Copernicus Global Land Operations "Vegetation and Energy"

"CGLOPS-1"

Framework Service Contract N° 199494 (JRC)

VALIDATION REPORT

MODERATE DYNAMIC LAND COVER

COLLECTION 100M

VERSION 3.0

Issue I3.00

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Please cite this publication the following:

Tsendbazar, N.E., Tarko, A., Linlin, L., Herold, M., Lesiv, M., Fritz, S., Maus. V; (2020): Copernicus Global Land Service: Land Cover 100m: Version 3 Globe 2015-2019: Validation Report; Zenodo, Geneve, Switzerland, September 2020; doi: 10.5281/zenodo.3938974

Document with version	DOI	Title
LC100 v3 VR I3.00	10.5281/zenodo.3938974	Copernicus Global Land Service: Land Cover 100m: version 3 Globe 2015-2019: Validation Report

Dissemination Level		
PU	Public	X
PP	Restricted to other programme participants (including the Commission Services)	
RE	Restricted to a group specified by the consortium (including the Commission Services)	
CO	Confidential, only for members of the consortium (including the Commission Services)	

Document Release Sheet

Book captain:	Nandika Tsendbazar	Sign	Date 31.08.2020
Approval:	Bruno Smets	Sign	Date 07.09.2020
Endorsement:	Michael Cherlet	Sign	Date
Distribution:	Public		

Change Record

Issue/Rev	Date	Page(s)	Description of Change	Release
	31.08.2020	All	First issue	I3.00

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List of Acronyms

AD	Applicable Documents
ATBD	Algorithm Technical Basis Document
BFAST	Breaks For Additive Season and Trend algorithm
CEOS-WGCV-LPV	Committee on earth Observing Satellites working Group on Calibration and Validation, Land Product Validation subgroup
CGLS	Copernicus Global Land Service
CGLS_LC100m	CGLS Dynamic Land Cover 100m
ECV	Essential Climate Variables
ESRI	Environmental Systems Research Institute
FAPAR	Fraction of Absorbed Photosynthetically Active Radiation
FAO	Food and Agriculture Organisation
GEE	Google Earth Engine
GeoTIFF	A metadata standard allowing georeferencing information to be embedded within a TIFF file
GIO	GMES Initial Operations
IIASA	International Institute for Applied Systems Analysis
JRC	Joint Research Center
LAI	Leaf Area Index
Landsat	American Earth observation satellite
MODIS	Moderate-resolution imaging spectroradiometer
NDVI	Normalized Difference Vegetation Index
NIRv	Near-infrared reflectance of vegetation
NRT	Near Real Time
MAE	Mean absolute error
OECD	Organisation for Economic Cooperation and Development
PROBA-V	Project for On-Board Autonomy – Vegetation satellite
PSD	Product Specifications Document
PUM	Product user manual
REDD	Reducing Emissions from Deforestation and forest Degradation
RMSE	Root mean square error
SDG	Sustainable Development Goal
SEEA	System of Environmental and Economic Accounting
SSD	Service Specifications Document
SVP	Service validation plan
TOC	Top of Canopy
UNCCD	United Nations Convention to Combat Desertification
UNFCCC	United Nations Framework Convention on Climate Change

UN LCCS	United Nations Land Cover Classification System
URD	User requirement document
UTM	Universal Transverse Mercator
VHR	Very High Resolution
VR	Validation Report
WGS	World Geodetic System
WU	Wageningen University

EXECUTIVE SUMMARY

The Copernicus Global Land Service (CGLS) is earmarked as a component of the Land service to operate "a multi-purpose service component" that provides a series of bio-geophysical products on the status and evolution of land surface at global scale. Production and delivery of the parameters take place in a reliable, automatic and timely manner and are complemented by the constitution of long-term time series.

From 1st January 2013, the Copernicus Global Land Service is providing a series of Essential Climate Variables (ECV) like Leaf Area Index (LAI), the Fraction of PAR absorbed by the vegetation (FAPAR), the surface albedo, the Land Surface Temperature, the soil moisture, the burnt areas, the areas of water bodies, and additional vegetation indices. These bio-geophysical products are generated every hour, every day or every 10 days from Earth Observation satellite data.

The CGLS delivers a dynamic global land cover product at 100m spatial resolution (CGLS_LC100m) for 2015 to 2019. The objective of this quality assessment was to validate the Version 3.0 of the discrete land cover map and fractional land cover layers of CGLS_LC100m product for 2015-2019, providing statistically robust estimates of overall and class specific accuracies. The validation was done using an independent set of sample points (~21 700) with additional 6700 sample points in possible land cover change areas, generated in collaboration with experts from the Wageningen University (WU) and regional land cover experts. The statistical validation of yearly maps meets the Stage 4 validation requirements of Committee on Earth Observing Satellites working Group on Calibration and Validation, Land Product Validation subgroup (CEOS-WGCV-LPV) (updated statistical validation). In addition, the validation includes assessments on land cover changes, qualitative and quantitative comparison of the CGLS_LC100m V3.0 discrete land cover map with the previous version CGLS_LC100m V2.0 and spatial uncertainty assessments.

Our validation shows that the discrete global CGLS_LC100m V3.0 2015 Level 1 map has an overall accuracy of 80.6+/-0.4%. In terms of land cover types, bare/sparse vegetation, snow/ice and permanent water are mapped with high accuracies, while shrubs and herbaceous wetland classes are mapped with lowest accuracies. The yearly (2016-2019) maps are assessed with around 80.3-80.5% accuracy, with the 2019 map in Near Real Time (NRT) mode having 80.3% accuracy. Overall accuracy at continental level is around 80%, with highest accuracy of 83.7% for Asia and the lowest accuracy of 77.6% for North America. At Level 2, when closed and open forests classes are separated, global overall accuracy is 75.4% +/-0.4% for 2015 while, for the other years (2016-2019), it ranges between 75.1-75.2%. Overall accuracies at global and continental levels show consistency in the quality of the yearly maps. Among the cover fraction layer, snow/ice, built-up, water and lichen/moss fraction maps show lowest errors, followed by crops and bare/sparse vegetation fraction types. On the other hand, herbaceous vegetation fraction product has the highest error.

Land cover change between 2015 and 2018 were assessed at change and no change level to gain understanding of the consistency and differences of the annual maps. The overall accuracy is 99.6% of the change/no-change map. Here, the no-change class is mapped with very high accuracy, while change class is more likely to be committed than omitted (land cover change commission error 45.6%, omission error 36%). At continental level, land cover change class has higher accuracies in

North Eurasia, North America, Australia and South America. This statistical assessment of land cover change offers the first statistical assessment of generic land cover change at global scale for the most recent time spans. Considering that land cover change detection is much more complex than land cover classification, based on our analysis, the CGLS-LC100 V3.0 yearly maps reflect reasonably well the land cover changes that occur in the recent years globally and offer sufficient stability and consistency in the land cover map accuracies for the yearly maps. Our visual analysis of areas that have changed reveals that they regularly correspond with changes that could be observed from higher resolution images such as Sentinel-2 and Landsat. Users should use the annual land cover maps with confidence but should be careful and critical when doing detailed land cover change analysis since uncertainties (i.e. land change commission and omission errors) and related limitations vary for different world regions.

Comparison of the CGLS_LC100m V3.0 discrete map with the V2.0 discrete map showed that these two versions have similar accuracies, with V3.0 map having marginally higher accuracy (0.1%). Similar tendency applies at continental level. Our visual comparison confirms the similarity of the versions. It also highlights some improvements in the CGLS_LC100m V3.0 with respect to characterizing forest, cropland and permanent water classes. These results indicate that the global CGLS_LC100m dynamic Land Cover V3.0 product is largely consistent with the V2.0 product for 2015. Moreover, CGLS_LC100m dynamic Land Cover V3.0 product show some additional improvements in characterizing land cover types as compared to CGLS_LC100m V2.0.

Spatial uncertainty assessments on the three aggregated classes (forest, cropland and natural vegetation) reveals high level of accuracy in different regions of the world. This achievement is significant considering that the spatial uncertainty assessment is based on large number of (>200 000) sample points that are fully independent from the map production. The assessment also highlights some regions where map quality is lower, possibly due to over-estimation of forest class. However, when analyzing three land cover classes, number of points for forest class is larger in comparison to the other two classes and therefore the spatial accuracy maybe biased towards forest rather than crop and natural vegetation.

The comprehensive assessment consisting of high-level statistical assessment (Stage 4 Validation), spatial uncertainty assessments and comparisons conform high quality of the CGLS_LC100m V3.0 land cover product and its improvements as compared to the previous version V2.0. We further highlight some limitations and potential improvements.

1 BACKGROUND OF THE DOCUMENT

1.1 SCOPE AND OBJECTIVES

This document describes the validation of the CGLS Dynamic Land Cover 100m product V3.0 (CGLS_LC100m V3.0). It presents the objectives of the map validation process, provides details on the methods and the results of the validation.

The quality assessment is performed on the CGLS_LC100m V3.0 product for 2015-2019 at global scale, including evaluations at a continent level.

1.2 CONTENT OF THE DOCUMENT

This document is structured as follows:

- Chapter 2 recalls the users' requirements and the expected performance
- Chapter 3 describes the data and methodology used for the validation
- Chapter 4 presents the results of the analysis
- Chapter 5 summarizes the main conclusions of the study
- Chapter 6 makes recommendations based upon the results

1.3 RELATED DOCUMENTS

1.3.1 Applicable documents

AD1: Annex I – Technical Specifications JRC/IPR/2015/H.5/0026/OC to Contract Notice 2015/S 151-277962 of 7th August 2015

AD2: Appendix 1 – Copernicus Global land Component Product and Service Detailed Technical requirements to Technical Annex to Contract Notice 2015/S 151-277962 of 7th August 2015

AD3: GIO Copernicus Global Land – Technical User Group – Service Specification and Product Requirements Proposal – SPB-GIO-3017-TUG-SS-004 – Issue I1.0 – 26 May 2015.

1.3.2 Input

Document ID	Descriptor
CGLOPS1_SSD	Service Specifications of the Copernicus Global Land Service "Vegetation and Energy" component
CGLOPS1_SVP	Service Validation Plan of the Copernicus Global Land Service

CGLOPS1_ATBD_LC100m-V3.0	Algorithm Theoretical Basis Document of the Moderate Dynamic Land Cover Version3.0 product
CGLOPS1_PUM_LC100m-V3.0	Product User Manual summarizing all information about the Moderate Dynamic Land Cover Version 3.0 product
CGLOPS1_URD_LC100m	Users Requirement Document of Moderate Dynamic Land Cover 100m product
CGLOPS1_PSD_LC100m	Product Specifications Document of the dynamic land cover 100m product.
CGLOPS1_TrainingDataReport_LC100m	Report describing the training dataset used for Dynamic Land Cover 100m product
CGLOPS1_VR_LC100m-V2.0	Validation report of the Moderate Dynamic Land Cover Version2 product

1.3.3 Output

Document ID	**Descriptor**
CGLOPS1_PUM_LC100m-V3.0	Product User Manual summarizing all information about the Moderate Dynamic Land Cover Version 3.0 product

2 REVIEW OF USERS REQUIREMENTS

According to the applicable documents [**Error! Unknown switch argument.**] and [AD3], the user's requirements relevant for Dynamic Moderate Land Cover are:

- **Definition**: Dynamic global land cover products at 300m and/or 100m resolution using UN Land Cover Classification System (LCCS)
- **Geometric properties**:
  - Pixel size of output data shall be defined on a per-product basis so as to facilitate the multi-parameter analysis and exploitation.
  - The baseline datasets pixel size shall be provided, depending on the final product, at resolutions of 100m and/or 300m and/or 1km.
  - The target baseline location accuracy shall be 1/3 of the at-nadir instantaneous field of view.
  - Pixel co-ordinates shall be given for centre of pixel.
- **Geographical coverage**:
  - geographic projection: lat long
  - geodetical datum: World Geodetic System 1984 (WGS84)
  - pixel size: 1/112° - accuracy: min 10 digits
  - coordinate position: pixel centre for netCDF and upper left corner for GeoTIFF
  - global window coordinates:
    - Upper Left: 180°W-75°N
    - Bottom Right: 180°E, 56°S

- Accuracy requirements: Overall thematic accuracy of dynamic land cover mapping products shall be >80%. The overall accuracy assessment (including confidence limits) will be based on a stratified random sampling design and the minimum number of sampling points per land cover class relevant to the product shall be calculated as described in Wagner and Stehman (2015).

Few workshops were held in 2016 to consult different stakeholders to understand users' needs for global land cover maps. A feasibility study was performed to define the guidelines to create the first LC100 map. More details can be found in [CGLOPS1_URD_LC100m]. Larger consultations in 2017 and 2018 allowed collecting the requirements of wide user communities which were translated in product specifications [CGLOPS1_PSD_LC100m].

Table 1 summarizes the usefulness of information on LC and LC change processes for different international actions and programmes. Table 2 includes the LC classes that are required by different JRC units and are marked by ("X"), respectively. The last column provides the following information: either a class is included in the LC100m V2.0 product's legend, or it can be derived by users from the fraction layers, or additional research is needed.

Table 1: Usefulness of information on LC and LC change processes for different international actions and programmes.

	LC types	Related land change processes	UNFCCC	UNCCD	OECD	SEEA/FAO	SDGs
1	Urban/built-up areas	Urbanization	✓	✓	✓	✓	✓
2	Cropland	Crop expansion	✓	✓	✓	✓	✓
3	Cropland and other vegetation	Land abandonment	✓	✓	✓	✓	✓
4	Forest	Deforestation	✓	✓	✓	✓	✓
5	Forest	Reforestation	✓	✓	✓	✓	✓
6	Wetland	Wetland degradation	✓	✓	✓	✓	✓
7	Water body	Expansion of water surface			✓	✓	✓
8	Water body	Reduction of water surface			✓	✓	✓
9	Bare areas	Desertification			✓	✓	✓

Table 2: List of land cover classes requested by users.

Code Level 1	Code Level 2	UN LCCS level	Land cover class	Forest modelling/REDD+	Crop monitoring	Biodiversity	Monitoring Environment and Security	Climate modelling	Class included in the product
10		A12A3A20B2	Forest/tree cover	X		X	X	X	Yes
	11	A12A3A20B2D 2E1	Evergreen Needleleaf forest	X			X	X	Yes
	12	A12A3A20B2D 1E1	Evergreen Broadleaf forest	X			X	X	Yes
	13	A12A3A20B2D 2E2	Deciduous Needleleaf forest	X			X	X	Yes
	14	A12A3A20B2D 1E2	Deciduous Broadleaf forest	X			X	X	Yes

Code Level 1	Code Level 2	UN LCCS level	Land cover class	Forest modelling/REDD+	Crop monitoring	Biodiversity	Monitoring Environment and Security	Climate modelling	Class included in the product
	15	A12A3A20B2D1D2	Mixed forest	X		X			Yes
	16	A12A3A10B2XXXX (assuming that an intact forest is a very dense forest)	Intact forest	X		X		X	To map these classes, addition research is required for methodology. Either we develop an expert rule based on other datasets such as: http://www.intactforests.org/data.ifl.html or new training and validation datasets. These classes could potentially be included in the next product evolutions.
	17	-	Secondary forest	X		X		X	
	18	A11A1	Managed forest	X		X		X	
		A11A1	Plantation forest/tree crops	X	X	X		X	
		A11A1	Oil palm plantation	X	X				
		-	Forest logging	X	X	X			
		A12A3	Dominant tree species, e.g. spruce, pine, birch	X		X			
		A11A1(A2/A3)	Shifting cultivation system	X	X			X	
20		AA12A4A20B3(B9)	Shrub			X	X	X	Yes
	21	A12A4A20B(B9)XXE1	Evergreen shrubs			X			These classes could be potentially included in the next product evolutions. We will have to collect corresponding training and validation data.
	22	A12A4A20B3(B9)XXE2	Deciduous shrubs			X			
30		A12A2(A6)A20B4	Herbaceous vegetation			X	X	X	Yes
		A12A6A10 // A11A1A11B4XXXXXXF2F4F7G4-F8	Pasture/managed grassland					X	To map these classes, addition research is required for methodology. Also we will have to develop
		A122(A6)A10	Natural grassland			X		X	

Code Level 1	Code Level 2	UN LCCS level	Land cover class	Forest modelling/REDD+	Crop monitoring	Biodiversity	Monitoring Environment and Security	Climate modelling	Class included in the product
		A12A2	Grass types for Western Africa			X			new training and validation datasets. These classes could potentially be included in the next product evolutions.
		A12A3A11B2XXXXXXF2F4F7G4-A12; A12A3A11B2-A13; A12A1A11	Savannas			X			The LC100 V3 product includes such a LC class as open forest, which is a mix of trees (more than 15%), shrubs and grassland. This class only partly corresponds to savannas because a 100m x100m pixel may include less trees but still be considered as savanna. However, users are encouraged to use the fraction layers to produce their own savanna layer by applying specific thresholds for tree, shrub and grass cover.
40		A11A3	Cultivated and managed vegetation/agriculture		X	X	X	X	Yes
	41	A11A3XXXXXXD3(D9)	Irrigated cropland		X			X	To map these classes, addition research is required for methodology. Also we
	42	A11A3XXXXXXD1	Rainfed cropland		X			X	

Code Level 1	Code Level 2	UN LCCS level	Land cover class	Forest modelling/REDD+	Crop monitoring	Biodiversity	Monitoring Environment and Security	Climate modelling	Class included in the product
	43	A11A3	Big and small farming/field size		X				will have to develop new training and validation datasets. These classes could potentially be included in the next product evolutions.
	44	A11A1-W8/A2	Permanent crops		X			X	
	45	A11A3	Row crops		X				
		A11A2	Crop types: long/short cycle or winter/summer crops		X				
		A11A2	Multiple crop cycles		X				
50		B15A1	Urban/built up			X	X	X	Yes
60		B16A1(A2)	Bare/sparse vegetation				X	X	Yes
70		B28A2(A3)	Snow and Ice				X	X	Yes
80		B28A1	Open water				X	X	Yes
90		A24A1(A2/A3/A4)	Wetland			X	X	X	Yes
		A24A3	Mangroves	X		X			To map this class, addition research is required for methodology. Also we will have to develop new training and validation datasets. These classes could potentially be included in the next product evolutions.

3 QUALITY ASSESSMENT METHOD

The objective is to validate the global CGLS_LC100m V3.0 product providing statistically robust estimates of overall and class specific accuracies. In contrast to CGLS_LC100m V2.0 product, CGLS_LC100m V3.0 includes an improved global land cover base map for 2015 and yearly global land cover map for 2016-2019. In addition to the statistical accuracy assessment for these V3.0 maps, comparative assessments with the CGLS_LC100m V2.0 product and spatial accuracy assessments are included in the validation.

3.1 OVERVALL PROCEDURE

The validation process follows clearly defined protocols that are detailed in the Service Validation Plan [CGLOPS1_SVP]. In addition, Tsendbazar et al. (2018) and [CGLOPS1_VR_LC100m-V2.0] were used as references for the validation data and methods. A global validation dataset used for assessing the CGLS_LC100m V2.0 product was updated, and additional validation dataset was collected to validate the CGLS_LC100m V3.0 product (yearly discrete and fractional maps for 2015-2019). By providing the statistical map accuracy for each year, the validation meets the highest stage validation (Stage 4) requirement stated by the CEOS-WGCV-LPV (Committee on Earth Observation Satellites- Working Group on Calibration and Validation-Land Product Validation) (Figure 1). It is worth to note that no other global land cover product has Stage 4 validation.

3	Uncertainties in the product and its associated structure are well quantified over a significant (typically > 30) set of locations and time periods representing global conditions by comparison with reference in situ or other suitable reference data. Validation procedures follow community-agreed-upon good practices. Spatial and temporal consistency of the product, and its consistency with similar products, has been evaluated over globally representative locations and time periods. Results are published in the peer-reviewed literature.
4	Validation results for stage 3 are systematically updated when new product versions are released or as the interannual time series expands. When appropriate for the product, uncertainties in the product are quantified using fiducial reference measurements over a global network of sites and time periods (if available).

Figure 1. Validation requirements for Stage 3 and 4 by CEOS-WGCV-LPV (https://lpvs.gsfc.nasa.gov/)

In addition, the CGLS_LC100m V3.0 product was qualitatively and quantitatively compared against the previous version, CGLS_LC100m V2.0. To provide information on the variation in map quality, the CGLS-LC100 V3.0 product for 2015 was also assessed in terms of spatial accuracy.

These steps are explained in detail in the following sub-sections which describe the CGLS_LC100m V3.0 product that was the subject of the validation (Section 3.2), in-situ reference dataset (Section 3.3), the methods for map assessment (Section 3.4), the comparison of the V3.0 vs V2.0 (Section 3.5) and spatial accuracy analysis (Section 3.6).

3.2 CGLS_LC100M V3 PRODUCT

The third version (V3.0) of the Dynamic Land Cover map at 100m resolution includes global scale discrete and fractional land cover layers for 2015-2019 as opposed to the second version (V2.0) of maps which were provided over the world 2015 only and 3 yearly maps for African continent (Buchhorn et al. 2020). These maps were generated from the PROBA-V 100 m time-series, a database of high quality land cover training sites and several ancillary datasets. The description of the map generation is detailed in the ATBD [CGLOPS1_ATBD_LC100m-V3.0]. The global discrete map provides 23 classes (Table 3: Discrete classification coding of the CGLS dynamic land cover map V3.0.) and is defined using the Land Cover Classification System (LCCS) developed by the United Nations (UN) Food and Agriculture Organization (FAO). The UN-LCCS system was designed as a hierarchical classification, which allows adjusting the thematic detail of the legend to the amount of information available:

- The “level 1” legend contains classes with codes that are multiples of ten in Table 3: Discrete classification coding of the CGLS dynamic land cover map V3.0. (i.e. class values of 10, 20, 30, etc.).
- The “level 2” legend, a more detailed legend known as regional legend, has class codes of two digits that is not a multiple of ten in Table 3: Discrete classification coding of the CGLS dynamic land cover map V3.0. (i.e. class values of 11, 12 are sub-classes of 10, and so on).
- The “level 3” legend has three digits (i.e. 111 – 116 and 121 – 126) and are used to further distinguish the forest types (sub-classes of 11 – open forest and 12 – closed forest).

The global discrete land cover CGLS-LC100-V3.0 2015 map is shown in Figure 2. Table 3: Discrete classification coding of the CGLS dynamic land cover map V3.0.The yearly global land cover maps for 2016-2019 are shown in Figure 3. The maps for 2016, 2017 and 2018 are in “CONSO” mode meaning that any changes that might have occurred between these years are consolidated as the map generation uses longer term satellite data (1year) after the end of the year. The map for 2019 is in NRT (near real time) mode which does not use longer term satellite data. For detailed explanations see CGLOPS1_ATBD_LC100m-V3.0. Next to the discrete map, the product also includes a set of ten continuous field layers (the range is 0%-100%) that provide proportional estimates for main land cover types (i.e. tree cover, shrub cover, herbaceous vegetation cover, crops, lichen/moss, bare/sparse vegetation, snow/ice, built-up, permanent water and seasonal water) for 2015-2019. This continuous classification scheme may depict areas of heterogeneous land cover better than the standard classification scheme and, as such, can be tailored for application use (e.g. forest monitoring, biodiversity and conservation, climate modelling, etc.).

Table 3: Discrete classification coding of the CGLS dynamic land cover map V3.0.

Map code	UN LCCS level	Land Cover Class	Definition according UN LCCS	Color code (RGB)
0	-	No input data available	-	40, 40, 40
111	A12A3A10B2D2E1	Closed forest, evergreen needle leaf	tree canopy >70 %, almost all needle leaf trees remain green all year. Canopy is never without green foliage.	88, 72, 31
113	A12A3A10B2D2E2	Closed forest, deciduous needle leaf	tree canopy >70 %, consists of seasonal needle leaf tree communities with an annual cycle of leaf-on and leaf-off periods	112, 102, 62
112	A12A3A10B2D1E1	Closed forest, evergreen, broad leaf	tree canopy >70 %, almost all broadleaf trees remain green year round. Canopy is never without green foliage.	0, 153, 0
114	A12A3A10B2D1E2	Closed forest, deciduous broad leaf	tree canopy >70 %, consists of seasonal broadleaf tree communities with an annual cycle of leaf-on and leaf-off periods.	0, 204, 0
115	A12A3A10	Closed forest, mixed	Closed forest, mix of types	78, 117, 31
116	A12A3A10	Closed forest, unknown	Closed forest, not matching any of the other definitions	0, 120, 0
121	A12A3A11B2D2E1	Open forest, evergreen needle leaf	top layer- trees 15-70 % and second layer- mixed of shrubs and grassland, almost all needle leaf trees remain green all year. Canopy is never without green foliage.	102, 96, 0
123	A12A3A11B2D2E2	Open forest, deciduous needle leaf	top layer- trees 15-70 % and second layer- mixed of shrubs and grassland, consists of seasonal needle leaf tree communities with an annual cycle of leaf-on and leaf-off periods	141, 116, 0
122	A12A3A11B2D1E1	Open forest, evergreen broad leaf	top layer- trees 15-70 % and second layer- mixed of shrubs and grassland, almost all broadleaf trees remain green year round. Canopy is never without green foliage.	141, 180, 0
124	A12A3A11B2D1E2	Open forest, deciduous broad leaf	top layer- trees 15-70 % and second layer- mixed of shrubs and grassland, consists of seasonal broadleaf tree communities with an annual cycle of leaf-on and leaf-off periods.	160, 220, 0
125	A12A3A12	Open forest, mixed	Open forest, mix of types	146, 153, 0
126	A12A3A12	Open forest, unknown	Open forest, not matching any of the other definitions	100, 140, 0
20	A12A4A20B3(B9)	Shrubs	These are woody perennial plants with persistent and woody stems and without any defined main stem being less than 5 m tall. The shrub foliage can be either evergreen or deciduous.	255, 187, 34
30	A12A2(A6)A20B4	Herbaceous vegetation	Plants without persistent stem or shoots above ground and lacking definite firm structure. Tree and shrub cover is less than 10 %.	255, 255, 76

Map code	UN LCCS level	Land Cover Class	Definition according UN LCCS	Color code (RGB)
90	A24A2A20	Herbaceous wetland	Lands with a permanent mixture of water and herbaceous or woody vegetation. The vegetation can be present in either salt, brackish, or fresh water.	0, 150, 160
100	A12A7	Moss and lichen	Moss and lichen	250, 230, 160
60	B16A1(A2)	Bare / sparse vegetation	Lands with exposed soil, sand, or rocks and never has more than 10 % vegetated cover during any time of the year	180, 180, 180
40	A11A3	Cultivated and managed vegetation/agriculture (cropland)	Lands covered with temporary crops followed by harvest and a bare soil period (e.g., single and multiple cropping systems). Note that perennial woody crops will be classified as the appropriate forest or shrub land cover type.	240, 150, 255
50	B15A1	Urban / built up	Land covered by buildings and other man-made structures	250, 0, 0
70	B28A2(A3)	Snow and Ice	Lands under snow or ice cover throughout the year.	240, 240, 240
80	B28A1B1	Permanent water bodies	lakes, reservoirs, and rivers. Can be either fresh or salt-water bodies.	0, 50, 200
200	B28A1B1[1]	Open sea	Oceans, seas. Can be either fresh or salt-water bodies.	0, 0, 128

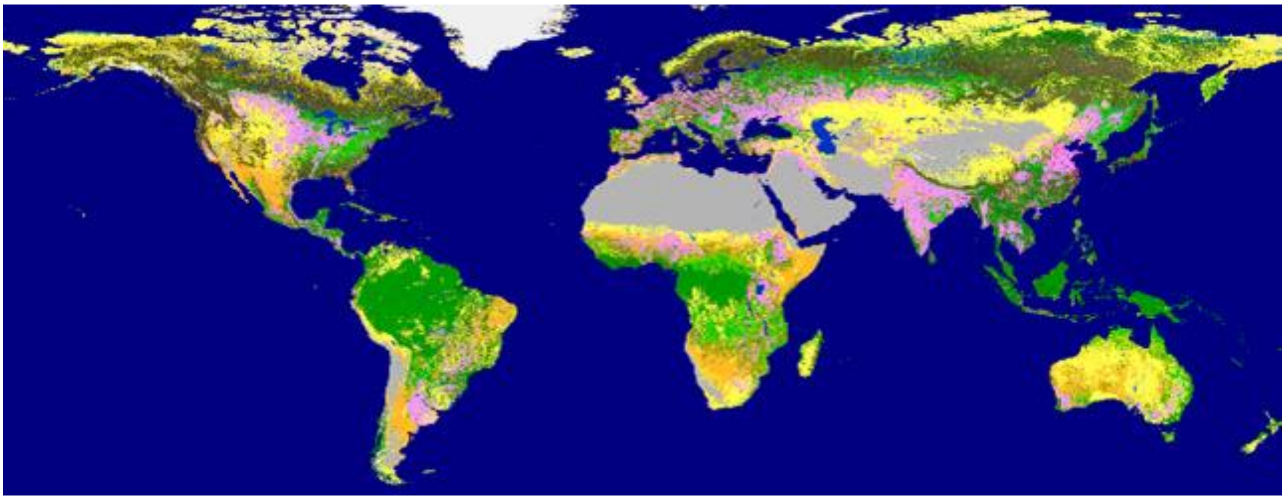

Figure 2. The CGLS Dynamic Land Cover Map V3.0 at 100 m for year 2015 with 23 discrete classes (detailed legend in Table 3)

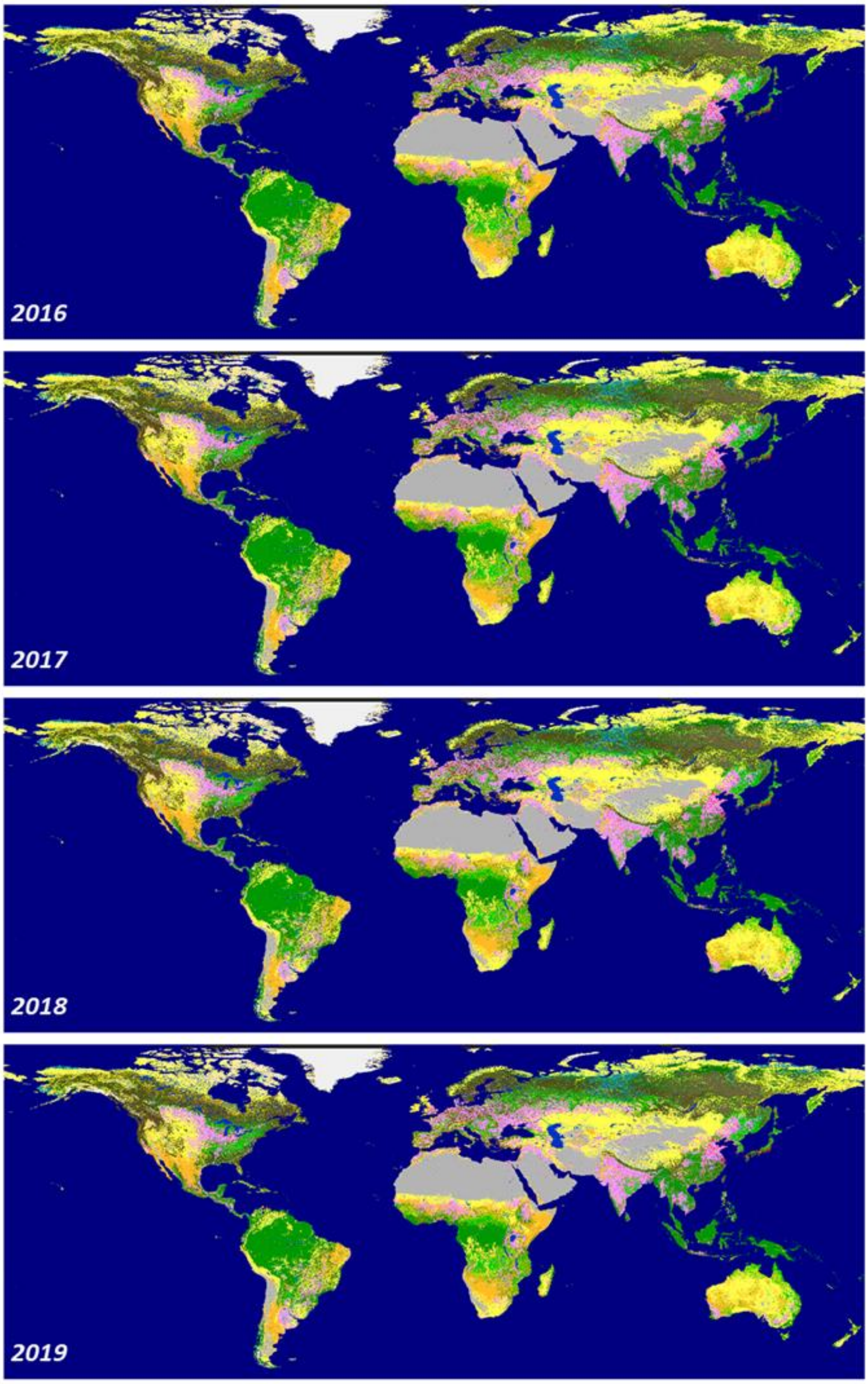

Figure 3. The CGLS Dynamic Land Cover Maps at 100 m for years 2016-2019 with 23 discrete classes (detailed legend in Table 3). Land cover change is not visible for a small display scale.

3.3 In-situ Reference Products

The land cover products were assessed using an independent validation dataset. This section describes briefly about the CGLS_LC100m validation dataset for 2015. Description of how this dataset was updated for the following years (2016-2019) and how additional datasets were collected for these years are also included. A more detailed information on the original data collection design can be found in the Service Validation Plan [CGLOPS1_SVP], Validation report of V.2.0 [CGLOPS1_SVP] and in (Buchhorn et al. 2020; Tsendbazar et al. 2018).

It is worth to mention that, although this validation dataset was collected on the Geo-Wiki platform and its set-up on labelling land cover at 10m resolution is similar to that of the training dataset used for the product mapping, the validation dataset is fully independent from the training dataset. The validation dataset was collected by a different group of experts than experts collecting reference data for the product creation. Validation data collection was managed independently by a separate institution (WU). Sample selection scheme of the validation dataset is different than that of the training datasets.

3.3.1 The CGLS_LC100m validation dataset for 2015

The detailed explanation on the collection of the CGLS-LC100m validation dataset for 2015 can be found in Validation report of V.2.0 [CGLOPS1_VR_LC100m-V2.0] and in (Tsendbazar et al. 2018). A brief description of the dataset is included here.

The validation dataset consists of 21,752 sampling locations across the globe, that is from 2889 to 3617 samples per continent (Africa, North America, Asia, Europe, Northern Eurasia, Oceania & Australia and South America (see Figure 4 for geographical distribution). The sites were selected using a stratification based on the Köppen climate zones and human population density with the assumption that these two factors are the main influencers on the worlds land cover [CGLOPS1_VR_LC100m-V2.0]. Sample allocation focused on areas that are more likely to be misclassified such as those that occur in heterogeneous landscapes (Jung et al. 2006; Tsendbazar et al. 2018). In addition, based on the CGLS-LC-100 V2.0 map some additional sample locations were selected to improve the representations of so-called rare classes such as urban, wetland and open water. We applied a requirement of, at least, 100 sample sites per LCCS level1 land cover type for each continent [CGLOPS1_SVP].

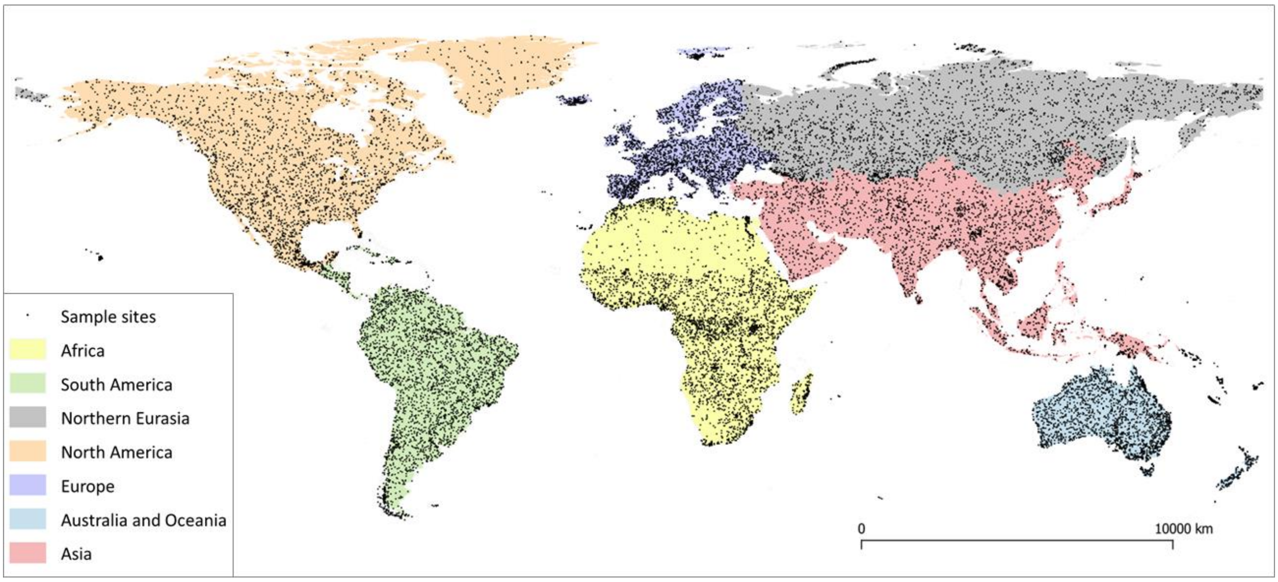

Figure 4. Continental distribution of the CGLS_LC100m validation dataset for reference year 2015.

CGLOPS1_VR_LC100m-V2.0**Error! Reference source not found.**The reference land cover at each sample site was interpreted visually by regional experts who have experiences of working with satellite-based land cover analysis and image interpretation. The experts were provided with an access to a designated validation data collection web-interface which is based on Geo-Wiki platform. Experts were offered a remote training and tutorials. Since a visual interpretation can be subject to interpreter variability and bias (Strahler et al. 2006), feedback loops were conducted in the process of interpretation (Tarko et al. 2020). Feedback was given for each validation interpretation. Quality checks and consolidation efforts were also carried out in order to select the updated interpretations, details on quality checks can be found in validation report of V.2.0 [CGLOPS1_VR_LC100m-V2.0], in (Tarko et al. 2020) and in (Tsendbazar et al. 2018).

Different information sources were provided to the regional experts for visual interpretation. These include Google, Bing maps, ESRI-WORLD imagery as well as Sentinel-2 images. Furthermore, time series of Normalized Difference Vegetation Index (NDVI) profiles based on MODIS (MOD13Q1.005 16 days composite), Landsat (32 days composite from Landsat-7 and 8 data), PROBA-V (maximum NDVI over 3 days from top of canopy (TOC) daily NDVI from PROBA-V 100m Collection 1 data) were used as information source of plant phenology: these dataset are available through Google Earth Engine (GEE: https://earthengine.google.com). Thumbnails of all available Sentinel-2 images were also made available for different band combinations. In addition, experts had the possibility to load the validation point location Google Earth to make use of historical very high-resolution images.

The validation sample site areas match with a PROBA-V pixel (100x100m), which is aligned to Sentinel-2 pixels based on UTM projection [CGLOPS1_PUM_LC100m-V3.0]. At each sample unit, 10mx10m subpixels were created and reference information on the land cover was labelled on each of the subpixel. Figure 5 shows an example of sample interpretation on the validation interface.

Figure 5. A screenshot of an example sample interpretation over the 10mx10m sub-pixels included into a PROBA-V pixel (100mx100m).

Land cover information per subpixel was combined for each sample site to obtain information on the fraction of land cover types within the sample sites. This information was then translated into the discrete map legend using the UN LCCS (United Nations Land Cover Classification System) as a basis (see [**Error! Unknown switch argument.**], [CGLOPS1_VR_LC100m-V2.0] and (Tsendbazar et al. 2018)).

3.3.2 Updating the CGLS-LC100 validation dataset for 2016-2019

The CGLS_LC100m validation dataset (see section 3.3.1) is for the reference year of 2015 [CGLOPS1_VR_LC100m-V2.0]. To make this dataset applicable for validating the CGLS-LC100m 2016-2019 maps, the dataset was updated. Updating was done in two ways:

- revising some points in the CGLS-LC100 2015 Validation data and
- collecting validation datasets in possible change areas (see section 3.3.3).

<u>Revising the CGLS-LC100m 2015 validation dataset</u>

The CGLS-LC100m validation dataset for 2015 (described in section above 3.3.1) has been revised. The revision aimed to confirm the land cover interpretation for reference year 2015 and update land cover interpretation in case of change in land cover.

In total, the revision concerned 43,5% of sample sites, which included 9465 locations. 40% of sample sites were randomly selected and 3,5% of sample sites were those in the area identified as unstable which were assessed by Breaks For Additive Season and Trend (BFAST) algorithm [CGLOPS1_ATBD_LC100m-V3.0]. These break maps show areas where breaks were identified between years 2015-2019 based on MODIS near-infrared reflectance of vegetation (NIRv) time series (Verbesselt et al. 2012) [CGLOPS1_ATBD_LC100m-V3.0]. For 607 sample sites, land cover for at least one subpixel has been updated and from those, the discrete map legend has been modified for 204 sample sites. This means that in the revised CGLS-LC100m 2015 validation dataset, the discrete map legend has been different for 204 locations.

The revision has been done by experts who worked on the generation of the CGLS-LC100 validation dataset for 2015 [CGLOPS1-VR-LC100m-V2.0] and who have experiences of working with satellite-based land cover analysis and image interpretation. Revision task has been performed using the dedicated interface in Geo-Wiki platform. Besides previously available images and data for visual interpretation (listed in previous section 3.3.1), experts could consult dedicated chipsets of Very High Resolution (VHR) Digital Globe images for the sample site which were purchased from the Digital Globe repository (see Figure 6).

Revisions of land cover in reference year 2015 resulting in modifications of dataset were caused by the availability of new image data of increased spatial and time resolution for the 2015 reference year, particularly in regions where satellite image coverage was scarce, i.e. in Siberia region.

Figure 6. Exemplary digital Globe VHR image square chipsets available in Geo-Wiki application displayed over Google Earth satellite image.

Change visual interpretation of the CGLS-LC100m 2015 validation dataset

The same 43,5% of the revised CGLS_LC100m 2015 validation dataset have been simultaneously evaluated to identify changes in land cover for reference years 2016-2019. Change was identified at the level of subpixel (10m x 10m).

Whenever land cover changed for a given sample site, a group of experts performing the revision also collected land cover for given sample site for years 2016-2019. Next to the land cover information for the years, the locations were also marked for cases where experts are not certain if there was a change or not. In total, 277 out of 9465 sample sites were evaluated as with change for at least one subpixel in sample site. For 151, the changes were big enough to have change in map legend (Level1) between years 2015 and 2019.

3.3.3 Collecting new validation dataset in possible change areas

To validate the CGLS-LC100 V3.0 2016-2019 maps, new sample sites were collected and interpreted in the possible change areas.

Sample stratification allocation

Additional sample points targeting changes in 2015-2019 can be selected based on the yearly CGLS-LC100 maps (2015-2019). For this, at the time of sample selection, the yearly maps are required to be available. However, since collecting new validation dataset can take significant amount of time, we used a map for possible change as a stratification for sample selection.

The possible change stratification was created using yearly land cover maps that were not temporally cleaned (draft versions). Due to time limitation of collecting new sample sites, we chose to use this draft version of the product. Based on the yearly land cover maps, we identified possible areas of change by selecting areas with different land cover classes between the pairs of years (2015-2016, 2016-2017, 2017-2018 and 2018-2019). Since the possible change areas based on the draft map before temporal cleaning could contain spurious changes due to misclassification, we further refined the change area using the break mask based on the BFAST algorithm (Verbesselt et al. 2012) and CGLOPS1_ATBD_LC100m-V3.0). We removed any possible change areas outside the break mask. For further details of this break mask, see CGLOPS1_ATBD_LC100m-V3.0. Next, the possible change areas were limited to land cover change transitions that are deemed probable taking into considerations of the land cover change processes identified as important in the Section 2. Here, change areas that are less than 3 ha (3 adjacent pixels) were also removed.

Table 4 presents those land cover transitions that were addressed in this stratification. For each pair year (e.g. 2015-2016), for each continent, 240 new random sample sites were created. This totals up to 1680 for each pair year (e.g., 2015-2016, 2016-2017) and 6720 new validation sample sites addressing likely land cover change (2015-2019). Sample allocation was based on the land cover type after the change, so each batch of 240 new sample sites was evenly distributed between land cover type after change. Figure 7 shows global spatial distribution of the 6720 new CGLS-LC100m land cover change validation dataset for reference years 2015–2019. Sample sites in validation dataset are clustered in the areas of potential change (such as the Iberian Peninsula and Baja Calinfornia penunsula).

Table 4: Land cover transitions that were used in selecting new sample sites in potential areas of change.

		Land cover before change									
		Forest	**Shrubs**	**Herbaceous vegetation**	**Croplands**	**Urban**	**Bare/sparse vegetation**	**Snow/ice**	**Permanent Water**	**Herbaceous Wetland**	**Lichen/ moss**
Land cover after change	**Forest**	x	yes	yes	yes	no	no	no	no	no	no
	Shrubs	yes	x	yes	yes	no	no	no	no	no	no
	Herbaceous vegetation	yes	yes	x	yes	yes	yes	yes	yes	yes	yes
	Croplands	yes	yes	yes	x	no	yes	no	yes	yes	no
	Urban	yes	yes	yes	yes	x	yes	yes	no	yes	yes
	Bare/sparse vegetation	yes	yes	yes	yes	yes	x	yes	yes	yes	yes
	Snow/ice	no	no	yes	no	no	yes	x	no	no	yes
	Permanent Water	yes	yes	yes	yes	no	yes	yes	x	yes	no
	Herbaceous Wetland	yes	yes	yes	yes	no	yes	yes	yes	x	no
	Lichen/moss	no	no	yes	no	no	yes	yes	yes	yes	x

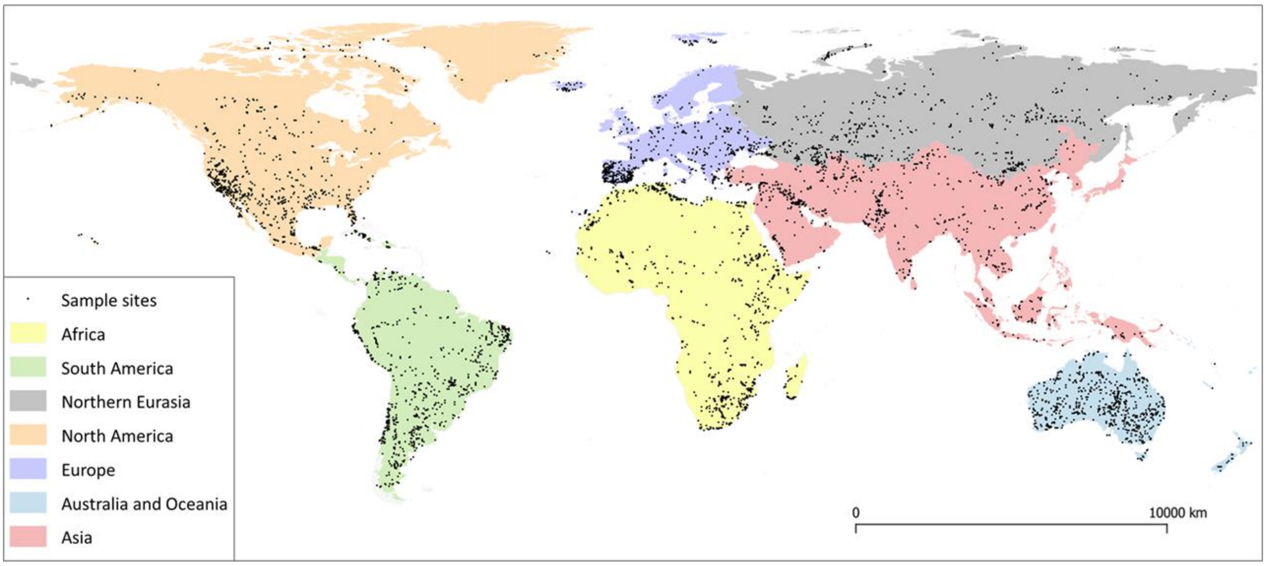

Figure 7. Continental distribution of the new CGLS_LC100m land cover change validation dataset for reference years 2015 - 2019.

Reference data collection

The new change validation sample sites were visually interpreted and mapped by experienced independent regional experts (list of experts participating validation data collection is in Table 5). There were 960 sample sites for each region/continent. Similar to the reference data collection for 2015 validation dataset (see Section 3.3.1), the experts were provided with an access to the validation data collection web-interface, based on Geo-Wiki platform. Experts were offered a remote training and dedicated tutorials. Experts received feedback on their first 10-20 collected sample sites at the beginning of the appointment. An online assistance and revision of at least 10% of collected sample sites was provided by validation experts from WU. The experts have corrected the interpretations where necessary.

Table 5. Regional experts who collected new sample sites in the areas of potential change

Region	Regional expert's name, academic title
Africa	Michele Downie, PhD
Asia	Tony Widianto, MSc
Australia and Oceania	Shirley Famelli da Costa, PhD
Europe	Paola Codipietro, MSc
	Maria Schepaschenko, PhD
North America	Yinan He, PhD
Northern Eurasia	Bayarsaikhan Sainbuyan, PhD
South America	Khalil Ganem, MSc

Similar to the CGLS-LC100m 2015 validation dataset, areas of new sample sites match with a PROBA-V pixel (100x100m) and are aligned to Sentinel-2 pixels based on UTM projection [CGLOPS1_PUM_LC100m-V3.0]. At each sample unit, 10mx10m subpixels were created and the land cover was interpreted for each reference year 2015-2019. In case of sample sites where all subpixels had the same land cover for all reference years, the reference information was labelled once on each of the subpixel. In case of sample sites where land cover for at least one subpixel was changed, information was labelled for all subpixels for each reference year 2015-2019 accordingly. Experts noted sample locations where the occurrence of change was not certain. Additionally, experts collected information on land cover interpretation confidence for each sample site. Confidence for given sample site interpretation could be chosen from four levels: unsure, less sure, quite sure, sure. Figure 8 shows Geo-Wiki based interface adjusted for validation data collection for land cover change and Figure 9 shows screen shots of an exemplary sample site with interpreted land cover for each reference year.

Newly added and updated Digital Globe VHR images (Figure 6) and time series Sentinel-2 images, along with the continuous NDVI profiles which were conveniently displayed for visual interpretation in the interface played an important role in visually interpreting land cover change. A screenshot of Geo-Wiki Sentinel-2 color infrared time series chipsets is in Figure 10.

Figure 8. Geo-Wiki based interface for interpreting land cover of change sample sites.

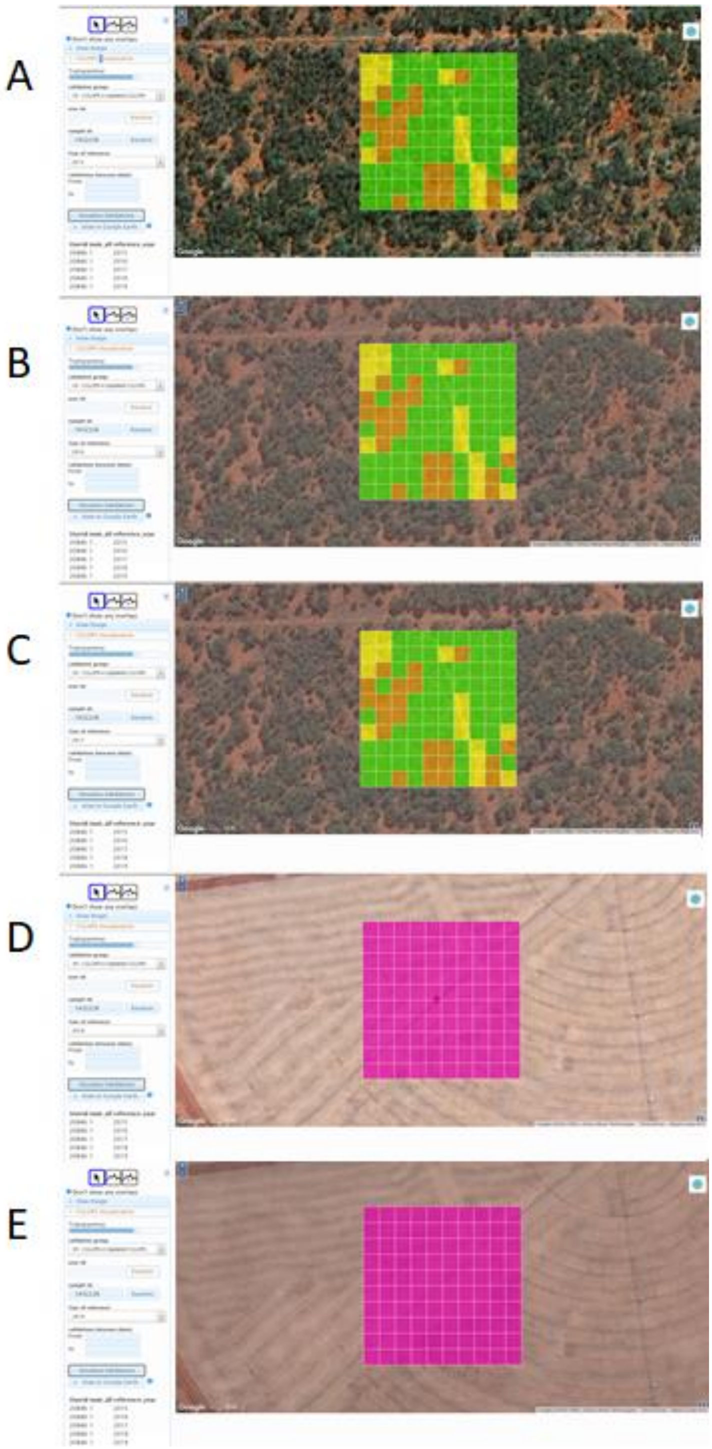

Figure 9. Screenshots of an example sample interpretation in Geo-Wiki application for each reference year 2015-2019 over the 10mx10m sub-pixels included into a PROBA-V pixel (100mx100m): A - reference year 2015, land cover is mix of trees, shrubs and grass; B – reference year 2016, land cover is mix of trees, shrubs and grass; C –reference year 2017, land cover is mix of trees, shrubs and grass and the land cover change occurred around fourth quarter of the year 2017 (see Figure 10); D – reference year 2018, land cover is cropland, E – reference year 2019, land cover is cropland

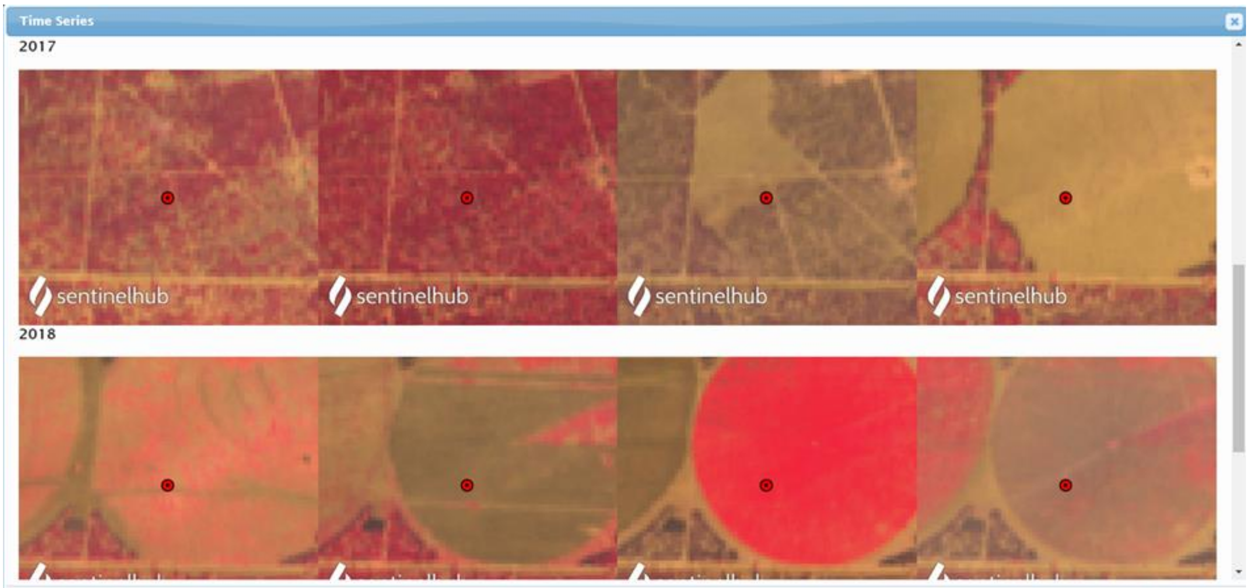

Figure 10. Screenshot of Sentinel-2 time series images in NIR for reference years 2017 (image acquisition dates from left: 5 Jan., 25 May, 28 Aug., 12 Oct.) and 2018 (image acquisition dates from left: 15 Jan., 10 May, 28 Aug., 16 Nov.) depicting land cover changes from mix of trees, shrubs and grass into a cropland. Images depict the same area as shown in Figure 9.

Similar to the validation report of map V2.0 ([CGLOPS1_VR_LC100m-V2.0] and (Tsendbazar et al. 2018), collected land cover fractions for new sample sites were converted to land cover classes:

- for homogeneous sample sites (e.g., 100% water proportion corresponds to water body class).
- for heterogeneous sample sites where conditions can meet the definitions of multiple land cover types, a priority rule was applied (Tsendbazar et al. 2018). The priority order was permanent water, urban, cropland, herbaceous wetland, forest, shrubs, herbaceous vegetation, bare/sparse vegetation, lichen/moss, and snow/ice. For example, if a validation site contains 30% trees and 70% grass, it meets the definitions of both land cover types, forest and grassland, based on the fractions. In such case, we apply the priority order and label this site as forest.

As a result, a sample site in one location had five land cover classes, one for each reference year 2015-2019.

3.4 MAP ACCURACY ASSESSMENT

3.4.1 Assessing the CGLS-LC100m V3.0 product for 2015

Based on the validation dataset, the discrete and fractional land cover layers for 2015 were assessed.

To estimate the accuracy of the land cover maps, we followed the same methods used in Tsendbazar et al. (2018) and [CGLOPS1_VR_LC100m-V2.0]. Specifically, we accounted for unequal inclusion probabilities between different strata because sample sites were not allocated proportionally to the strata areas (Olofsson et al., 2012; Wickham et al., 2010). Based on Pengra et al. (2015), the inclusion probability for stratum h is defined as $\pi_h = {}^{k_h}/_{K_h}$, where k_h is number of sample sites in stratum h and K_h is the population size for stratum h. Number of sites is based on the 100m × 100m units. Inclusion probability for the additional sample sites for the rare classes were calculated based on the population of possible sample sites within the rare classes of the CGLS_LC100m V2.0 map. The estimation weight is calculated as the inverse of inclusion probability (${}^{1}/_{\pi_h}$). With the inclusion probabilities and the estimation weights for the sample locations, we constructed the confusion matrix based on the mapped and reference land cover classes. We then estimated the overall and class specific accuracies and their confidence intervals (at 95% confidence level).

Validation of the discrete maps focused on Level 1 and Level 2 legends which differ in terms of number of forest related classes (see Section 3.2). Accuracies of the discrete map was calculated at global scale and as well as at seven (sub) continent levels (Figure 4) described in Section 3.3. Not all Level 1 classes are validated at (sub) continent level due to their very limited or no appearance in some continents. These include snow/ice in Africa and Oceania & Australia; lichen and moss in Africa, Asia, Oceania and South America.

Out of 21,752, some validation sites had no data in the CGLS-LC100m V3.0 product. These locations are mostly in the extreme north, outside the mapped region of the CGLS-LC100m product. Therefore, 21,601 sites were used to validate the map.

In addition to the accuracy assessment of the discrete land cover map, quality assessment was conducted for the fractional land cover layers. Validation of the fractional layers focused on Level 1 legend which includes nine fractional layers, i.e. trees, shrubs, herbaceous vegetation, crops, moss/lichen, bare/sparse vegetation, snow/ice, built-up and permanent water fraction layers. Seasonal water fraction was not validated as Level 1 legend does not include seasonal water. The fraction information of the land cover types in the validation dataset was directly used. For each fractional land layer, the mean absolute error (MAE) and root mean square error (RMSE) were calculated [CGLOPS1_VR_LC100m-V2.0].

3.4.2 Assessing the CGLS-LC100m V3.0 product for 2016-2019

The revised validation dataset (Section 3.3.2) with 21752 locations together with the additional possible change sites (6720) were used to assess the accuracy of the yearly maps for 2016-2019.

In total 28,321 sample sites were used for assessing the maps for 2016-2019. For the additional sample sites, the inclusion probability and the estimation weights were calculated based on the area of the sample stratification similar that of the original validation dataset (Section 3.4.1). For each year, validation land cover labels were updated in case there was a change. For each year, by comparing the land cover class at the validation locations and corresponding map land cover class, the map confusion matrix was created using the methods described in Section 3.4.1

For level 1 classes, map overall accuracy, class specific accuracies and confidence intervals were calculated for each year (2016-2019) similar to the accuracy estimation of 2015. Continental scale accuracies were also calculated. For level 2 classes, only overall map accuracy was reported at global and continental scales. The accuracy of the fractional layers were also assessed for 2016-2019 using the same approach as 2015 V3.0.

Next to updating the map accuracies for the yearly maps, we assessed the accuracy of land cover change detection between 2015 and 2018. The year 2018 was selected since this is a consolidated version which is more reliable than the NRT version for 2019. Between 2015-2018, if there is change recorded in any of the years, it was considered change. In case, change in land cover class was not reported in any of the years between 2015-2018, it was considered no-change. For the change assessment, sample sites tagged as not certain for change occurrence were not included. In total 27,861 (2326 locations with change and 25535 locations with no-change) sample sites were used. The confusion matrix of the change detection was created both using the sample count and area weights (inclusion probability). Accuracies were reported both at global scale and continental levels.

In addition, some change processes were visually assessed by comparing the mapped change areas with VHR images as well as time series snippets of Sentinel-2 and Landsat images.

3.5 Comparison between the CGLS-LC100m V3.0 and V2.0 products

Compared to the CGLS-LC100m V2.0 product (Buchhorn et al. 2020), the V3.0 adds the change detection methodology to generate consistent land cover maps over time (2015-2019). Due to the introduction of consistent change detection methods and additional training data collection on the some poorly mapped areas in V2.0, the V3.0 product differs to a small extent from the V2.0 for the reference year 2015. Therefore, we compared the V2.0 product with the V3.0 product for the reference year 2015 qualitatively and quantitatively for both the discrete map and fraction layers for 2015. Figure 11 depicts the CGLS-LC100m V2.0 product-discrete land cover map.

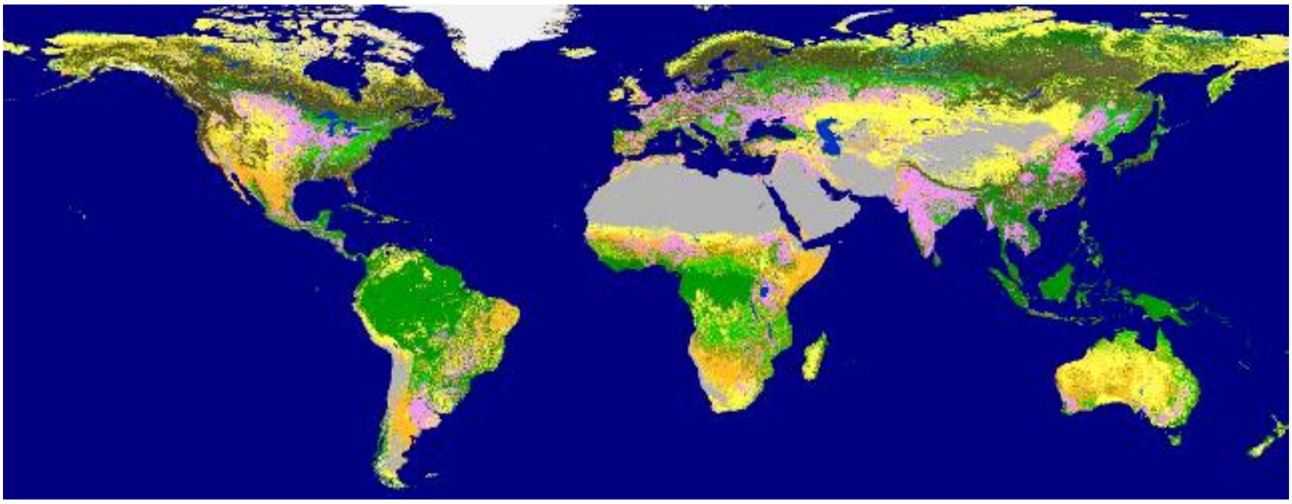

Figure 11. The CGLS Dynamic Land Cover Map V2.0 at 100 m (detailed legend in Table 3).

We assessed the CGLS-LC100m V3.0 discrete map qualitatively by comparing it with the VHR images available in Google Map and the CGLS-LC100m V2.0 product. In addition, we assessed the accuracy of the CGLS-LC100m V2.0 product using the updated validation dataset used to assess the V3.0 product (Section 3.3).

3.6 SPATIAL UNCERTAINTY ASSESSMENT

The spatial accuracy was calculated for the CGLS-LC100m V3.0 for the year 2015 and three aggregated land cover classes: forest (all forest classes aggregated), cropland, and other natural vegetation (shrubs and grassland). The spatial accuracy assessment could only be done for these 3 classes since high quality reference points available were limited and needed to be of high geographical density. The spatial accuracy was derived from sets of independent datasets (i.e., samples that were not used to train the classifier) (Table 6). Having independent reference datasets for the spatial accuracy assessment was critical in order to make sure the spatial accuracy map is entirely independent from the training dataset used.

Each land cover class (forest, crop and other natural vegetation) was assessed independently from each other, focusing on how well the mapped classes represent the real world (user's accuracy).

After combining the datasets listed in Table 6, the accuracy of forest class was calculated based 217,761 points which are divided into 169,593 forest points, and 48,168 non-forest points. The accuracy of the cropland was calculated from 212,933 sample points divided into 8,885 cropland and 204,048 non-cropland. Other natural vegetation accuracy was calculated using 189,423 samples, divided into 6,188 other natural vegetation and 183,235 non other natural vegetation class.

For each class, we calculated the spatially explicit user's accuracy, as proposed by (Comber et al. 2012). The method calculates the accuracy of the classification in a given location based on geographically weighted validation points. We calculated the spatial accuracy for each class at a resolution of 0.5 degrees for the whole globe. We then resampled the accuracy to the spatial resolution of the CGLS-LC100 map and masked out all pixels that are not classified as one of the three classes mentioned above. Finally, we merged the accuracy maps of the three classes into one single map. The final accuracy map shows the probability (from 0 to 100) that the classifier has correctly classified each pixel. Note that only three aggregated land cover classes were used in the accuracy calculation. The map gives an overview of how well the mapped land cover classes represent the real world in different regions.

Table 6: List of datasets used for spatial accuracy assessment

Dataset name	Classes	Number of sample sites	Description	Reference
C-GLS-LC100 validation dataset	forest, crop, and other natural vegetation	21700	The dataset is used for statistical accuracy assessment of the C-GLS-LC100 product and is independent of product generation.	CGLOPS1_VR_LC100m-V2.0
SIGMA cropland campaign	crop	30 000	This global reference data set on cropland was collected through a crowdsourcing campaign using the Geo-Wiki platform. The dataset was generated by over 80 participants from around the world focusing on cropland identification. The dataset contains the cropland area fraction in a 300 meter Proba-V pixel. The sampling stratification focused on areas with higher probability of misclassification based on a cropland probability map from IIASA.	(Fritz et al. 2015)
NatureMap	forest	170 000	This dataset was produced as part of a forest management crowdsourcing campaign organized by the NatureMap project. The campaign collected for around 450 K locations information about the type of forest management (e.g., intact forest, forest with signs of management, planted forests, agroforestry). The data collected was based on the 100 meter Proba-V grid. Forest and non-forest sample locations were used.	https://naturemap.earth/
Hybrid forest cover dataset	forest	16 800	This is a crowdsourcing data on forest cover which were collected through the Geo-Wiki platform. Over numerous campaigns, volunteers have been asked to visually estimate land cover visible in cells of a grid overlaid onto very high resolution Google Earth imagery. Based on the hybrid forest cover map, data points that were based on 1-km grid was used. The dataset contains presence/absence of forest information.	(Lesiv et al. 2016)

4 RESULTS

4.1 ACCURACY OF THE CGLS_LC100M V3.0 PRODUCT FOR 2015

The CGLS_LC100m V3.0 product (the discrete map and the nine fraction layers) were assessed using the independent CGLS_LC100m validation dataset described in Section 3.3. The results of the accuracy assessment are detailed below.

Discrete map 2015 V 3.0

Based on the mapped and reference land cover types, a confusion or an error matrix was calculated. The error matrix was corrected by sample inclusion probabilities. Table 7 shows the confusion matrix for the discrete CGLS_LC100m V3.0 Level 1 map at global scale for the reference year 2015.

Table 7: Confusion matrix (%) for the discrete CGLS-LC100m V3.0 Level 1 map at global scale for 2015, corrected by sample inclusion probabilities.

	Forest	Shrubs	Herbaceous vegetation	Croplands	Urban	Bare/sparse vegetation	Snow/ice	Permanent Water	Herbaceous Wetland	Lichen/ moss	Correct	Total	User's accuracy	Confidence interval ±
Forest	33.3	1.8	0.9	0.5	0	0		0	0.1	0.1	33.3	36.7	90.7	0.4
Shrubs	1.7	5.5	1	0.3	0	0.2	0	0	0.1	0	5.5	8.9	62.1	1.6
Herbaceous vegetation	1.4	2.4	14.5	0.9	0	0.5	0	0.1	0.4	1.1	14.5	21.2	68.2	0.9
Croplands	0.9	0.4	1.4	7.8	0	0		0	0.1	0	7.8	10.8	72.5	1.1
Urban	0.1	0	0.1	0	0.6	0		0			0.6	0.9	68.2	3
Bare/sparse vegetation	0	0.3	0.8	0	0	13.6	0	0	0	0	13.6	14.8	91.6	0.9
Snow/ice			0			0.1	1.9	0		0	1.9	2	94.8	1.8
Permanent Water	0	0	0	0	0	0		1.9	0		1.9	2	96.9	0.9
Herbaceous Wetland	0.1	0.1	0.3	0	0	0		0.1	0.6	0.1	0.6	1.2	44.9	2.7
Lichen/moss			0.1			0.4	0	0		0.9	0.9	1.4	62.2	3.6
Correct	33.3	5.5	14.5	7.8	0.6	13.6	1.9	1.9	0.6	0.9				
Total	37.6	10.5	19.2	9.7	0.7	14.8	2	2.3	1.2	2.2		100		
Producer's accuracy	88.6	52.4	75.5	80.9	89	91.8	99	86	46.9	39.6			**80.6**	
Confidence interval ±	0.4	1.5	0.9	1.1	2.6	0.8	0.5	1.6	3.4	2.7				**0.4**

The overall accuracy of the CGLS_LC100m V3.0 discrete global land cover map is 80.6% +/-0.4% (confidence intervals at 95% confidence level). In terms of class specific accuracies, forest, bare/sparse vegetation, snow/ice and permanent water are mapped with very high accuracies (> 85%). The class accuracies of herbaceous vegetation, croplands and urban are moderate (65%-85%) while herbaceous wetlands, lichen/moss and shrubs have lower class accuracies (<65%).

Specifically, croplands are in general overestimated at the cost of herbaceous vegetation class. The same also applies for urban class which tends to be overestimated. Herbaceous wetlands have high confusion error with herbaceous vegetation and shrubs have high confusion error with forest and herbaceous vegetation class, which was expected considering the spectral similarity of these classes. Lichen/moss class has higher confusion error with herbaceous vegetation and bare/sparse vegetation class. All continents are mapped with overall accuracies around 80% with lowest 77.6% for North America and highest 83.5 % for Asia at Level 1 (Table 8). The overall accuracies and confusion matrices were also calculated for each continent (Table 9-Table 15).

Table 8: Overall accuracy of the discrete CGLS-LC100m V3.0 2015 Level 1 map per continent.

Continent	Number of samples	Overall accuracy (%)	Confidence intervals ±
Africa	3616	80.3	1.0
Asia	3071	83.5	0.7
Northern Eurasia	2976	80.9	0.8
Europe	3125	80.2	0.8
North America	2846	77.6	0.8
Oceania & Australia	2950	81.5	1.0
South America	3017	80.1	0.7

Table 9: Confusion matrix (%) for the discrete CGLS-LC100m V3.0 Level 1 2015 map over Africa.

Africa	**Forest**	**Shrubs**	**Herbaceous vegetation**	**Croplands**	**Urban**	**Bare/sparse vegetation**	**Permanent Water**	**Herbaceous Wetland**	**Correct**	**Total**	**User's accuracy**	**Confidence interval ±**
Forest	25.1	1.3	0.7	0.9			0	0	25.1	28	89.4	1
Shrubs	3.5	10.5	2	1.1	0	0.3	0	0.1	10.5	17.6	59.8	3.1
Herbaceous vegetation	1.1	1.3	9.9	1.2		0.5	0	0.4	9.9	14.4	68.5	3.2
Croplands	0.6	0.7	1.3	4.3	0	0	0	0	4.3	7	62.4	3.7
Urban	0.2	0	0.2	0	0.3	0			0.3	0.8	39.3	8.5
Bare/sparse vegetation	0	0.2	1.3		0	28.8	0	0	28.8	30.4	94.7	1.6
Permanent Water							1	0	1	1	99.6	0.9
Herbaceous Wetland	0.2	0	0.1	0	0	0	0.1	0.4	0.4	0.9	49.3	8.1
Correct	25.1	10.5	9.9	4.3	0.3	28.8	1	0.4				
Total	30.7	14.1	15.5	7.6	0.3	29.7	1.2	1		100		
Producer's accuracy	81.7	74.7	63.8	57.3	98.4	97.1	82.9	41.2			**80.3**	
Confidence interval ±	1.3	3	3.4	3.6	0.8	1.2	4.1	8.8				**1.0**

Table 10: Confusion matrix for the discrete CGLS-LC100m V3.0 Level 1 2015 over Asia.

Asia	**Forest**	**Shrubs**	**Herbaceous vegetation**	**Croplands**	**Urban**	**Bare/sparse vegetation**	**Snow/ice**	**Permanent Water**	**Herbaceous Wetland**	**Correct**	**Total**	**User's accuracy**	**Confidence interval ±**
Forest	27.6	1.2	0.7	0.8		0			0	27.6	30.3	91	1
Shrubs	0.3	1.1	0.3	0.1		0.1		0.1	0	1.1	1.9	55.7	6.3
Herbaceous vegetation	0.8	1.7	10.3	0.7		0.3		0.1	0.1	10.3	14	73.7	2.4
Croplands	2	0.7	2	13.5	0.1			0.2	0.3	13.5	19	71.4	2
Urban	0.2		0.1	0.1	1.3	0		0.1		1.3	1.8	74.7	4.7
Bare/sparse vegetation	0	0.8	1.9	0.1		27.7		0.1	0	27.7	30.6	90.4	1.2
Snow/ice			0			0	0.4			0.4	0.5	90.9	2.9
Permanent Water	0			0		0		1.5		1.5	1.6	94.8	3.3
Herbaceous Wetland	0		0	0		0		0.1	0.1	0.1	0.4	24.3	8.4
Correct	27.6	1.1	10.3	13.5	1.3	27.7	0.4	1.5	0.1				
Total	31	5.4	15.4	15.4	1.5	28.2	0.4	2.1	0.6		100		
Producer's accuracy	88.9	20	66.9	87.9	90.8	98.1	100	70.9	15.1			**83.5**	
Confidence interval ±	1	3	2.4	1.6	4	0.6	0	4.7	10				**0.7**

Table 11: Confusion matrix (%) for the discrete CGLS-LC100 V3.0 Level 1 2015 over Northern Eurasia.

Northern Eurasia	**Forest**	**Shrubs**	**Herbaceous vegetation**	**Croplands**	**Urban**	**Bare/sparse vegetation**	**Snow/ice**	**Permanent Water**	**Herbaceous Wetland**	**Lichen/ moss**	**Correct**	**Total**	**User's accuracy**	**Confidence interval ±**
Forest	41.6	2.4	1.5	0.1	0	0		0.1		0.2	41.6	45.9	90.7	0.9
Shrubs	0.4	1.2	0.5						0.2		1.2	2.3	52.7	6.1
Herbaceous vegetation	1.6	2.3	24.7	0.6		0.8		0.1	0.6	2.9	24.7	33.6	73.5	1.5
Croplands	0.3	0.1	1.5	5.1					0.1		5.1	6.9	72.8	3.3
Urban	0.1		0	0	0.1						0.1	0.2	49.4	9.4
Bare/sparse vegetation			0.4			2.9	0	0			2.9	3.3	87.9	3.4
Snow/ice						0	0.1			0	0.1	0.1	93	2.5
Permanent Water	0		0					3			3	3	97.9	1.6
Herbaceous Wetland	0.1	0.5	1			0		0.1	1.7	0.5	1.7	3.9	43	4.1
Lichen/moss			0			0.2				0.5	0.5	0.7	74.3	6.3
Correct	41.6	1.2	24.7	5.1	0.1	2.9	0.1	3	1.7	0.5				
Total	44.1	6.5	29.6	5.7	0.1	3.9	0.1	3.4	2.5	4.1		100		
Producer's accuracy	94.4	18.9	83.4	88	99.3	74.2	100	88.1	66.7	12.3			**80.9**	
Confidence interval ±	0.7	2.5	1.3	2.8	0.7	4.1	0	3.1	5.1	1.9				0.8

Table 12: Confusion matrix (%) for the discrete CGLS-LC100 V3.0 Level 1 2015 over Europe.

Europe	Forest	Shrubs	Herbaceous vegetation	Croplands	Urban	Bare/sparse vegetation	Snow/ice	Permanent Water	Herbaceous Wetland	Lichen/ moss	Correct	Total	User's accuracy	Confidence interval ±
Forest	40.4	0.9	1.8	1.1	0.1			0	0.1	0.1	40.4	44.5	90.7	0.9
Shrubs	1.2	1	0.3	0.1	0	0	0	0		0	1	2.7	36.2	5.5
Herbaceous vegetation	1.6	1	8.1	0.9	0	0.6	0	0	0.1	0.9	8.1	13.3	61.2	2.6
Croplands	2.7	0.7	3.8	25.1	0.1				0.1	0	25.1	32.5	77.2	1.5
Urban	0.2	0	0.3	0.2	2.5			0			2.5	3.3	76.9	4
Bare/sparse vegetation			0.1			0.5	0	0		0.1	0.5	0.7	68.7	7.6
Snow/ice						0.1	0.3				0.3	0.4	85.8	3.4
Permanent Water	0			0				2			2	2.1	97	1.7
Herbaceous Wetland	0.1	0	0.1	0				0	0.2		0.2	0.5	46.2	6.7
Lichen/moss			0			0	0	0		0	0	0	7	4.1
Correct	40.4	1	8.1	25.1	2.5	0.5	0.3	2	0.2	0				
Total	46.3	3.6	14.5	27.5	2.9	1.2	0.4	2.1	0.5	1.1		100		
Producer's accuracy	87.2	27.5	56	91.3	87.9	42.2	88.1	97.8	47	0.1			**80.2**	
Confidence interval ±	1	4.5	2.5	1.1	3.3	5.8	3.3	0.8	10.3	0.1				**0.8**

Table 13: Confusion matrix (%) for the discrete CGLS-LC100 V3.0 Level 1 2015 over North America.

North America	Forest	Shrubs	Herbaceous vegetation	Croplands	Urban	Bare/sparse vegetation	Snow/ice	Permanent Water	Herbaceous Wetland	Lichen/ moss	Correct	Total	User's accuracy	Confidence interval ±
Forest	31.7	1.9	0.7	0.3	0			0	0.3	0.2	31.7	35.1	90.3	1
Shrubs	1.8	6.8	1	0.2	0.1	0			0	0.2	6.8	10.1	67	2.9
Herbaceous vegetation	1.1	3.5	10	0.7	0	0.6		0.1	0.5	3.2	10	19.6	51.1	2.3
Croplands	0.6	0.2	0.9	7.2	0				0		7.2	8.9	81.2	2.4
Urban	0.1	0	0		0.6						0.6	0.8	79.7	6.8
Bare/sparse vegetation	0	0.1	0			1.8	0			0.2	1.8	2.1	82.7	3.9
Snow/ice						0.5	10.4				10.4	10.9	95.3	2
Permanent Water						0		4.1	0		4.1	4.2	98	1.4
Herbaceous Wetland	0	0.1	0.2	0		0		0	0.5	0.1	0.5	0.9	55.6	6.8
Lichen/moss			0.6			2.1	0	0.1		4.5	4.5	7.4	61.3	3.9
Correct	31.7	6.8	10	7.2	0.6	1.8	10.4	4.1	0.5	4.5				
Total	35.3	12.5	13.5	8.5	0.7	5.1	10.4	4.4	1.3	8.4		100		
Producer's accuracy	89.8	54.2	73.8	85.5	85.3	35.1	99.4	94.8	40.5	54			**77.6**	
Confidence interval ±	1	2.8	2.3	2.2	8.5	3.3	0.4	2.2	7.9	3.6				**0.8**

Table 14: Confusion matrix (%) for the discrete CGLS-LC100 V3.0 Level 1 2015 over Oceania and Australia.

Oceania and Australia	Forest	Shrubs	Herbaceous vegetation	Croplands	Urban	Bare/sparse vegetation	Permanent Water	Herbaceous Wetland	Correct	Total	User's accuracy	Confidence interval ±
Forest	24.2	2.7	0.9	0	0	0	0	0.1	24.2	27.9	86.8	1.5
Shrubs	2.5	11.1	1.8			0.1		0	11.1	15.5	71.8	3
Herbaceous vegetation	2.1	5.4	41.4	0.6		0.8	0	0	41.4	50.4	82.2	1.4
Croplands	0	0.1	1.1	3.3			0	0	3.3	4.6	72.1	4.4
Urban	0	0	0		0.1				0.1	0.2	73.3	13
Bare/sparse vegetation			0.1		0	1.1	0		1.1	1.1	94.1	7.2
Permanent Water	0		0		0	0	0.2		0.2	0.2	77.1	7.6
Herbaceous Wetland	0	0	0			0	0	0	0	0	31.4	22.2
Correct	24.2	11.1	41.4	3.3	0.1	1.1	0.2	0				
Total	29	19.4	45.3	4	0.1	2	0.2	0.1		100		
Producer's accuracy	83.6	57.6	91.5	83.8	96.8	55	85.8	7.3			**81.5**	
Confidence interval ±	1.6	3	1	3.6	2.9	6.4	6.1	28.4				**1.0**

Table 15: Confusion matrix (%) for the discrete CGLS-LC100 V3.0 Level 1 2015 over South America.

South America	Forest	Shrubs	Herbaceous vegetation	Croplands	Urban	Bare/sparse vegetation	Snow/ice	Permanent Water	Herbaceous Wetland	Correct	Total	User's accuracy	Confidence interval ±
Forest	80.1	2.3	0.9	0.3				0.1	0.1	49.2	52.9	93	0.7
Shrubs	2.1	6.4	1.2	0.1		0.4			0	6.4	10.2	62.4	2.9
Herbaceous vegetation	2.5	3.3	12.5	1.6	0	0.2		0	0.6	12.5	20.8	59.9	2.1
Croplands	0.7	0.3	0.9	5.4	0				0.1	5.4	7.4	72.2	3
Urban	0.1	0	0		0.3					0.3	0.4	76.2	7.9
Bare/sparse vegetation	0	0.4	0.5		0	4.8	0.1	0		4.8	5.8	82	3.1
Snow/ice			0			0	0.2	0		0.2	0.2	81	3.8
Permanent Water	0	0	0			0		0.9	0	0.9	1	90.1	3.8
Herbaceous Wetland	0.2	0.2	0.1			0		0.1	0.6	0.6	1.2	45.6	5.1
Correct	49.2	6.4	12.5	5.4	0.3	4.8	0.2	0.9	0.6				
Total	54.8	12.9	16.2	7.4	0.4	5.5	0.2	1.2	1.4		100		
Producer's accuracy	89.7	49.3	77	72.7	73.3	86.7	74.6	78.1	41.5			**80.1**	
Confidence interval ±	0.7	2.6	2	3.1	10.9	2.9	11.2	5.2	7				**0.7**

Class specific accuracies at each continent followed a similar trend as the class specific accuracies at global scale. The class accuracies of forest and snow/ice are high for all continents. For permanent water, accuracies are high for all continents except for Oceania & Australia (Table 14). For bare/sparse vegetation, accuracies are high except in continents such as Europe (Table 12), North America (Table 13), and Oceania & Australia (Table 14) where this class is underestimated.

Accuracy of herbaceous vegetation is moderate in all continents other than Oceania & Australia where this class is mapped with high accuracy (Table 14). Cropland class is also mapped with moderate accuracy, although this class tend to be overestimated in most continents. Similarly, for urban class, the accuracies are relatively high except for in Africa (**Error! Reference source not found.**) and Northern Eurasia (Table 11).

For all continents, herbaceous wetland class is mapped with low accuracy. For lichen/moss class, accuracy is relatively better in North America (Table 13), while it tends to be underestimated in Europe (Table 12) and Northern Eurasia (Table 11). This class has higher confusion error with herbaceous vegetation and bare/sparse vegetation. Shrub class has lower accuracies in Asia (

Table 10), Northern Eurasia (Table 11) and Europe (Table 12), where it is underestimated. In Europe, this class had high confusion error with forest and herbaceous vegetation. The class accuracies are estimated mostly within range of 10% (confidence interval). But some classes in continents have higher confidence interval. This could be related to map misclassification at some validation sites that carry larger weights (sample sites representing strata with larger areas – see section **Error! Unknown switch argument.**). These sample weights are used in confidence interval calculation.

The accuracy of the CGLS_LC100m V3.0 2015 discrete map is also calculated at Level 2 that separates open and closed forests (Table 16).

Table 16: Confusion matrix for the discrete CGLS-LC100m V3.0 Level 2 map for 2015 at global scale, corrected by sample inclusion probaiblities.

	Closed forest	**Open forest**	**Shrubs**	**Herbaceous vegetation**	**Croplands**	**Urban**	**Bare/sparse vegetation**	**Snow/ice**	**Permanent Water**	**Herbaceous Wetland**	**Lichen/ moss**	**Correct**	**Total**	**User's accuracy**	**Confidence interval ±**
Closed forest	22.1	3.6	0.8	0.4	0.1	0	0		0	0	0	22.1	27	81.8	0.6
Open forest	1.3	6	1.2	0.6	0.4	0	0		0	0.1	0	6	9.6	62	1.2
Shrubs	0.2	1.5	5.5	1	0.3	0	0.2	0	0	0.1	0	5.5	8.9	62.1	1.6
Herbaceous vegetation	0.2	1.2	2.4	14.5	0.9	0	0.5	0	0.1	0.4	1.1	14.5	21.2	68.2	0.9
Croplands	0.1	0.8	0.4	1.4	7.8	0	0		0	0.1	0	7.8	10.8	72.5	1.1
Urban	0	0.1	0	0.1	0	0.6	0		0			0.6	0.9	68.2	3
Bare/sparse vegetation		0	0.3	0.8	0	0	13.6	0	0	0	0	13.6	14.8	91.6	0.9
Snow/ice				0			0.1	1.9	0		0	1.9	2	94.8	1.8
Permanent Water	0	0	0	0	0	0	0		1.9	0		1.9	2	96.9	0.9
Herbaceous Wetland	0	0.1	0.1	0.3	0	0	0		0.1	0.6	0.1	0.6	1.2	44.9	2.7
Lichen/moss				0.1			0.4	0	0		0.9	0.9	1.4	62.2	3.6
Correct	22.1	6	5.5	14.5	7.8	0.6	13.6	1.9	1.9	0.6	0.9				
Total	23.9	13.4	10.7	19.2	9.7	0.7	14.8	2	2.3	1.2	2.2		100		
Producer's accuracy	92.3	44.7	51.6	75.3	80.8	88.3	91.8	99	86	46.6	39.6			**75.4**	
Confidence interval ±	0.4	1.1	1.4	0.9	1.1	2.7	0.8	0.5	1.6	3.4	2.7				**0.4**

At Level 2, when open and closed forests are separated, the overall accuracy at global scale is 75.4% +/-0.4. All the class accuracies are the same as Level 1 (Table 7), except for the open forest and closed forest classes. Here, closed forest class has higher accuracy than open forest class. However, closed forest class tends to be overestimated at the cost of open forest class.

Overall accuracies are also calculated at Level 2 for each continent. Continental level overall accuracies range from 71% (Northern Eurasia) to 79.9% (Asia) (

Table 17).

Table 17: Overall accuracy of the discrete CGLS-LC100 V3.0 Level 2 map for 2015 per continent.

	Number of samples	Overall accuracy	Confidence interval ±
Africa	3616	76.8	1.0
Asia	3071	79.9	0.8
Northern Eurasia	2976	71.1	0.9
Europe	3125	73.0	0.9
North America	2846	72.7	0.9
Oceania & Australia	2950	77.5	1.0
South America	3017	74.9	0.8

Fractional land cover layers for 2015

The CGLS-LC100m V3.0 fractional land cover layers, tree cover, shrub cover, herbaceous vegetation cover, crops, lichen/moss, bare/sparse vegetation, snow/ice, built-up and permanent water, were assessed using the cover fraction information in the validation dataset.

Table 18 lists the mean absolute error (MAE) and root mean square error (RMSE) for the fractional land cover layers.

Table 18: Accuracy of the fraction land cover layers at global scale for 2015.

	Trees	Shrub	Herbaceous vegetation	Crops	Lichen/ Moss	Bare/sparse vegetation	Snow/ice	Built-up	Water
Mean absolute error % (MAE)	8.9	9.1	17.3	5.4	2.8	5.5	0.1	0.8	0.8
Root mean square error % (RMSE)	16.8	16.4	27.2	15	14.8	14.3	3.3	5.7	5.8

Among the fraction land cover layers, rare classes, such as snow/ice, water and built-up area, show the lowest errors with an average deviation (MAE) from the validation data of maximum 0.8% and RMSE lower than 6%, followed by lichen/moss, crops and bare/sparse vegetation fractions layers (MAE ~ 5% and RMSE ~ 15%) and trees and shrubs fraction layers (MAE ~ 9%, RMSE ~ 16%). Herbaceous vegetation fraction product has the highest error with MAE of 17.3% and RMSE of 27.2%. This can be due to difficulty in separating herbaceous vegetation from other land cover types.

MAE and RMSE were also calculated at continental scale (Table 19). Tree fraction layer has lower errors in Africa, Asia, North America and Oceania & Australia, followed by South America, Northern

Eurasia and Europe. Shrub fraction layer has lower MAE in Asia and Europe. Herbaceous vegetation has highest errors for all the continents comparing to other classes. Among different continents, Northern Eurasia and North America have higher errors while Asia, Africa and South America have lower errors. Crop fraction layer has the highest errors in Europe while the errors are lower in Oceania & Australia, Northern Eurasia and North America. Lichen moss class has higher errors in North America and Northern Eurasia. For bare/sparse vegetation layer, the errors are higher in Oceania & Australia and North America, while the errors are less in Northern Eurasia and Europe. For all continents, snow/ice, built-up, and water fraction layers have less errors compared to other fraction layers.

Table 19: Accuracy of the fraction land cover layers at continental scale for 2015.

MAE (%)									
	Trees	**Shrub**	**Herbaceous vegetation**	**Crops**	**Lichen/ moss**	**Bare/sparse vegetation**	**Snow/ ice**	**Built-up**	**Water**
Africa	8.0	10.3	15.7	6.2	0.0	5.1	0.0	0.7	0.4
Asia	7.9	6.4	12.5	7.2	0.2	5.6	0.1	1.5	0.9
Northern Eurasia	10.5	8.6	23.0	3.3	5.7	3.8	0.0	0.3	1.0
Europe	11.8	8	17.7	11.1	1.2	2.7	0.2	2.5	0.6
North America	8.3	9.6	20.4	3.7	10.4	7.8	0.6	0.6	1.2
Oceania & Australia	9.0	10.8	18.5	2.5	0.1	8.6	0.0	0.2	0.2
South America	9.5	11.0	16.0	5.5	0.2	4.6	0.1	0.3	0.8
RMSE (%)									
	Trees	**Shrub**	**Herbaceous vegetation**	**Crops**	**Lichen/ moss**	**Bare/sparse vegetation**	**Snow/ ice**	**Built-up**	**Water**
Africa	15.0	16.0	24.2	16.7	0.5	13.6	0.0	6.1	4.7
Asia	16.3	12.6	21.1	16.5	2.5	13.4	2.1	7.9	7.0
Northern Eurasia	20.1	18.2	35.6	11.8	21.4	13.1	1.0	3.4	6.1
Europe	17.6	13.7	25.2	19.5	9.1	8.7	3.2	9.8	4.0
North America	15.8	17.9	31.1	12.4	28.3	18.0	7.0	4.6	6.1
Oceania & Australia	14.4	15.2	24.4	10.1	2.7	17.5	0.0	2.3	3.2
South America	17.8	19.0	25.1	16.3	3.3	12.9	2.8	3.4	6.1

4.2 ACCURACY OF THE CGLS-LC100M V3.0 PRODUCT FOR 2016-2019

We also provide the accuracy of yearly land cover maps. Table 20 lists the overall accuracies of the Level 1 and 2 yearly maps (2016-2019) for both global and continental levels. Detailed confusion matrices showing the class specific accuracies can be found in the Annex.

Table 20: Overall accuracy of the discrete CGLS_LC100m V3.0 Level 1 and 2 maps for 2016-2019, global and continental levels.

Scale	Number of samples	Overall accuracy (%) at Level 1				Overall accuracy (%) at Level 2			
		2016	2017	2018	2019	2016	2017	2018	2019
Global	28321	80.4	80.5	80.4	80.3	75.2	75.2	75.1	75.1
Africa	4576	80.2	80.4	80.1	80.0	76.7	76.8	76.6	76.5
Asia	4031	83.3	83.4	83.5	83.5	79.7	79.7	79.8	79.8
Northern Eurasia	3936	80.6	80.5	80.3	80.1	70.9	70.8	70.5	70.3
Europe	4085	80.2	80.0	79.9	79.9	73.0	72.8	72.7	72.8
North America	3806	77.7	77.6	77.5	77.5	72.7	72.6	72.4	72.5
Oceania & Australia	3910	80.1	79.9	80.2	79.9	76.0	75.7	76.0	75.7
South America	3977	80.0	80.1	80.0	80.0	74.9	74.9	74.8	74.8

At Level 1, overall accuracy ranges between 80.3-80.5% at global scale between 2016 and 2019 indicating high level of consistency between the yearly maps. At Level 2, accuracy is 75.1-75.2%. Compared to V3.0 2015, the overall accuracies of the yearly (2016-2019) maps are slightly less, but well within the range of the confidence interval.

At continental level, the accuracies are very similar to those of V3.0 2015 (Table 8). Generally, 2019 map is assessed with lower accuracy than the other years. This is expected considering that this map is in NRT mode. Among the continents, Northern Eurasia has decreased in overall accuracy of 0.5% 2019, which is the largest decrease compared to other continents. The accuracy of the most of the continents stayed largely consistent over the years.

In terms of class specific accuracies (Annex, Table 28-to Table 35), the yearly maps remain similar. Forest, bare/sparse vegetation, cropland and snow/ice classes haver lower variations in terms of class specific accuracy (~ 0.5%) over the years. On the other hand, wetland class has the highest variation followed by permanent water class. Next, urban and shrubs classes have around 1% variations in terms of class accuracies between 2015-2019. Among the years, 2019 has the lowest accuracies for most of classes compared to other years.

Table 36 in Annex also lists the accuracies for the fractions land cover types for the 2016-2019. The RMSE and MAE are generally similar to that of 2015 (Table 18). With the increment of the years, the fractional accuracy reduced slightly. For example, cropland class has higher increase in errors as compared to the other classes.

4.3 ASSESSMENT OF THE LAND COVER CHANGE

4.3.1 Quantitative assessment of the land cover change

We assessed the quality of land cover change using the CGLS-LC100-V3 yearly maps based on the validation dataset developed for that purpose. Here we created a change map by differencing the yearly maps from 2015 to 2018. 2019 is not included, due to its NRT (near real time) mode.

Table 21 shows the confusion matrix based on sample count (not area weighted or considering inclusion probabilities). For this sample count case, the overall accuracy is 88.4% for change/no-change detection. No change class accuracy is very high (>88%). For the change class, producer's accuracy is high meaning that we are not missing many land cover changes observed in the validation data. The change user's accuracy is lower. This shows that the detected change is overestimated in the CGLS-LC100 V3 yearly products. However, most of the sample locations which show overestimation of change are concentrated in smaller proportions of the world land mass Table 22.

Table 21: Land cover change/no change matrix based on sample counts (2015-2018).

	Ref No Change	Ref Change	Correct	Total	User's Accuracy
Map No Change	**22682**	388	22682	23070	**98.3**
Map Change	2853	**1938**	1938	4791	**40.5**
Correct	22682	1938			
Total	25535	2326		27861	
Producer's Accuracy	88.8	**83.3**			**88.4**

When corrected by sample inclusion probability, the change/no change overall accuracy increased to 99.6%± 0.1, indicating high quality in characterizing change/no change across the world (Table 22). No change class occupies large fraction of the world and it is mapped with very high accuracy. Compared to the sample count matrix, the producer's accuracy for change class is reduced from 83% to 64%. This is due to sample sites that are missed by the product as change and that carry larger area weights even though they are not very large in number (388 sites, Table 21). On the other hand, user's accuracy of change class is increased from 40.5% to 54.4% when sample inclusion probability is accounted. Although large in number (~2800 sites), most of the sample points which show change overestimation are from very small proportion of the world (0.23%, Table 22). In general, error of commission (100-user's accuracy) is larger than error of omission (100-producer's accuracy) for change (45% vs 36%).

Table 22: Land cover change/no-change matrix (2015-2018), corrected by sample inclusion probabilities.

	No Change	Change	Correct	Total	Use's Accuracy	Confidence interval
No Change	**99.3**	0.2	99.3	99.5	**99.8**	0.1
Change	0.2	**0.3**	0.3	0.5	**54.4**	5.9
Correct	99.3	0.3				
Total	99.6	0.4		**100**		
Producer's Accuracy	**99.8**	**63.9**			**99.6**	
Confidence interval	0.0	9.8				0.1

At continental level, similar accuracy as the global level could be found based on count based and area based (sample inclusion probability) (Table 23). Generally, all continents have area-based change/no change accuracy of 98% and more. The same applies for the accuracies for no change class. For change class, North Eurasia, North America, Australia and South America have higher accuracies. In Asia, North Eurasia, Oceania & Australia and South America, commission error of change is slightly higher than the omission error of change. While in Africa and North America, omission error is larger than the commission error. North America has the lowest commission error of change followed by North Eurasia. The change class is less omitted in Australia and Oceania, North Eurasia and South America, while it is omitted more in Africa, Europe and Asia.

Table 23: Land cover change/no-change accuracy (%) (2015-2018) at continental scale.

	Count based					**Area based**				
	Overall accuracy	No-change user's accuracy	No-change producer's accuracy	Change user's accuracy	Change producer's accuracy	Overall accuracy	No-change user's accuracy	No-change producer's accuracy	Change user's accuracy	Change producer's accuracy
Africa	**90.0**	98.0	90.9	46.7	81.3	**99.7**	99.8	99.9	42.5	25.6
Asia	**85.8**	98.4	86.3	26.3	77.9	**99.5**	99.8	99.7	39.3	45.6
Northern Eurasia	**88.0**	98.6	88.3	33.7	82.7	**99.9**	100.0	99.9	66.5	71.7
Europe	**89.4**	98.6	89.8	40.1	83.8	**99.9**	100.0	100.0	34.9	34.8
North America	**88.5**	97.9	89.2	44.4	81.4	**99.8**	99.9	99.9	70.8	52.2
Oceania & Australia	**87.9**	98.6	87.8	44.2	88.7	**98.1**	99.9	98.2	58.0	94.6
South America	**88.9**	98.2	89.3	47.0	85.2	**99.7**	99.9	99.8	57.7	61.0

By assessing the accuracy of change/no change of land cover, this analysis goes a step forward than updating map accuracies for yearly land cover map presented in Section 4.2. Similar to map validation updating which is done for the first time among the global land cover products, the analysis on the change validation is also the first to be done at global scale for generic land cover using statistically design-based validation dataset. Considering that land cover change detection is much more complex than land cover classification, based on our analysis, we believe that the CGLS-LC100 V3.0 yearly maps reflect reasonably well the land cover changes that occur in the recent years globally. This is supported by the stability and consistency in the land cover map accuracies for the yearly maps (Section 4.2). However, it also should be noted that annual classification differences are subject to both map temporal inconsistency and land cover changes. This could be seen in the lower user's accuracy (or higher commission error). For the 2015-2018 period, more differences are due to land cover changes (~55%) (Table 22). The commission errors are 45% (100%-user's accuracy), which are due to the temporal inconsistencies and interannual variabilities resulting from the classification. The confidence in representation of land cover changes varies by continent with higher confidence in North Eurasia, North America, Australia and South America. Map users should take these results into account for their analysis and use of the maps.

4.3.2 Qualitative assessment of land cover change

To investigate if the land cover change is well captured by the product, we have performed visual validation by comparing the change maps with available satellite imagery from Google Earth, Landsat and Sentinel-2 imagery. Below are examples for several land change processes (i.e. deforestation, water expansion, desertification, and crop expansion,).

Figure 12 shows two examples of deforestation in Chile and Portugal. It can be seen from Figure 12 (a) that this area was forest in 2015 and 2016. In 2018 and 2019, forest was lost to the widespread fires in February, 2017 (confirmed from Sentinel-2 imagery). Grass regrowth was also detected in 2017 and 2018, e.g. Sentinel-2 imagery shows red in July 2018. Same with Figure 12 (b), which also had forest loss due to fire in October 2017. The CGLS_LCC100m V3.0 yearly maps have well detected the forest loss and regrowth of grass for these areas, though some small patches were wrongly labelled as crops.

Water expansion was also well captured by the CGLS_LCC100m V3.0 yearly maps (Figure 13). Figure 13 (a) shows the expansion of a lake in China between 2015 and 2018, and this was well captured by the yearly maps (confirmed from Landsat and Sentinel imagery). In Figure 13(b), this region was mostly covered with crops and urban in 2015. However, during 2016-2018, it was covered by water. This was caused by the heavy rain and the ensuing flooding in 2016 in Central Java of Indonesia which was reported by the Indonesia’s National Disaster Management Authority.

Figure 14 shows an example of the CGLS_LC100m V3.0 yearly maps successfully detected greening in China. As seen from the time series Landsat imagery, this region was desert during 2015-2017, but turned green in August 2018. The yearly maps mapped correctly as bare in 2015-2017, and grass in 2018. Some small temporary water bodies also appeared in August 2018 looking from the Landsat imagery. But these waters were not shown on map 2018 as CGLS_LC100m V3.0 only map permanent water (water appear most of the whole year).

Figure 15 shows an example of a region in Saudi Arabia which has many crop circles. Time series Sentinel-2 imagery reveals an increase in the number of crop circles in the northern and western part of this region. This has been well detected by the CGLS_LC100m V3.0 yearly maps.

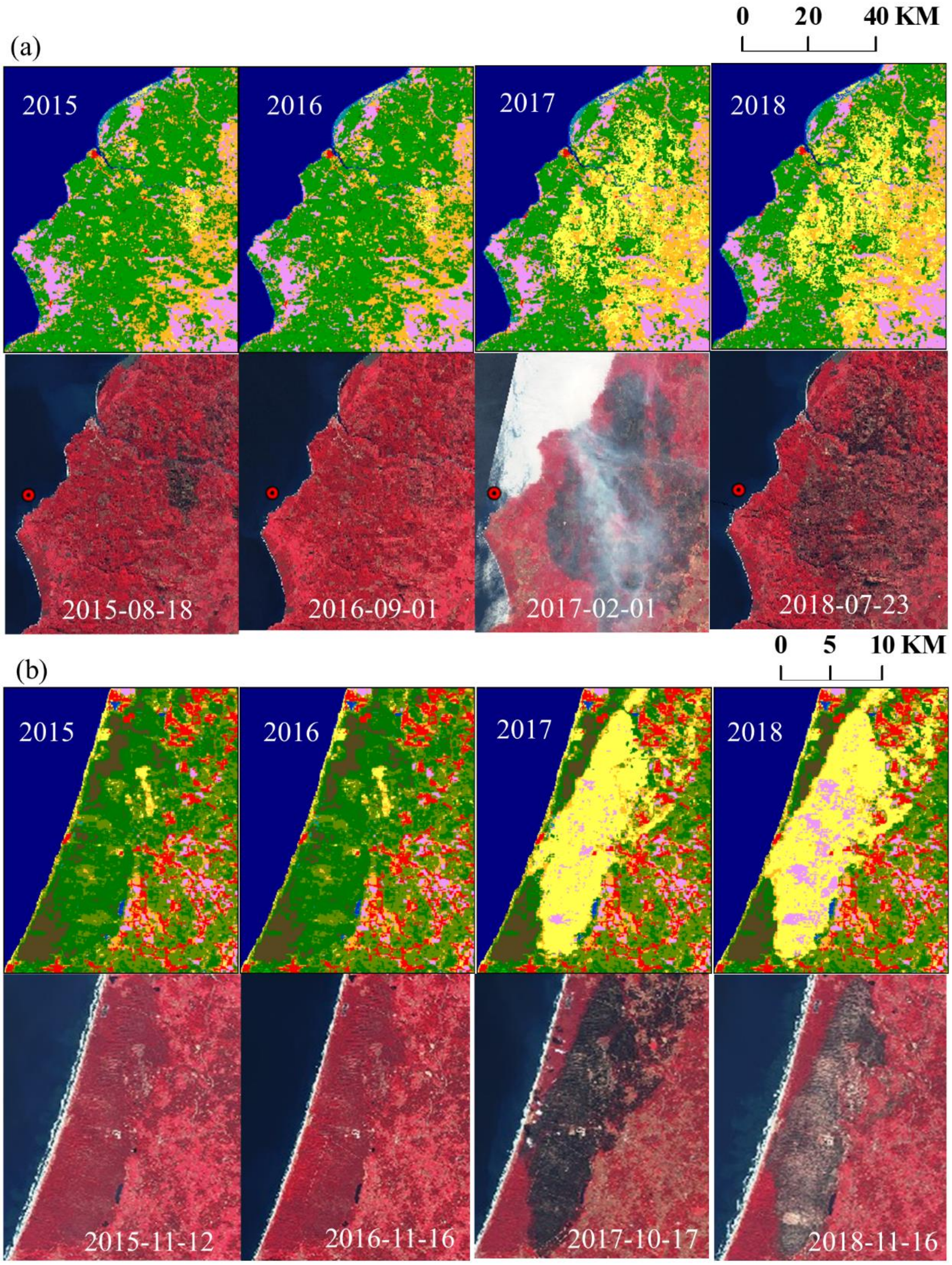

Figure 12. Examples showing the CGLS_LC100m V3.0 yearly maps successfully detected the deforestation process in (a) Chile and (b) Portugal. Top images show the yearly maps and the color legend is shown in Table 3. Bottom images are Sentinel-2 (bands 843 in RGB) images.

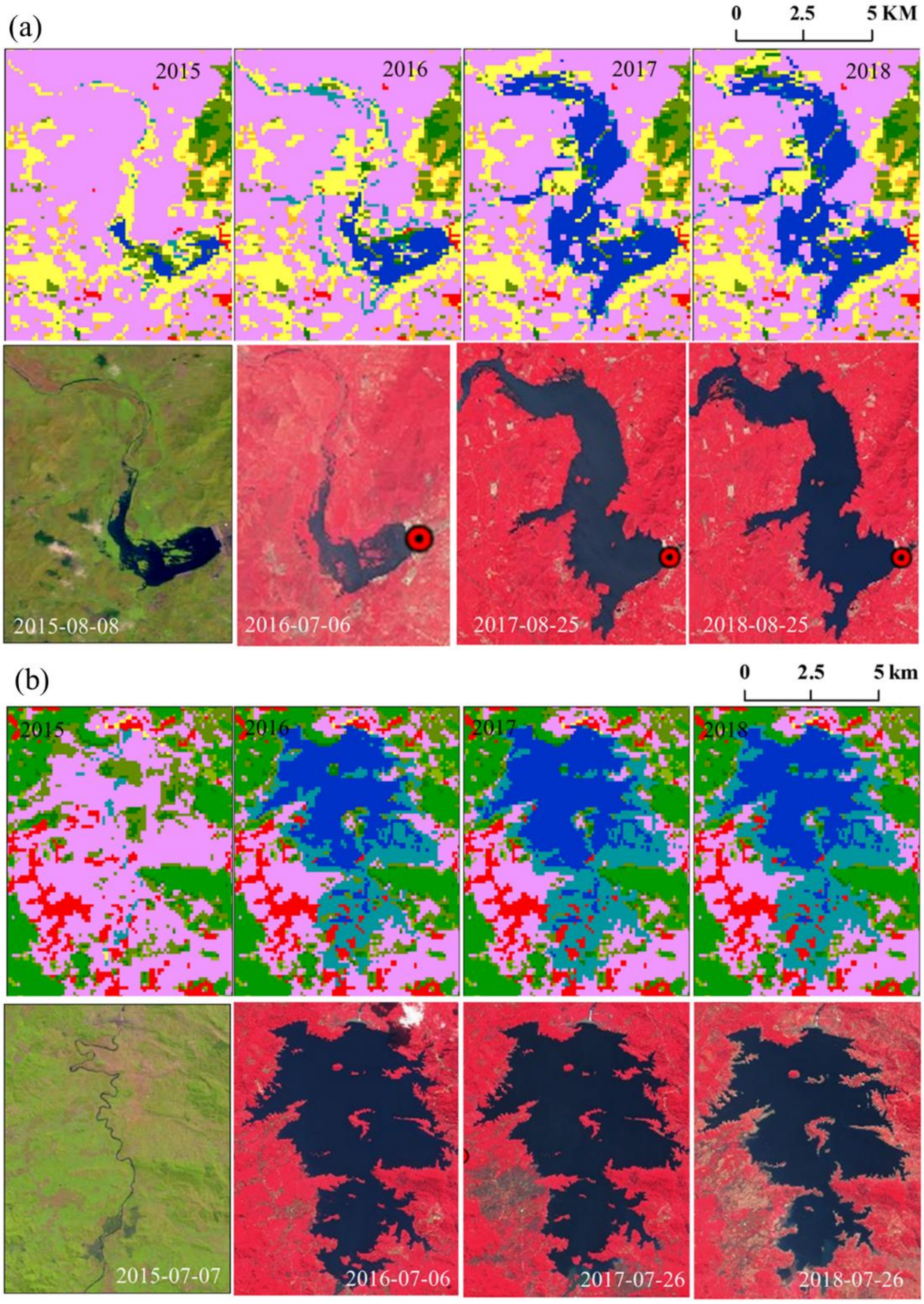

Figure 13. Examples showing the CGLS_LC100m V3.0 yearly maps successfully detected water expansion in (a) China and (b) Indonesia. Top images show the yearly maps and the color legend is shown in Table 3. Bottom images are Landsat (bands 432 in RGB) and Sentinel-2 (bands 843 in RGB) images.

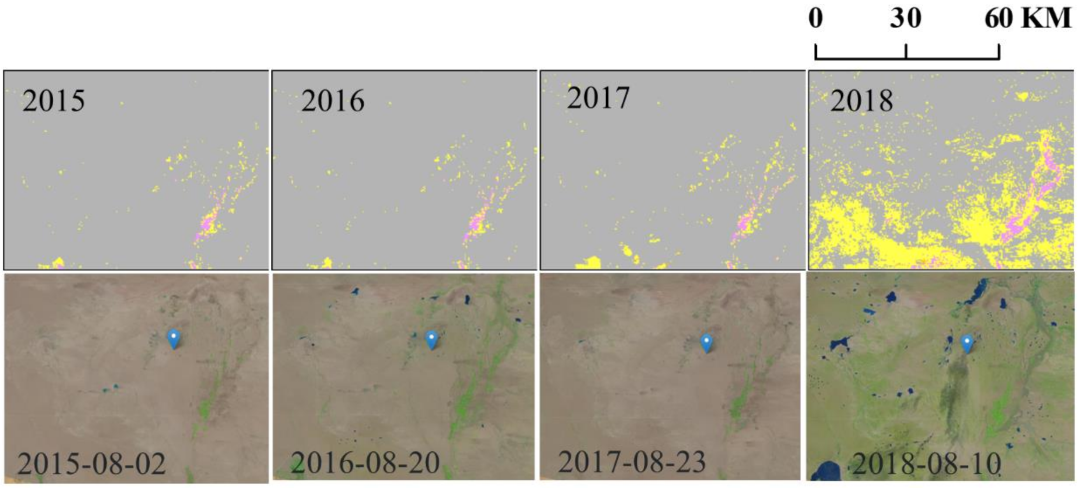

Figure 14. An example showing the CGLS_LC100m V3.0 yearly maps successfully detected greening in China. Top images show the yearly maps and the color legend is shown in Table 3. Bottom images are Landsat (bands 432 in RGB) images.

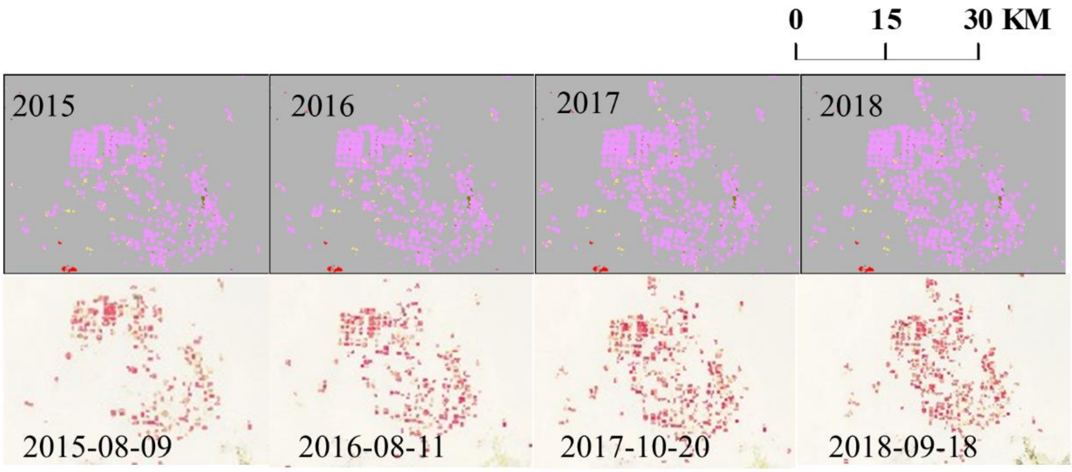

Figure 15. An example showing the CGLS_LC100m V3.0 yearly maps successfully detected Crop expansion in Saudi Arabia. Top images show the yearly maps and the color legend is shown in Table 3. Bottom images are Sentinel-2 (bands 843 in RGB) images.

Although the CGLS_LCC100m V3.0 yearly maps have correctly captured some land cover changes, still they have some omission and commission errors. For example, water usually has omission errors especially in Asia and Oceania & Australia. Some obvious commission errors were observed for urban such as in Africa, Asia and North America.

Figure 16 shows a spurious change of water. According to the time series Landsat imagery, this area was covered with water during 2015 and 2018 (confirmed from time series Landsat imagery). Due to the water omission in 2015, change detection between years resulted an error.

Figure 17 shows two examples with large commission errors for urban in Russia and Turkmenistan. In Figure 17 (a), this area was forest during 2015 and 2018 (confirmed from time series Sentinel-2 imagery). However, the yearly maps wrongly mapped it as urban. In Figure 17 (b), this area was mostly covered with crops and grass in 2015. There was barely any change during 2015-2018. However, the commission errors in 2017-2018 map further lead to errors in the change detection between years. These large urban commission errors are due to the scaling issues in the OpenStreetMap layer, which is used as input data for identifying urban areas.

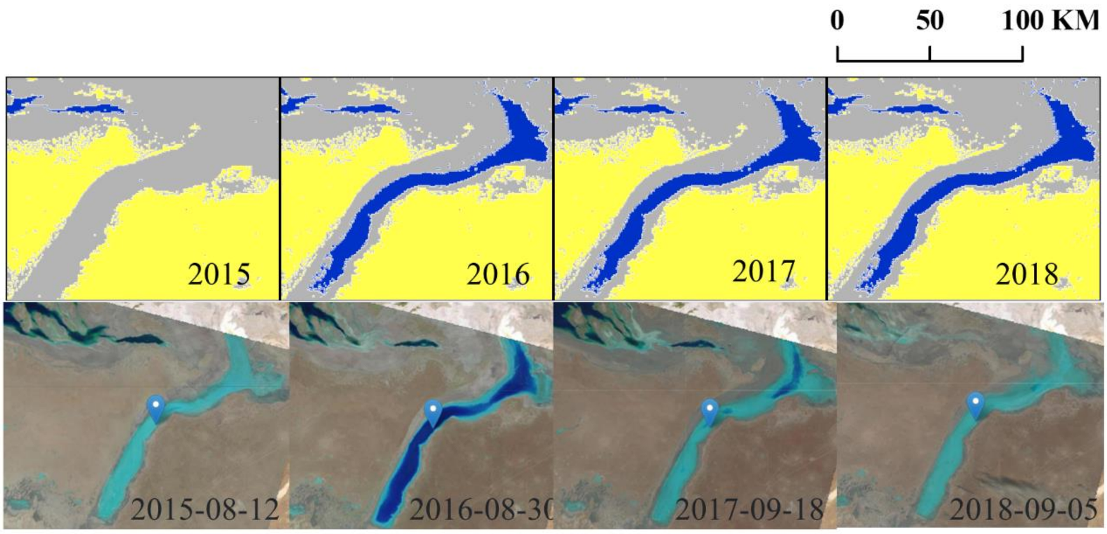

Figure 16. Water omission errors within CGLS_LC100m V3.0 yearly maps. An example in Kazakhstan. Top images show the yearly maps and the color legend is shown in Table 3. Bottom images are Landsat (bands 432 in RGB) images.

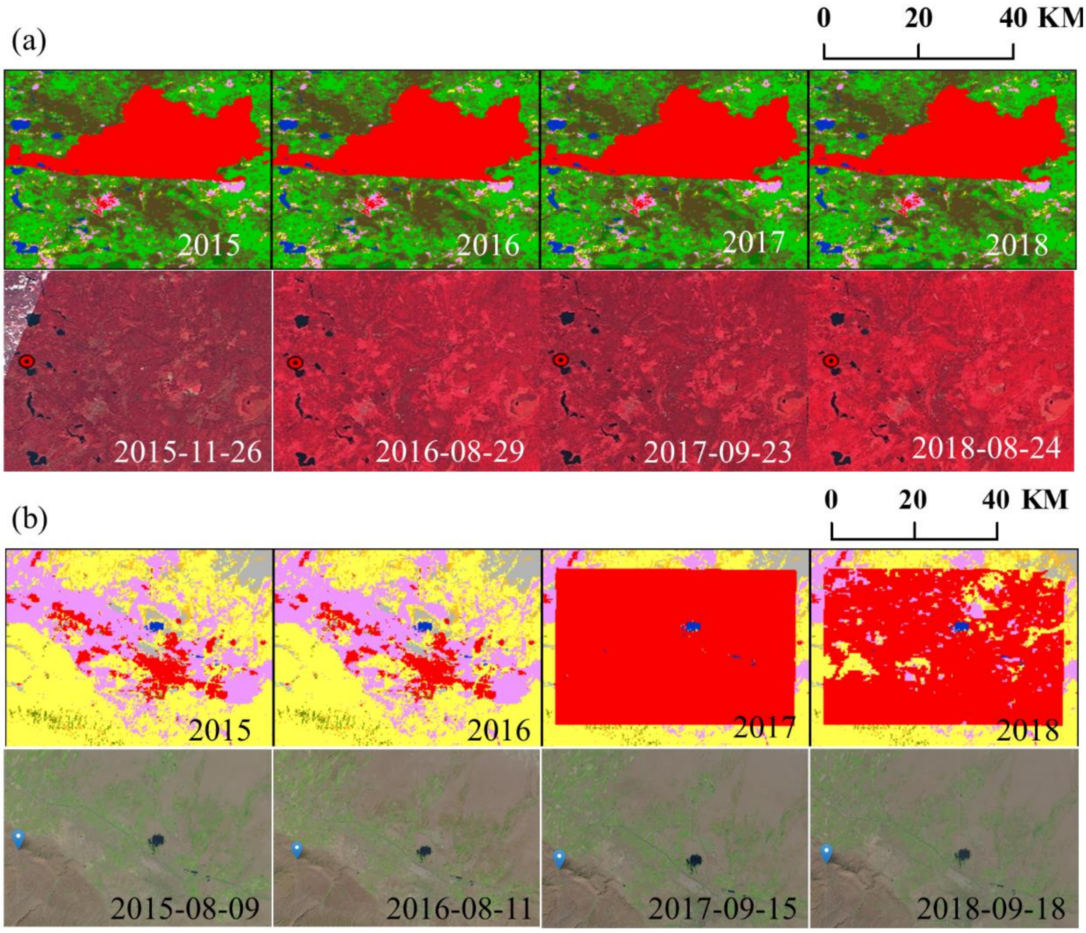

Figure 17. Urban commission errors within CGLS_LC100m V3.0 yearly maps. Two examples in (a) Russia and (b) Turkmenistan. Top images show the yearly maps and the color legend is shown in Table 3. Bottom images are Sentinel-2 (bands 843 in RGB) and Landsat (bands 432 in RGB) images.

4.4 COMPARISON WITH CGLS-LC100M V2.0 PRODUCT

4.4.1 Qualitative comparison

Visual comparison of the CGLS-LC100m V3.0 base map with the V2.0 base map was performed in order to highlight the differences between the two versions. Figure 18 shows both the versions (V2.0 and V3.0).

A visual comparison at global scale shows that the CGLS-LC100m V3.0 2015 discrete map agrees with the CGLS-LC100m V2.0 2015 discrete map in terms of spatial distribution of the main land cover types. The legend is identical, and the general patterns of the land cover types in the CGLS-LC100m V3.0 2015 discrete map look similar to the V2.0 map (Figure 18).

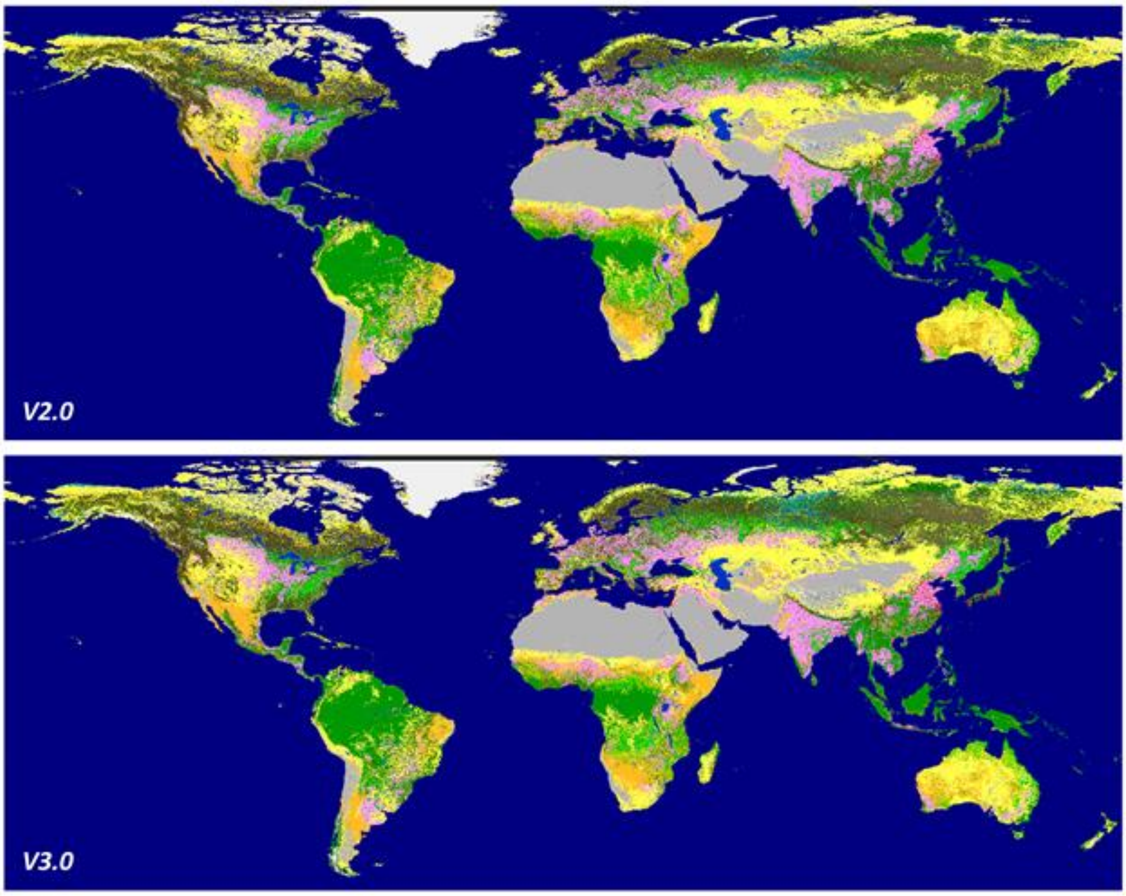

Figure 18. Comparison of CGLS_LC100m 2015 base maps: V2.0 (top) and V3.0 (bottom). When displaying at global scale, the differences are not noticeable.

Table 24: Percentage of each land cover class pixels over the globe (excluded the Ocean) based on Collection 2 and Collection 3 map

		Collection 2 (%)	Collection 3 (%)
No data		1.1	0.9
Shrubs		7.8	7.4
Herbaceous vegetation		21.1	22.7
Croplands		10.7	9.9
Urban		0.5	0.8
Bare/sparse vegetation		12.9	12.8
Snow/ice		3.2	3.2
Permanent water		2.8	2.8
Herbaceous wetland		1.3	1.6
Lichen/moss		2.2	2.1
Forest	All forest (class 111-116 and 121-126)	36.4	35.9
	Forest type identified (class 111-115 and 121-125)	25.1	25.4
	Unknown forest type (class 116 and 126)	11.3	10.5

Visual assessment of forest land cover class shows that, in V3.0, more forest areas have been correctly identified as forest as compared to the V2.0 map which tended to overestimate forests. This is consistent with the statistics from Table 24, which shows 36.4% of the globe was forest based on V2.0 map detected while 35.9% base on V3.0. This can also be seen in exemplary areas on Figure 19 where, in column 1, areas that have been deforested in SE Australia showed overestimation of forest in V2.0 of the map (chipset “B”) and are correctly mapped as grassland in V3.0 (chipset “C”). In column 2, depicting a tree re-growth in Borneo’s plantation (tree-crop in this product is classified as forest land cover), the mix of vegetation of different height and type, where there are no sharp land cover boundaries, are better represented by the map V3.0 (chipset “C”) than V2.0 (chipset “B”). Finally, the example in column 3 from Java shows an area dominated by forest in the north and by agriculture in the south. Here forest is not overestimated in V3.0 (chipset “C”) as it happened in previous V2.0 (chipset “B”). The agricultural area with sparse trees is correctly mapped as cropland in map V3.0 (chipset “C”).

Visual assessment of forest land cover also shows that in map V3.0 there is less forest classified as “unknown” (“Closed forest, unknown” and “Open forest, unknown”, see Table 3) as compared to V2.0. It diminished from 11.3% for V2.0 to 10.5% for V3.0 of global land (Oceans were excluded from the calculation). However, “Unknown” forest class is still present in the Northern Eurasia, North America and in Brazil and Bolivia in South America. Figure 20 shows such an area in Ivory Coast where in V2.0 the “unknown” forest class was dominant (dark green area on Figure 20 “A”) and in V3.0 the large forest types are now defined as closed and open forest, evergreen, broad leaf (Figure 20 “B”).

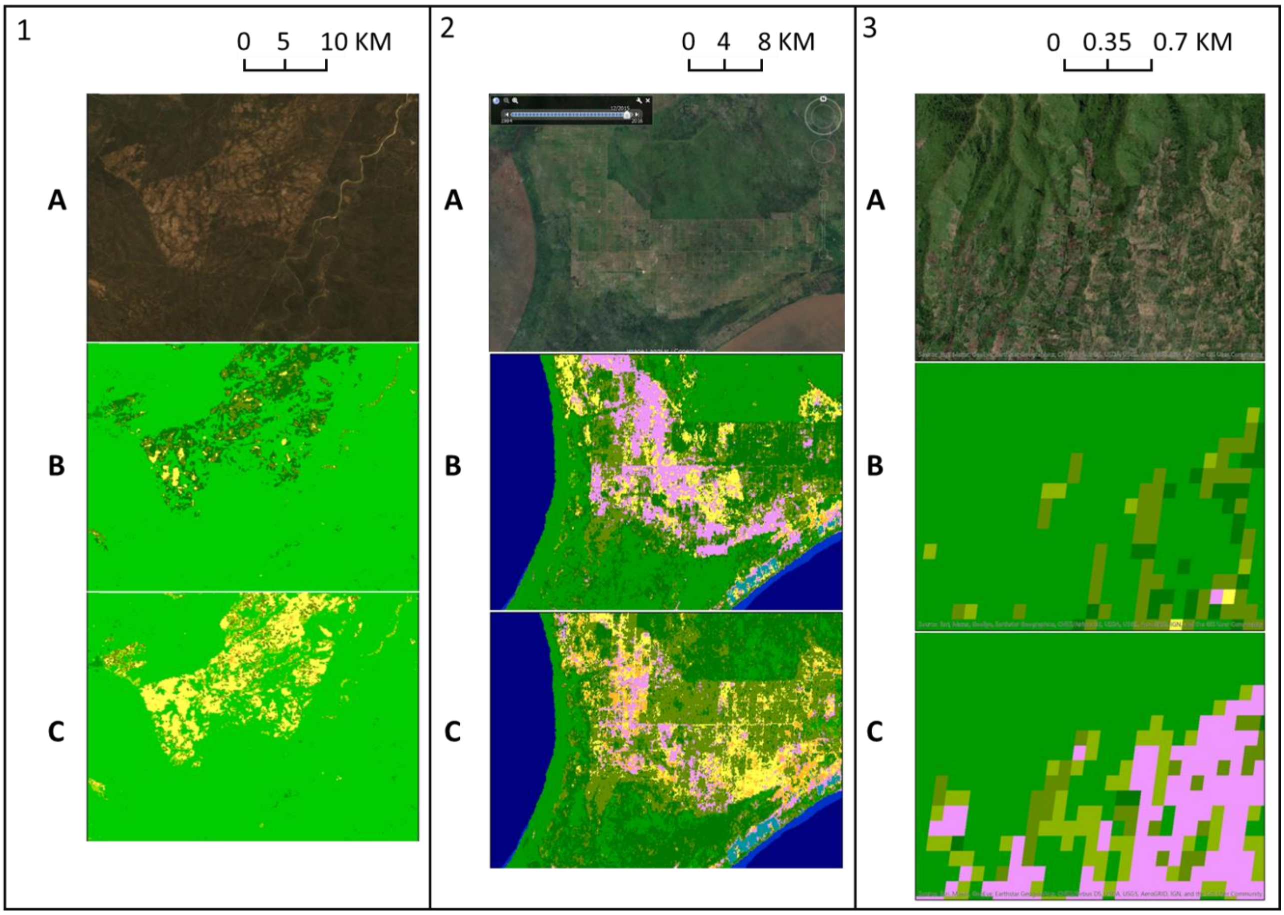

Figure 19. Comparison of forest land cover: 1-SE Australia; 2-S Borneo, Indonesia; 3-Java, Indonesia. Chipsets "A" show reference Bong/Google satellite based RGB image; chipsets "B" show CGLS_LC100m 2015 base map V2.0; chipsets "C" show CGLS_LC100m 2015 base map V3.0.

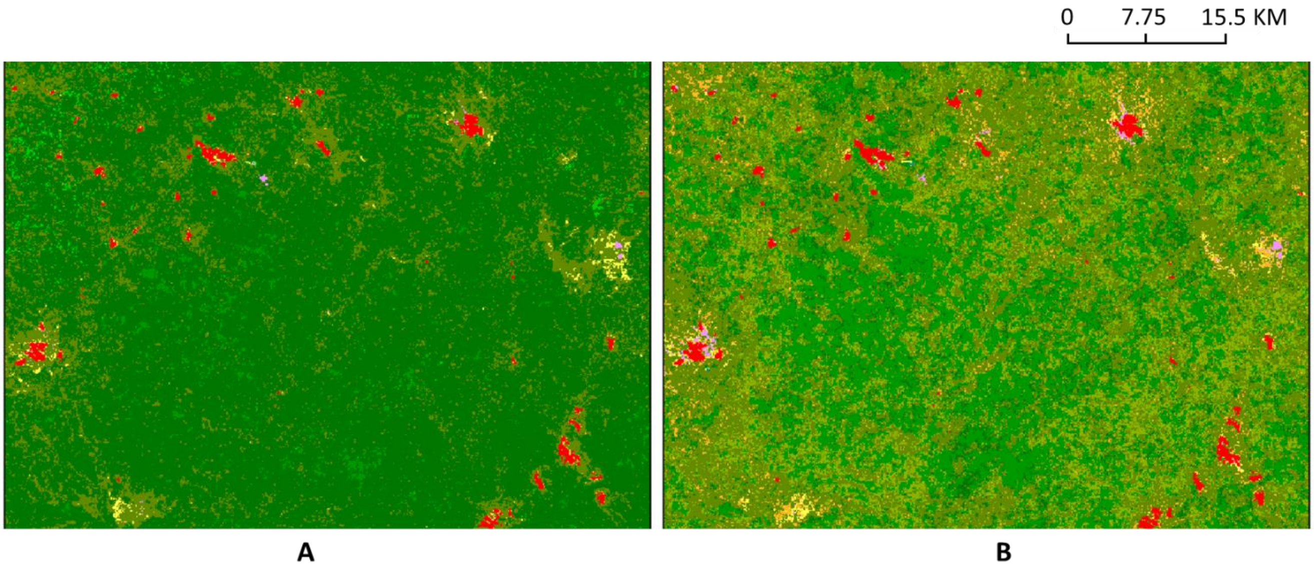

Figure 20. Comparison of forest land cover in Ivory Coast: chipsets "A" show CGLS-LC100m 2015 base map V2.0; chipsets "C" show CGLS-LC100m 2015 base map V3.0.

For urban land cover class, the CGLS-LC100m 2015 map V3.0 characterizes more areas as urban as compared with the V2.0 map (0.5% for V2.0 and 0.8% for V3.0, see Table 24). In Figure 21, column 1 shows an example of densely populated area of Nile Delta where patches depicting urban and built-up areas are slightly bigger and more homogeneous for map V3.0 (chipset "C") than for map V2.0 (chipset "B"). While some of the regions could be correct for the V3.0 map, depicting more areas as urban could lead to overestimation of this land cover (user's accuracy is 68.2% for V3.0 and 77.3% for V2.0, see Table 7 and Table 25). In V3.0 also the road network is depicted (which is lacking in V2.0), the difference are likely due to the change in characterizing urban areas. V3.0 used the OpenStreetMap as input for urban while V2.0 didn't [CGLOPS1_ATBD_LC100m-V3.0]. Long water canals are mapped as continuous land cover, and forest is not overestimated (smaller forest patches in center-north of the chipset in V3.0).

For snow/ice land cover, CGLS_LC100m 2015 map V3.0 detects lightly more areas comparing to the V2.0 map (3.17% for V3.0 Vs 3.15% for V2.0). This is due to the no data areas in V2.0 were labelled as snow/ice in V3.0 map. In Figure 21, column 2 shows an example of Svalbard, where pixels without data (black) in V2.0 (chipset "B") have been classified in V3.0 (chipset "C").

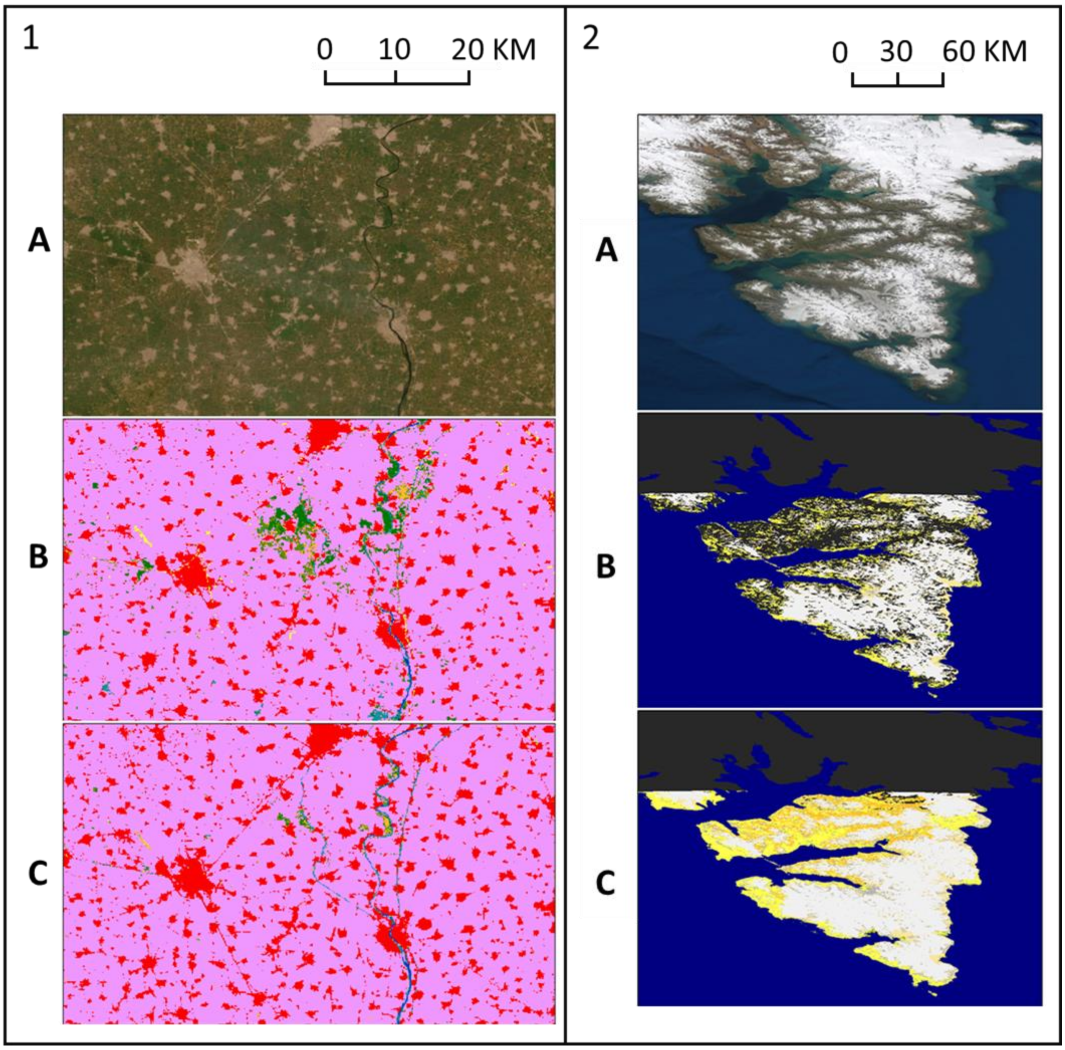

Figure 21. Comparison of urban and snow/ice land cover: 1-Nile Delta; 2-Svalbard. Chipsets "A" show reference Bing RGB map; chipsets "B" show CGLS_LC100m 2015 base map V2.0; chipsets "C" show CGLS_LC100m 2015 base map V3.0.

V3.0 and V2.0 map detect similar amount of permanent water (2.8%). For wetland land cover, the V3.0 map has more wetlands overall compared to the V2.0 map (Table 24). This characterization appears to represent the reality better. This can be seen in Figure 22 where in the Amazon river valley (column 1) there are much more wetland mapped in V3.0 (chipset "C") than in V2.0 (chipset "B"). Similarly, wetland land cover is larger in Kenya's coastal area in V3.0 (column 2, chipset "C") than in V2.0 (chipset "B"). Increased area of wetland may be correct in some areas; however, it also might overestimate this class. There are also areas where the depiction of wetland is less in V3.0 than in V2.0, such as southern coast of Iceland (Figure 23, column 2), where wetland appears to be less in map V3.0 than in V2.0).

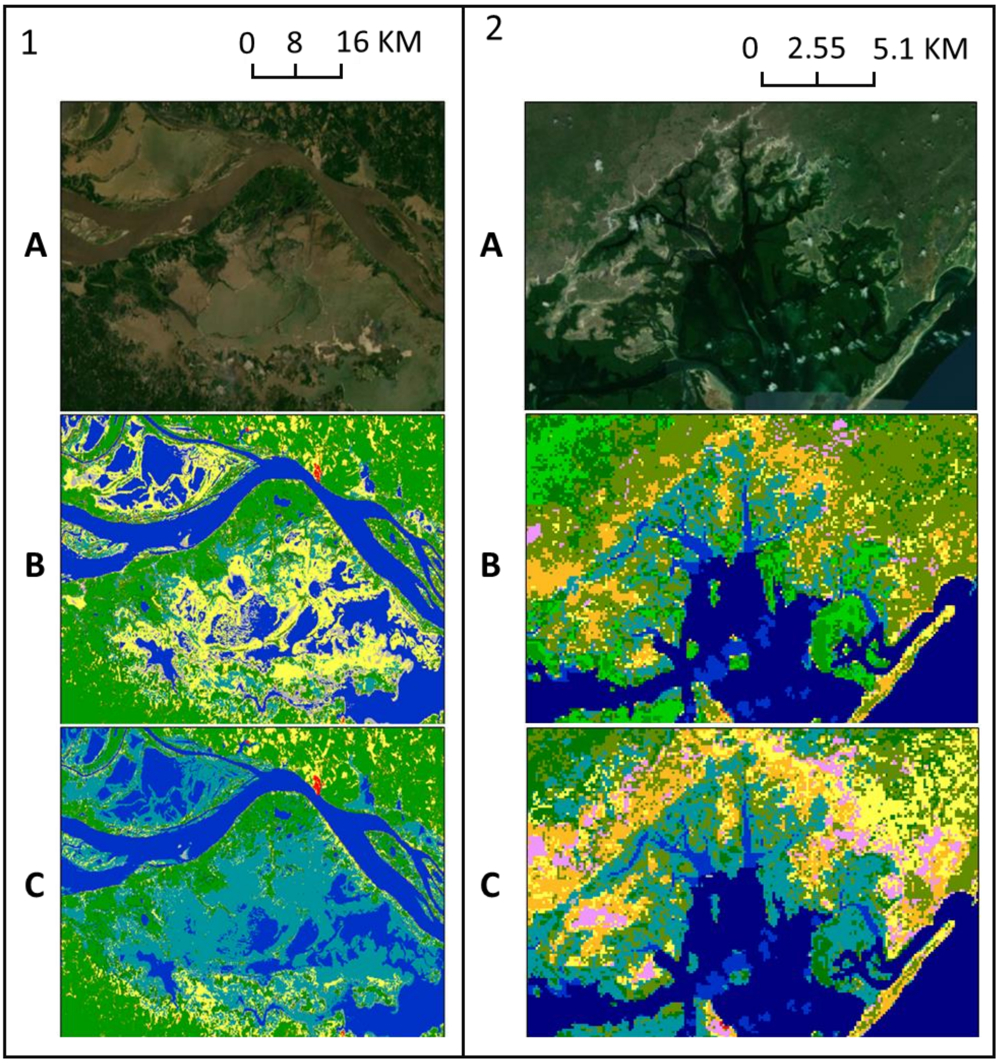

Figure 22. Comparison of permanent water and wetland land cover: 1-River Amazon; 2-Coastal area in Kenya. Chipsets "A" show Bing reference satellite based RGB image; chipsets "B" show CGLS_LC100m 2015 base map V2.0; chipsets "C" show CGLS_LC100m 2015 base map V3.0.

For crop land cover, the CGLS_LC100m 2015 map V3.0 have less areas as crop than compared to the V2.0 (Table 24). Figure 23 shows a rural area in Venezuela (column 1) where in V3.0 (chipset "C") much less fields were classified as crop land cover than in V2.0 (chipset "B"). The distinction between crop and herbaceous land covers are often challenging, as the herbaceous vegetation class for the both products, V2.0 and V3.0, includes natural grassland as well as sawn grassland, which makes it challenging for classification. However, there are also areas where the V3.0 mapped more crop land cover than the V2.0 such as in previous figures in Java, in Nile Delta and in coastal area of Kenya. In Figure 23, in column 2, there is an example of an area on Iceland, where overestimated crop areas in V2.0 (chipset "B") were correctly classified as grassland in V3.0 (chipset 3.0).

To summarize, visual comparison between the CGLS_LC100m 2015 V3.0 and V2.0 shows some improvements in V3.0 compared to the V2.0 map. The improvements are apparent in characterizing forest, cropland, water classes as compared to the V2.0 map. There have been improvements made in V3.0 with respect to forest type classification. Extreme north regions which were mapped as no data in V2.0 are also correctly mapped in V3.0. Urban characterization improved with identification of roads and canals, however, there is also some overestimation of this class. Similarly, wetland is improved in some regions, however not everywhere.

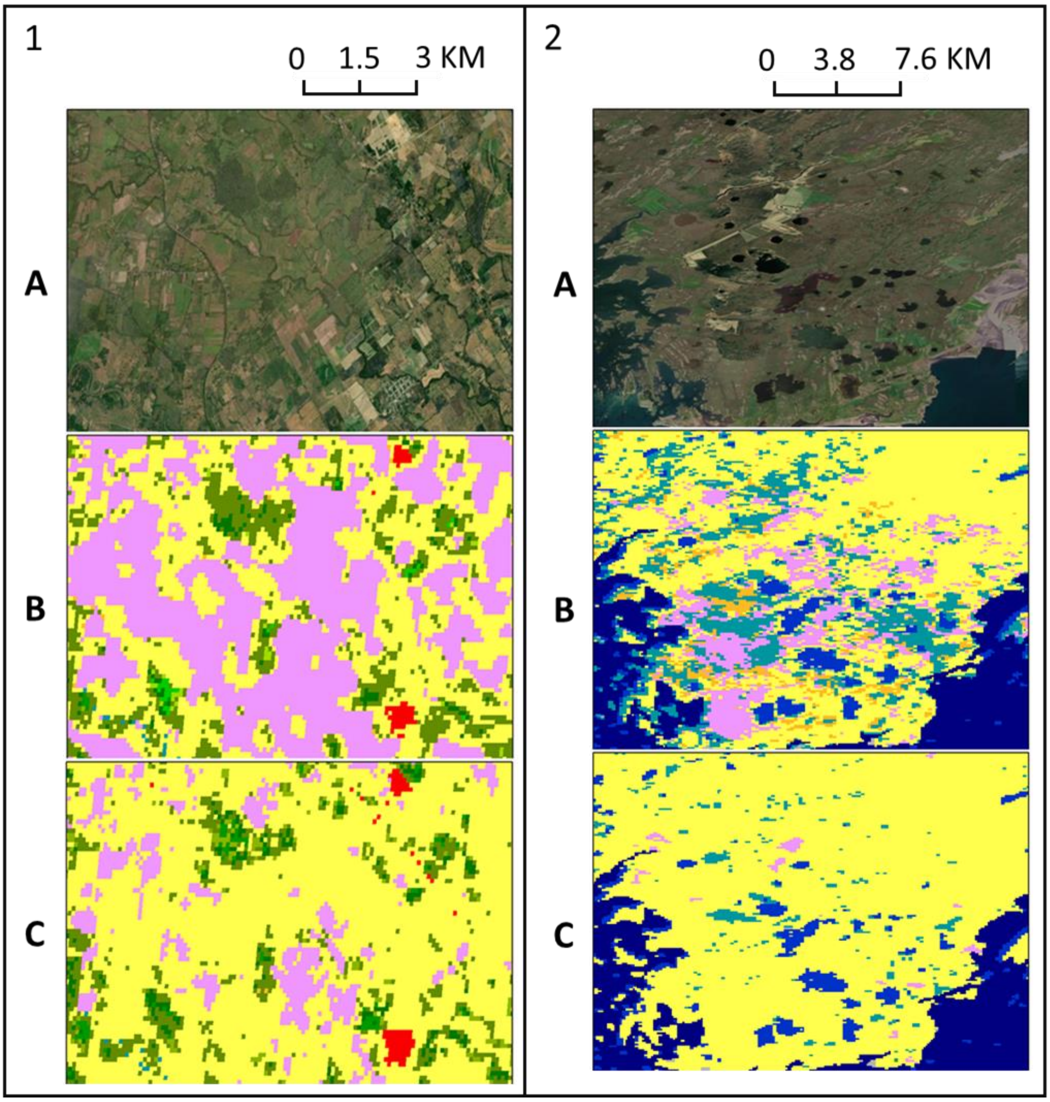

Figure 23. Comparison of crop land cover: 1-Rural area in Venezuela; 2-Iceland. Chipsets "A" show reference Bing satellite based RGB image; chipsets "B" show CGLS_LC100m 2015 base map V2.0; chipsets "C" show CGLS_LC100m 2015 base map V3.0.

4.4.2 Quantitative comparison

We used the CGLS-LC100 validation dataset for 2015, described in Section **Error! Unknown switch argument.**, to assess the accuracy of the CGLS-LC100-V2.0 map. The confusion matrix of the CGLS-LC100-V2.0 2015 map is provided in Table 25.

Overall accuracy is 80.5% +/-0.7% (at 95% confidence level) which is marginally lower (by 0.1) compared to the overall accuracy of the CGLS_LC100m V3.0 map at Level 1 (80.6% +/-0.4%,Table 7). The difference is within the limit of the confidence interval. At level 2, V2.0 map has 0.2% lower accuracy than the V3.0 map. Here, too, the difference is within the limit of confidence interval. Statistically, these two map versions are similar in terms of accuracy.

In terms of class specific accuracies, the two versions are statistically quite similar, varied by around 2% except for cropland and urban classes. The cropland class in V2.0 had larger overestimation (70.2 and 83.8% for user's and producer's accuracies respectively). In V3.0, the class accuracies for cropland are 72.5 and 80.9% indicating less bias for overestimation. For urban, however, V3.0 has more overestimation compared with V2.0, this could also be seen in the visual assessment. At Level 2, the difference between the user's and producer's accuracy for closed forest was 12.5% (Table 26), which indicated overestimation of closed forest. This difference is reduced slightly (by 2%) in the V3.0 map which indicates that the V3.0 map has improved in separating closed and open forest classes.

Table 25: Confusion matrix (%) for the discrete CGLS-LC100m V2.0 Level 1 map at global scale, corrected by sample inclusion probabilities.

	Forest	Shrubs	Herbaceous vegetation	Croplands	Urban	Bare/sparse vegetation	Snow/ice	Permanent Water	Herbaceous Wetland	Lichen/ moss	Correct	Total	User's accuracy	Confidence interval ±
Forest	33.4	1.8	1	0.6	0	0		0	0.1	0.1	33.4	37.1	90.2	0.8
Shrubs	1.5	5.8	1.4	0.3	0	0.2		0	0.1	0	5.8	9.3	62.3	3.1
Herbaceous vegetation	1.3	2.3	13.8	0.7	0	0.5		0	0.4	1.0	13.8	20.0	68.9	1.8
Croplands	1.1	0.5	1.6	8.2	0.1	0		0.1	0.1		8.2	11.6	70.2	2.1
Urban	0.1	0	0	0	0.5	0		0			0.5	0.6	77.3	5.7
Bare/sparse vegetation	0	0.3	0.7	0	0	13.6	0	0	0	0	13.6	14.7	92.0	1.7
Snow/ice			0			0.1	1.9	0		0	1.9	2.0	94.7	3.5
Permanent Water	0	0	0	0	0	0.1		2.0	0		2.0	2.1	95.0	1.9
Herbaceous Wetland	0.1	0.1	0.3	0	0	0		0.1	0.5	0.1	0.5	1.1	46.5	6.3
Lichen/moss		0	0.1			0.4	0	0	0	0.9	0.9	1.4	63.9	7.0
Correct	33.4	5.8	13.8	8.2	0.5	13.6	1.9	2.0	0.5	0.9				
Total	37.6	10.7	19.0	9.7	0.7	14.8	2.0	2.3	1.2	2.2				
Producer's accuracy	89	54.2	72.4	83.9	76.1	91.5	99	87.2	42.6	42.5			**80.5**	
Confidence interval ±	0.8	2.9	1.8	2.0	7.6	1.5	0.9	3.2	6.2	5.3				**0.7**

Table 26: Confusion matrix for the discrete CGLS_LC100m V2.0 Level 2 map at global scale, corrected by sample inclusion probabilities.

	Closed forest	Open forest	Shrubs	Herbaceous vegetation	Croplands	Urban	Bare/sparse vegetation	Snow/ice	Permanent Water	Herbaceous Wetland	Lichen/ moss	Correct	Total	User's accuracy	Confidence interval ±
Closed forest	22.2	4.0	0.9	0.4	0.1	0	0		0	0.1	0	22.2	27.6	80.4	1.2
Open forest	1.2	5.9	1.0	0.7	0.5	0	0		0	0	0	5.9	9.4	62.0	2.5
Shrubs	0.2	1.3	5.8	1.4	0.3	0	0.2		0	0.1	0	5.8	9.3	62.3	3.1
Herbaceous vegetation	0.1	1.1	2.3	13.8	0.7	0	0.5		0	0.4	1.0	13.8	20	68.9	1.8
Croplands	0.2	0.9	0.5	1.6	8.2	0.1	0		0.1	0.1		8.2	11.6	70.2	2.1
Urban	0	0.1	0	0	0	0.5	0		0			0.5	0.6	77.3	5.7
Bare/sparse vegetation		0	0.3	0.7	0	0	13.6	0	0	0	0	13.6	14.7	92.0	1.7
Snow/ice				0			0.1	1.9	0		0	1.9	2.0	94.7	3.5
Permanent Water	0	0	0	0	0	0	0.1		2.0	0		2.0	2.1	95.0	1.9
Herbaceous Wetland	0	0.1	0.1	0.3	0	0	0		0.1	0.5	0.1	0.5	1.1	46.5	6.3
Lichen/moss			0	0.1			0.4	0	0	0	0.9	0.9	1.4	63.9	7.0
Correct	22.2	5.9	5.8	13.8	8.2	0.5	13.6	1.9	2.0	0.5	0.9				
Total	23.9	13.4	10.8	19.1	9.8	0.7	14.8	2.0	2.3	1.2	2.2				
Producer's accuracy	92.9	43.6	53.6	72.2	83.8	76.1	91.5	99.0	87.1	42.3	42.5			**75.2**	
Confidence interval ±	0.8	2.1	2.9	1.8	2.0	7.6	1.5	0.9	3.2	6.2	5.3				**0.7**

At continental level, generally similar accuracies are obtained for the V2.0 map to V3.0 map. V2.0 (

Table **27**) has marginally lower accuracy for Africa, North America and South America than those of V3.0 map (Table 8). At level two, similarly, these continents obtained higher accuracy for V3.0 (Table 17) as compared with V2.0 map (Table 27). The differences in the accuracy are within the confidence intervals.

Table 27: Overall accuracy of the discrete CGLS_LC100m V2.0 map at continental level

	Number of samples	Overall accuracy at level 1(%)	Confidence intervals ±	Overall accuracy at level 2 (%)	Confidence intervals ±
Africa	3616	80.0	2.0	76.2	2.0
Asia	3071	83.7	1.5	79.8	1.6
Northern Eurasia	2976	81.1	1.5	71.6	1.8
Europe	3120	80.4	1.6	73.2	1.7
North America	2843	77.2	1.7	72.3	1.8
Oceania & Australia	2951	82.0	1.9	77.6	2.0
South America	3017	79.6	1.5	74.1	1.6

4.5 SPATIAL UNCERTAINTY ASSESSMENT

Figure 24 shows the composite spatial accuracy map for the 3 aggregated land cover classes forest, cropland and other natural vegetation.

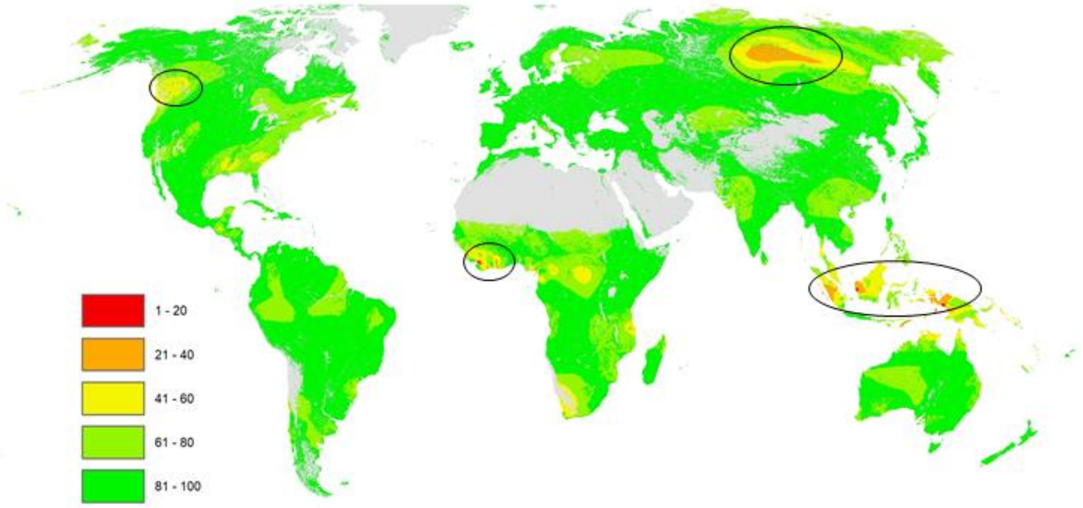

Figure 24. Composite map representing spatial accuracy outlining 4 hotspot areas of lower spatial accuracy

The map overall shows a very high spatial accuracy in most places of the world which are depicted in green with a spatial accuracy of more than 80%. Some areas also show accuracy numbers between 60% and 80% shown in lighter green.

In orange and yellow you can see places where the used independent reference data disagrees with the map classification and therefore shows lower values of spatial accuracy. One hotspot can be found in Siberia which is dominated by a complex hilly landscape of deciduous needleleaf forest and valleys of grasses and lichen/moss. The map is mostly in accordance with the reference datasets, but with some misclassifications with the other natural vegetation class. The second hotspot in Asia is found in Indonesia which has recently undergone large replacement of natural forests by plantations. The map tends to have more forested areas than the independent reference data. The largest hotspot in Africa is found in West Africa where complex landscapes of forest fragmentation and increasing more intensive agricultural activities are ongoing. A further hotspot can be found in north western Canada, a very mountainous area where a continuous transition between grass, shrub and forest can be found.

When compared against large quantity of independent reference datasets, the CGLS-LC100 map V3 has quite high local accuracies in majority of the considered land cover classes. This gives confidence for the users to use this product for their region of interests. Nevertheless, it has to be highlighted that it was not possible to get a high number of global high-quality reference datasets systematically distributed which is normally a precondition for spatial accuracy assessment for the entire globe. Since the independent reference data was not homogeneously and systematically available for all places in the world, some inconsistencies might occur due to legend harmonization and possibly difference in spatial resolution of the reference data. In particular, the low number of available crop and other natural vegetation reference data might bias the spatial accuracy towards the forest domain and possibly highlight more areas where the forest classification represents uncertainties when compared to the relatively high number of dense forest reference data.

Furthermore, it is worth to note that the spatial accuracy map for the three aggregated class shows the map quality compared to the reference datasets in a local to regional level, not at per pixel level.

5 CONCLUSIONS

This document reports the validation process of the CGLS-LC100m Dynamic Land Cover V3.0 product of the Copernicus Global Land Service. The yearly maps for 2015-2019 including discrete land cover map and the nine cover fraction layers were validated using an independent validation dataset generated in collaboration with regional experts. The validation dataset includes updated versions for different years, therefore making it possible to validate yearly maps of the CGLS-LC100 V3.0. By doing this, the CGLS-LC100 V3.0 product has reached Stage 4 validation according to the CEOS-WGCV validation guidelines.

Our assessments showed that the overall accuracy of the discrete CGLS-LC100m V3.0 Level 1 map reaches 80.6+/-0.4% for 2015. In terms of land cover types, bare/sparse vegetation, snow/ice and permanent water are mapped with high accuracies, while shrubs and herbaceous wetland classes are mapped with lowest accuracies. The maps for the following years (2016-2019) are assessed with around 80.3-80.5%. Targeted overall accuracy 80% (Chapter 2) has therefore been met for the yearly land cover maps. Overall accuracy at continental level is around 80%, with highest accuracy of 83.7% for Asia and the lowest accuracy of 77.6% for North America (for 2015). At Level 2, when closed and open forests classes are separated, global overall accuracy is 75.4% +/-0.4% for 2015 while for the other years (2016-2019) it ranges between 75.1-75.2%. Overall accuracies at global and continental levels show consistency in the quality of the yearly maps. Among the cover fraction layer, snow/ice, built-up, water and lichen/moss fraction maps show lowest errors, followed by crops and bare/sparse vegetation fraction types. On the other hand, herbaceous vegetation fraction product has the highest error.

Land cover change between 2015 and 2018 were assessed at change and no change level. The overall accuracy of the change/no-change map (2015-2018) is 99.6%. No-change class covers most of the land area and it is mapped with very high accuracy, while change class is more likely to be committed than omitted (land cover commission error 45.6%, omission error 36%). At continental level, land cover change class has higher accuracies in North Eurasia, North America, Australia and South America. This statistical assessment of land cover change offers the first statistical assessment of generic land cover change at global scale. Considering that land cover change detection is much more complex than land cover classification, based on our analysis, the CGLS-LC100 V3.0 yearly maps reflect reasonably well the land cover changes that occur in the recent years globally. This is supported by the stability and consistency in the land cover map accuracies for the yearly maps. Furthermore, our visual analysis of areas that are changed reveals that the mapped changes do correspond with changes that could be seen from higher resolution images such as Sentinel-2 and Landsat. However, users should be reminded that (for the 2015-2018 period) the differences between the annual maps is coming from both land cover changes (~55%) and inconsistencies and interannual variabilities resulting from the classification (~45%) and any change analysis should take this uncertainties into account; in particular since there also significant differences for the various World regions.

Comparison of the CGLS_LC100m V3.0 discrete map with the V2.0 discrete map showed that these two versions have similar accuracies with V3.0 map having marginally higher accuracy (0.1%).

Similar tendency applies at continental level. Our visual comparison confirms the similarity of the versions. It also highlights some improvements in the CGLS_LC100m V3.0 with respect to characterizing forest, cropland and permanent water classes. These results indicate that the global CGLS_LC100m dynamic Land Cover V3.0 product is largely consistent with the V2.0 product for 2015 and some additional improvements in characterizing land cover types as compared to CGLS_LC100m V2.0.

Spatial uncertainty assessments on the three aggregated classes (forest, cropland and natural vegetation) reveals high level of accuracy in different regions of the world. This achievement is significant considering that the spatial uncertainty assessment is based on large number (>200 000) sample points that are fully independent from the map production. The assessment also highlights some regions where map quality is lower, possible due to over-estimation of forest class. Due to larger number of points for forest class compared to the other two classes, the spatial accuracy maybe biased towards forest rather than crop and natural vegetation.

The comprehensive assessment consisting of high-level statistical accuracy assessment (Stage 4 Validation) and spatial uncertainty assessments and comparisons conform high quality of the CGLS_LC100m V3.0 land cover product and its improvements as compared to the previous version V2.0. The product provides good quality characterization of global scale land cover in the recent years.

6 RECOMMENDATIONS

Validation of the CGLS_LC100m V3.0 land cover product shows noticeable improvements in land cover mapping as compared with the previous version 2.0. In addition, the product provides consistent and quality representation of land cover in the recent years (2015-2019). The product also reflects reasonably well the land cover changes that might have occurred in these time frame. These achievements can be further improved by focusing on the main limitations.

Characterization of classes such as wetlands, lichen/moss and shrubs needs improvement as they have low class specific accuracies. In particular, wetland area characterization is challenging, considering its high-level variation of water influence in these areas. Additional rules could be applied to refine this class such as using existing global wetland layers (e.g. Global saltmarsh by (McOwen et al. 2017) and (Xu et al. 2018)) after checking their reliability or adding additional training sites in areas indicated by the existing wetland products. Herbaceous vegetation fraction layer remains a challenge as its error is the largest among the other fraction layers. Use of other remote sensing data with more spectral bands such as Sentinel-1 and Sentinel-2 might help to solve this issue.

Although the CGLS_LC100m V3.0 has less area as unknown forest types than the CGLS_LC100m V2.0, it still covers significant areas. For the communities that are interested in forest type information, unknown forest type class could be a limiting issue. Therefore, further effort is required to reduce areas mapped as “Unknown forest type”. Next to obtaining additional training data for forest type, use of other remote sensing data with more spectral bands could improve forest type characterization.

The global CGLS_LC100m V3.0 product has yearly maps for 2015-2019. These maps are assessed with high consistency in terms of accuracy estimates. Our assessment of land cover change revealed some level of overestimation of land cover change, although most detected change correspond well to the reference land cover change in the validation data. Attention should be paid to further reduce year to year inconsistency between the yearly land cover products. For this purpose, inconsistencies between the yearly land cover maps should be assessed (such as those related to urban) and additional training datasets could be collected in the inconsistent areas which can be useful for improving the land cover mapping as well as land cover change detection. In addition, to reduce spurious changes, land cover change detection algorithm could be improved further, for example by using images with higher resolution than MODIS.

Spatial uncertainty of three land cover types were assessed to provide information on the regional quality of the map. Although this assessment used large number of validation points (>200 000) that are independent from map production, sample representation could be improved by using more suitable datasets focusing on balanced and more class representations.

The validation presented in this report meets the Stage 4 validation requirement the CEOS WGCV. Although this is statistically robust and capable of validating updated yearly maps, further attention should be paid to improve the representation of land cover changes such as improving land cover change sampling stratification.

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ANNEX

Table 28: Confusion matrix (%) for the discrete CGLS_LC100m V3.0 Level 1 map at global scale for 2016, corrected by sample inclusion probabilities.

	Forest	Shrubs	Herbaceous vegetation	Croplands	Urban	Bare/sparse vegetation	Snow/ice	Permanent Water	Herbaceous Wetland	Lichen/ moss	Correct	Total	User's accuracy	Confidence interval ±
Forest	33.3	1.8	0.9	0.5	0.0	0.0		0.0	0.0	0.1	33.3	36.6	90.9	0.7
Shrubs	1.7	5.4	1.1	0.3	0.0	0.2	0.0	0.0	0.0	0.0	5.4	8.8	61.8	3.2
Herbaceous vegetation	1.4	2.4	14.4	0.9	0.0	0.5	0.0	0.0	0.3	1.1	14.4	21.1	68.2	1.7
Croplands	0.9	0.4	1.4	7.8	0.0	0.0		0.1	0.1	0.0	7.8	10.8	72.3	2.2
Urban	0.1	0.0	0.1	0.0	0.6	0.0		0.0			0.6	0.9	68.2	6.0
Bare/sparse vegetation	0.0	0.3	0.8	0.0	0.0	13.5	0.0	0.0	0.0	0.0	13.5	14.7	91.7	1.8
Snow/ice			0.0			0.1	1.9	0.0		0.0	1.9	2.0	94.7	3.5
Permanent Water	0.0	0.0	0.0	0.0	0.0	0.0	0.0	2.0	0.0	0.0	2.0	2.1	94.9	1.9
Herbaceous Wetland	0.1	0.1	0.4	0.0	0.0	0.0		0.1	0.7	0.1	0.7	1.6	42.1	5.7
Lichen/moss			0.1			0.4	0.0	0.0		0.9	0.9	1.4	62.2	7.2
Correct	33.3	5.4	14.4	7.8	0.6	13.5	1.9	2.0	0.7	0.9				
Total	37.6	10.5	19.1	9.7	0.7	14.7	2.0	2.3	1.2	2.2		100		
Producer's accuracy	88.5	51.8	75.1	80.7	87.8	91.6	98.9	85.9	55.1	39.6			**80.4**	
Confidence interval ±	0.8	2.9	1.8	2.1	5.8	1.4	0.9	3.2	6.7	5.3				**0.7**

Table 29: Confusion matrix (%) for the discrete CGLS_LC100m V3.0 Level 1 map at global scale for 2017, corrected by sample inclusion probabilities.

	Forest	**Shrubs**	**Herbaceous vegetation**	**Croplands**	**Urban**	**Bare/sparse vegetation**	**Snow/ice**	**Permanent Water**	**Herbaceous Wetland**	**Lichen/ moss**	**Correct**	**Total**	**User's accuracy**	**Confidence interval ±**
Forest	33.3	1.8	0.9	0.5	0.0	0.0		0.0	0.0	0.1	33.3	36.6	90.9	0.7
Shrubs	1.7	5.4	1.1	0.3	0.0	0.2	0.0	0.0	0.0	0.0	5.4	8.8	61.9	3.2
Herbaceous vegetation	1.4	2.4	14.3	0.9	0.0	0.5	0.0	0.0	0.3	1.1	14.3	21.0	68.4	1.7
Croplands	0.9	0.4	1.4	7.8	0.0	0.0		0.0	0.1	0.0	7.8	10.8	72.7	2.2
Urban	0.1	0.0	0.1	0.0	0.6	0.0		0.0	0.0		0.6	0.9	67.3	6.0
Bare/sparse vegetation	0.0	0.3	0.8	0.0	0.0	13.5	0.0	0.0	0.0	0.0	13.5	14.7	91.9	1.8
Snow/ice			0.0			0.1	1.9	0.0		0.0	1.9	2.1	94.2	3.6
Permanent Water	0.0	0.0	0.0	0.0	0.0	0.0	0.0	2.0	0.0	0.0	2.0	2.1	95.2	1.8
Herbaceous Wetland	0.1	0.2	0.4	0.0	0.0	0.0		0.1	0.7	0.1	0.7	1.7	40.8	5.4
Lichen/moss			0.1			0.4	0.0	0.0		0.9	0.9	1.4	62.8	7.2
Correct	33.3	5.4	14.3	7.8	0.6	13.5	1.9	2.0	0.7	0.9				
Total	37.6	10.5	19.1	9.7	0.7	14.7	2.0	2.3	1.2	2.2		100		
Producer's accuracy	88.4	51.9	74.9	80.5	87.8	91.8	98.9	86.5	58.9	39.6			**80.5**	
Confidence interval ±	0.8	2.9	1.8	2.1	5.7	1.3	0.9	3.2	6.7	5.3				**0.7**

Table 30: Confusion matrix (%) for the discrete CGLS_LC100m V3.0 Level 1 map at global scale for 2018, corrected by sample inclusion probabilities.

	Forest	Shrubs	Herbaceous vegetation	Croplands	Urban	Bare/sparse vegetation	Snow/ice	Permanent Water	Herbaceous Wetland	Lichen/ moss	Correct	Total	User's accuracy	Confidence interval ±
Forest	33.3	1.7	0.9	0.5	0.0	0.0	0.0	0.0	0.0	0.1	33.3	36.6	90.9	0.7
Shrubs	1.7	5.4	1.0	0.3	0.0	0.2	0.0	0.0	0.0	0.0	5.4	8.7	61.8	3.2
Herbaceous vegetation	1.4	2.5	14.3	0.9	0.0	0.5	0.0	0.0	0.3	1.1	14.3	21.0	68.3	1.7
Croplands	0.9	0.5	1.4	7.8	0.0	0.0		0.1	0.1	0.0	7.8	10.8	72.5	2.2
Urban	0.1	0.0	0.1	0.0	0.6	0.0		0.0	0.0		0.6	0.9	67.7	6.0
Bare/sparse vegetation	0.0	0.3	0.8	0.0	0.0	13.4	0.0	0.0	0.0	0.0	13.4	14.6	91.9	1.8
Snow/ice			0.0			0.1	1.9	0.0		0.0	1.9	2.1	94.1	3.6
Permanent Water	0.0	0.0	0.0	0.0	0.0	0.0	0.0	2.0	0.0	0.0	2.0	2.1	95.4	1.8
Herbaceous Wetland	0.2	0.2	0.5	0.1	0.0	0.0		0.1	0.7	0.1	0.7	1.9	38.8	5.2
Lichen/moss			0.1			0.4	0.0	0.0		0.9	0.9	1.4	62.8	7.2
Correct	33.3	5.4	14.3	7.8	0.6	13.4	1.9	2.0	0.7	0.9				
Total	37.6	10.5	19.2	9.7	0.7	14.7	2.0	2.3	1.2	2.2		100		
Producer's accuracy	88.4	51.4	74.9	80.2	89.3	91.5	98.9	86.5	59.8	39.6			**80.4**	
Confidence interval ±	0.8	2.9	1.8	2.1	5.3	1.3	0.9	3.2	6.7	5.3				**0.7**

Table 31: Confusion matrix (%) for the discrete CGLS_LC100m V3.0 Level 1 map at global scale for 2019, corrected by sample inclusion probabilities.

	Forest	Shrubs	Herbaceous vegetation	Croplands	Urban	Bare/sparse vegetation	Snow/ice	Permanent Water	Herbaceous Wetland	Lichen/ moss	Correct	Total	User's accuracy	Confidence interval ±
Forest	33.3	1.7	0.9	0.5	0.0	0.0	0.0	0.0	0.0	0.1	33.3	36.6	90.9	0.7
Shrubs	1.7	5.4	1.0	0.3	0.0	0.2	0.0	0.0	0.0	0.0	5.4	8.7	61.8	3.2
Herbaceous vegetation	1.4	2.5	14.3	0.9	0.0	0.5	0.0	0.0	0.3	1.1	14.3	21.0	68.3	1.7
Croplands	0.9	0.5	1.4	7.8	0.0	0.0		0.1	0.1	0.0	7.8	10.8	72.5	2.2
Urban	0.1	0.0	0.1	0.0	0.6	0.0		0.0	0.0		0.6	0.9	67.7	6.0
Bare/sparse vegetation	0.0	0.3	0.8	0.0	0.0	13.4	0.0	0.0	0.0	0.0	13.4	14.6	91.9	1.8
Snow/ice			0.0			0.1	1.9	0.0		0.0	1.9	2.1	94.1	3.6
Permanent Water	0.0	0.0	0.0	0.0	0.0	0.0	0.0	2.0	0.0	0.0	2.0	2.1	95.4	1.8
Herbaceous Wetland	0.2	0.2	0.5	0.1	0.0	0.0		0.1	0.7	0.1	0.7	1.9	38.8	5.2
Lichen/moss			0.1			0.4	0.0	0.0		0.9	0.9	1.4	62.8	7.2
Correct	33.3	5.4	14.3	7.8	0.6	13.4	1.9	2.0	0.7	0.9				
Total	37.6	10.5	19.2	9.7	0.7	14.7	2.0	2.3	1.2	2.2		100		
Producer's accuracy	88.4	51.4	74.9	80.2	89.3	91.5	98.9	86.5	59.8	39.6			**80.4**	
Confidence interval ±	0.8	2.9	1.8	2.1	5.3	1.3	0.9	3.2	6.7	5.3				**0.7**

Table 32: Confusion matrix (%) for the discrete CGLS_LC100m V3.0 Level 2 map at global scale for 2016, corrected by sample inclusion probabilities.

	Closed forest	**Open forest**	**Shrubs**	**Herbaceous vegetation**	**Croplands**	**Urban**	**Bare/sparse vegetation**	**Snow/ice**	**Permanent Water**	**Herbaceous Wetland**	**Lichen/ moss**	**Correct**	**Total**	**User's accuracy**	**Confidence interval ±**
Closed forest	22.1	3.6	0.8	0.4	0.1	0.0	0.0		0.0	0.0	0.0	22.1	27.1	81.7	1.2
Open forest	1.3	6.0	1.1	0.6	0.4	0.0	0.0		0.0	0.0	0.0	6.0	9.6	62.3	2.5
Shrubs	0.2	1.5	5.4	1.1	0.3	0.0	0.2	0.0	0.0	0.0	0.0	5.4	8.8	61.8	3.2
Herbaceous vegetation	0.2	1.2	2.4	14.4	0.9	0.0	0.5	0.0	0.0	0.3	1.1	14.4	21.1	68.2	1.7
Croplands	0.1	0.8	0.4	1.4	7.8	0.0	0.0		0.1	0.1	0.0	7.8	10.8	72.3	2.2
Urban	0.0	0.1	0.0	0.1	0.0	0.6	0.0		0.0			0.6	0.9	68.2	6.0
Bare/sparse vegetation		0.0	0.3	0.8	0.0	0.0	13.5	0.0	0.0	0.0	0.0	13.5	14.7	91.7	1.8
Snow/ice				0.0			0.1	1.9	0.0		0.0	1.9	2.0	94.7	3.5
Permanent Water	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	2.0	0.0	0.0	2.0	2.1	94.9	1.9
Herbaceous Wetland	0.0	0.1	0.1	0.4	0.0	0.0	0.0		0.1	0.7	0.1	0.7	1.6	42.1	5.7
Lichen/moss				0.1			0.4	0.0	0.0		0.9	0.9	1.4	62.2	7.2
Correct	22.1	6.0	5.4	14.4	7.8	0.6	13.5	1.9	2.0	0.7	0.9				
Total	24.0	13.4	10.6	19.2	9.7	0.7	14.7	2.0	2.3	1.2	2.2		100		
Producer's accuracy	92.3	44.5	51.0	74.8	80.6	87.1	91.6	98.9	85.9	54.7	39.6			**75.2**	
Confidence interval ±	0.9	2.1	2.9	1.8	2.1	5.8	1.4	0.9	3.2	6.7	5.3				**0.7**

Table 33: Confusion matrix (%) for the discrete CGLS_LC100m V3.0 Level 2 map at global scale for 2017, corrected by sample inclusion probabilities.

	Closed forest	Open forest	Shrubs	Herbaceous vegetation	Croplands	Urban	Bare/sparse vegetation	Snow/ice	Permanent Water	Herbaceous Wetland	Lichen/ moss	Correct	Total	User's accuracy	Confidence interval ±
Closed forest	22.1	3.7	0.8	0.4	0.1	0.0	0.0		0.0	0.0	0.0	22.1	27.1	81.6	1.2
Open forest	1.3	6.0	1.2	0.6	0.4	0.0	0.0		0.0	0.0	0.0	6.0	9.6	62.2	2.5
Shrubs	0.2	1.5	5.4	1.1	0.3	0.0	0.2	0.0	0.0	0.0	0.0	5.4	8.8	61.9	3.2
Herbaceous vegetation	0.2	1.2	2.4	14.3	0.9	0.0	0.5	0.0	0.0	0.3	1.1	14.3	21.0	68.4	1.7
Croplands	0.1	0.8	0.4	1.4	7.8	0.0	0.0		0.0	0.1	0.0	7.8	10.8	72.7	2.2
Urban	0.0	0.1	0.0	0.1	0.0	0.6	0.0		0.0	0.0		0.6	0.9	67.3	6.0
Bare/sparse vegetation	0.0	0.0	0.3	0.8	0.0	0.0	13.5	0.0	0.0	0.0	0.0	13.5	14.7	91.9	1.8
Snow/ice				0.0			0.1	1.9	0.0		0.0	1.9	2.1	94.2	3.6
Permanent Water	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	2.0	0.0	0.0	2.0	2.1	95.2	1.8
Herbaceous Wetland	0.0	0.1	0.2	0.4	0.0	0.0	0.0		0.1	0.7	0.1	0.7	1.7	40.8	5.4
Lichen/moss				0.1			0.4	0.0	0.0		0.9	0.9	1.4	62.8	7.2
Correct	22.1	6.0	5.4	14.3	7.8	0.6	13.5	1.9	2.0	0.7	0.9				
Total	23.9	13.4	10.6	19.2	9.7	0.7	14.7	2.0	2.3	1.2	2.2		100		
Producer's accuracy	92.3	44.3	51.1	74.6	80.4	87.1	91.8	98.9	86.5	58.5	39.6			**75.2**	
Confidence interval ±	0.9	2.1	2.9	1.8	2.1	5.8	1.3	0.9	3.2	6.7	5.3				**0.7**

Table 34: Confusion matrix (%) for the discrete CGLS_LC100m V3.0 Level 2 map at global scale for 2018, corrected by sample inclusion probabilities

	Closed forest	**Open forest**	**Shrubs**	**Herbaceous vegetation**	**Croplands**	**Urban**	**Bare/sparse vegetation**	**Snow/ice**	**Permanent Water**	**Herbaceous Wetland**	**Lichen/ moss**	**Correct**	**Total**	**User's accuracy**	**Confidence interval ±**
Closed forest	22.1	3.7	0.8	0.4	0.1	0.0	0.0		0.0	0.0	0.0	22.1	27.0	81.6	1.2
Open forest	1.3	6.0	1.1	0.6	0.5	0.0	0.0	0.0	0.0	0.0	0.0	6.0	9.5	62.3	2.5
Shrubs	0.2	1.5	5.4	1.0	0.3	0.0	0.2	0.0	0.0	0.0	0.0	5.4	8.7	61.8	3.2
Herbaceous vegetation	0.2	1.2	2.5	14.3	0.9	0.0	0.5	0.0	0.0	0.3	1.1	14.3	21.0	68.3	1.7
Croplands	0.1	0.8	0.5	1.4	7.8	0.0	0.0		0.1	0.1	0.0	7.8	10.8	72.5	2.2
Urban	0.0	0.1	0.0	0.1	0.0	0.6	0.0		0.0	0.0		0.6	0.9	67.7	6.0
Bare/sparse vegetation	0.0	0.0	0.3	0.8	0.0	0.0	13.4	0.0	0.0	0.0	0.0	13.4	14.6	91.9	1.8
Snow/ice				0.0			0.1	1.9	0.0		0.0	1.9	2.1	94.1	3.6
Permanent Water	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	2.0	0.0	0.0	2.0	2.1	95.4	1.8
Herbaceous Wetland	0.0	0.2	0.2	0.5	0.1	0.0	0.0		0.1	0.7	0.1	0.7	1.9	38.8	5.2
Lichen/moss				0.1			0.4	0.0	0.0		0.9	0.9	1.4	62.8	7.2
Correct	22.1	6.0	5.4	14.3	7.8	0.6	13.4	1.9	2.0	0.7	0.9				
Total	23.9	13.4	10.6	19.2	9.7	0.7	14.7	2.0	2.3	1.2	2.2		100		
Producer's accuracy	92.3	44.3	50.6	74.6	80.2	88.5	91.5	98.9	86.5	59.4	39.6			**75.1**	
Confidence interval ±	0.9	2.1	2.9	1.8	2.1	5.5	1.3	0.9	3.2	6.6	5.3				**0.7**

Table 35: Confusion matrix (%) for the discrete CGLS_LC100m V3.0 Level 2 map at global scale for 2019, corrected by sample inclusion probabilities.

	Closed forest	**Open forest**	**Shrubs**	**Herbaceous vegetation**	**Croplands**	**Urban**	**Bare/sparse vegetation**	**Snow/ice**	**Permanent Water**	**Herbaceous Wetland**	**Lichen/ moss**	**Correct**	**Total**	**User's accuracy**	**Confidence interval ±**
Closed forest	22.0	3.6	0.8	0.4	0.1	0.0	0.0		0.0	0.0	0.0	22.0	27.0	81.6	1.2
Open forest	1.3	5.9	1.1	0.6	0.4	0.0	0.0		0.0	0.0	0.0	5.9	9.6	62.3	2.5
Shrubs	0.2	1.5	5.3	1.0	0.3	0.0	0.2	0.0	0.0	0.0	0.0	5.3	8.6	61.7	3.3
Herbaceous vegetation	0.2	1.2	2.5	14.3	0.9	0.0	0.5	0.0	0.0	0.3	1.1	14.3	21.0	68.2	1.7
Croplands	0.1	0.8	0.4	1.4	7.8	0.0	0.0		0.1	0.1	0.0	7.8	10.8	72.5	2.2
Urban	0.0	0.1	0.0	0.1	0.0	0.6	0.0		0.0	0.0		0.6	0.9	67.7	6.0
Bare/sparse vegetation	0.0	0.0	0.3	0.8	0.0	0.0	13.4	0.0	0.0	0.0	0.0	13.4	14.6	91.9	1.8
Snow/ice				0.0			0.1	1.9	0.0		0.0	1.9	2.1	94.1	3.6
Permanent Water	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	2.0	0.0	0.0	2.0	2.1	95.3	1.8
Herbaceous Wetland	0.0	0.2	0.2	0.5	0.1	0.0	0.0	0.0	0.1	0.7	0.1	0.7	1.9	37.6	5.1
Lichen/moss				0.1			0.4	0.0	0.0		0.9	0.9	1.4	62.8	7.2
Correct	22.0	5.9	5.3	14.3	7.8	0.6	13.4	1.9	2.0	0.7	0.9				
Total	23.9	13.4	10.6	19.3	9.8	0.7	14.7	2.0	2.3	1.2	2.2		100		
Producer's accuracy	92.2	44.3	50.3	74.4	80.3	88.3	91.5	98.9	86.2	59.6	39.6			**75.1**	
Confidence interval ±	0.9	2.1	2.9	1.8	2.1	5.5	1.3	0.9	3.2	6.7	5.3				**0.7**

Table 36: Accuracy of the fraction land cover layers at global scale for 2016-2019.

Year		Trees	Shrub	Herbaceous vegetation	Crops	Lichen/ Moss	Bare/sparse vegetation	Snow/ice	Built-up	Permanent Water
2016	Mean absolute error % (MAE)	8.9	9.2	17.3	5.6	2.8	5.5	0.1	0.8	0.8
	Root mean square error % (RMSE)	16.8	16.3	27.0	15.2	14.8	14.2	3.3	5.7	6.1
2017	Mean absolute error % (MAE)	9.1	9.3	17.3	5.7	2.8	5.7	0.2	0.8	0.8
	Root mean square error % (RMSE)	17.0	16.4	26.8	15.2	14.9	14.4	3.5	5.8	5.7
2018	Mean absolute error % (MAE)	9.2	9.4	17.5	5.8	2.8	5.8	0.1	0.8	0.8
	Root mean square error % (RMSE)	17.2	16.5	27.0	15.4	14.8	14.5	3.4	5.7	5.9
2019	Mean absolute error % (MAE)	9.6	9.7	18.1	6.9	2.8	6.0	0.1	0.8	0.8
	Root mean square error % (RMSE)	17.6	16.8	27.3	16.6	14.7	14.7	3.3	5.7	5.9