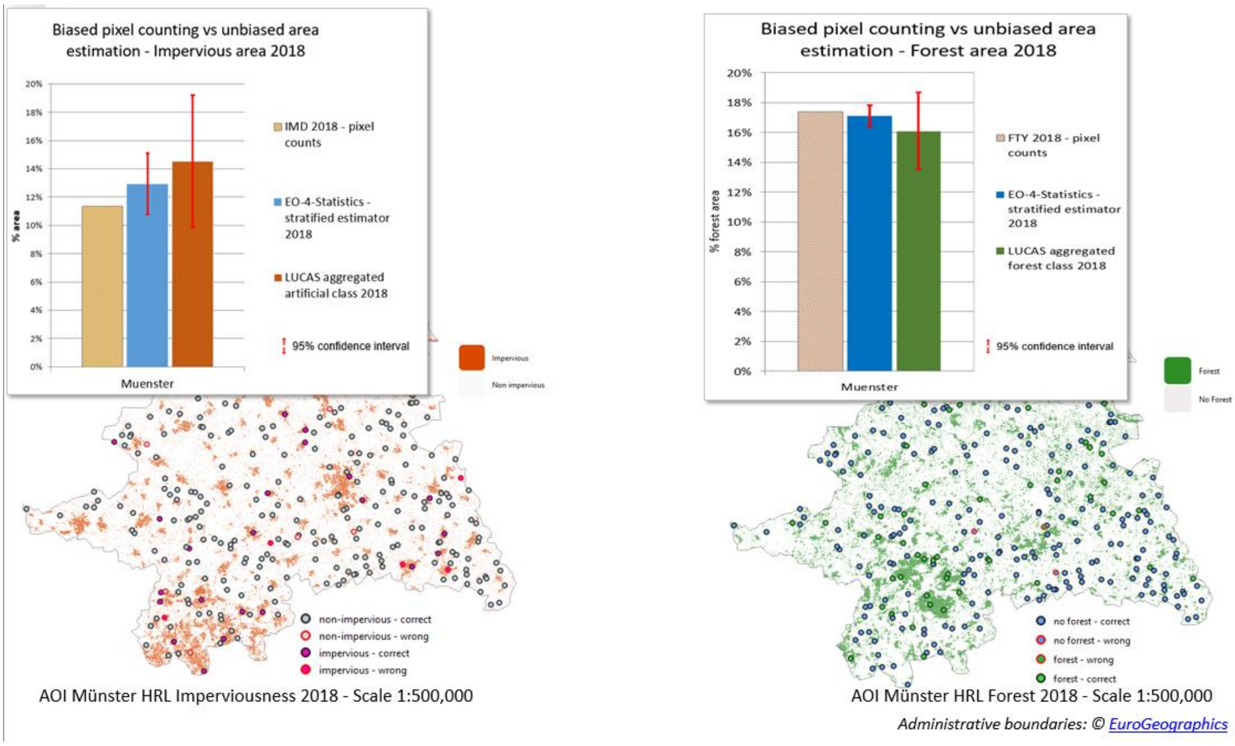
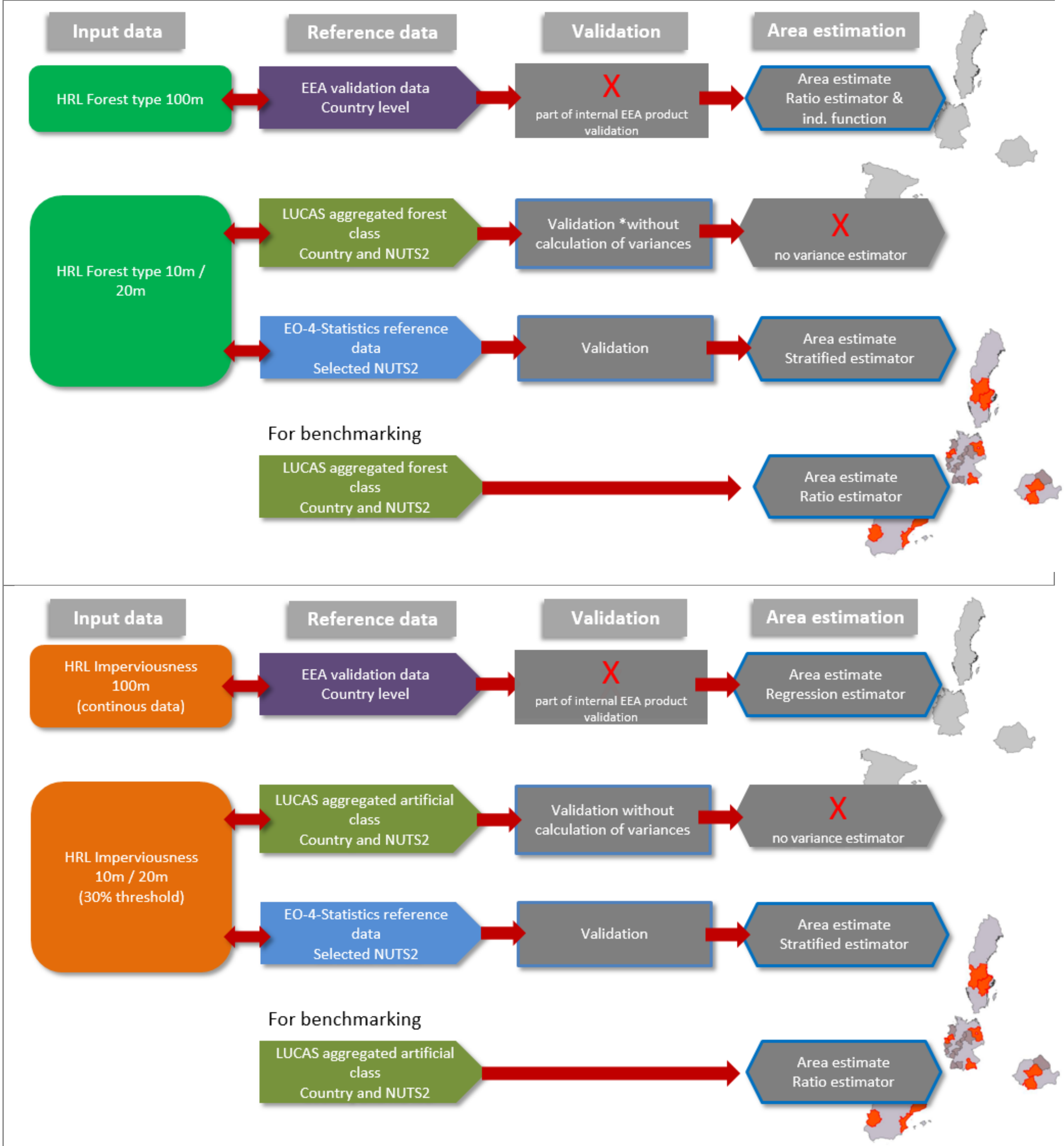


Figure 64 a-c: Example of an *EO-4-Statistics* assessment of "biased" versus "unbiased" estimates.

In general, it was planned to perform all similar set of tests for both HRL products across all selected AOIs, as defined in a dedicated test-protocol. In reality it turned out that with the applied reference data sets this could not be achieved. Given the dedicated purposes of the investigated data sets, a sufficient probability sampling that allowed "unbiased" estimation of area at all levels was per design not available. Among the employed tests, there was no reference data set available, that fully covered the principle requirements of a proven 1:1 relation in terms of spatial, temporal, or thematic aspects, nor at the required administrative units. The first reference data set, which was the EEA validation data set, for instance was sampled at country level only. Calculation of "unbiased" estimates were possible at this level, but not at NUTS2 level. Another limitation in the EEA validation data was a not clearly documented stratification step on basis of Open Street Map. This was by-passed in the current project, by "approximation" of the required strata information. The second attempt, using LUCAS data, which are sampled at NUTS2 level and cover countries are stratified according to a dedicated sampling scheme, which is not providing a suitable probability sampling that fits for the HRL products. It could be used for product validation, but not for the generation of variances per class. Finally, an individually created reference data set by means of visual interpretation allowed to employ "unbiased" estimators at NUTS2 level for selected AOIs, but not at entire country levels.



Administrative boundaries: © EuroGeographics

Figure 65: Overview about *EO-4-Statistics* assessments

6.2 Leading contractual questions

The sub chapters below summarise the findings of task 1 assessments on leading contractual questions.

6.2.1 Impact of mixed pixels

Mixed pixels are pixels of an EO classification which contain more than one land cover class. The opposite are "pure pixels" which contain only one land cover class. Mixed pixels appear typically along borders of land cover classes. The presence of mixed pixels is determined by the spatial resolution of the map pixels and the land cover to be mapped, the structure of the land cover and landscape (fragmented or not) and the technical limitations and resolution of the input satellite data. In general higher fragmentation and larger pixel resolution leads to higher rate of mixed pixels (see 3.1.1 Sources of bias in the map).

The problem with mixed pixels is that in a hard coded map each pixel is assigned to one land cover category based on the applied classification routine, proportions of other land cover classes in mixed pixels are not considered. This creates a bias when the map is used to estimate area and the sub-pixel proportions of land cover are not considered. Estimators which require hard classification into categorical classes of the map (and also reference data) i.e. to build a confusion matrix, are therefore more affected by mixed pixels. The problem of mixed pixels is not only relevant for area estimation but also for map validation.

The impact of mixed pixels is not only limited to the problem of pixels that are along the border of different land cover but rather a technical impact on the digital sensing of the satellite sensor itself see for instance the example of overexposure described in chapter 3.1.1 Sources of bias in the map. This leads to an increase of "mixed pixels" impact beyond the actual land cover borders and a possible overestimation of the specific land cover.

The issue of mixed pixels also applies for the reference data used for the validation of categorical maps in case different land cover classes are present in the reference unit and a class is assigned based on the majority found in the unit. There are different ways to deal with mixed land cover in the reference data by using shifting rules, applying weights or recording proportions and applying the corresponding estimator, see chapter 5.4.1.3 Issues related to EO classification.

Map validation or better accuracy assessment is a tool to detect and quantify classification errors in a map, but not specifically errors due to mixed pixels. Chapter 4.3 Accuracy and area estimation using EO-4-Statistics reference data and 4.2.2 Accuracy and 4.3.3 Accuracy and area estimation provide the results from comparison of the reference data with the HRL products.

Overall the analysis shows higher rates of map errors in regions with fragmented landscapes (for example forest in Spain). The impact of mixed pixels is assumed to be higher in 2015 due to a lower spatial resolution of 20m compared to 10m in 2018. In addition the production method of the HRL layers has changed in 2018, in particular the use of Sentinel image time series should lead to an increase in the product quality in addition to the increase in spatial resolution.

In the forest product the specific impact of mixed pixels is difficult to assess. Forest is not a clear distinguishable land cover class and may include per definition different land cover classes (pixels with tree cover and without tree cover) and may contain different proportions of tree cover. The impact of mixed pixels for the forest layer are therefore only clearly detectable in cases where a pixel falls on a visual detectable border between forest and no forest defined by tree cover.

The 100m forest product is further aggregated from the 10m or 20m resolution products. Here the effect of mixed pixels can be expected to be higher than in the full resolution products.

Artificial surfaces are a very fragmented land cover and a high rate of mixed pixels can be expected in particular in areas with a more fragmented settlement structure. The IMD layer is not affected by mixed pixels, since it already considers the proportion of the impervious area in each pixel. Here the issue is more related to defining a threshold to classify the impervious value to built-up and non-built up pixels. The application of a threshold like 30% intentionally excludes up to 29% of impervious area in pixels. An assessment of the IMD threshold compared to LUCAS data is provided in chapter 3.2.1.1 Threshold for assessment of impervious area (continuous data). Biased area estimation considering the proportion of impervious area and not a threshold is described in chapter 3.1 Biased area estimation - Simple pixel counting estimator.

A further important aspect is the spatial resolution of the map unit or sample unit to assess imperviousness. With the increased spatial resolution in the 2018 products, it can be expected that imperviousness is captured more precise than in the 2015 product. It is obvious that a 10x10m pixel is more suitable to adequately capture a road with e.g. 6m width compared to a 20x20m pixel. The results from the different assessments of the IMD product in 2018 and 2015 in chapter 5.3.2 Impervious area and change show the improvement of thematic accuracy from 2015 to 2018.

To minimise the effect of mixed pixels in "unbiased" area estimation there are some recommendations:

- ⇨ For the assessment of categorical maps a practical solution to reduce the impact of mixed pixels is the application of weights to the "mixed" sample units (pixels). The weight, similar as a proportion, ensures that the sample unit contributes only with a certain weight e. g. 0.5, to the estimation approach. In an accuracy assessment this means that the mixed pixel in the sample is considered as "half" correct and "half" wrong. Weights have been used in the assessment with the LUCAS data in chapter 4.2.1.3 Verification of LUCAS land cover extent and with the EO-4-reference data in chapter 4.3.2 Reference data interpretation.
- ⇨ Recording proportions of land cover in the sample unit and in the map can be considered as the best approach to avoid the issue of mixed pixels. For continuous data such as the IMD it can be readily applied. For categorical data such as the FTY product the use of large sample units, which cover several pixels, is recommended. The proportion is then calculated from the number of forest pixels in the sample unit, see further in chapter 5.4.1.2 Issues related to reference data.

  The regression estimator is an appropriate estimator for large sample units which provide area proportions of a land cover class, see chapter 3 Using EO classifications for area estimation and the applied example in chapter 3.2.4 Estimating area using proportions - Regression estimator.

6.2.2 Factors determining the entity of the bias

The bias of a pixel counting estimator is the difference to the "true" area of the land cover in the AOI. The bias in pixel counting is therefore not only determined by the thematic accuracy of a map classification (e. g. derived from a validation), but by the difference between the map errors in the different map classes (errors of omission and commission). In theory the classification errors in the different map classes can outbalance each other. This makes it more difficult to assess the bias and its sources since even maps with low thematic accuracies could provide acceptable area estimates.

Nevertheless the major sources of bias in pixel counting are due to classification errors and mixed pixels in the map which are related to the land cover to be mapped, the structure of the land cover (fragmented or not) and the technical limitations and resolution of the input satellite data. This is further discussed in chapter 3.1.1 Sources of bias in the map and 5.4.1.3 Issues related to EO classification. The factors determining the entity of bias in the regional context of the selected AOIs is further elaborated in the validation of the HRL products for the chapter 4.3 Accuracy and area estimation using EO-4-Statistics reference data and 4.2.2 Accuracy and in the section below.

The assessment of the bias from pixel counting is done by benchmarking the obtained area against area derived from "unbiased" area estimation approaches using accurate reference data and from LUCAS data, see chapter 5.3 Achieved benchmarks. The assumption is that the estimates from the LUCAS data provide the most accurate area estimate for forest and imperviousness in the selected AOIs. The benchmark shows that in the 4 selected countries the area of imperviousness and forest derived from the HRL products is not within the estimated area range from the LUCAS data. The only exception is impervious area in Germany in 2018.

Table 45 and Table 46 show the difference between the area obtained from the simple pixel counting (map area) and the area obtained from the estimates using the EEA validation data compared to the area estimated from the LUCAS aggregated class. The difference is expressed as a percentage from the area estimated from the LUCAS data. Uncertainties in the estimates are not considered since they are rather low on country level.

Pixel counting using the IMD and a threshold (30%) is underestimating the area of imperviousness in all countries and both years except for 2018 in Germany. In Spain and Sweden the area from the pixel counting in 2015 is only about half of the area estimated from the LUCAS data. The highest agreement is reached in Germany where the area from pixel counting is only 3% higher than the estimate from the LUCAS data. Using the EEA validation data and the regression estimator provided in all cases estimates closer to the estimates from the LUCAS data, except in Germany in 2018.

- ⇨ In general the IMD product seems to provide better results for Germany than for other countries. The lowest agreement is in Sweden where the proportion of artificial area is lower and the artificial area is more fragmented than in Germany.

Table 45: Impervious area derived from pixel counting and from the EEA validation data compared to area estimates from LUCAS aggregated artificial class

Imperviousness	IMD Pixel counts (30% threshold)	EEA validation data - Regression estimator
2015	% difference to LUCAS aggregated class	% difference to LUCAS aggregated class
Germany	2.2%	7.8%
Spain*	-42.3%	1.3%
Romania	-19.8%	10.8%
Sweden	-48.6%	39.1%
2018		
Germany	3.4%	4.2%
Spain*	-32.5%	-1.6%
Romania	-13.0%	11.1%
Sweden	-36.7%	31.9%

* LUCAS data excludes Canary Islands

On NUTS 2 level, due to few sample units in the impervious class, the uncertainty of the LUCAS and EO-4-statistics estimates are higher than on country level. The meaningfulness of a comparison of the area from the pixel counting with the unbiased estimation results without considering the uncertainty is therefore limited. A benchmark of the areas obtained from the different estimators including the uncertainties of estimates is provided in chapter 5.3.2 Impervious area and change.

- ⇨ The benchmark indicates lower bias in the IMD products for regions with higher proportions of artificial areas. Such as the small NUTS2 regions in West Germany (e.g. Duesseldorf, Koeln) compared to regions with very low proportion of artificial area such as the NUTS2 regions in Sweden.

- ⇨ Biggest differences in the area from the pixel counts compared to the LUCAS estimate appear in both years in Spain. This indicates a higher bias in the IMD product in the Mediterranean landscape.
- ⇨ With very few exceptions the area from the pixel counts is lower than the area from the aggregated LUCAS estimates in both years, the differences are lower in 2018, indicating a reduction of map bias due to the new HRL production method.

The results from the forest assessment in Table 46, show a reduction of the bias in the HRL map area from 2015 to 2018 for Germany and Spain. In Sweden with the highest absolute and relative area of forest the results are in both years close to the estimates from the LUCAS data. Again, except for Sweden in 2018 the application of unbiased estimators provided results closer to the aggregated LUCAS estimates.

- ⇨ The reduction of the bias seems to be clearly related to the change in resolution and / or production method.

On NUTS 2 level, with few exceptions the forest area from the FTY pixel counts is larger than the area from the aggregated LUCAS estimates, the exception is again Sweden, see chapter 5.3.2 Impervious area and change. In 2018 in 18 out of 22 NUTS2 regions the difference to the aggregated LUCAS estimates is below 10% and with differences below 2% in at least one NUTS2 region from each of the selected countries.

- ⇨ There is no clear regional trend visible which indicates factors determining the bias of the forest map area.
- ⇨ The highest reduction of the map bias is between 2015 and 2018, obviously determined by the changed HRL production method and higher resolution in 2018.

Table 46: Forest area derived from pixel counting and from the EEA validation data compared to forest area estimates from LUCAS aggregated forest class

Forest	FTY Pixel counts	EEA validation data - Stratified estimator
2015	% difference to aggregated LUCAS class	% difference to LUCAS aggregated class
Germany	16.4%	11.5%
Spain*	22.2%	6.7%
Romania	8.3%	8.3%
Sweden	-0.9%	-1.6%
2018		
Germany	5.8%	4.5%
Spain*	-4.3%	-0.8%
Romania	7.0%	5.3%
Sweden	-5.1%	-7.5%

* LUCAS data exclude Canary Islands

The assessment shows clearly the impact of the bias of the pixel counting estimator and the need for unbiased estimation approaches for area estimation. In some exceptions the area derived from the map alone is close to the unbiased estimates, but without an assessment of the map, this exceptions remain unknown. There are considerable differences in the map related bias between different European regions and between NUTS2 regions of the same country, this requires that unbiased assessments are applied on the relevant administrative level of interest. The assessment further showed that there is an overall reduction of map bias in the 2018 product.

6.2.3 Change assessment

Change of impervious area and forest area was assessed by comparing the results from the estimated area for 2015 and 2018 from the different applied biased and unbiased estimators and compared to aggregated

LUCAS estimates. The difference between the lower 95% confidence interval in 2015 and the upper 95% confidence interval in 2018 is included in order to consider the uncertainty of the estimates in both years. Figure 66: Benchmarking of area change considering the uncertainty of the estimates illustrates the applied change assessment for the imperviousness results on country level. Chapter 5.3 Achieved benchmarks contains the change assessment for forest and imperviousness for all applied estimators and for the 4 selected countries and 22 NUTS2 regions. To summarize:

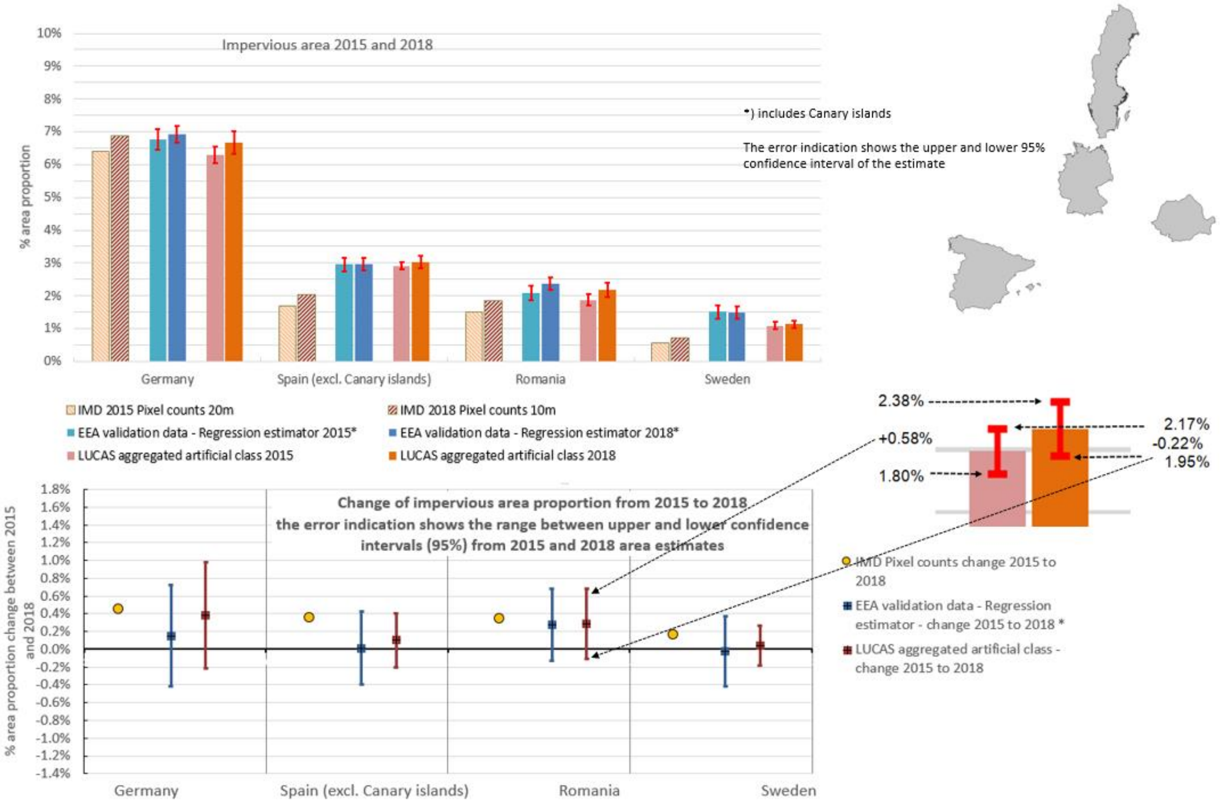
Change of impervious area from 2015 to 2018

- ⇨ Area from pixel counting shows an increase of impervious area in nearly all AOIs, this is very likely affected by the technical change in the production method and resolution of the IMD product from 2015 to 2018.
- ⇨ Unbiased area estimators of impervious area show change rates which are in all cases below the uncertainty of the estimates. That means the change (in case there is change from 2015 to 2018) is too small to be assessed with a statistical significance with the applied methods.

Change of forest area from 2015 to 2018

- ⇨ Area from pixel counting shows a decrease of forest area in nearly all AOIs, this might be related to the technical change in the production method and resolution of the IMD product from 2015 to 2018.
- ⇨ Area from "unbiased" estimators of forest show change rates which are in most cases below the uncertainty of the estimates. An exception is a small increase in forest area in Germany and Spain in the LUCAS data used for benchmarking.

As a conclusion this change assessment shows the importance of considering the expected range of the parameter to be assessed and the uncertainty of the used estimation approach. The applied area estimation approach and in particular the underlying sampling design has to be chosen in order to provide estimates with an uncertainty which is significantly below the parameter to be assessed. For example, estimating area change of expected 0.5% of the total area with an estimation approach that provides an uncertainty of +/-1% will not provide a meaningful result. This is further discussed in chapter 5.4.2 Target scale and expected CV and chapter 4.3.1 Sample design considerations.



Administrative boundaries: © EuroGeographics

Figure 66: Benchmarking of area change considering the uncertainty of the estimates

An alternative and usually applied approach to estimate area of change is the use of classified change maps and reference data containing information from 2015 and 2018 for the sample units.

- ⇨ A HRL forest change layer is not available. To support the change assessment the HRL tree cover change layer was assessed and change area estimated in order to support the assessment of forest change. The results are provided in chapter 4.3.3.3 Tree cover change 2015 - 2018 and show no significant change between 2015 and 2018 with the applied estimator.
- ⇨ The HRL imperviousness change products are reported to be unreliable because of a change in the methodology and spatial resolution of the status products from 2015 and 2018. Nevertheless an assessment of the change products was done for the 22 selected NUTS2 regions and unbiased area was calculated, see chapter 4.3.3.4 Imperviousness change 2015 - 2018.

7 Conclusions and recommendations

The EO-4-Statistics project proofed the general feasibility to calculate "unbiased" area estimates by means of Copernicus HRL data with different reference data sets, across selected member states and NUTS2 regions (about 10% of EU 27 territory).
In order to increase the efficiency for land resource monitoring the following key findings and recommendations are listed:

I) Using EO classification as sole source of data is not a reliable method for area estimation.
Using only the Copernicus maps and simple pixel counting is a biased approach and does not allow to create reliable area or area change statistics. On country level none of the area results derived from simple pixel counting of the HRL products were confirmed with statistical representativeness through the independent "unbiased" approaches. Although this has been discussed over decades, with the increased availability of EO data and means for classification the use of maps for area estimation is tempting and to prevent repeating past mistakes and stepping into traps it is recommended:

⇨ Help non-experts to get on board and understand the everlasting expert's debate on "biased" versus "unbiased" estimation by means of EO through:

  - Easy to digest glossaries, guidelines and tangible examples.
  - More precise information about the applied approaches.
  - Not promising tempting "fast lane" solutions for area estimation through inappropriate approaches, such as pixel counting.

⇨ Clearly indicate limitations and pitfalls of pixel counting

⇨ Clearly call pixel counting by its name in case no proper "unbiased" area estimation was done and areas are derived from the map

⇨ Don´t mix purposes such as validation and area estimation

⇨ "Unbiased" estimation approaches are required to estimate area

II) Statistical assessment of reliability (uncertainty) of results is crucial.
"Unbiased" area estimation approaches combining a map with adequate reference data, are available to generate area statistics. The crucial element of this estimators is the provision of the uncertainty of the results, usually expressed as coefficient of variation (CV), which provides the information if the estimated area is reliable or not. The final benchmarks with the Eurostat LUCAS based estimates demonstrate the importance of adequate planning and design with a clear consideration of the **targeted precision and expected range** of the assessed estimates at a targeted administrative level, in particular when targeting rare classes such as imperviousness or change. To ensure highest efficiency of scientifically sound statistical area estimation approaches while fully employing the power of contemporary remote sensing and earth observation methods it is recommended:

⇨ Carefully plan resources for reference data collection and the sampling design in order to realise results which have an uncertainty (range of error) that is lower than the expected area, otherwise the result is meaningless. For example estimating impervious area of 500 km² with an uncertainty of +/- 700 km² is not a reliable result. To reduce the uncertainty in an estimate a higher number of sample units is required or a more efficient approach, e.g. better stratification, different estimator.

- ⇨ Statistical estimators for area and accuracy are available and have to be applied correctly considering the sampling design and response design of the input data.
- ⇨ Be clear about the scope of the exercise: area estimation / change monitoring / decision making / or just product validation.
- ⇨ Estimates are only applicable for the defined geographic entity they have been estimated for and cannot be used for spatial analysis such as through intersections with geo data. There are specific methods available for such requirements (e.g. small area estimation).
- ⇨ Quickly available LUCAS estimates including CV via the web site are important for benchmarking.
- ⇨ Don't misuse validation results in case sampling design and/ or response design are not sufficiently considered.

III) The need for a proper reference data infrastructure on European level.

Prerequisites for unbiased area estimation are the availability of reference data with adequate **probability sampling** and sound response design ensuring a **proven 1:1 match** between EO and reference data. This project showed that a key limitation in the creation of unbiased estimates using EO products is the availability of adequate reference data at the targeted administrative level and its applicability for the assessment of EO based classifications. This reference data should be easily available and provide:

- Standardized quasi "tamper-proof" data collection and data flow through GeoIT
- Ensure full understanding and documentation of the technical approaches
- Documentation and tracing of possible non-sampling errors

LUCAS and the Copernicus validation data can provide such information if specific improvements are envisaged.

Recommendations for the EEA validation data:

- ⇨ Publication of HRL validation data with full documentation and sampling strata in case the strata are not based on the HRL map products
- ⇨ Validation data at full HRL product resolution (10m and 20m)
- ⇨ Assessment based on the same administrative level e.g. NUTS0, rather than grouping of countries.
- ⇨ Specify product definitions for heterogeneous surfaces and differentiate between land use and land cover (e.g. roads)
- ⇨ Specify product validation criteria for Forest in full resolution considering MMU, woodland in urban areas, clear cuts, …
- ⇨ Further assess the effect of using "blind" or "plausibility" interpretation in the reference data creation in the context of "product validation" versus "area estimation".

Recommendations for the LUCAS sampling design:

- ⇨ Publish LUCAS sampling weights
- ⇨ Simplify the LUCAS sampling design in order to improve integration with other datasets and the calculation of variances.
- ⇨ Or simplify only the sampling design for the specific EO modules (Copernicus module, Imperviousness). For example select the points for Copernicus from the Master grid and add them on top of the LUCAS sample. Many of those points would possibly already belong to the selected sample for the regular survey. To be clarified are, the method how to select the points for the Copernicus module and the number of points required on different administrative levels:

- E.g. systematic by selecting every x point in the grid. Advantage: independent from any stratification. Disadvantage: how to ensure that sufficient number of points are collected from the classes to be validated (e.g. artificial class)?
- E.g. stratified selection using the LUCAS strata to select the points. Allows to better (more efficiently) select the points, but the selection probability is different between the strata and analysis becomes again more complicated.

IV) Better adapt planning of both programs HRL Copernicus and LUCAS.

With the Copernicus HRL and LUCAS two major complementary data sets are available at EU level with exhaustive documentation for the requested assessments. Copernicus contribute with excellent products to the available EO data infrastructure for the EU, which is complemented with a globally unique reference data source of LUCAS. Yet, technical limitations had been identified that limited the full application at the given time. In order to increase the efficiency for land resource monitoring it is recommended to explore ways to better adapt planning of both programs.
Recommendations to increase synergies between both programs are:

⇨ Ensure methodological continuity of the HRL products and prevent fundamental changes / ongoing evolution of existing products considering e.g. MMU, class definitions, methods, …

⇨ Possibly consider HRL for LUCAS stratification, provided that the methodological continuity of HRL is ensured

⇨ Consider LUCAS data for validation of Copernicus products, provided the technical limitations in compatibility of the data is overcome

⇨ Systematically elaborate on improved response design for better synergies between both programs

Recommendations for specific LUCAS modules:

i. LUCAS “Copernicus” module:

⇨ Consider doing LUCAS Copernicus observation at the LUCAS point to apply and use the full LUCAS parameters and nomenclature

- And, if it is done at the point, then assessment of LUCAS Copernicus could be realised also in case of PI, using the Ground document as reference (if reliable)
- The land cover at the point reached by the surveyor could still be registered, to be in compliance with land cover photos

⇨ Change ”minimum 5m extent “ observation rule for Copernicus, to increase number of possible observations also in fragmented land cover, such as urban areas

⇨ LUCAS Copernicus LC classification considering bird’s eye view for better application with remote sensing. Extra tick box to mark cases where the Copernicus land cover is superimposing the LUCAS land cover (e.g. road under tree canopy).

ii. LUCAS Imperviousness

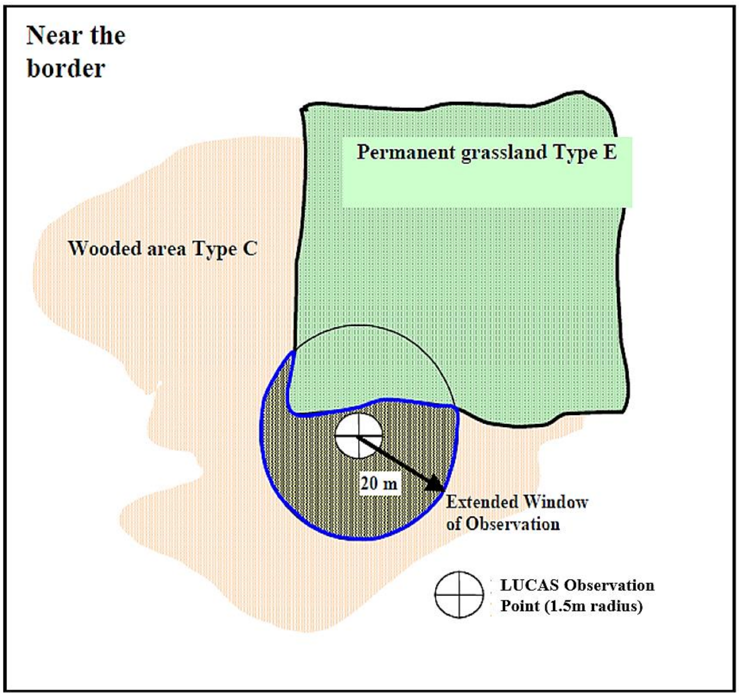
⇨ Revise LUCAS Imperviousness using latest HRL IMD definitions and a fixed radius, with bird’s eye view and only artificial sealed surface, for better thematic compliance with evolved HRL impervious EO product and other EO applications.

iii. LUCAS Inspire PLCC module

⇨ Extent the PLCC observation for all points, not limited to certain land covers

⇨ For the extended windows include also proportions (from the birds-eye-view), summing up to 100%

  - Below example: "E" – 30%; "C" – 70%



References

Ballin, M., Barcaroli, G., Masselli, M., Scarnò and Scarnò, M. (2018) Redesign sample for Land Use/Cover Area frame Survey (LUCAS) 2018, Statistical Working Papers Eurostat.

Benedetti, R., Bee, M., Espa, G. and Piersimoni, F. (eds.) (2010) *Agricultural survey methods*, Chichester, U.K., John Wiley & Sons.

Buck, O., Haub, C., Woditsch, S., Lindemann, D., Kleinewillinghöfer, L., Hazeu, G., Kosztra, B., Kleeschulte, S., Arnold, S. and Hölzl, M. (2015) *Task 1.9 - Analysis of the LUCAS nomenclature and proposal for adaptation of the nomenclature in view of its use by the Copernicus land monitoring services*, Service contract report No. 3436/B2015/R0-GIO/EEA.56166, Copenhagen, Denmark, European Environment Agency (EEA), [online] Available at: https://www.eftas.de/en/eftas-content-pool.php?selection=Download#post-lucas-and-copernicus (Accessed 9 May 2020).

Carfagna, E. and Gallego, F. J. (2005) 'Using Remote Sensing for Agricultural Statistics', International Statistical Review, 73(3), pp. 389–404.

Casella, G. and Berger, R. L. (2002) *Statistical Inference*. Thomson Learning.

Cochran, W. G. (1977) *Sampling techniques*, 3rd ed, New York, John Wiley & Sons.

Congalton, R. G. (1991) A review of assessing the accuracy of classifications of remotely sensed data, *Remote sensing of Environment*, 37(1), pp. 35–46, [online] Available at: http://www.sciencedirect.com/science/article/pii/003442579190048B (Accessed 27 November 2013).

Congalton, R. G. and Green, K. (2008) *Assessing the accuracy of remotely sensed data: principles and practices*, 2nd ed, Boca Raton, CRC Press/Taylor & Francis.

d'Andrimont, R., Verhegghen, A., Meroni, M., Lemoine, G., Strobl, P., Eiselt, B., Yordanov, M., Martinez-Sanchez, L. and van der Velde, M. (2020) LUCAS Copernicus 2018: Earth Observation relevant in-situ data on land cover throughout the European Union, Earth System Science Data Discussions, pp. 1–19, [online] Available at: https://essd.copernicus.org/preprints/essd-2020-178/ (Accessed 4 December 2020).

Data is available at https://figshare.com/articles/dataset/LUCAS_2018_Copernicus/1238266

Deville, J.-C. and Särndal, C.-E. (1992) Calibration estimators in survey sampling, *Journal of the American Statistical Association*, 87(418), pp. 376–382.

Eurostat (2016) LUCAS: Land Use and Land Cover Survey. http://ec.europa.eu/eurostat/statistics-explained/index.php/LUCAS_-_Land_use_and_land_cover_survey

Eurostat (2018) LUCAS 2018 Technical reference document C4 – Quality Control Procedures.

Eurostat (2018) LUCAS 2018 Technical reference document C1 – Instruction for Surveyors https://ec.europa.eu/eurostat/documents/205002/8072634/LUCAS2018-C1-Instructions.pdf

Eurostat (2015) LUCAS 2015 Technical reference document C1 – Instruction for Surveyors https://ec.europa.eu/eurostat/documents/205002/6786255/LUCAS2015-C1-Instructions-20150227.pdf

Eurostat (2009a) LUCAS 2009 Technical reference document M2 – Quality Assurance https://ec.europa.eu/eurostat/documents/205002/769457/LUCAS2009_M2-QualityAssurance_20131004.pdf

Eurostat (2009b) LUCAS 2009 Technical reference document M3 – Non Sampling Error Report. https://ec.europa.eu/eurostat/documents/205002/769457/LUCAS2009-M3-NonSamplingError-20130414.pdf

FAO (ed.) (2016) *Map Accuracy Assessment and Area Estimation*, *National forest monitoring assessment working paper*, Rome.

Gallego, F. J. (2004) Remote sensing and land cover area estimation, *International Journal of Remote Sensing*, 25(15), pp. 3019–3047, [online] Available at: http://www.tandfonline.com/doi/abs/10.1080/01431160310001619607 (Accessed 27 November 2013).

Gallego J., (2017a) *Copernicus Land Services to improve EU statistics*, EUR 29027 EN, Publications Office of the European Union, Luxembourg. [online] Available at: https://op.europa.eu/en/publication-detail/-/publication/75af3b8f-f74d-11e7-b8f5-01aa75ed71a1/language-en (Accessed 19 November 2020).

Gallego, F. J. (2017b) Estimating and correcting the bias of pixel counting, In Global Strategy to improve Agricultural and Rural Statistics (GSARS) (ed.), *Handbook on Remote Sensing for Agricultural Statistics*, *GSARS Handbook*, Rome, pp. 249–257.

Gallego, J., Carfagna, E. and Baruth, B. (2010) Accuracy, objectivity and efficiency of remote sensing for agricultural statistics, In Benedetti, R., Bee, M., Espa, G., and Piersimoni, F. (eds.), *Agricultural survey methods*, Chichester, U.K., John Wiley & Sons, pp. 193–211.

Gallego, F. J., Palmieri, A. and Ramos, H. (2015) Sampling system for LUCAS 2015., LU, Publications Office, [online] Available at: https://data.europa.eu/doi/10.2788/963 (Accessed 2 March 2021).

Gallego, J. and Delincé, J. (2010) The European land use and cover area-frame statistical survey, In Benedetti, R., Bee, M., Espa, G., and Piersimoni, F. (eds.), *Agricultural survey methods*, Chichester, U.K., John Wiley & Sons, pp. 151–168.

Gallego J., Sannier Ch., Pennec A. (2016) Validation of Copernicus Land Monitoring Services and Area Estimation. *International Conference of Agricultural Statistics* (*ICAS) VII*, Rome, October 26-28 2016.

GEOSS (2009) Best practices for crop area estimation with remote sensing, In Ispra, JRC, [online] Available at: https://www.earthobservations.org/documents/cop/ag_gams/GEOSS%20best%20practices%20area%20estimation%20final.pdf.

GFOI (2016) Integration of remote-sensing and ground-based observations for estimation of emissions and removals of greenhouse gases in forests: Methods and Guidance from the Global Forest Observations Initiative, Edition 2.0, Rome, Food and Agriculture Organization, [online] Available at: https://core.ac.uk/download/pdf/76975176.pdf (Accessed 2 March 2021).

Haub, C., Kleinewillinghöfer, L., Garcia Millan, V. & Di Gregorio, A. (2015) '*Protocol for land cover validation*'. Project deliverable D33.2 of the EU FP7 Stimulating Innovation for Global Monitoring of Agriculture project – EU grant agreement No 603719. Available online: https://www.eftas.de/upload/15357037-SIGMA-D33-2-Protocol-for-land-cover-validation-v2.0-2015-06-22vprint.pdf [Online: accessed on 08.04.2020].

Haub, C., Kleinewillinghöfer, L. & Gilliams, S. (2018): New understanding of thematic Land Cover validation on basis of the SIGMA validation protocol and QGIS Plug-in. Oral presentation in the session "Guidelines and Protocols for Validation" of the European Space Agency (ESA) Workshop on Land Product Validation and Evolution 2018, 27.02.-01.03.2018, Frascati, Italy. Available online: https://earth.esa.int/documents/700255/3506752/13.00%20-%2013.20_Haub_eftas%20validation.pdf [Online: accessed on 08.04.2020].

Jacques, P. and Gallego, F. J. (2006) The LUCAS 2006 project–A new methodology, *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, *Workshop proceedings: Remote sensing support to crop yield forecast and area estimates*, XXXVI(8/W48),

Lohr, S. L. (2010) *Sampling: Design and Analysis*. Second Edition. Brooks/Cole.

Olofsson, P., Foody, G. M., Herold, M., Stehman, S. V., Woodcock, C. E. and Wulder, M. A. (2014) Good practices for estimating area and assessing accuracy of land change, *Remote Sensing of Environment*, 148, pp. 42–57, [online] Available at: http://linkinghub.elsevier.com/retrieve/pii/S0034425714000704 (Accessed 10 November 2014).

Olofsson, P., Foody, G. M., Stehman, S. V. and Woodcock, C. E. (2013) Making better use of accuracy data in land change studies: Estimating accuracy and area and quantifying uncertainty using stratified estimation, *Remote Sensing of Environment*, 129, pp. 122–131, [online] Available at: http://linkinghub.elsevier.com/retrieve/pii/S0034425712004191 (Accessed 8 September 2016).

Pennec, A., Sannier, C & Smith, G. (2019) '*Comparative validation of Artificial Land Products*'. Final report of the 'GMES Initial Operations / Copernicus Land monitoring services – Validation of products. Validation services for the geospatial products of the Copernicus land continental and local components including in-situ data (lot 1), third specific contract - N°3436/R0-COPERNICUS/EEA.57056. Copenhagen, Denmark, European Environment Agency

(EEA) [online]. Available at: https://land.copernicus.eu/user-corner/technical-library/comparative-validation-of-artificial-land-products/ [Accessed on 23 September 2020].

Rice, J. A. (1995) Mathematical Statistics and Data Analysis: 2nd (second) Edition. Brooks/Cole.

Ruas A. (2008) Map Generalization. In: Shekhar S., Xiong H. (eds) Encyclopedia of GIS. Springer, Boston, MA.

Särndal, C.-E., Swensson, B. and Wretman, J. (1992) Model Assisted Survey Sampling. New York: Springer-Verlag (Springer Series in Statistics).

Stehman, S. V. (1997) 'Selecting and interpreting measures of thematic classification accuracy', Remote Sensing of Environment, 62(1), pp. 77–89. Stehman, S. V. and Foody, G. M. (2019) Key issues in rigorous accuracy assessment of land cover products, *Remote Sensing of Environment*, 231, p. 111199, [online] Available at: https://linkinghub.elsevier.com/retrieve/pii/S0034425719302111 (Accessed 16 December 2020).

Stehman, S.V., (1999), Basic probability sampling designs for thematic map accuracy assessment. International Journal of Remote Sensing, 20, pp. 2423–2441.

Stehman, S. V. (2013) 'Estimating area from an accuracy assessment error matrix', Remote Sensing of Environment, 132, pp. 202–211.

Stehman, S. V. (2014) Estimating area and map accuracy for stratified random sampling when the strata are different from the map classes, *International Journal of Remote Sensing*, 35(13), pp. 4923–4939.

Strahler, A. H., Boschetti, L., Foody, G. M., Friedl, M. A., Hansen, M. C., Herold, M., Mayaux, P., Morisette, J. T., Stehman, S. V. and Woodcock, C. E. (2006) *Global land cover validation: Recommendations for evaluation and accuracy assessment of global land cover maps*, *Global Observation of Forest and Land Cover Dynamics (GOFC-GOLD)*, Luxemburg, Office for Official Publications of the European Communities, p. 51, [online] Available at: http://cndwebzine.hcp.ma/cnd_sii/IMG/pdf/Document22222222222-17.pdf (Accessed 28 November 2013).

Upton, G., & Cook, I. (2008). A Dictionary of Statistics. : Oxford University Press. Retrieved 8 Jun. 2021, from https://www.oxfordreference.com/view/10.1093/acref/9780199541454.001.0001/acref-9780199541454.

ANNEX

ANNEX I: Input data table

Table 47: List of input data used for the assessment

Date of access	Product ID	Description	Source	Reference year	version	Geographical coverage
05.10.2020	IMD 2015	HRL Imperviousness Degree 2015	EEA	2015	v05	EU
05.10.2020	IMC1518	HRL Imperviousness change 2015-2018	EEA	2015-2018	v10	EU
05.10.2020	IMCC 1518	HRL Imperviousness Change Classified (IMCC) 2015-2018	EEA	2015-2018	v10	EU
05.10.2020	IMD 2018	HRL Imperviousness Degree 2018	EEA	2018	v20	EU
05.10.2020	TCD 2018	HRL Tree Cover Density 10m	EEA	2018	v02	EU
05.10.2020	TCD 2015	HRL Tree Cover Density 2015 20m	EEA	2015	v05	EU
05.10.2020	FTY 2015	HRL Forest Type 2015	EEA	2015	v04	EU
07.10.2020	LUCAS MASTER GRID 2018	LUCAS Master Frame Gird stratified in 2017	EUROSTAT	2017	n/a	EU
07.10.2020	LUCAS micro data 2015	LUCAS micro data 2015	EUROSTAT	2015	n/a	DE
07.10.2020	LUCAS micro data 2015	LUCAS micro data 2015	EUROSTAT	2015	n/a	ES
07.10.2020	LUCAS micro data 2015	LUCAS micro data 2015	EUROSTAT	2015	n/a	RO
07.10.2020	LUCAS micro data 2015	LUCAS micro data 2015	EUROSTAT	2015	n/a	SE
07.10.2020	LUCAS micro data 2018	LUCAS micro data 2018	EUROSTAT	2018	n/a	DE
07.10.2020	LUCAS micro data 2018	LUCAS micro data 2018	EUROSTAT	2018	n/a	ES
07.10.2020	LUCAS micro data 2018	LUCAS micro data 2018	EUROSTAT	2018	n/a	RO
07.10.2020	LUCAS micro data 2018	LUCAS micro data 2018	EUROSTAT	2018	n/a	SE
09.10.2020	FTY 2018	HRL Forest Type 2018 (Vorab Version der EEA)	EEA	2018	v1_0	EU
09.10.2020	NUTS	NUTS - NOMENCLATURE OF TERRITORIAL UNITS FOR STATISTICS	EUROSTAT	2016	n/a	EU
30.11.2020	TCCM_1215	Tree Cover Change Mask 20m 2012-2015	EEA	2015-2018	v1_0	EU
16.12.2020	EEA validation data	EEA HRL validation data shapefiles	EEA	2015-2018	n/a	EU
23.12.2020	IMD18_100m	HRL Imperviousness 2018 100m	EEA	2018	v2_0	EU
23.12.2020	IMD15_100m	HRL Imperviousness 2015 100m	EEA	2015	d03_full	EU
23.12.2020	FTY15_100m	HRL Forest Type 2015 100m	EEA	2015	d02_full	EU
23.12.2020	FTY18_100m	HRL Forest Type 2018 100m	EEA	2018	v1_0	EU
23.12.2020	OSM	Open street map vector data		various		DE, ES, RO, SE
23.12.2020	Corine land cover	Corine land cover 2012	Copernicus	2012	v.2020_20u1	DE, ES, RO, SE
23.12.2020	IMC1518_100m	HRL Degree of Imperviousness Change - 2015-2018 100m	EEA	2015-2018	v1_0	EU

ANNEX II: Results from the biased pixel counting

Impervious density change 2015-2018

Table 48: Simple pixel counting for Imperviousness change 2015 - 2018 from the IMCC1518

IMCC 2015-2018			HRL Pixel counting			
			non-sealed in both years (stable non-built up)	sealed in both years (stable built-up)	decreased imperviousness density	increased imperviousness density
NUTS ID	NUTS Name	Total area (HRL layer)	proportion	proportion	proportion	proportion
DE13	Freiburg	9,402	0.903	0.094	0.000	0.003
DE14	Tuebingen	9,136	0.905	0.093	0.000	0.002
DE21	Oberbayern	17,531	0.898	0.100	0.000	0.002
DE40	Brandenburg	29,654	0.933	0.065	0.000	0.002
DE71	Darmstadt	7,444	0.851	0.146	0.000	0.003
DE73	Kassel	8,290	0.921	0.077	0.000	0.002
DE91	Braunschweig	8,122	0.906	0.093	0.000	0.002
DE94	Weser-Ems	14,987	0.889	0.107	0.000	0.004
DEA1	Duesseldorf	5,293	0.718	0.278	0.000	0.005
DEA2	Koeln	7,366	0.811	0.185	0.000	0.004
DEA3	Muenster	6,920	0.837	0.159	0.000	0.004
DEB2	Trier	4,928	0.937	0.061	0.000	0.002
DEB3	Rheinhessen-Pfalz	6,851	0.888	0.110	0.000	0.002
DEE0	Sachsen-Anhalt	20,553	0.928	0.070	0.000	0.002
ES43	Extremadura	41,631	0.987	0.012	0.000	0.000
ES51	Catalunia	32,113	0.948	0.051	0.000	0.001
ES52	Comunidad Valenciana	23,261	0.945	0.053	0.000	0.002
RO12	Centru	34,107	0.975	0.025	0.000	0.001
RO21	Nord-Est	36,851	0.960	0.039	0.000	0.001
RO41	Sud-Vest Oltenia	29,207	0.963	0.036	0.000	0.000
SE12	Oestra Mellansverige	43,298	0.977	0.022	0.000	0.002
SE31	Norra Mellansverige	72,023	0.987	0.012	0.000	0.001
Countries						
DE	Germany	357,661	0.899	0.098	0.000	0.002
ES	Spain	506,004	0.972	0.027	0.000	0.001
RO	Romania	238,368	0.965	0.034	0.000	0.001
SE	Sweden	449,657	0.987	0.012	0.000	0.001

Tree cover density change 2015-2018

The table below provides the pixel counting estimates from the Tree cover change product TCCM1518

Table 49: Simple pixel counting for Tree cover change 2015 - 2018 from the TCCM1518

TCCM 2015-2018			HRL Pixel counting			
			unchanged areas with no tree cover	new tree cover	loss of tree cover	unchanged areas with tree cover
NUTS ID	NUTS Name	Total area	proportion	proportion	proportion	proportion
DE13	Freiburg	9,402	0.490	0.000	0.001	0.510
DE14	Tuebingen	9,136	0.628	0.000	0.002	0.370
DE21	Oberbayern	17,531	0.597	0.000	0.001	0.402
DE40	Brandenburg	29,654	0.590	0.000	0.001	0.409
DE71	Darmstadt	7,444	0.533	0.000	0.001	0.467
DE73	Kassel	8,290	0.527	0.000	0.002	0.471
DE91	Braunschweig	8,122	0.607	0.000	0.004	0.388
DE94	Weser-Ems	14,987	0.807	0.000	0.001	0.193
DEA1	Duesseldorf	5,293	0.739	0.000	0.001	0.261
DEA2	Koeln	7,366	0.623	0.000	0.001	0.376
DEA3	Muenster	6,920	0.787	0.000	0.001	0.212
DEB2	Trier	4,928	0.493	0.000	0.001	0.506
DEB3	Rheinhessen-Pfalz	6,851	0.580	0.000	0.000	0.420
DEE0	Sachsen-Anhalt	20,553	0.737	0.000	0.002	0.261
ES43	Extremadura	41,631	0.525	0.000	0.000	0.475
ES51	Catalunia	32,113	0.445	0.000	0.001	0.555
ES52	Comunidad Valenciana	23,261	0.522	0.000	0.001	0.477
RO12	Centru	34,107	0.497	0.000	0.001	0.502
RO21	Nord-Est	36,851	0.610	0.000	0.001	0.389
RO41	Sud-Vest Oltenia	29,207	0.628	0.000	0.001	0.371
SE12	Oestra Mellansverige	43,298	0.395	0.001	0.014	0.591
SE31	Norra Mellansverige	72,023	0.307	0.000	0.014	0.679
Countries						
DE	Germany	357,661	0.634	0.000	0.001	0.365
ES	Spain	506,004	0.606	0.000	0.001	0.392
RO	Romania	238,368	0.627	0.000	0.001	0.372
SE	Sweden	449,657	0.392	0.001	0.010	0.597

ANNEX III: Results from the accuracy assessment and area estimation with EO-4-Statistics reference data

Forest 2015 and 2018

Table 50: Accuracy assessment of FTY 2015 for 11 NUTS2 regions using EO-4-statistics reference data

FTY2015		Error matrix		Num. sample units	Map area	UA and margin of error CI95		PA and margin of error CI95		OA and margin of error CI95	
AOI	strata	forest	no-forest		prop.						
de21	forest	0.353	0.038	177	0.39	90.4%	4.4%	98.3%	1.9%	95.6%	1.8%
	no-forest	0.006	0.603	298	0.61	99.0%	1.1%	94.1%	2.5%	NA	NA
de40	forest	0.375	0.013	275	0.39	96.7%	2.1%	95.9%	2.3%	97.1%	1.2%
	no-forest	0.016	0.597	425	0.61	97.4%	1.5%	97.9%	1.3%	NA	NA
dea1	forest	0.175	0.085	46	0.26	67.4%	13.7 %	94.8%	6.9%	90.6%	3.8%
	no-forest	0.01	0.73	154	0.74	98.7%	1.8%	89.6%	3.9%	NA	NA
dea3	forest	0.154	0.068	75	0.22	69.3%	10.5 %	97.8%	4.2%	92.9%	2.4%
	no-forest	0.003	0.775	225	0.78	99.6%	0.9%	91.9%	2.5%	NA	NA
es43	forest	0.330	0.081	107	0.41	80.4%	7.6%	81.6%	7.6%	84.5%	4.9%
	no-forest	0.074	0.515	103	0.59	87.4%	6.4%	86.5%	4.5%	NA	NA
es51	forest	0.411	0.108	455	0.52	79.1%	3.7%	91.3%	2.5%	85.2%	2.3%
	no-forest	0.039	0.442	441	0.48	91.8%	2.6%	80.3%	2.8%	NA	NA
es52	forest	0.229	0.179	320	0.41	56.2%	5.4%	86.4%	4.1%	78.5%	2.5%
	no-forest	0.036	0.556	494	0.59	93.9%	2.1%	75.7%	2.3%	NA	NA
ro12	forest	0.465	0.005	94	0.47	98.9%	2.1%	90.2%	5.0%	94.5%	3.0%
	no-forest	0.05	0.48	116	0.53	90.5%	5.4%	99.0%	2.0%	NA	NA
ro41	forest	0.343	0.024	667	0.37	93.6%	1.9%	94.4%	1.6%	95.6%	0.9%
	no-forest	0.02	0.613	1213	0.63	96.8%	1.0%	96.3%	1.0%	NA	NA
se12	forest	0.508	0.055	112	0.56	90.2%	5.5%	91.3%	4.5%	89.6%	4.1%
	no-forest	0.048	0.388	99	0.44	88.9%	6.2%	87.5%	6.2%	NA	NA
se31	forest	0.644	0.014	143	0.66	97.9%	2.4%	94.1%	3.6%	94.6%	3.1%
	no-forest	0.040	0.302	68	0.34	88.2%	7.7%	95.6%	4.7%	NA	NA

Table 51: Accuracy assessment of FTY 2018 for 11 NUTS2 regions using EO-4-statistics reference data

FTY2018		Error matrix		Num. sample units	Map area	UA and margin of error CI95		PA and margin of error CI95		OA and margin of error CI95	
AOI	strata	forest	no-forest		prop						
de21	forest	0.353	0.028	175	0.38	92.6%	3.9%	98.3%	1.9%	96.6%	1.6%
	no-forest	0.006	0.613	300	0.62	99.0%	1.1%	95.6%	2.2%	NA	NA
de40	forest	0.368	0.015	273	0.38	96.0%	2.3%	94.1%	2.7%	96.1%	1.4%
	no-forest	0.023	0.593	427	0.62	96.3%	1.8%	97.5%	1.4%	NA	NA
dea1	forest	0.171	0.011	33	0.18	93.9%	8.3%	94.6%	7.1%	97.9%	2.0%
	no-forest	0.01	0.808	167	0.82	98.8%	1.7%	98.7%	1.8%	NA	NA
dea3	forest	0.164	0.01	54	0.17	94.4%	6.2%	96.1%	5.2%	98.4%	1.4%
	no-forest	0.007	0.819	246	0.83	99.2%	1.1%	98.8%	1.3%	NA	NA
es43	forest	0.328	0.056	103	0.39	85.4%	6.9%	82.6%	7.7%	87.5%	4.5%
	no-forest	0.069	0.546	107	0.62	88.8%	6.0%	90.7%	4.0%	NA	NA
es51	forest	0.414	0.061	418	0.48	87.1%	3.2%	89.0%	2.7%	88.8%	2.1%
	no-forest	0.051	0.474	483	0.53	90.3%	2.6%	88.5%	2.5%	NA	NA
es52	forest	0.231	0.070	232	0.30	76.7%	5.5%	84.2%	4.2%	88.7%	2.1%
	no-forest	0.043	0.656	583	0.70	93.8%	2.0%	90.3%	2.0%	NA	NA
ro12	forest	0.472	0.015	99	0.49	97.0%	3.4%	92.7%	4.5%	94.8%	3.0%
	no-forest	0.037	0.477	111	0.51	92.8%	4.8%	97.0%	3.3%	NA	NA
ro41	forest	0.329	0.018	638	0.35	94.8%	1.7%	91.5%	2.0%	95.2%	1.0%
	no-forest	0.03	0.622	1242	0.65	95.3%	1.2%	97.2%	0.9%	NA	NA
se12	forest	0.533	0.041	112	0.57	92.9%	4.8%	93.9%	3.8%	92.5%	3.6%
	no-forest	0.034	0.391	99	0.43	91.9%	5.4%	90.5%	5.8%	NA	NA
se31	forest	0.578	0.086	138	0.66	97.1%	2.8%	92.7%	3.7%	93.0%	3.3%
	no-forest	0.048	0.288	73	0.34	94.9%	8.3%	93.7%	5.7%	NA	NA

Imperviousness 2015 and 2018

Table 52: Accuracy assessment of IMD 2015 for 11 NUTS2 regions using EO-4-statistics reference data

IMD 2015		Error matrix				Map area						
AOI	strata	IMD-0	IMD-1-29	IMD-30-100	Num. sample units	prop.	UA and margin of error CI95		PA and margin of error CI95		OA and margin of error CI95	
DE21	IMD-0	0.885	0.028	0.015	435	0.93	95.4%	2.0%	99.7%	0.5%	94.4%	2.0%
	IMD-1-29	0.002	0.004	0.002	4	0.01	50.0%	56.6%	10.9%	11.8%	NA	NA
	IMD-30-100	0.000	0.009	0.054	36	0.06	86.1%	11.5%	76.0%	12.8%	NA	NA
DE40	IMD-0	0.918	0.020	0.014	672	0.95	96.4%	1.4%	99.2%	0.3%	95.3%	1.5%
	IMD-1-29	0.006	0.000	0.000	2	0.01	0.0%	0.0%	0.0%	0.0%	NA	NA
	IMD-30-100	0.002	0.005	0.035	26	0.04	84.6%	14.1%	71.1%	13.1%	NA	NA
DEA1	IMD-0	0.619	0.086	0.075	155	0.78	79.4%	6.4%	97.5%	3.7%	81.4%	5.7%
	IMD-1-29	0.012	0.012	0.000	2	0.02	50.0%	98.0%	10.8%	19.4%	NA	NA
	IMD-30-100	0.005	0.009	0.183	43	0.20	93.0%	7.7%	70.8%	10.1%	NA	NA
DEA3	IMD-0	0.818	0.034	0.034	263	0.89	92.4%	3.2%	98.4%	1.4%	91.3%	3.0%
	IMD-1-29	0.007	0.000	0.007	4	0.01	0.0%	0.0%	0.0%	0.0%	NA	NA
	IMD-30-100	0.006	0.000	0.094	33	0.10	93.9%	8.3%	69.9%	11.5%	NA	NA
ES43	IMD-0	0.991	0.000	0.000	30	0.99	100%	0.0%	99.9%	0.1%	99.7%	0.1%
	IMD-1-29	0.001	0.000	0.000	30	0.00	30.0%	16.7%	26.0%	20.8%	NA	NA
	IMD-30-100	0.001	0.001	0.006	30	0.01	76.7%	15.4%	96.7%	2.7%	NA	NA
ES51	IMD-0	0.920	0.031	0.013	879	0.96	95.4%	1.4%	99.6%	0.5%	95.0%	1.5%
	IMD-1-29	0.000	0.002	0.001	3	0.00	66.7%	65.3%	6.3%	6.2%	NA	NA
	IMD-30-100	0.004	0.002	0.028	19	0.03	84.2%	16.8%	66.3%	12.9%	NA	NA
ES52	IMD-0	0.883	0.048	0.027	779	0.96	92.2%	1.9%	99.9%	0.3%	91.8%	1.9%
	IMD-1-29	0.001	0.001	0.002	4	0.01	25.0%	49.0%	2.3%	4.5%	NA	NA
	IMD-30-100	0.000	0.003	0.033	32	0.04	90.6%	10.3%	53.0%	10.1%	NA	NA
RO12	IMD-0	0.983	0.000	0.000	30	0.98	100%	0.0%	99.9%	0.1%	99.6%	0.1%
	IMD-1-29	0.001	0.002	0.002	30	0.01	46.7%	18.2%	85.7%	24.4%	NA	NA
	IMD-30-100	0.000	0.000	0.011	30	0.01	93.3%	9.1%	86.7%	6.0%	NA	NA
RO41	IMD-0	0.952	0.018	0.005	1,827	0.98	97.6%	0.7%	99.7%	0.2%	97.0%	0.7%
	IMD-1-29	0.002	0.003	0.003	18	0.01	38.9%	23.2%	15.3%	8.8%	NA	NA
	IMD-30-100	0.001	0.000	0.015	35	0.02	91.4%	9.4%	65.5%	11.1%	NA	NA
SE12	IMD-0	0.919	0.066	0.000	30	0.99	93.3%	9.1%	99.8%	0.1%	93.0%	8.9%
	IMD-1-29	0.001	0.003	0.001	30	0.01	56.7%	18.0%	4.5%	5.9%	NA	NA
	IMD-30-100	0.000	0.002	0.007	30	0.01	76.7%	15.4%	86.7%	8.7%	NA	NA
SE31	IMD-0	0.991	0.000	0.000	30	0.99	100%	0.0%	99.8%	0.1%	99.7%	0.1%
	IMD-1-29	0.001	0.003	0.001	30	0.01	56.7%	18.0%	80.0%	15.7%	NA	NA
	IMD-30-100	0.000	0.001	0.004	30	0.01	76.7%	15.4%	80.2%	12.0%	NA	NA

Table 53: Accuracy assessment of IMD 2018 for 11 NUTS2 regions using EO-4-statistics reference data

IMD 2018		Error matrix				Map area						
AOI	strata	IMD-0	IMD-1-29	IMD-30-100	Num. sample units	prop.	UA and margin of error CI95		PA and margin of error CI95		OA and margin of error CI95	
DE21	IMD-0	0.871	0.030	0.013	433	0.91	95.4%	2.0%	99.6%	0.5%	94.8%	1.9%
	IMD-1-29	0.004	0.011	0.004	10	0.02	60.0%	32.0%	25.7%	13.9%	NA	NA
	IMD-30-100	0.000	0.002	0.067	32	0.07	96.9%	6.1%	80.4%	10.8%	NA	NA
DE40	IMD-0	0.929	0.007	0.008	669	0.94	98.4%	1.0%	97.9%	0.5%	95.9%	1.1%
	IMD-1-29	0.014	0.000	0.000	2	0.01	0.0%	0.0%	0.0%	0.0%	NA	NA
	IMD-30-100	0.006	0.006	0.030	29	0.04	72.4%	16.6%	77.9%	14.3%	NA	NA
DEA1	IMD-0	0.669	0.053	0.021	141	0.74	90.1%	5.0%	95.9%	3.1%	87.0%	4.3%
	IMD-1-29	0.020	0.014	0.020	8	0.05	25.0%	32.1%	18.2%	20.8%	NA	NA
	IMD-30-100	0.008	0.008	0.187	51	0.20	92.2%	7.5%	81.9%	10.2%	NA	NA
DEA3	IMD-0	0.827	0.013	0.017	257	0.86	96.5%	2.3%	98.2%	1.5%	93.5%	2.5%
	IMD-1-29	0.008	0.008	0.013	11	0.03	27.3%	27.6%	27.8%	25.8%	NA	NA
	IMD-30-100	0.007	0.007	0.099	32	0.11	87.5%	11.6%	76.9%	10.4%	NA	NA
ES43	IMD-0	0.956	0.033	0.000	30	0.99	96.7%	6.5%	99.9%	0.1%	96.5%	6.5%
	IMD-1-29	0.001	0.000	0.000	30	0.00	30.0%	16.7%	1.1%	2.2%	NA	NA
	IMD-30-100	0.000	0.001	0.008	30	0.01	86.7%	12.4%	98.0%	1.9%	NA	NA
ES51	IMD-0	0.934	0.012	0.010	872	0.96	97.7%	1.0%	99.2%	0.7%	96.5%	1.2%
	IMD-1-29	0.002	0.002	0.002	3	0.01	33.3%	65.3%	11.4%	20.6%	NA	NA
	IMD-30-100	0.006	0.003	0.030	26	0.04	76.9%	16.5%	71.6%	13.6%	NA	NA
ES52	IMD-0	0.904	0.026	0.023	777	0.95	94.9%	1.6%	99.7%	0.3%	94.0%	1.6%
	IMD-1-29	0.000	0.000	0.005	2	0.01	0.0%	0.0%	0.0%	0.0%	NA	NA
	IMD-30-100	0.002	0.003	0.036	36	0.04	86.1%	11.5%	55.9%	9.6%	NA	NA
RO12	IMD-0	0.881	0.098	0.000	30	0.98	90.0%	10.9%	99.5%	0.2%	89.6%	10.7%
	IMD-1-29	0.003	0.002	0.001	30	0.01	30.0%	16.7%	1.7%	2.0%	NA	NA
	IMD-30-100	0.002	0.001	0.013	30	0.02	86.7%	12.4%	92.2%	5.3%	NA	NA
RO41	IMD-0	0.961	0.006	0.004	1,819	0.97	98.9%	0.5%	99.7%	0.2%	98.0%	0.6%
	IMD-1-29	0.001	0.004	0.003	14	0.01	50.0%	27.2%	32.1%	15.3%	NA	NA
	IMD-30-100	0.002	0.003	0.015	47	0.02	76.6%	12.2%	66.7%	11.7%	NA	NA
SE12	IMD-0	0.949	0.000	0.033	30	0.98	96.7%	6.5%	99.7%	0.1%	96.3%	6.4%
	IMD-1-29	0.002	0.002	0.001	30	0.01	40.0%	17.8%	69.1%	30.6%	NA	NA
	IMD-30-100	0.000	0.001	0.012	30	0.01	90.0%	10.9%	26.2%	37.0%	NA	NA
SE31	IMD-0	0.958	0.033	0.000	30	0.99	96.7%	6.5%	99.8%	0.1%	96.4%	6.5%
	IMD-1-29	0.001	0.001	0.001	30	0.00	36.7%	17.5%	4.0%	7.7%	NA	NA
	IMD-30-100	0.001	0.000	0.004	30	0.01	80.0%	14.6%	80.7%	9.8%	NA	NA

Imperviousness change 2015-2018

Table 54: Accuracy assessment of IMCC 2015-2018 NUTS2 regions using EO-4-statistics reference data - DE

IMCC 1518		Error matrix				Num. sample units	Map	UA and margin of error CI95 (%)		PA and margin of error CI95 (%)		OA and margin of error CI95 (%)	
AOI	strata	decrease	increase	non-sealed	sealed		prop.						
DE13	decrease	0.000	0.000	0.000	0.002	30	0.003	0.0	0.0	0.0	0.0	89.9	8.4
	increase	0.000	0.000	0.000	0.000	30	0.000	60.0	17.8	0.0	0.0	NA	NA
	non-sealed	0.000	0.000	0.843	0.060	30	0.903	93.3	9.1	98.1	1.5	NA	NA
	sealed	0.000	0.022	0.016	0.057	30	0.094	60.0	17.8	47.5	33.5	NA	NA
DE14	decrease	0.000	0.000	0.000	0.002	30	0.002	0.0	0.0	NA	0.0	88.9	10.0
	increase	0.000	0.000	0.000	0.000	30	0.000	56.7	18.0	0.1	0.1	NA	NA
	non-sealed	0.000	0.000	0.815	0.091	30	0.905	90.0	10.9	98.9	1.2	NA	NA
	sealed	0.000	0.009	0.009	0.074	30	0.093	80.0	14.6	44.5	26.8	NA	NA
DE21	decrease	0.000	0.000	0.000	0.004	30	0.004	3.3	6.5	2.7	7.3	90.8	7.9
	increase	0.000	0.000	0.000	0.000	30	0.000	46.7	18.2	2.0	3.9	NA	NA
	non-sealed	0.000	0.000	0.781	0.056	30	0.837	93.3	9.1	96.7	2.6	NA	NA
	sealed	0.005	0.000	0.026	0.127	30	0.159	80.0	14.6	68.0	28.0	NA	NA
DE40	decrease	0.000	0.000	0.000	0.001	30	0.001	0.0	0.0	NA	0.0	98.5	0.4
	increase	0.000	0.000	0.000	0.000	30	0.000	26.7	16.1	0.1	0.1	NA	NA
	non-sealed	0.000	0.000	0.975	0.000	30	0.975	100.0	0.0	99.1	0.4	NA	NA
	sealed	0.000	0.005	0.009	0.011	30	0.025	43.3	18.0	94.7	2.2	NA	NA
DE71	decrease	0.000	0.000	0.000	0.002	30	0.002	0.0	0.0	0.0	0.0	91.8	6.1
	increase	0.000	0.000	0.000	0.000	30	0.000	60.0	17.8	0.0	0.0	NA	NA
	non-sealed	0.000	0.000	0.868	0.030	30	0.898	96.7	6.5	97.7	1.6	NA	NA
	sealed	0.000	0.030	0.020	0.050	30	0.100	50.0	18.2	60.8	44.1	NA	NA
DE73	decrease	0.000	0.000	0.000	0.004	30	0.004	0.0	0.0	0.0	0.0	89.8	7.9
	increase	0.000	0.000	0.000	0.000	30	0.000	36.7	17.5	0.0	0.0	NA	NA
	non-sealed	0.000	0.000	0.757	0.054	30	0.811	93.3	9.1	96.8	2.8	NA	NA
	sealed	0.000	0.018	0.025	0.142	30	0.185	76.7	15.4	70.9	26.4	NA	NA
DE91	decrease	0.000	0.000	0.000	0.001	30	0.002	0.0	0.0	0.0	0.0	97.3	1.2
	increase	0.000	0.000	0.000	0.000	30	0.000	20.0	14.6	0.0	0.0	NA	NA
	non-sealed	0.000	0.000	0.928	0.000	30	0.928	100.0	0.0	98.5	1.1	NA	NA
	sealed	0.000	0.012	0.014	0.045	30	0.070	63.3	17.5	96.8	0.9	NA	NA
DE94	decrease	0.000	0.000	0.000	0.004	30	0.005	0.0	0.0	0.0	0.0	90.6	6.3
	increase	0.000	0.000	0.000	0.000	30	0.000	33.3	17.2	0.0	0.0	NA	NA
	non-sealed	0.000	0.000	0.694	0.024	30	0.718	96.7	6.5	96.1	4.0	NA	NA
	sealed	0.000	0.037	0.028	0.213	30	0.278	76.7	15.4	88.3	17.3	NA	NA
DEA1	decrease	0.000	0.000	0.000	0.003	30	0.004	0.0	0.0	NA	0.0	86.8	9.9
	increase	0.000	0.000	0.000	0.000	30	0.003	56.7	18.0	0.0	0.0	NA	NA
	non-sealed	0.000	0.000	0.800	0.089	30	0.000	90.0	10.9	98.7	1.4	NA	NA
	sealed	0.000	0.029	0.011	0.068	30	0.903	63.3	17.5	42.4	26.6	NA	NA
DEA2	decrease	0.000	0.000	0.000	0.002	30	0.094	0.0	0.0	0.0	0.0	98.0	1.2
	increase	0.000	0.000	0.000	0.000	30	0.002	30.0	16.7	0.0	0.0	NA	NA
	non-sealed	0.000	0.000	0.921	0.000	30	0.000	100.0	0.0	99.2	0.9	NA	NA

IMCC 1518		Error matrix				Num. sample units	Map	UA and margin of error CI95 (%)		PA and margin of error CI95 (%)		OA and margin of error CI95 (%)	
AOI	strata	decrease	increase	non-sealed	sealed		prop.						
	sealed	0.000	0.010	0.008	0.059	30	0.905	76.7	15.4	97.2	0.6	NA	NA
DEA3	decrease	0.000	0.000	0.000	0.002	30	0.093	0.0	0.0	0.0	0.0	94.6	6.2
	increase	0.000	0.000	0.000	0.000	30	0.004	23.3	15.4	0.0	0.1	NA	NA
	non-sealed	0.000	0.000	0.902	0.031	30	0.000	96.7	6.5	98.1	1.1	NA	NA
	sealed	0.000	0.004	0.017	0.043	30	0.837	66.7	17.2	57.0	46.2	NA	NA
DEB2	decrease	0.000	0.000	0.000	0.002	30	0.159	0.0	0.0	0.0	0.0	98.9	1.0
	increase	0.000	0.000	0.000	0.000	30	0.001	30.0	16.7	100.0	0.0	NA	NA
	non-sealed	0.000	0.000	0.906	0.000	30	0.000	100.0	0.0	99.3	0.9	NA	NA
	sealed	0.003	0.000	0.006	0.083	30	0.975	90.0	10.9	98.0	0.2	NA	NA
DEB3	decrease	0.000	0.000	0.000	0.003	30	0.025	0.0	0.0	0.0	0.0	96.8	2.1
	increase	0.000	0.000	0.000	0.000	30	0.002	53.3	18.2	0.0	0.0	NA	NA
	non-sealed	0.000	0.000	0.851	0.000	30	0.000	100.0	0.0	97.8	2.0	NA	NA
	sealed	0.000	0.010	0.019	0.117	30	0.898	80.0	14.6	97.5	0.5	NA	NA
DEE0	decrease	0.000	0.000	0.000	0.002	30	0.100	0.0	0.0	0.0	0.0	98.1	1.0
	increase	0.000	0.000	0.000	0.000	30	0.004	33.3	17.2	0.1	0.1	NA	NA
	non-sealed	0.000	0.000	0.937	0.000	30	0.000	100.0	0.0	98.7	0.9	NA	NA
	sealed	0.000	0.004	0.012	0.045	30	0.811	73.3	16.1	95.7	1.1	NA	NA

Table 55: Accuracy assessment of IMCC 2015-2018 NUTS2 regions using EO-4-statistics reference data - ES-RO-SE

IMCC 1518		Error matrix				Num. sample units	Map	UA and margin of error CI95 (%)		PA and margin of error CI95 (%)		OA and margin of error CI95 (%)	
AOI	strata	decrease	increase	non-sealed	sealed		prop						
ES43	decrease	0.000	0.000	0.001	0.001	30	0.002	6.7	9.1	100.0	0.0	96.5	6.4
	increase	0.000	0.000	0.000	0.000	30	0.000	3.3	6.5	100.0	0.0	NA	NA
	non-sealed	0.000	0.000	0.944	0.033	30	0.977	96.7	6.5	99.8	0.2	NA	NA
	sealed	0.000	0.000	0.001	0.020	30	0.022	93.3	9.1	37.7	45.1	NA	NA
ES51	decrease	0.000	0.000	0.000	0.000	30	0.000	0.0	0.0	NA	0.0	90.0	10.8
	increase	0.000	0.000	0.000	0.000	30	0.000	6.7	9.1	100.0	0.0	NA	NA
	non-sealed	0.000	0.000	0.889	0.099	30	0.987	90.0	10.9	99.8	0.2	NA	NA
	sealed	0.000	0.000	0.001	0.011	30	0.012	90.0	10.9	10.2	10.0	NA	NA
ES52	decrease	0.000	0.000	0.000	0.001	30	0.001	3.3	6.5	100.0	0.0	86.9	11.9
	increase	0.000	0.000	0.000	0.000	30	0.000	26.7	16.1	100.0	0.0	NA	NA
	non-sealed	0.000	0.000	0.832	0.128	30	0.960	86.7	12.4	99.7	0.4	NA	NA
	sealed	0.000	0.000	0.003	0.036	30	0.039	93.3	9.1	22.0	15.9	NA	NA
RO12	decrease	0.000	0.000	0.002	0.000	30	0.002	13.3	12.4	100.0	0.0	98.3	1.4
	increase	0.000	0.000	0.000	0.000	30	0.000	30.0	16.7	100.0	0.0	NA	NA
	non-sealed	0.000	0.000	0.888	0.000	30	0.888	100.0	0.0	98.2	1.5	NA	NA
	sealed	0.000	0.000	0.015	0.095	30	0.110	86.7	12.4	99.7	0.3	NA	NA
RO21	decrease	0.001	0.000	0.000	0.000	30	0.001	40.0	17.8	100.0	0.0	96.4	6.2
	increase	0.000	0.000	0.000	0.000	30	0.000	23.3	15.4	100.0	0.0	NA	NA

IMCC 1518		Error matrix				Num. sample units	Map	UA and margin of error CI95 (%)		PA and margin of error CI95 (%)		OA and margin of error CI95 (%)	
AOI	strata	decrease	increase	non-sealed	sealed		prop						
	non-sealed	0.000	0.000	0.916	0.032	30	0.948	96.7	6.5	99.6	0.5	NA	NA
	sealed	0.000	0.000	0.003	0.047	30	0.051	93.3	9.1	59.6	46.6	NA	NA
RO41	decrease	0.001	0.000	0.001	0.000	30	0.002	60.0	17.8	100.0	0.0	99.0	0.7
	increase	0.000	0.000	0.000	0.000	30	0.000	36.7	17.5	100.0	0.0	NA	NA
	non-sealed	0.000	0.000	0.945	0.000	30	0.945	100.0	0.0	99.0	0.7	NA	NA
	sealed	0.000	0.000	0.009	0.044	30	0.053	83.3	13.6	99.6	0.4	NA	NA
SE12	decrease	0.000	0.000	0.000	0.000	30	0.001	0.0	0.0	NA	0.0	90.1	10.8
	increase	0.000	0.000	0.000	0.000	30	0.000	46.7	18.2	100.0	0.0	NA	NA
	non-sealed	0.000	0.000	0.889	0.099	30	0.988	90.0	10.9	100.0	0.0	NA	NA
	sealed	0.000	0.000	0.000	0.012	30	0.012	100.0	0.0	10.7	10.4	NA	NA
SE31	decrease	0.000	0.000	0.000	0.000	30	0.000	3.3	6.5	100.0	0.0	99.4	0.5
	increase	0.000	0.000	0.000	0.000	30	0.000	20.0	14.6	100.0	0.0	NA	NA
	non-sealed	0.000	0.000	0.963	0.000	30	0.963	100.0	0.0	99.4	0.5	NA	NA
	sealed	0.000	0.000	0.005	0.031	28	0.036	85.7	13.2	99.6	0.3	NA	NA

Table 56: Area estimates - Imperviousness change 2015-2018 in the selected NUTS2 regions using EO-4-Statistics reference data - 2018

2015-2018		IMD >30% in map	Adjusted area		Margin of error 95CI		CV of area estimate
AOI	strata	proportion	km²	%	prop.	km²	%
DE13	imd-decrease	0.003	0.0	0.0%	0.0%	0.0	NA
DE13	imd-increase	0.000	207	2.2%	1.4%	136	33.6%
DE13	non-sealed	0.903	8,082	85.9%	8.3%	781	4.9%
DE13	sealed	0.094	1,120	11.9%	8.4%	787	35.9%
DE14	imd-decrease	0.002	0.0	0.0%	0.0%	0.0	NA
DE14	imd-increase	0.000	85	0.9%	1.0%	92	55.2%
DE14	non-sealed	0.905	7,533	82.4%	9.9%	908	6.2%
DE14	sealed	0.093	1,523	16.7%	10.0%	912	30.6%
DE21	imd-decrease	0.004	38	0.5%	1.0%	72	97.2%
DE21	imd-increase	0.000	1	0.0%	0.0%	2	98.1%
DE21	non-sealed	0.837	5,594	80.8%	7.9%	547	5.0%
DE21	sealed	0.159	1,293	18.7%	7.9%	550	21.7%
DE40	imd-decrease	0.001	0.0	0.0%	0.0%	0.0	NA
DE40	imd-increase	0.000	170	0.5%	0.4%	123	36.9%
DE40	non-sealed	0.975	33,561	98.4%	0.4%	148	0.2%
DE40	sealed	0.025	387	1.1%	0.4%	152	20.1%
DE71	imd-decrease	0.002	0.0	0.0%	0.0%	0.0	NA
DE71	imd-increase	0.000	527	3.0%	1.7%	293	28.4%
DE71	non-sealed	0.898	15,570	88.8%	6.0%	1,060	3.5%
DE71	sealed	0.100	1,444	8.2%	6.1%	1,077	38.1%
DE73	imd-decrease	0.004	0.0	0.0%	0.0%	0.0	NA
DE73	imd-increase	0.000	136	1.8%	2.0%	149	55.7%
DE73	non-sealed	0.811	5,762	78.2%	7.7%	568	5.1%
DE73	sealed	0.185	1,473	20.0%	7.9%	582	20.2%
DE91	imd-decrease	0.002	0.0	0.0%	0.0%	0.0	NA
DE91	imd-increase	0.000	241	1.2%	1.0%	196	41.5%
DE91	non-sealed	0.928	19,377	94.2%	1.0%	210	0.6%
DE91	sealed	0.070	945	4.6%	1.2%	254	13.7%
DE94	imd-decrease	0.005	0.0	0.0%	0.0%	0.0	NA
DE94	imd-increase	0.000	196	3.7%	3.4%	182	47.3%

2015-2018		IMD >30% in map	Adjusted area		Margin of error 95CI		CV of area estimate
AOI	strata	proportion	km²	%	prop.	km²	%
DE94	non-sealed	0.718	3,824	72.2%	5.6%	296	3.9%
DE94	sealed	0.278	1,277	24.1%	6.3%	336	13.4%
DEA1	imd-decrease	0.004	0.0	0.0%	0.0%	0.0	NA
DEA1	imd-increase	0.000	429	2.9%	1.7%	259	30.8%
DEA1	non-sealed	0.889	12,164	81.1%	9.8%	1,467	6.2%
DEA1	sealed	0.107	2,404	16.0%	9.9%	1,483	31.5%
DEA2	imd-decrease	0.002	0.0	0.0%	0.0%	0.0	NA
DEA2	imd-increase	0.000	85	1.0%	1.0%	79	47.3%
DEA2	non-sealed	0.921	7,708	92.9%	0.8%	70	0.5%
DEA2	sealed	0.077	505	6.1%	1.2%	99	9.9%
DEA3	imd-decrease	0.002	0.0	0.0%	0.0%	0.0	NA
DEA3	imd-increase	0.000	128	0.4%	0.6%	175	69.4%
DEA3	non-sealed	0.933	27,284	92.0%	6.2%	1,836	3.4%
DEA3	sealed	0.065	2,254	7.6%	6.2%	1,839	41.6%
DEB2	imd-decrease	0.002	25	0.3%	0.6%	49	100.0%
DEB2	imd-increase	0.000	0.0	0.0%	0.0%	0.0	NA
DEB2	non-sealed	0.906	7,411	91.2%	0.8%	68	0.5%
DEB2	sealed	0.093	692	8.5%	1.0%	82	6.1%
DEB3	imd-decrease	0.003	0.0	0.0%	0.0%	0.0	NA
DEB3	imd-increase	0.000	73	1.0%	1.3%	99	69.5%
DEB3	non-sealed	0.851	6,485	87.0%	1.8%	135	1.1%
DEB3	sealed	0.146	893	12.0%	2.1%	158	9.0%
DEE0	imd-decrease	0.002	0.0	0.0%	0.0%	0.0	NA
DEE0	imd-increase	0.000	20	0.4%	0.6%	27	68.2%
DEE0	non-sealed	0.937	4,682	94.9%	0.9%	44	0.5%
DEE0	sealed	0.061	230	4.7%	1.0%	48	10.7%
ES43	imd-decrease	0.002	4	0.0%	0.0%	6	69.5%
ES43	imd-increase	0.000	0.0	0.0%	0.0%	0.0	NA
ES43	non-sealed	0.977	40,996	94.7%	6.4%	2,766	3.4%
ES43	sealed	0.022	2,312	5.3%	6.4%	2,766	61.1%
ES51	imd-decrease	0.000	0.0	0.0%	0.0%	0.0	NA
ES51	imd-increase	0.000	0.0	0.0%	0.0%	0.0	NA
ES51	non-sealed	0.987	37,059	89.0%	10.8%	4,489	6.2%
ES51	sealed	0.012	4,583	11.0%	10.8%	4,489	50.0%
ES52	imd-decrease	0.001	1	0.0%	0.0%	2	85.9%
ES52	imd-increase	0.000	0.0	0.0%	0.0%	0.0	NA
ES52	non-sealed	0.960	30,785	83.5%	11.9%	4,382	7.2%
ES52	sealed	0.039	6,075	16.5%	11.9%	4,382	36.8%
RO12	imd-decrease	0.002	2	0.0%	0.0%	2	47.7%
RO12	imd-increase	0.000	0.0	0.0%	0.0%	0.0	NA
RO12	non-sealed	0.888	6,198	90.4%	1.4%	93	0.8%
RO12	sealed	0.110	655	9.6%	1.4%	93	7.2%
RO21	imd-decrease	0.001	19	0.1%	0.0%	8	22.8%
RO21	imd-increase	0.000	0.0	0.0%	0.0%	0.0	NA
RO21	non-sealed	0.948	29,557	92.0%	6.2%	1,995	3.4%
RO21	sealed	0.051	2,548	7.9%	6.2%	1,995	39.9%
RO41	imd-decrease	0.002	24	0.1%	0.0%	7	15.2%
RO41	imd-increase	0.000	0.2	0.0%	0.0%	0.1	20.6%
RO41	non-sealed	0.945	22,211	95.4%	0.7%	168	0.4%
RO41	sealed	0.053	1,035	4.4%	0.7%	168	8.3%
SE12	imd-decrease	0.001	0.0	0.0%	0.0%	0.0	NA
SE12	imd-increase	0.000	0.0	0.0%	0.0%	0.1	NA
SE12	non-sealed	0.988	64,049	88.9%	10.8%	7,767	6.2%
SE12	sealed	0.012	7,981	11.1%	10.8%	7,767	49.6%
SE31	imd-decrease	0.000	0.6	0.0%	0.0%	0.9	79.5%
SE31	imd-increase	0.000	0.0	0.0%	0.0%	0.1	NA
SE31	non-sealed	0.963	28,305	96.9%	0.5%	140	0.3%
SE31	sealed	0.036	912	3.1%	0.5%	140	7.8%

Tree cover change 2015-2018

Table 57: Accuracy assessment of TCCM1518 using EO-4Statistics reference data - DE

c		Error matrix				Num. sample units	Map area	UA and margin of error CI95 (%)		PA and margin of error CI95 (%)		OA and margin of error CI95 (%)	
AOI	strata	tc_ loss	tc_ new	no_tc	tc		prop.						
DE13	tc_loss	0.001		0.000	0.000	30	0.001	86.7	12.4	100	0.0	82.0	8.6
	tc_new	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
	no_tc	0.000		0.310	0.180	30	0.490	63.3	17.5	100	0.0	NA	NA
	tc	0.000		0.000	0.510	30	0.510	100	0.0	73.9	9.2	NA	NA
DE14	tc_loss	0.002		0.000	0.000	29	0.002	82.8	14.0	100	0.0	85.3	9.7
	tc_new	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
	no_tc	0.000		0.481	0.147	30	0.628	76.7	15.4	100	0.0	NA	NA
	tc	0.000		0.000	0.370	30	0.370	100	0.0	71.6	13.4	NA	NA
DE21	tc_loss	0.001	0.000	0.000	0.000	30	0.001	86.7	12.4	5.8	10.8	87.4	8.9
	tc_new	0.000	0.000	0.000	0.000	30	0.000	93.3	9.1	100	0.0	NA	NA
	no_tc	0.000	0.000	0.498	0.100	30	0.597	83.3	13.6	97.4	5.0	NA	NA
	tc	0.013	0.000	0.013	0.375	30	0.402	93.3	9.1	79.0	13.6	NA	NA
DE40	tc_loss	0.001	0.000	0.000	0.000	30	0.001	90.0	10.9	100	0.0	88.2	8.6
	tc_new	0.000	0.000	0.000	0.000	30	0.000	90.0	10.9	100	0.0	NA	NA
	no_tc	0.000	0.000	0.472	0.118	30	0.590	80.0	14.6	100	0.0	NA	NA
	tc	0.000	0.000	0.000	0.409	30	0.409	100	0.0	77.6	12.6	NA	NA
DE71	tc_loss	0.001		0.000	0.000	30	0.001	90.0	10.9	4.7	8.7	84.2	9.1
	tc_new	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
	no_tc	0.000		0.391	0.142	30	0.533	73.3	16.1	100	0.0	NA	NA
	tc	0.016		0.000	0.451	30	0.467	96.7	6.5	76.0	11.1	NA	NA
DE73	tc_loss	0.002	0.000	0.000	0.000	30	0.002	83.3	13.6	10.3	18.2	91.4	7.2
	tc_new	0.000	0.000	0.000	0.000	30	0.000	93.3	9.1	100	0.0	NA	NA
	no_tc	0.000	0.000	0.457	0.070	30	0.527	86.7	12.4	100	0.0	NA	NA
	tc	0.016	0.000	0.000	0.455	30	0.471	96.7	6.5	86.6	10.8	NA	NA
DE91	tc_loss	0.004	0.000	0.000	0.001	30	0.004	86.7	12.4	100	0.0	91.8	7.5
	tc_new	0.000	0.000	0.000	0.000	30	0.000	90.0	10.9	100	0.0	NA	NA
	no_tc	0.000	0.000	0.526	0.081	30	0.607	86.7	12.4	100	0.0	NA	NA
	tc	0.000	0.000	0.000	0.388	30	0.388	100	0.0	82.6	13.2	NA	NA
DE94	tc_loss	0.001	0.000	0.000	0.000	30	0.001	83.3	13.6	100	0.0	86.5	10.9
	tc_new	0.000	0.000	0.000	0.000	30	0.000	100	0.0	100	0.0	NA	NA
	no_tc	0.000	0.000	0.672	0.134	30	0.807	83.3	13.6	100	0.0	NA	NA
	tc	0.000	0.000	0.000	0.193	30	0.193	100	0.0	58.9	19.7	NA	NA
DEA1	tc_loss	0.001	0.000	0.000	0.000	30	0.001	76.7	15.4	100	0.0	87.7	10.0
	tc_new	0.000	0.000	0.000	0.000	30	0.000	100	0.0	100	0.0	NA	NA
	no_tc	0.000	0.000	0.616	0.123	30	0.739	83.3	13.6	100	0.0	NA	NA
	tc	0.000	0.000	0.000	0.261	30	0.261	100	0.0	67.9	17.7	NA	NA
DEA2	tc_loss	0.001	0.000	0.000	0.000	30	0.001	90.0	10.9	6.4	11.8	87.1	9.1
	tc_new	0.000	0.000	0.000	0.000	30	0.000	100	0.0	0.0	0.0	NA	NA
	no_tc	0.000	0.000	0.519	0.104	30	0.623	83.3	13.6	100	0.0	NA	NA
	tc	0.013	0.013	0.000	0.351	30	0.376	93.3	9.1	77.2	14.4	NA	NA
DEA3	tc_loss	0.001		0.000	0.000	30	0.001	76.7	15.4	9.6	17.0	91.4	8.7
	tc_new	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
	no_tc	0.000		0.708	0.079	30	0.787	90.0	10.9	100	0.0	NA	NA
	tc	0.007		0.000	0.205	30	0.212	96.7	6.5	72.3	21.9	NA	NA
DEB2	tc_loss	0.000	0.000	0.000	0.000	30	0.001	76.7	15.4	2.9	5.5	91.7	6.9
	tc_new	0.000	0.000	0.000	0.000	30	0.000	100	0.0	41.9	47.7	NA	NA
	no_tc	0.016	0.000	0.428	0.049	30	0.493	86.7	12.4	96.2	7.2	NA	NA
	tc	0.000	0.000	0.017	0.489	30	0.506	96.7	6.5	90.8	9.1	NA	NA
DEB3	tc_loss	0.000		0.000	0.000	30	0.000	76.7	15.4	100	0.0	90.3	7.9
	tc_new	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
	no_tc	0.000		0.484	0.097	30	0.580	83.3	13.6	100	0.0	NA	NA
	tc	0.000		0.000	0.420	30	0.420	100	0.0	81.3	12.4	NA	NA
DEE0	tc_loss	0.002	0.000	0.000	0.000	30	0.002	86.7	12.4	100	0.0	90.1	9.1

c		Error matrix				Num. sample units	Map area	UA and margin of error CI95 (%)		PA and margin of error CI95 (%)		OA and margin of error CI95 (%)	
AOI	strata	tc_ loss	tc_ new	no_tc	tc		prop.						
	tc_new	0.000	0.000	0.000	0.000	11	0.000	0.0	0.0	0.0	0.0	NA	NA
	no_tc	0.000	0.000	0.639	0.098	30	0.737	86.7	12.4	100	0.0	NA	NA
	tc	0.000	0.000	0.000	0.261	30	0.261	100	0.0	72.6	18.4	NA	NA

Table 58: Accuracy assessment of TCCM1518 using EO-4Statistics reference data - ES-RO-SE

TCCM1518		Error matrix				Num. sample units	Map area	UA and margin of error CI95 (%)		PA and margin of error CI95 (%)		OA and margin of error CI95 (%)	
AOI	strata	tc_ loss	tc_ new	no_tc	tc		prop %						
ES43	tc_loss	0.000	0.000	0.000	0.000	25	0.000	20.0	16.0	100	0.0	79.2	10.1
	tc_new	0.000	0.000	0.000	0.000	30	0.047	66.7	17.2	2.2	4.3	NA	NA
	no_tc	0.000	0.000	0.385	0.140	30	0.525	73.3	16.1	87.6	10.4	NA	NA
	tc	0.000	0.014	0.054	0.407	35	0.475	85.7	11.8	74.4	11.8	NA	NA
ES51	tc_loss	0.000	0.000	0.000	0.000	30	0.001	76.7	15.4	100	0.0	68.6	10.4
	tc_new	0.000	0.000	0.000	0.000	21	0.003	95.2	9.3	0.0	0.0	NA	NA
	no_tc	0.000	0.025	0.229	0.191	35	0.445	51.4	16.8	87.5	15.3	NA	NA
	tc	0.000	0.065	0.033	0.457	34	0.555	82.4	13.0	70.6	8.7	NA	NA
ES52	tc_loss	0.001	0.000	0.000	0.000	30	0.001	56.7	18.0	100	0.0	72.1	9.5
	tc_new	0.000	0.000	0.000	0.000	30	0.000	60.0	17.8	76.8	35.3	NA	NA
	no_tc	0.000	0.000	0.244	0.278	30	0.522	46.7	18.2	99.9	0.1	NA	NA
	tc	0.000	0.000	0.000	0.477	30	0.477	100	0.0	63.1	7.9	NA	NA
RO12	tc_loss	0.001	0.000	0.000	0.000	30	0.001	83.3	13.6	100	0.0	91.7	6.7
	tc_new	0.000	0.000	0.000	0.000	30	0.000	46.7	18.2	0.0	0.1	NA	NA
	no_tc	0.000	0.017	0.414	0.066	30	0.497	83.3	13.6	100	0.0	NA	NA
	tc	0.000	0.000	0.000	0.502	30	0.502	100	0.0	88.3	9.6	NA	NA
RO21	tc_loss	0.001	0.000	0.000	0.000	30	0.001	90.0	10.9	100	0.0	88.5	8.7
	tc_new	0.000	0.000	0.000	0.000	30	0.004	80.0	14.6	0.2	0.4	NA	NA
	no_tc	0.000	0.000	0.508	0.102	30	0.610	83.3	13.6	100	0.0	NA	NA
	tc	0.000	0.013	0.000	0.376	30	0.389	96.7	6.5	78.7	13.7	NA	NA
RO41	tc_loss	0.000	0.000	0.000	0.000	30	0.001	66.7	17.2	100	0.0	95.8	5.7
	tc_new	0.000	0.000	0.000	0.000	30	0.000	93.3	9.1	100	0.0	NA	NA
	no_tc	0.000	0.000	0.587	0.042	30	0.628	93.3	9.1	100	0.0	NA	NA
	tc	0.000	0.000	0.000	0.371	30	0.371	100	0.0	89.8	12.4	NA	NA
SE12	tc_loss	0.011	0.000	0.000	0.002	30	0.014	83.3	13.6	46.3	48.9	86.5	6.8
	tc_new	0.000	0.000	0.000	0.000	30	0.001	30.0	16.7	100	0.0	NA	NA
	no_tc	0.013	0.000	0.263	0.119	30	0.395	66.7	17.2	99.9	0.1	NA	NA
	tc	0.000	0.000	0.000	0.591	30	0.591	100	0.0	83.0	7.7	NA	NA
SE31	tc_loss	0.013	0.000	0.000	0.001	30	0.014	90.0	10.9	99.9	0.1	86.3	7.0
	tc_new	0.000	0.000	0.000	0.000	30	0.000	43.3	18.0	0.4	0.8	NA	NA
	no_tc	0.000	0.000	0.195	0.113	30	0.307	63.3	17.5	100	0.0	NA	NA
	tc	0.000	0.023	0.000	0.656	30	0.679	96.7	6.5	85.2	6.0	NA	NA

Table 59: Accuracy assessment of TCCM1518 using EO-4Statistics reference data - Countries

TCCM1518		Error matrix				Num. sample units	Map area	UA and margin of error CI95 (%)		PA and margin of error CI95 (%)		OA and margin of error CI95 (%)	
AOI	strata	tc_ loss	tc_ new	no_tc	tc		prop						
	tc_loss	0.001	0.000	0.000	0.000	30	0.001	100.0	0.0	100.0	0.0	91.6	7.8
	tc_new	0.000	0.000	0.000	0.000	30	0.000	80.0	14.6	100.0	0.0	NA	NA
	no_tc	0.000	0.000	0.549	0.084	30	0.634	86.7	12.4	100.0	0.0	NA	NA
DE	tc	0.000	0.000	0.000	0.365	30	0.365	100.0	0.0	81.2	14.2	NA	NA
	tc_loss	0.001	0.000	0.000	0.000	30	0.001	90.0	10.9	100.0	0.0	78.3	10.8
	tc_new	0.000	0.000	0.000	0.000	30	0.000	80.0	14.6	100.0	0.0	NA	NA
	no_tc	0.000	0.000	0.404	0.202	30	0.606	66.7	17.2	96.5	6.6	NA	NA
ES	tc	0.000	0.000	0.015	0.378	27	0.392	96.3	7.3	65.1	11.8	NA	NA
	tc_loss	0.001	0.000	0.000	0.000	30	0.001	80.0	14.6	100.0	0.0	85.3	9.7
	tc_new	0.000	0.000	0.000	0.000	30	0.000	90.0	10.9	100.0	0.0	NA	NA
	no_tc	0.000	0.000	0.481	0.146	30	0.627	76.7	15.4	100.0	0.0	NA	NA
RO	tc	0.000	0.000	0.000	0.372	30	0.372	100.0	0.0	71.7	13.4	NA	NA
	tc_loss	0.010	0.000	0.000	0.000	30	0.010	100.0	0.0	100.0	0.0	97.4	3.6
	tc_new	0.000	0.001	0.000	0.000	30	0.001	86.7	12.4	100.0	0.0	NA	NA
	no_tc	0.000	0.000	0.366	0.026	30	0.392	93.3	9.1	100.0	0.0	NA	NA
SE	tc	0.000	0.000	0.000	0.597	30	0.597	100.0	0.0	95.8	5.5	NA	NA

Table 60: Area estimates - tree cover change 2015-2018 in the NUTS2 regions using EO-4-Statistics reference data - 2018

		Map area	Adjusted map area		Margin of error CI95%		CV of area estimate
AOI	strata	Prop %	km²	%	prop	km²	%
DE13	tc_loss	0.001	9	0.1%	0.000	1	3.9%
	tc_new	NA	NA	NA	NA	NA	NA
	no_tc	0.490	2,917	31.0%	0.086	808	14.1%
	tc	0.510	6,483	68.9%	0.086	808	6.4%
DE14	tc_loss	0.002	14	0.2%	0.000	2	8.6%
	tc_new	NA	NA	NA	NA	NA	NA
	no_tc	0.628	4,401	48.1%	0.097	884	10.3%
	tc	0.370	4,726	51.7%	0.097	884	9.5%
DE21	tc_loss	0.001	249	1.4%	0.026	460	94.2%
	tc_new	0.000	0	0.0%	0.000	0	5.6%
	no_tc	0.597	8,966	51.1%	0.085	1,494	8.5%
	tc	0.402	8,325	47.5%	0.089	1,558	9.5%
DE40	tc_loss	0.001	26	0.1%	0.000	3	6.2%
	tc_new	0.000	2	0.0%	0.000	0	6.2%
	no_tc	0.590	14,002	47.2%	0.086	2,548	9.3%
	tc	0.409	15,636	52.7%	0.086	2,548	8.3%
DE71	tc_loss	0.001	122	1.6%	0.030	227	95.4%
	tc_new	NA	NA	NA	NA	NA	NA
	no_tc	0.533	2,910	39.1%	0.086	639	11.2%
	tc	0.467	4,419	59.3%	0.091	678	7.8%
DE73	tc_loss	0.002	145	1.7%	0.031	255	89.7%
	tc_new	0.000	0	0.0%	0.000	0	4.3%
	no_tc	0.527	3,792	45.7%	0.065	541	7.3%
	tc	0.471	4,361	52.6%	0.072	598	7.0%
DE91	tc_loss	0.004	30	0.4%	0.001	4	7.3%
	tc_new	0.000	0	0.0%	0.000	0	6.8%
	no_tc	0.607	4,278	52.6%	0.075	611	7.3%
	tc	0.388	3,820	47.0%	0.075	611	8.2%
DE94	tc_loss	0.001	8	0.1%	0.000	1	8.3%
	tc_new	0.000	0	0.0%	0.000	0	0.0%
	no_tc	0.807	10,082	67.2%	0.109	1,641	8.3%

AOI	strata	Map area	Adjusted map area		Margin of error CI95%		CV of area estimate
		Prop %	km²	%	prop	km²	%
	tc	0.193	4,907	32.7%	0.109	1,641	17.0%
DEA1	tc_loss	0.001	3	0.1%	0.000	1	10.3%
	tc_new	0.000	0	0.0%	0.000	0	0.0%
	no_tc	0.739	3,261	61.6%	0.1	531	8.3%
	tc	0.261	2,033	38.4%	0.1	531	13.3%
DEA2	tc_loss	0.001	99	1.3%	0.025	181	93.6%
	tc_new	0.000	92	1.3%	0.025	181	99.9%
	no_tc	0.623	3,827	51.9%	0.085	623	8.3%
	tc	0.376	3,353	45.5%	0.091	672	10.2%
DEA3	tc_loss	0.001	54	0.8%	0.014	96	90.4%
	tc_new	NA	NA	NA	NA	NA	NA
	no_tc	0.787	4,903	70.8%	0.086	595	6.2%
	tc	0.212	1,968	28.4%	0.087	603	15.6%
DEB2	tc_loss	0.001	84	1.7%	0.032	159	97.1%
	tc_new	0.000	0	0.0%	0.000	0	53.4%
	no_tc	0.493	2,193	44.5%	0.069	342	8.0%
	tc	0.506	2,656	53.9%	0.063	312	6.0%
DEB3	tc_loss	0.000	0	0.0%	0.000	0	10.9%
	tc_new	NA	NA	NA	NA	NA	NA
	no_tc	0.580	3,316	48.4%	0.079	540	8.3%
	tc	0.420	3,540	51.6%	0.079	540	7.8%
DEE0	tc_loss	0.002	33	0.2%	0.000	5	7.3%
	tc_new	0.000	0	0.0%	0.000	0	NA
	no_tc	0.737	13,132	63.9%	0.091	1,875	7.3%
	tc	0.261	7,398	36.0%	0.091	1,875	12.9%
ES43	tc_loss	0.000	0	0.0%	0.000	0	40.0%
	tc_new	0.000	578	1.4%	0.027	1,108	97.8%
	no_tc	0.525	18,279	43.9%	0.099	4,103	11.4%
	tc	0.475	22,784	54.7%	0.101	4,215	9.4%
ES51	tc_loss	0.001	14	0.0%	0.000	3	10.2%
	tc_new	0.000	2,914	9.1%	0.070	2,254	39.5%
	no_tc	0.445	8,395	26.1%	0.087	2,793	17.0%
	tc	0.555	20,801	64.8%	0.103	3,319	8.2%
ES52	tc_loss	0.001	12	0.1%	0.000	4	16.3%
	tc_new	0.000	3	0.0%	0.000	2	25.1%
	no_tc	0.522	5,675	24.4%	0.095	2,206	19.8%
	tc	0.477	17,580	75.5%	0.095	2,206	6.4%
RO12	tc_loss	0.001	33	0.1%	0.000	5	8.3%
	tc_new	0.000	566	1.7%	0.032	1,108	100.0%
	no_tc	0.497	14,140	41.4%	0.067	2,301	8.3%
	tc	0.502	19,378	56.8%	0.062	2,099	5.5%
RO21	tc_loss	0.001	32	0.1%	0.000	4	6.2%
	tc_new	0.000	479	1.3%	0.025	937	99.8%
	no_tc	0.610	18,732	50.8%	0.083	3,049	8.3%
	tc	0.389	17,618	47.8%	0.087	3,190	9.2%
RO41	tc_loss	0.001	11	0.0%	0.000	3	13.2%
	tc_new	0.000	1	0.0%	0.000	0	4.9%
	no_tc	0.628	17,138	58.7%	0.057	1,667	4.9%
	tc	0.371	12,067	41.3%	0.057	1,667	7.0%
SE12	tc_loss	0.014	1,063	2.5%	0.026	1,121	53.8%
	tc_new	0.001	11	0.0%	0.000	6	28.1%
	no_tc	0.395	11,422	26.4%	0.068	2,936	13.1%
	tc	0.591	30,828	71.2%	0.066	2,855	4.7%
SE31	tc_loss	0.014	912	1.3%	0.002	111	6.2%
	tc_new	0.000	1,636	2.3%	0.044	3,194	99.6%
	no_tc	0.307	14,018	19.5%	0.054	3,882	14.1%
	tc	0.679	55,478	77.0%	0.07	5,028	4.6%