Climate Change Initiative Extension (CCI+) Phase 1

New Essential Climate Variables (NEW ECVS)

High Resolution Land Cover ECV (HR_LandCover_cci)

Product Validation and Intercomparison Report

(PVIR)

Part A – Intercomparison Report

Prepared by:

Università degli Studi di Trento
Fondazione Bruno Kessler
Université Catholique de Louvain
Università degli Studi di Pavia
Università degli Studi di Genova
Politecnico di Milano
Université de Versailles Saint Quentin
CREAF
e-GEOS s.p.a.
Planetek Italia
GeoVille

Changelog

Issue	Changes	Date
1.0	First version.	17/07/2020
1.1	Second version with the results of the visual qualitative assessment of the RR prototypes	18/08/2020
1.2	Third version including a section on the quantitative assessment of the RR prototypes for Africa and a section about the qualitative assessment of Amazon and Siberia. It also includes results of inter-comparison with existing land cover for all RR prototypes and static maps in Siberia and Amazon.	18/11/2020
1.3	Updated version according to CCI_HRLC_Ph1_AR2_RID-ESA.xlsx Sections 4.2.2 and 4.2.3 updated to include results of inter-comparison with Atlas of Urban Expansion as suggested during AR2.	07/12/2020
1.4	Updated with the quantitative assessment of the RR prototypes for Amazonia and Siberia, update of the quantitative assessment of the RR prototype for Africa. Also includes qualitative assessment of the African zoom area and Amazonian historical maps. Regarding inter-comparison with existing the results of land cover data in Amazon zoom area are added (Section 3.3)	04/02/2021
2.0	Executive summary updated with dates of the second production product delivery. Updated section 2 with current current area locations. The introductory part of Section 3 was expanded to explain how the results are interpreted. When the first production is concerned section 3.2.3 is updated with benchmarking results of Africa product for static region, and Section 4.3 with benchmarking results of products for Siberia (3.3.7 -3.3.12) and Africa (3.3.13 - 3.3.18) historical regions. Benchmarking results of the second production related to static maps are added in Section 3.5, and those related to the historic maps in Section 3.6. Moreover, Section 3.4 related to the estimation of the reliability of the existing data was added too. In this issue the intercomparison analysis (PVIR-Part A) has been separated from the validation one (PIVIR-Part B). This document refers to intercomparison analysis (PVIR-Part A), only.	28/10/2022
2.1	Correction of Table 65 and related parts in 3.5.2.1.	01/02/2023

Detailed Change Record

Issue	RID	Description of discrepancy	Sections	Change
1.3	FR-01	It does not match with the document version. It should be 'CCI_HRLC_Ph1-PVIR_1.2' instead of 'CCI_HRLC_Ph1-PVIR_2.1'.		Filename of version v1.2 is fixed.
	FR-02	In the table reporting the new legend is not present the 'No Data' class (0 value).	Section 2	Updated Table 1.

Contents

1 Introduction

1.1 Executive summary

The Product Validation and Intercomparison Report (PVIR) is a living document that describes and presents all activities aimed at evaluating the quality of the various CCI HRLC products and at comparing them to existing LC maps.

The quality assessments included in the present document are first made on **RR prototypes** whose areas correspond to one S2 tile for Africa (T37PCP), two for Amazonia (21KUQ and 21KXT) and one for Siberia (42WXS). A first delivery was done in July 2020 but the SAR S1 prototypes for Siberia and Amazonia had smaller area than other prototypes. Therefore, these prototypes were updated 02/10/2020 and 09/10/2020 respectively. While fusion products were updated on 10/10/2020 for MRF algorithm, and 15/10/2020 for LOGP algorithm. Some of the analyses were already done by the time the problem with SAR S1 size was noticed and were not repeated. The quality of all RR prototypes have been evaluated qualitatively and the Africa RR prototypes were quantitatively assessed.

Second, **static land cover maps over a "zoom area"** were made available on 21/10/2020 for Amazonia and Siberia. The PVIR includes their qualitative assessment and reports about the improvements brought from the RR stage to these LC maps classified at a larger extent.

Inter-comparison was done for all the products available at the time of the document conclusion. However, problem of SAR S1 size affected the RR products inter-comparison in case of 21KUQ and 21KXT tiles. Additional details are provided in Section 4.1.

Regarding the second production, the products were delivered on the following dates. The static map for Siberia was provided initially on 04/02/2022, but the reprocessed and final version was provided on 24/06/2022. The static map in Amazon was provided on 15/04/2022. The static map for Africa was provided on 18/07/2022. The first versions of historical maps for Siberia were provided on 12/08/2022, while the second and final versions of products for Siberia were provided on 22/08/2022. Historical products for Amazon were provided on 01/09/2022, and for Africa on 06/10/2022. This report refers to the final versions of products.

This document (PIVIR-Part A) only includes intercomparison analysis. For validation analysis refer to PIVIR – Part B.

1.2 Purpose and scope

The Product Validation and Intercomparison Report Part A and B give a complete report of the activities executed to assess the quality of the following CCI HR Land Cover products:

- HRLC prototypes on limited spatial extents dedicated to a Round Robin (RR) assessment.
- An HRLC map at the zoom level at a spatial resolution 10m that is a precursor to the HRLC maps at the subcontinental level.
- An HRLC map at the subcontinental level at a spatial resolution of 10m as reference static input to the climate models.
- A long-term record of regional HRLC maps at a spatial resolution of 30m in sub-regions of the static input for historical analysis every 5 years.
- The change information at 30 m and yearly scale for HRLC map update.

1.3 Applicable documents

Ref. **Title, Issue/Rev, Date, ID**

[AD1] CCI HR Technical Proposal, v1.1, 16/03/2018
[AD2] CCI Extension (CCI+) Phase 1 – New ECVs – Statement of Work, v1.3, 22/08/2017, ESA-CCI-PRGM-EOPS-SW-17-0032
[AD3] Data Standards Requirements for CCI Data Producers, v2.0, 17/09/2018, CCI-PRGM-EOPS-TN-13-0009
[AD4] CCI_HRLC_Ph1-D1.1_URD, the latest version
[AD5] CCI Extension (CCI+) Phase 1 – Product User Guide (PUG) – v2.0.3, 29/10/2022, ESA-CCI-HRLC
[AD6] CCI_HRLC_Ph1-D2.5_PVP, the latest version

1.4 Reference documents

Ref. **Title, Issue/Rev, Date, ID**

[RD1] The Global Climate Observing System: Implementation Needs, 01/10/2016, GCOS-200

[RD2] Bartsch, Annett; Widhalm, Barbara; Pointner, Georg; Ermokhina, Ksenia; Leibman, Marina; Heim, Birgit (2019): Landcover derived from Sentinel-1 and Sentinel-2 satellite data (2015-2018) for subarctic and arctic environments. Zentralanstalt für Meteorologie und Geodynamik, Wien, PANGAEA, https://doi.org/10.1594/PANGAEA.897916

1.5 Acronyms and abbreviations

AUE	Atlas of Urban Expansion
CCI	Climate Change Initiative
ESA	European space agency
FAO	Food and Agriculture Organization
FCMU – SBB	Forest Cover Monitoring Unit Foundation for Forest Management and Production Control
FNF	Forest / Non-Forest map
FROM-GLC	Finer Resolution Observation and Monitoring of Global Land Cover
GHS BU	Both GHS BU LDS and GHS BU S1
GHS BU LDS	Global Human Settlement Built-Up Grid – Landsat
GHS BU S1	Global Human Settlement Built-Up Grid – Sentinel-1
GL30	GlobeLand30
GSW	Global Surface Water
GUF	Global Urban Footprint
HR	High resolution
INPE	Brazilian National Institute for Space Research
LC	Land cover
LCC	Land cover change
LCCS	Land cover classification system
LOGP	Logarithmic opinion pool decision fusion
LSTM	Long Short-Term Memory
LSTM – MC	LSTM Monthly Composite
LSTM – TS	LSTM Time Series
MRF	Markov Random Field decision fusion
OA	Overall accuracy
PA	Producer's accuracy
PA_b	Benchmark producer's accuracy
PVIR	Product Validation and Intercomparison Report
PVP	Product Validation Plan
RF	Random Forest classification algorithm
RR	Round Robin
SVM	Support Vector Machine classification algorithm
UA	User's accuracy
UA_b	Benchmark user's accuracy
WSF	World Settlement Footprint

2 Overview of the CCI HR LC products

2.1 Overview

In the second and final production three types of land cover products were generated and validated thematically within the ESA CCI HRLC project:

- 10-m static sub-continental LC maps for the year 2019.
- 30-m regional historical (1990-2019) LC maps, generated every five years, since 1990 on reduced areas.

- 30-m land cover change detected on an annual basis on Landsat time series. It was used to backdate, on a 5-year basis back to 1990, the detailed spatio-temporal 10-m static LC map.

In the first production, there was a fourth product, 10-m Round Robin local LC prototypes for the year 2019, produced through a Round Robin (RR) exercise during which optical and SAR classifications. This product was benchmarked with the aim of selecting the best algorithm, therefore it was not included in the second production. In the first production, the historical maps for 2019 were not included.

All three types of land cover products were generated over three areas selected through key users' consultation and internal consultation regarding feasibility and needs (Figure 1). The RR sites, in gray, covered 4 Sentinel-2 (S2) tiles located in the Amazonian region (21KUQ, 21KXT), in Siberia (42WXS), and in Africa (T37PCP). The static LC maps, in green, cover the regions of Amazon, Sahel and Siberia. The historical LC maps are restricted to the orange areas. The geographical coordinates of the three regions are the following:

Amazonia:

- Static map: (23.6°S - 0°S; 42.9°W – 62.1°W)
- Historical LC and LCC map: (23.6°S – 11.7°S; 46.7°W – 62.1°W)

Sahel:

- Static map: (0.1°S – 18.1°N; 9.9°E – 43.3°E),
- Historical LC and LCC map: (3.5°N – 16.3°N; 27.0°E – 43.3°E)

Siberia:

- Static map: (51.3°N – 75.7°N; 64.4°E – 93.4°E),
- Historical LC and LCC map: (59.4°N – 73.9°N; 64.8°E – 87.4°E).

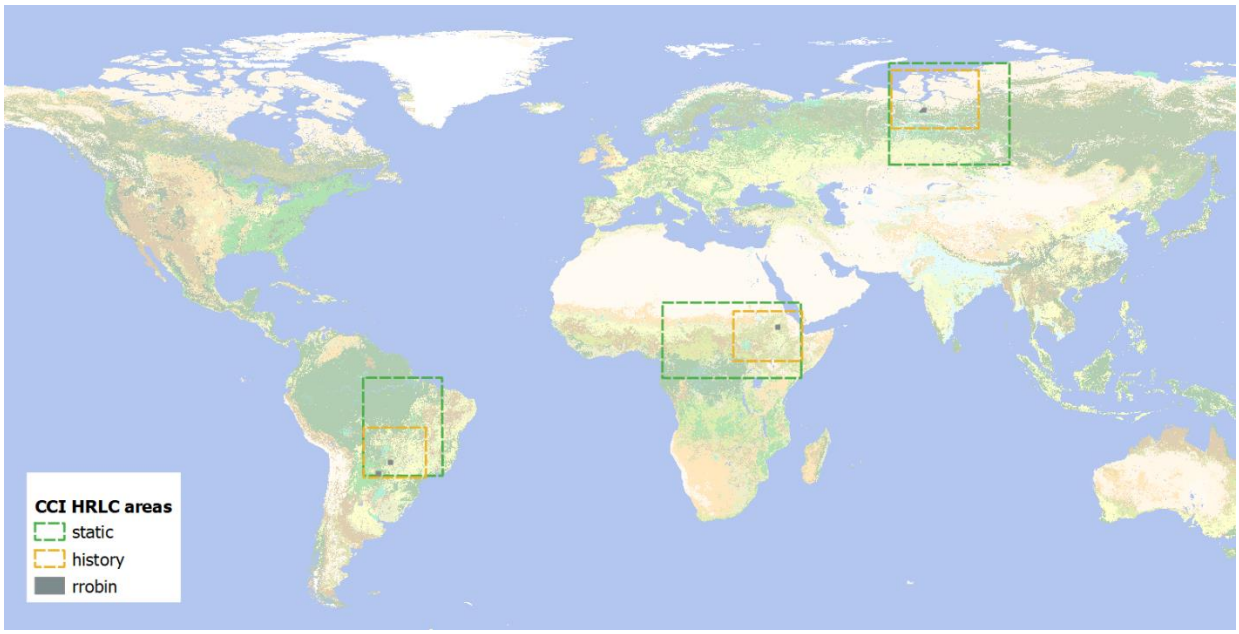

Figure 1. Final localisation of the 3 study areas for the static and historical map [AD5].

2.2 Legend

Table 1 details the levels of the land cover legend associated with the CCI HRLC products. This legend is used both for the classification of the static map and for historical maps [AD5].

Table 1. Legend for the CCI HRLC [AD5]

HRLC CLASSES			
CODE	DESCRIPTION		
0	No data		
10	Tree cover evergreen broadleaf		
20	Tree cover evergreen needleleaf		
30	Tree cover deciduous broadleaf		
40	Tree cover deciduous needleleaf		
50	Shrub cover evergreen		
60	Shrub cover deciduous		
70	Grasslands		
80	Croplands		
90	Woody vegetation aquatic or regularly flooded		
100	Grassland vegetation aquatic or regularly flooded		
110	Lichens and mosses		
120	Bare areas		
130	Built-up		
140	**Open water**	141	Open water seasonal
		142	Open water permanent
150	Permanent snow and/or ice		

3 Benchmarking with other existing products

For benchmarking, Overall accuracy (OA), Producer's accuracy (PA) and User's accuracy (UA) are computed for each RR product and static product using the existing land cover maps as a reference. Although the names of the indicators are referring to the accuracy, in case of inter-comparison they are expressing agreement between the products that are supposed to have the same accuracy/level of details. The computation is the same as for OA, PA and UA, however the existing land cover maps cannot be considered as actual reference data set and therefore they will be denoted with "b" in the subscript to refer to benchmark accuracy. The results will be shown in the separate subsections depending on if the metrics are for overall assessment or class specific. Individual accuracy indexes the classification are interpreted as "Excellent" if both scores PA_b and UA_b are above 90% % for most of the compared datasets, "Well" if the scores are between 70% and 90%, and "Relatively good" if the scores are between 50% and 70%. The classes for which individual accuracy indexes are less than 50% for most of the compared datasets are not considered in the conclusions.

3.1 RR prototypes

At the moment of inter-comparison, the delivered prototypes from the SAR chain had a defect in terms of tile size for 21KXT and 21QUQ regions – they were smaller than the prototypes from optical chain. The black area in Figure 2 represents the area that is missing – 47% in 21KXT and 38% in 21KUQ tiles - in case of RF (S1) algorithm. The discrepancy in size between SAR and optical prototypes is present also in Africa, but it is negligible. Since size discrepancy also affects fusion prototypes, correcting the defect and recomputing results would take significant amount of time, so it is omitted.

The size defect affects the possibility of comparison of prototypes from SAR processing chain (RF(S1)) results and results from the optical chain (SVM (S2)), LSTM – TS (S2), and LSTM - MC (S2)) for 21KXT and 21KUQ regions.

Despite this issue, it is possible to compare results between different prototypes derived from optical chain as well as the two fusion types. In regions 37PCP and 42WXS there are no constraints for comparison, since in these regions the size if correct.

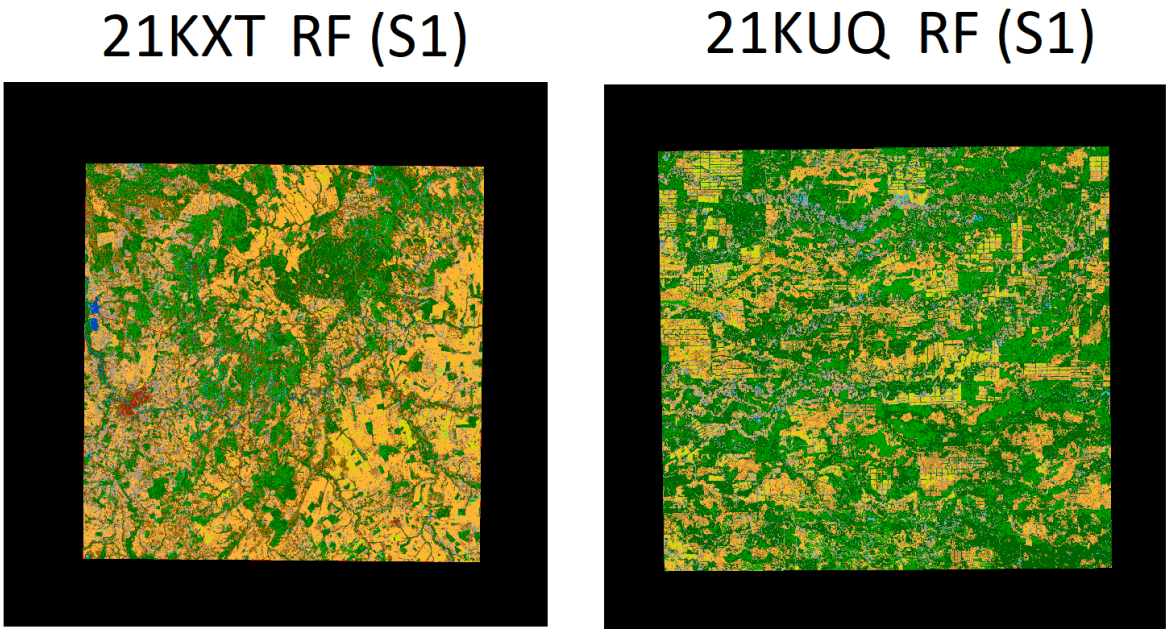

Figure 2. RF (S1) size defect illustration

3.1.1 Overall benchmark accuracy of RR products

RR products OA_b results are shown in the two tables, one classification outputs (Table 2) and one for fusion outputs (Table 3).

In Table 2 coloured values represent the highest scores among different algorithms. In case of 21KXT and 21KUQ only optical algorithms – SVM, LSTM-TS and LSTM – MC - were compared and the highest score is highlighted

with red colour. For 37PCP and 42WXS all algorithms, including RF (S1), were compared and the highest one is emphasised in green.

Table 2. Overall accuracy for SAR and optical processing chain RR prototypes

RR tile	Algorithm	FNF	FROM-GLC	GHS BU S1	GL30	GSW seasonality	GSW_v1_2	MapBiomas	ESA DUE GlobPermafrost
21KUQ	RF (S1)	69%	51%	100%	50%	100%	100%		
	SVM (S2)	55%	51%	100%	54%	99%	99%		
	LSTM - TS (S2)	61%	47%	99%	51%	98%	98%		
	LSTM - MC (S2)	58%	47%	100%	53%	98%	98%		
21KXT	RF (S1)	77%	50%	98%	23%	99%	99%	49%	
	SVM (S2)	84%	52%	100%	36%	100%	99%	52%	
	LSTM - TS (S2)	83%	44%	99%	32%	99%	99%	43%	
	LSTM - MC (S2)	84%	48%	99%	34%	99%	99%	47%	
37PCP	RF (S1)	89%	54%	88%	56%	99%	99%		
	SVM (S2)	93%	60%	98%	58%	99%	99%		
	LSTM - TS (S2)	91%	55%	96%	51%	98%	98%		
	LSTM - MC (S2)	92%	58%	97%	53%	98%	98%		
42WXS	RF (S1)	80%	41%	100%	38%	95%	94%		28%
	SVM (S2)	75%	35%	100%	36%	93%	93%		35%
	LSTM - TS (S2)	77%	37%	100%	36%	95%	95%		40%

In Table 3 better performance of different fusion algorithms is highlighted in orange colour.

Table 3. Overall accuracy for fusion RR prototypes

RR tile	Algorithm	FNF	FROM-GLC	GHS BU S1	GL30	GSW seasonality	GSW_v1_2	MapBiomas	ESA DUE Glob-Permafrost
21KUQ	LOGP	56%	53%	100%	54%	99%	99%		
	MRF	56%	53%	100%	54%	99%	99%		
21KXT	LOGP	85%	55%	100%	36%	99%	99%	54%	
	MRF	85%	56%	100%	36%	100%	99%	55%	
37PCP	LOGP	92%	61%	97%	60%	99%	99%		
	MRF	93%	62%	98%	61%	99%	99%		
42WXS	LOGP	78%	38%	100%	39%	95%	94%		31%
	MRF	78%	35%	100%	40%	95%	94%		33%

OA_b results were used to calculate the yield from fusion. The fusion algorithm with better performance MRF was compared to RF and SVM algorithms since these are the two algorithms involved in the fusion. Comparison is done by mean of difference shown in the Table 4 where positive yield is highlighted in green and negative in red.

Table 4. Yield from fusion

RR tile	Comparison	FNF	FROM GLC	GHS BU S1	GL30	GSW seasonality	GSW_v1_2	MapBiomas	ESA DUE Glob-Permafrost
37PCP	MRF-RF	4%	8%	10%	5%	0%	0%	0%	0%

	MRF-SVM	0%	2%	0%	3%	0%	0%	0%	0%
42WXS	MRF-RF	-2%	-6%	0%	2%	0%	0%	0%	5%
	MRF-SVM	3%	0%	0%	4%	2%	1%	0%	-2%

3.1.2 Per class benchmark accuracies – Producer's accuracy (PA_b) and User's accuracy (UA_b) – RR products

In this section results of UA_b and PA_b for RR products are presented. The results are organized in the tables where each table consists of results for two types of algorithms for producing RR products for single RR region as follows:

- Table 5. UA_b and PA_b for Amazon 21KUQ – RF (S1) and SVM (S2) algorithms
- Table 6. UA_b and PA_b for Amazon 21KUQ – LOGP and MRF decision fusion algorithms
- Table 7. UA_b and PA_b for Amazon 21KUQ – LSTM - TS (S2) and LSTM - MC (S2) algorithms
- Table 8. UA_b and PA_b for Amazon 21KXT – RF (S1) and SVM (S2)
- Table 9. UA_b and PA_b for Amazon 21KXT – LOGP and MRF decision fusion algorithms
- Table 10. UA_b and PA_b for Amazon 21KXT – LSTM - TS (S2) and LSTM - MC (S2) algorithms
- Table 11. UA_b and PA_b for Africa 37PCP – RF (S1) and SVM (S2) algorithms

- Table 12. UA_b and PA_b Africa 37PCP – LOGP and MRF decision fusion algorithms
- Table 13. UA_b and PA_b for Africa 37PCP – LSTM - TS (S2) and LSTM - MC (S2) algorithms
- Table 14. UA_b and PA_b for Siberia 42WXS – RF (S1) and SVM (S2) algorithms – part 1
- Table 15. UAb and PAb for Siberia 42WXS – RF (S1) and SVM (S2) algorithms – part 2
- Table 16. UA_b and PA_b for Siberia 42WXS – LOGP and MRF decision fusion algorithms – part 1
- Table 17. UA_b and PA_b for Siberia 42WXS – LOGP and MRF decision fusion algorithms – part 2
- Table 18. UA_b and PA_b for Siberia 42WXS – LSTM – TS

In these tables the UA_b and PA_b scores above 50% are highlighted in red as this amount of agreement with existing data can be considered more than random.

Furthermore, average of UA_b and PA_b was computed for summarizing numerous results and determining best performing algorithm. For comparison purposes average value for each of the indexes is separately shown for fusion algorithms and for classification algorithms as follows:

- Table 19. Average UA_b per fusion algorithm and RR region
- Table 20. Average UA_b per classification algorithm and RR region
- Table 21. Average PA_b per fusion algorithm and RR region
- Table 22. Average PA_b per classification algorithm and RR region
- Table 23. Mean and standard deviation of UA and PA of SVM algorithm

In Tables Table 19-Table 22 the highest score among algorithms is highlighted in yellow. Furthermore, last rows of the table highlighted in orange contain count of number of times when algorithm was better than the others.

3.1.2.1 Table 5. UA_b and PA_b for Amazon 21KUQ – RF (S1) and SVM (S2) algorithms

Algorithm	Dataset	Index	Bareland	Built-up	Cropland	Forest	Grassland	Shrubland	Water	Water Permanent	Water Seasonal	Wetland
RF (S1) 21 KUQ	GL30	PA_b	55%	2%	21%	82%	20%	21%	22%			1%
		UA_b	0%	0%	74%	70%	23%	24%	37%			14%
	FROM-GLC	PA_b	26%	4%	32%	92%	24%	15%	67%			4%
		UA_b	0%	0%	5%	66%	88%	13%	16%			14%
	FNF	PA_b				57%			1%			
		UA_b				46%			1%			
	GSW seasonality	PA_b								0%	7%	
		UA_b								1%	19%	
	GSW_v1_2	PA_b								0%	8%	
		UA_b								0%	35%	
	GHS BU S1	PA_b		0%								
		UA_b		0%								
SVM (S2) 21KUQ	GL30	PA_b	64%	3%	30%	92%	20%	6%	53%			4%
		UA_b	0%	9%	73%	64%	22%	20%	16%			17%
	FROM-GLC	PA_b	54%	8%	42%	96%	24%	3%	88%			10%
		UA_b	0%	5%	6%	57%	89%	7%	12%			9%
	FNF	PA_b				95%			90%			
		UA_b				39%			10%			
	GSW seasonality	PA_b								74%	7%	
		UA_b								10%	24%	
	GSW_v1_2	PA_b								81%	8%	
		UA_b								10%	42%	
	GHS BU S1	PA_b		10%								
		UA_b		2%								

3.1.2.2 Table 6. UA_b and PA_b for Amazon 21KUQ – LOGP and MRF decision fusion algorithms

Algorithm	Dataset	Index	Bareland	Built-up	Cropland	Forest	Grassland	Shrubland	Water	Water Permanent	Water Seasonal	Wetland
LOGP 21 KUQ	GL30	PA_b	69%	3%	28%	92%	24%	7%	51%			4%
		UA_b	0%	13%	73%	65%	23%	22%	24%			25%
	FROM-GLC	PA_b	54%	7%	42%	96%	27%	4%	89%			9%
		UA_b	0%	7%	6%	57%	90%	8%	18%			13%
	FNF	PA_b				95%			89%			
		UA_b				39%			15%			
	GSW seasonality	PA_b								73%	8%	
		UA_b								16%	24%	
	GSW_v1_2	PA_b								81%	8%	
		UA_b								15%	42%	
	GHS BU S1	PA_b		10%								
		UA_b		3%								
MRF 21 KUQ	GL30	PA_b	72%	2%	28%	92%	24%	7%	51%			4%
		UA_b	0%	14%	73%	65%	23%	22%	25%			25%
	FROM-GLC	PA_b	53%	6%	43%	97%	27%	3%	89%			9%
		UA_b	0%	8%	6%	57%	90%	8%	19%			13%
	FNF	PA_b				95%			90%			
		UA_b				39%			16%			
	GSW seasonality	PA_b								74%	7%	
		UA_b								17%	23%	
	GSW_v1_2	PA_b								81%	8%	
		UA_b								16%	42%	
	GHS BU S1	PA_b		8%								
		UA_b		3%								

3.1.2.3 Table 7. UA_b and PA_b for Amazon 21KUQ – LSTM - TS (S2) and LSTM - MC (S2) algorithms

Algorithm	Dataset	Index	Bareland	Built-up	Cropland	Forest	Grassland	Shrubland	Water	Water Permanent	Water Seasonal	Wetland
LSTM - MC (S2) 21 KUQ	GL30	PA_b	62%	13%	30%	90%	12%	16%	62%			4%
		UA_b	0%	4%	76%	66%	22%	19%	12%			13%
	FROM-GLC	PA_b	42%	24%	42%	95%	14%	9%	94%			10%
		UA_b	0%	2%	6%	59%	90%	8%	8%			6%
	FNF	PA_b				94%			93%			
		UA_b				41%			6%			
	GSW seasonality	PA_b								65%	23%	
		UA_b								6%	27%	
	GSW_v1_2	PA_b								74%	23%	
		UA_b								6%	44%	
	GHS BU S1	PA_b		24%								
		UA_b		0%								
LSTM - TS (S2) 21 KUQ	GL30	PA_b	42%	29%	26%	86%	14%	19%	57%			6%
		UA_b	0%	2%	75%	68%	23%	19%	14%			13%
	FROM-GLC	PA_b	8%	66%	37%	93%	15%	15%	94%			13%
		UA_b	0%	1%	6%	62%	86%	11%	10%			6%
	FNF	PA_b				91%			91%			
		UA_b				42%			8%			
	GSW seasonality	PA_b								65%	24%	
		UA_b								8%	26%	
	GSW_v1_2	PA_b								73%	23%	
		UA_b								7%	42%	
	GHS BU S1	PA_b		51%								
		UA_b		0%								

3.1.2.4 Table 8. UA_b and PA_b for Amazon 21KXT – RF (S1) and SVM (S2)

Algorithm	Dataset	Index	Bareland	Built-up	Cropland	Forest	Grassland	Shrubland	Water	Water Permanent	Water Seasonal	Wetland	Wetland Herbaceous
RF (S1) 21 KXT	GL30	PA_b	0%	45%	4%	74%	11%	25%	64%			1%	
		UA_b	0%	6%	97%	60%	0%	8%	27%			4%	
	FROM-GLC	PA_b	27%	51%	9%	79%	39%	37%	88%			12%	
		UA_b	0%	3%	4%	77%	98%	8%	23%			12%	
	MapBiomas	PA_b	0%	60%	18%	76%	38%	28%	81%				5%
		UA_b	0%	5%	3%	76%	98%	5%	22%				4%
	FNF	PA_b				41%			5%				
		UA_b				80%			5%				
	GSW seasonality	PA_b								58%	22%		
		UA_b								35%	6%		
	GSW_v1_2	PA_b								64%	17%		
		UA_b								27%	10%		
	GHS BU S1	PA_b		56%									
		UA_b		4%									
SVM (S2) 21 KXT	GL30	PA_b	0%	29%	25%	79%	41%	13%	39%			18%	
		UA_b	0%	21%	91%	55%	4%	8%	28%			36%	
	FROM-GLC	PA_b	17%	40%	47%	86%	40%	24%	71%			61%	
		UA_b	0%	16%	4%	74%	94%	9%	30%			16%	
	MapBiomas	PA_b	1%	42%	65%	83%	40%	17%	59%				56%
		UA_b	0%	18%	3%	73%	95%	5%	22%				23%
	FNF	PA_b				76%			4%				
		UA_b				76%			4%				
	GSW seasonality	PA_b								70%	18%		
		UA_b								36%	5%		
	GSW_v1_2	PA_b								77%	14%		
		UA_b								27%	10%		
	GHS BU S1	PA_b		36%									
		UA_b		12%									

3.1.2.5 Table 9. UA_b and PA_b for Amazon 21KXT – LOGP and MRF decision fusion algorithms

Algorithm	Dataset	Index	Bareland	Built-up	Cropland	Forest	Grassland	Shrubland	Water	Water Permanent	Water Seasonal	Wetland	Wetland Herbaceous
LOGP 21KXT	GL30	PA_b	0%	40%	24%	81%	43%	12%	41%			19%	
		UA_b	0%	27%	91%	56%	4%	8%	25%			35%	
	FROM-GLC	PA_b	20%	51%	50%	88%	43%	23%	74%			61%	
		UA_b	0%	19%	4%	75%	95%	9%	25%			15%	
	MapBiomas	PA_b	0%	58%	68%	85%	43%	16%	63%				56%
		UA_b	0%	24%	3%	74%	96%	5%	20%				22%
	FNF	PA_b				78%			4%				
		UA_b				77%			4%				
	GSW seasonality	PA_b								71%	20%		
		UA_b								35%	5%		
	GSW_v1_2	PA_b								77%	16%		
		UA_b								27%	9%		
	GHS BU S1	PA_b		50%									
		UA_b		16%									
MRF 21 KXT	GL30	PA_b	0%	42%	24%	82%	45%	11%	41%			19%	
		UA_b	0%	31%	92%	56%	4%	8%	29%			35%	
	FROM-GLC	PA_b	19%	53%	50%	89%	45%	22%	74%			61%	
		UA_b	0%	22%	4%	75%	95%	10%	30%			16%	
	MapBiomas	PA_b	0%	61%	69%	86%	44%	15%	63%				57%
		UA_b	0%	28%	3%	75%	96%	5%	23%				23%
	FNF	PA_b				79%			4%				
		UA_b				77%			4%				
	GSW seasonality	PA_b								71%	19%		
		UA_b								37%	5%		
	GSW_v1_2	PA_b								78%	14%		
		UA_b								28%	10%		
	GHS BU S1	PA_b		53%									
		UA_b		19%									

3.1.2.6 Table 10. UA_b and PA_b for Amazon 21KXT – LSTM - TS (S2) and LSTM - MC (S2) algorithms

Algorithm	Dataset	Index	Bareland	Built-up	Cropland	Forest	Grassland	Shrubland	Water	Water Permanent	Water Seasonal	Wetland	Wetland Herbaceous
LSTM - MC (S2) 21 KXT	GL30	PA_b	0%	39%	22%	76%	35%	16%	50%			21%	
		UA_b	0%	10%	92%	57%	4%	8%	15%			35%	
	FROM-GLC	PA_b	14%	51%	38%	84%	33%	29%	83%			55%	
		UA_b	0%	7%	4%	78%	94%	9%	15%			12%	
	MapBiomas	PA_b	3%	55%	51%	81%	33%	22%	72%				58%
		UA_b	0%	9%	3%	77%	95%	5%	11%				20%
	FNF	PA_b				73%			5%				
		UA_b				78%			2%				
	GSW seasonality	PA_b								83%	13%		
		UA_b								20%	2%		
	GSW_v1_2	PA_b								88%	11%		
		UA_b								15%	3%		
	GHS BU S1	PA_b		47%									
		UA_b		6%									
LSTM - TS (S2) 21 KXT	GL30	PA_b	0%	41%	19%	73%	32%	17%	50%			20%	
		UA_b	0%	11%	92%	56%	4%	7%	12%			34%	
	FROM-GLC	PA_b	16%	54%	37%	81%	28%	31%	82%			53%	
		UA_b	0%	8%	4%	76%	95%	8%	12%			12%	
	MapBiomas	PA_b	3%	57%	50%	78%	28%	23%	73%				56%
		UA_b	0%	9%	3%	75%	95%	4%	9%				20%
	FNF	PA_b				71%			5%				
		UA_b				78%			2%				
	GSW seasonality	PA_b								76%	26%		
		UA_b								28%	2%		
	GSW_v1_2	PA_b								83%	22%		
		UA_b								21%	4%		
	GHS BU S1	PA_b		49%									
		UA_b		6%									

3.1.2.7 Table 11. UA_b and PA_b for Africa 37PCP – RF (S1) and SVM (S2) algorithms

Algorithm	Dataset	Index	Bareland	Built-up	Cropland	Forest	Grassland	Shrubland	Water	Water Permanent	Water Seasonal	Wetland
RF (S1) 37PCP	GL30	PA_b	0%	58%	53%	41%	13%	4%	99%			31%
		UA_b	0%	2%	88%	22%	12%	2%	96%			25%
	FROM-GLC	PA_b	23%	85%	55%	59%	13%	7%	100%			8%
		UA_b	2%	0%	87%	5%	7%	28%	96%			4%
	FNF	PA_b				26%			100%			
		UA_b				12%			95%			
	GSW seasonality	PA_b								97%	80%	
		UA_b								100%	25%	
	GSW_v1_2	PA_b								97%	66%	
		UA_b								100%	33%	
	GHS BU S1	PA_b		84%								
		UA_b		0%								
SVM (S2) 37PCP	GL30	PA_b	0%	46%	53%	32%	34%	8%	99%			36%
		UA_b	0%	10%	89%	27%	18%	1%	98%			25%
	FROM-GLC	PA_b	53%	92%	56%	89%	42%	30%	100%			10%
		UA_b	17%	0%	89%	13%	14%	33%	97%			4%
	FNF	PA_b				27%			100%			
		UA_b				21%			96%			
	GSW seasonality	PA_b								96%	90%	
		UA_b								100%	29%	
	GSW_v1_2	PA_b								96%	75%	
		UA_b								100%	39%	
	GHS BU S1	PA_b		72%								
		UA_b		2%								

3.1.2.8 Table 12. UA_b and PA_b Africa 37PCP – LOGP and MRF decision fusion algorithms

Algorithm	Dataset	Index	Bareland	Built-up	Cropland	Forest	Grassland	Shrubland	Water	Water Permanent	Water Seasonal	Wetland
LOGP 37PCP	GL30	PA_b	0%	50%	56%	35%	32%	7%	99%			38%
		UA_b	0%	9%	89%	29%	18%	1%	98%			32%
	FROM-GLC	PA_b	52%	95%	59%	90%	38%	28%	100%			10%
		UA_b	19%	0%	89%	13%	13%	34%	97%			5%
	FNF	PA_b				28%			100%			
		UA_b				21%			96%			
	GSW seasonality	PA_b								97%	91%	
		UA_b								100%	34%	
	GSW_v1_2	PA_b								98%	77%	
		UA_b								100%	47%	
	GHS BU S1	PA_b		77%								
		UA_b		2%								
MRF 37PCP	GL30	PA_b	0%	52%	57%	36%	32%	6%	99%			38%
		UA_b	0%	11%	89%	30%	18%	1%	98%			32%
	FROM-GLC	PA_b	53%	96%	60%	91%	38%	28%	100%			10%
		UA_b	19%	0%	89%	13%	13%	35%	97%			5%
	FNF	PA_b				28%			100%			
		UA_b				22%			96%			
	GSW seasonality	PA_b								97%	92%	
		UA_b								100%	35%	
	GSW_v1_2	PA_b								98%	77%	
		UA_b								100%	47%	
	GHS BU S1	PA_b		79%								
		UA_b		2%								

3.1.2.9 Table 13. UA_b and PA_b for Africa 37PCP – LSTM - TS (S2) and LSTM - MC (S2) algorithms

Algorithm	Dataset	Index	Bareland	Built-up	Cropland	Forest	Grassland	Shrubland	Water	Water Permanent	Water Seasonal	Wetland
LSTM - MC (S2) 37PCP	GL30	PA_b	0%	47%	47%	31%	24%	13%	99%			50%
		UA_b	0%	7%	90%	24%	18%	1%	98%			17%
	FROM-GLC	PA_b	61%	91%	49%	91%	35%	44%	100%			17%
		UA_b	11%	0%	90%	12%	16%	29%	97%			3%
	FNF	PA_b				27%			100%			
		UA_b				19%			96%			
	GSW seasonality	PA_b								93%	84%	
		UA_b								100%	19%	
	GSW_v1_2	PA_b								93%	70%	
		UA_b								100%	25%	
	GHS BU S1	PA_b		71%								
		UA_b		2%								
LSTM - TS (S2) 37PCP	GL30	PA_b	0%	49%	43%	35%	22%	20%	99%			47%
		UA_b	0%	6%	90%	22%	16%	1%	97%			13%
	FROM-GLC	PA_b	60%	91%	46%	92%	31%	40%	100%			13%
		UA_b	14%	0%	92%	10%	13%	27%	97%			2%
	FNF	PA_b				30%			100%			
		UA_b				18%			96%			
	GSW seasonality	PA_b								94%	88%	
		UA_b								100%	20%	
	GSW_v1_2	PA_b								94%	75%	
		UA_b								100%	28%	
	GHS BU S1	PA_b		72%								
		UA_b		1%								

3.1.2.10 Table 14. UA_b and PA_b for Siberia 42WXS – RF (S1) and SVM (S2) algorithms – part 1

Algorithm	Dataset	Index	Bareland	Built-up	Forest	Forest deciduous broadleaf	Forest evergreen needleleaf	Grassland	Lichens and Mosses
RF (S1) 42WXS	FROM-GLC	PA_b	47%	0%	77%			24%	5%
		UA_b	9%	0%	90%			73%	5%
	ESA DUE GlobPermafrost	PA_b	22%			4%	33%	46%	53%
		UA_b	17%			5%	35%	12%	0%
	GL30	PA_b	29%	0%	40%			10%	0%
		UA_b	3%	0%	88%			4%	0%
	FNF	PA_b			75%				
		UA_b			66%				
	GSW seasonality	PA_b							
		UA_b							
	GSW_v1_2	PA_b							
		UA_b							
	GHS BU S1	PA_b		0%					
		UA_b		0%					
SVM (S2) 42WXS	FROM-GLC	PA_b	58%	0%	69%			16%	5%
		UA_b	19%	0%	79%			84%	6%
	ESA DUE GlobPermafrost	PA_b	1%			2%	25%	84%	89%
		UA_b	2%			2%	35%	31%	2%
	GL30	PA_b	80%	0%	37%			6%	0%
		UA_b	14%	0%	80%			4%	0%
	FNF	PA_b			66%				
		UA_b			57%				
	GSW seasonality	PA_b							
		UA_b							
	GSW_v1_2	PA_b							
		UA_b							
	GHS BU S1	PA_b		0%					
		UA_b		0%					

3.1.2.11 Table 15. UA_b and PA_b for Siberia 42WXS – RF (S1) and SVM (S2) algorithms – part 2

Algorithm	Dataset	Index	Permanent ice and snow	Shrubland	Shrubland evergreen	Water	Water Permanent	Water Seasonal	Wetland
RF (S1) 42WXS	FROM-GLC	PA_b	0%	53%		92%			40%
		UA_b	0%	1%		63%			13%
	ESA DUE GlobPermafrost	PA_b			19%		61%	38%	28%
		UA_b			58%		96%	29%	22%
	GL30	PA_b		0%		88%			33%
		UA_b		0%		63%			76%
	FNF	PA_b				53%			
		UA_b				40%			
	GSW seasonality	PA_b					63%	45%	
		UA_b					93%	16%	
	GSW_v1_2	PA_b					62%	33%	
		UA_b					96%	12%	
	GHS BU S1	PA_b							
		UA_b							
SVM (S2) 42WXS	FROM-GLC	PA_b	0%	43%		96%			50%
		UA_b	0%	0%		56%			15%
	ESA DUE GlobPermafrost	PA_b			25%		56%	47%	49%
		UA_b			62%		88%	25%	33%
	GL30	PA_b		0%		89%			30%
		UA_b		0%		55%			61%
	FNF	PA_b				53%			
		UA_b				34%			
	GSW seasonality	PA_b					55%	40%	
		UA_b					82%	11%	
	GSW_v1_2	PA_b					55%	34%	
		UA_b					86%	9%	
	GHS BU S1	PA_b							
		UA_b							

3.1.2.12 Table 16. UA_b and PA_b for Siberia 42WXS – LOGP and MRF decision fusion algorithms – part 1

Algorithm	Dataset	Index	Bareland	Built-up	Forest	Forest deciduous broadleaf	Forest evergreen needleleaf	Grassland	Lichens and Mosses
LOGP 42WXS	FROM-GLC	PA_b	59%	0%	74%			18%	3%
		UA_b	8%	11%	90%			78%	4%
	ESA DUE GlobPermafrost	PA_b	3%			6%	13%	64%	64%
		UA_b	2%			5%	24%	20%	1%
	GL30	PA_b	81%	23%	39%			7%	0%
		UA_b	15%	23%	87%			4%	0%
	FNF	PA_b			71%				
		UA_b			65%				
	GSW seasonality	PA_b							
		UA_b							
	GSW_v1_2	PA_b							
		UA_b							
	GHS BU S1	PA_b		34%					
		UA_b		9%					
MRF 42WXS	FROM-GLC	PA_b	58%	29%	72%			15%	2%
		UA_b	10%	4%	88%			79%	3%
	ESA DUE GlobPermafrost	PA_b	3%			9%	6%	66%	66%
		UA_b	2%			6%	20%	25%	1%
	GL30	PA_b	81%	23%	38%			6%	0%
		UA_b	7%	23%	87%			4%	0%
	FNF	PA_b			68%				
		UA_b			63%				
	GSW seasonality	PA_b							
		UA_b							
	GSW_v1_2	PA_b							
		UA_b							
	GHS BU S1	PA_b		35%					
		UA_b		9%					

3.1.2.13 Table 17. UA_b and PA_b for Siberia 42WXS – LOGP and MRF decision fusion algorithms – part 2

Algorithm	Dataset	Index	Permanent ice and snow	Shrubland	Shrubland evergreen	Water	Water Permanent	Water Seasonal	Wetland
LOGP 42WXS	FROM-GLC	PA_b	0%	59%		97%			46%
		UA_b	0%	1%		58%			13%
	ESA DUE GlobPermafrost	PA_b			23%		68%	58%	38%
		UA_b			64%		97%	38%	24%
	GL30	PA_b		0%		93%			36%
		UA_b		0%		58%			72%
	FNF	PA_b				57%			
		UA_b				37%			
	GSW seasonality	PA_b					70%	59%	
		UA_b					96%	17%	
	GSW_v1_2	PA_b					68%	47%	
		UA_b					99%	14%	
	GHS BU S1	PA_b							
		UA_b							
MRF 42WXS	FROM-GLC	PA_b	0%	58%		97%			50%
		UA_b	0%	0%		58%			13%
	ESA DUE GlobPermafrost	PA_b			25%		68%	59%	44%
		UA_b			65%		98%	38%	24%
	GL30	PA_b		0%		94%			39%
		UA_b		0%		58%			69%
	FNF	PA_b				57%			
		UA_b				37%			
	GSW seasonality	PA_b					70%	60%	
		UA_b					96%	17%	
	GSW_v1_2	PA_b					68%	48%	
		UA_b					99%	14%	
	GHS BU S1	PA_b							
		UA_b							

3.1.2.14 Table 18. UA_b and PA_b for Siberia 42WXS – LSTM – TS algorithm

Algorithm	Dataset	Index	Bareland	Built-up	Forest	Forest deciduous broadleaf	Forest evergreen needleleaf	Grassland	Lichens and Mosses	Permanent ice and snow	Shrubland	Shrubland evergreen	Water	Water Permanent	Water Seasonal	Wetland
LSTM - TS (S2) 42WXS	FROM-GLC	PA_b	57%	0%	79%			14%	6%	0%	49%		98%			50%
		UA_b	8%	0%	84%			87%	6%	0%	0%		57%			20%
	ESA DUE GlobPermafrost	PA_b	1%			3%	14%	84%	92%			31%		90%	58%	48%
		UA_b	1%			2%	26%	35%	2%			67%		92%	58%	42%
	GL30	PA_b	78%	0%	42%			4%	0%		13%		93%			25%
		UA_b	6%	0%	84%			3%	0%		0%		57%			71%
	FNF	PA_b			74%								57%			
		UA_b			59%								36%			
	GSW seasonality	PA_b												88%	43%	
		UA_b												86%	17%	
	GSW_v1_2	PA_b												87%	42%	
		UA_b												90%	17%	
	GHS BUS1	PA_b		0												
		UA_b		0%												

3.1.2.15 Table 19. Average UA_b per fusion algorithm and RR region

Algorithm	RR tile	Bareland	Built-up	Cropland	Forest	Forest deciduous broadleaf	Forest evergreen needleleaf	Grassland	Lichens and Mosses	Permanent ice and snow	Shrubland	Shrubland evergreen	Water	Water permanent	Water seasonal	Wetland	Wetland Herbaceous
MRF	21KUQ	0	0.08	0.4	0.54			0.57			0.15		0.2	0.16	0.32	0.19	
LOGP	21KUQ	0	0.08	0.4	0.54			0.57			0.15		0.19	0.16	0.33	0.19	
MRF	21KXT	0	0.25	0.33	0.71			0.65			0.08		0.22	0.32	0.08	0.26	0.23
LOGP	21KXT	0	0.22	0.33	0.7			0.65			0.07		0.18	0.31	0.07	0.25	0.22
MRF	37PCP	0.1	0.04	0.89	0.22			0.15			0.18		0.97	1	0.41	0.18	
LOGP	37PCP	0.1	0.04	0.89	0.21			0.15			0.18		0.97	1	0.4	0.18	
MRF	42WXS	0.06	0.12		0.79	0.06	0.2	0.36	0.01	0	0	0.65	0.51	0.98	0.23	0.35	
LOGP	42WXS	0.05	0.12		0.81	0.05	0.24	0.34	0.02	0	0	0.64	0.51	0.97	0.23	0.36	
MRF	39	2	4	3	3	1	0	4	1	1	3	1	4	4	4	3	1
LOGP	26	1	1	3	3	0	1	2	1	1	3	0	2	2	2	4	0

3.1.2.16 Table 20. Average UA_b per classification algorithm and RR region

Algorithm	RR tile	Bareland	Built-up	Cropland	Forest	Forest deciduous broadleaf	Forest evergreen needleleaf	Grassland	Lichens and Mosses	Permanent ice and snow	Shrubland	Shrubland evergreen	Water	Water permanent	Water seasonal	Wetland	Wetland Herbaceous
LSTM - MC (S2)	21KUQ	0	0.02	0.41	0.56			0.56			0.13		0.09	0.06	0.36	0.1	
RF (S1)	21KUQ	0	0	0.39	0.61			0.55			0.18		0.18	0.01	0.27	0.14	
SVM (S2)	21KUQ	0	0.05	0.4	0.53			0.56			0.14		0.13	0.1	0.33	0.13	
LSTM - TS (S2)	21KUQ	0	0.01	0.4	0.57			0.55			0.15		0.11	0.07	0.34	0.1	
LSTM - MC (S2)	21KXT	0	0.08	0.33	0.73			0.64			0.07		0.11	0.18	0.02	0.24	0.2
RF (S1)	21KXT	0	0.04	0.35	0.73			0.65			0.07		0.19	0.31	0.08	0.08	0.04
SVM (S2)	21KXT	0	0.17	0.33	0.70			0.65			0.07		0.21	0.32	0.08	0.26	0.23
LSTM - TS (S2)	21KXT	0	0.08	0.33	0.71			0.64			0.06		0.09	0.24	0.03	0.23	0.2
LSTM - MC (S2)	37PCP	0.06	0.03	0.9	0.19			0.17			0.15		0.97	1	0.22	0.1	
RF (S1)	37PCP	0.01	0.01	0.88	0.13			0.1			0.15		0.96	1	0.29	0.14	
SVM (S2)	37PCP	0.09	0.04	0.89	0.2			0.16			0.17		0.97	1	0.34	0.15	
LSTM - TS (S2)	37PCP	0.08	0.02	0.91	0.17			0.15			0.14		0.97	1	0.24	0.08	
RF (S1)	42WXS	0.1	0		0.81	0.05	0.35	0.3	0.02	0	0	0.58	0.56	0.95	0.19	0.37	
SVM (S2)	42WXS	0.12	0		0.72	0.02	0.35	0.4	0.03	0	0	0.62	0.48	0.85	0.14	0.36	
LSTM - TS (S2)	42WXS	0.05	0.25		0.76	0.02	0.26	0.42	0.03	0	0	0.67	0.5	0.89	0.31	0.44	
LSTM - MC (S2)	6			2	1			1			1				1		
LSTM - TS (S2)	18		1	1	2	1		3	1	1	1	1	2	2	1	1	
SVM (S2)	23	1	3	2		1	1	2	1	1	1		3	3	1	2	1

3.1.2.17 Table 21. Average PA_b per fusion algorithm and RR region

Algorithm	RR tile	Bareland	Built-up	Cropland	Forest	Forest deciduous broadleaf	Forest evergreen needleleaf	Grassland	Lichens and Mosses	Permanent ice and snow	Shrubland	Shrubland evergreen	Water	Water permanent	Water seasonal	Wetland	Wetland Herbaceous
MRF		0.62	0.05	0.36	0.95			0.26			0.05		0.77	0.78	0.08	0.06	
LOGP	21KUQ	0.62	0.07	0.35	0.94			0.26			0.06		0.76	0.77	0.08	0.06	
MRF		0.06	0.52	0.48	0.84			0.45			0.16		0.45	0.74	0.16	0.4	0.57
LOGP	21KXT	0.07	0.5	0.47	0.83			0.43			0.17		0.45	0.74	0.18	0.4	0.56
MRF		0.26	0.76	0.58	0.52			0.35			0.17		1	0.98	0.84	0.24	
LOGP	37PCP	0.26	0.74	0.57	0.51			0.35			0.18		1	0.98	0.84	0.24	
MRF		0.47	0.29		0.59	0.09	0.06	0.29	0.23	0	0.29	0.25	0.83	0.69	0.56	0.44	
LOGP	42WXS	0.47	0.28		0.61	0.06	0.13	0.3	0.22	0	0.3	0.23	0.82	0.69	0.55	0.4	
MRF	36	4	3	3	3	1	0	3	1	0	2	1	4	3	3	4	1
LOGP	23	2	1	0	1	0	1	2	0	0	4	0	3	4	2	3	0

3.1.2.18 Table 22. Average PA_b per classification algorithm and RR region

Algorithm	RR tile	Bareland	Built-up	Cropland	Forest	Forest deciduous broadleaf	Forest evergreen needleleaf	Grassland	Lichens and Mosses	Permanent ice and snow	Shrubland	Shrubland evergreen	Water	Water permanent	Water seasonal	Wetland	Wetland Herbaceous
LSTM - MC (S2)	21KUQ	0.52	0.2	0.36	0.93			0.13			0.12		0.83	0.69	0.23	0.07	
RF (S1)		0.41	0.02	0.27	0.77			0.22			0.18		0.3	0	0.07	0.03	
SVM (S2)		0.59	0.07	0.36	0.94			0.22			0.05		0.77	0.78	0.08	0.07	
LSTM - TS (S2)		0.25	0.49	0.32	0.9			0.14			0.17		0.81	0.69	0.24	0.09	
LSTM - MC (S2)	21KXT	0.1	0.48	0.37	0.79			0.34			0.22		0.53	0.85	0.12	0.38	0.58
RF (S1)		0.13	0.53	0.1	0.67			0.29			0.3		0.6	0.61	0.19	0.06	0.05
SVM (S2)		0.1	0.37	0.46	0.81			0.4			0.18		0.43	0.73	0.16	0.39	0.56
LSTM - TS (S2)		0.11	0.5	0.35	0.76			0.29			0.24		0.52	0.8	0.24	0.37	0.56
LSTM - MC (S2)	37PCP	0.37	0.7	0.48	0.5			0.3			0.28		1	0.93	0.77	0.33	
RF (S1)		0.18	0.76	0.54	0.42			0.13			0.05		0.99	0.97	0.73	0.19	
SVM (S2)		0.33	0.7	0.54	0.49			0.38			0.19		1	0.96	0.83	0.23	
LSTM - TS (S2)		0.36	0.71	0.44	0.52			0.27			0.3		1	0.94	0.82	0.3	
RF (S1)	42WXS	0.32	0		0.64	0.04	0.33	0.27	0.24	0	0.33	0.19	0.77	0.62	0.39	0.34	
SVM (S2)		0.47	0		0.58	0.02	0.25	0.35	0.35	0	0.28	0.25	0.79	0.55	0.4	0.43	
LSTM - TS (S2)		0.45	0		0.65	0.03	0.14	0.34	0.37	0	0.31	0.31	0.82	0.88	0.48	0.41	
LSTM - MC (S2)	8	1		1									3	1		1	1
LSTM - TS (S2)	20	1	3		2	1			1		4	1	2	1	3	1	
SVM (S2)	20	2	1	3	2		1	4		1			1	2	1	2	

3.1.2.19 Table 23. Mean and standard deviation of UA and PA of SVM algorithm

RR tile	Statistic	Index	Bareland	Built-up	Cropland	Forest	Forest deciduous broadleaf	Forest evergreen needleleaf	Grassland	Lichens and Mosses	Permanent ice and snow	Shrubland	Shrubland evergreen	Water	Water permanent	Water seasonal	Wetland	Wetland Herbaceous
	mean	PA	0.59	0.07	0.36	0.94			0.22			0.04		0.77	0.78	0.08	0.07	
21KUQ	mean	UA	0	0.05	0.4	0.53			0.56			0.14		0.13	0.1	0.33	0.13	
	mean	PA	0.06	0.37	0.46	0.81			0.4			0.18		0.43	0.74	0.16	0.4	0.56
21KXT	mean	UA	0	0.17	0.33	0.7			0.64			0.07		0.21	0.32	0.08	0.26	0.23
	mean	PA	0.26	0.7	0.55	0.49			0.38			0.19		1	0.96	0.82	0.23	
37PCP	mean	UA	0.08	0.04	0.89	0.2			0.16			0.17		0.97	1	0.34	0.14	
	mean	PA	0.46	0		0.57	0.02	0.25	0.35	0.31	0	0.22	0.25	0.79	0.55	0.4	0.43	
42WXS	mean	UA	0.12	0		0.72	0.02	0.35	0.4	0.03	0	0	0.62	0.48	0.85	0.15	0.36	
	std	PA	0.07	0.04	0.08	0.02			0.03			0.02		0.21	0.05	0.01	0.04	
21KUQ	std	UA	0	0.04	0.47	0.13			0.47			0.09		0.03	0	0.13	0.06	
	std	PA	0.1	0.06	0.2	0.04			0.01			0.06		0.29	0.05	0.03	0.3	
21KXT	std	UA	0	0.04	0.51	0.1			0.52			0.02		0.12	0.06	0.04	0.14	
	std	PA	0.37	0.23	0.02	0.34			0.06			0.16		0.01	0	0.11	0.18	
37PCP	std	UA	0.12	0.05	0	0.07			0.03			0.23		0.01	0	0.07	0.15	
	std	PA	0.41	0		0.18			0.42	0.5		0.3		0.23	0.01	0.07	0.11	
42WXS	std	UA	0.09	0		0.13			0.41	0.03		0		0.12	0.03	0.09	0.23	

3.1.3 Conclusions

This section provides insight into performance of the algorithms as well as into benchmark accuracy. Since the results are based on the inter-comparison with existing land cover products term “the best” is equivalent to "the best agreement with the other products".

3.1.3.1 Algorithm comparison – RR products

With respect to the algorithm comparison in case of Amazon (21KXT and 21KUQ) only optical algorithms – SVM, LSTM-TS and LSTM – MC - were compared, while for 37PCP and 42WXS all algorithms, including RF, were compared in terms of their OA_b scores.

SVM (S2) algorithm from optical chain is the best according to OA_b (Table 2) in all regions except in 42WXS (Siberia) where RF (S1) is slightly better. From the point of view of class indexes, UA_b and PA_b, RF (S1) was not considered for comparison with other algorithms because size discrepancy of RF (S1) prototypes makes it difficult to summarize results. Only in case of Siberia SVM (S2) was compared with RF (S1) because only in this case OA_b was somewhat higher for RF (S1) than for the SVM (S2). The SVM (S2) and RF (S1) comparison relies on Table 14 and Table 15 and it suggest that better performance of RF (S1) can be attributed to the more successful classification of Forest, Forest deciduous broadleaf, Forest evergreen needleleaf, and Shrubland. Nevertheless, SVM was more successful with Bareland, Grassland, Lichens and Mosses, Shrubland evergreen and Wetland, so the difference in performance of the two algorithms is small.

Regarding comparison of optical chain algorithms from the point of view of individual class indexes they were compared taking into consideration count of number of times when an algorithm had better average PA_b or UA_b score than the others in a region for a class. Average UA_b (Table 20) is showing that SVM (S2) was better than other two algorithms 23 times, LSTM-TS (S2) 18 times, while LSTM-MC (S2) only 6 times. Looking at the average PA_b (Table 22), SVM (S2) and LSTM-TS (S2) were better than other algorithms equal number of times - 20, while LSTM - MS (S2) 8 times. Therefore, average PA_b or UA_b are also indicating that SVM (S2) is performing better than other algorithms.

Regarding fusion algorithms, MRF had slightly better scores than LOGP (Table 3, Table 19 and Table 21). In addition, success of fusion algorithm was estimated based on the difference between OA_b of fusion algorithms and of SVM and RF algorithms since these are the two algorithms involved in the fusion (Table 4). From Table 4 it can be seen that in most of the cases the yield from fusion is positive. However, in case of 42WXS there are some negative values. That is probably due to the fact that MRF gives more weight to the optical chain outputs, while in the case of 42WXS SAR chain outputs (i.e. RF (S1)) had better OA_b score.

3.1.3.2 Benchmark accuracy – RR products

From the point of view of benchmark accuracy, for binary maps that are specifically derived for certain class – FNF, GHS BU S1, GSW seasonality, GSW_v1_2 - OA_b is very high due to the presence of the class that represent all the other classes but the one of interest for the map. Therefore OA_b for these maps is not informative, and only PA_b and UA_b were taken into consideration for the following conclusions.

On average OA_b with multiple-class existing maps is around 50% being the highest in comparison of SVM algorithm with FROM-GLC map (60%) in 37PCP. Agreement of 60% can be considered moderately good given that also other map contains certain errors.

Regarding individual accuracy indexes the classification are interpreted as “excellent” if both scores PA_b and UA_b (in the Table 5- Table 18,) are above 90%, “well” if the scores are between 70% and 90% and “relatively good” if the scores are between 50% and 70%.

Forest is classified relatively good or well by majority of the algorithms in all regions except in 37PCP. In case of 21KUQ and 42WXS forest is classified relatively good, while in the case of 21KXT it is well classified.

In case of 37PCP Water and Water Permanent have excellent accuracy. This is probably due to the big water body present in the 37PCP region. The large water body might be the reason why also OA_b is higher for 37PCP than for the other tiles. Also Cropland is relatively good classified in 37PCP.

For 42WXS Forest, Water, Water Permanent are classified relatively good.

Other classes either have low scores or the scores from comparison with different existing datasets are contradictory therefore it is not possible to derive conclusions.

Moreover, standard deviation was computed for UA_b and PA_b for SVM (S1) algorithm (Table 23) in order to have insight into variation of scores. Large variation among the scores indicate that there is large variation in the existing maps regarding a certain class, therefore at least some of the maps are not accurate enough regarding that class. The highest deviation was present for Grassland, Cropland and Lichens and Mosses classes. Out of the classes for which were labeled with at least "relatively good" score, Forest and Water Permanent have low standard deviation, while for the Water class it is moderate.

3.2 HRLC static maps – first production

Static maps in zoom area for Amazon and Siberia were provided on 23/10/2020. The maps are provided as set of tiles for each region. There is 266 tiles in Amazon and 204 tiles in Siberia. Some of the tiles are partially or completely out of the region of interest. This impacts inter-comparison in some cases because existing datasets were collected based on the region of interest of the project. More in detail, existing dataset were collected within a bounding box which is slightly bigger than the region of interest of the project to take into account possible change of size due to reprojection. However, it did not capture all the tiles included in the static map of Amazon and Siberia. In Figure 3 and Figure 4 it is precisely highlighted for which tiles of static map existing data are not collected for Siberia and Amazonia respectively.

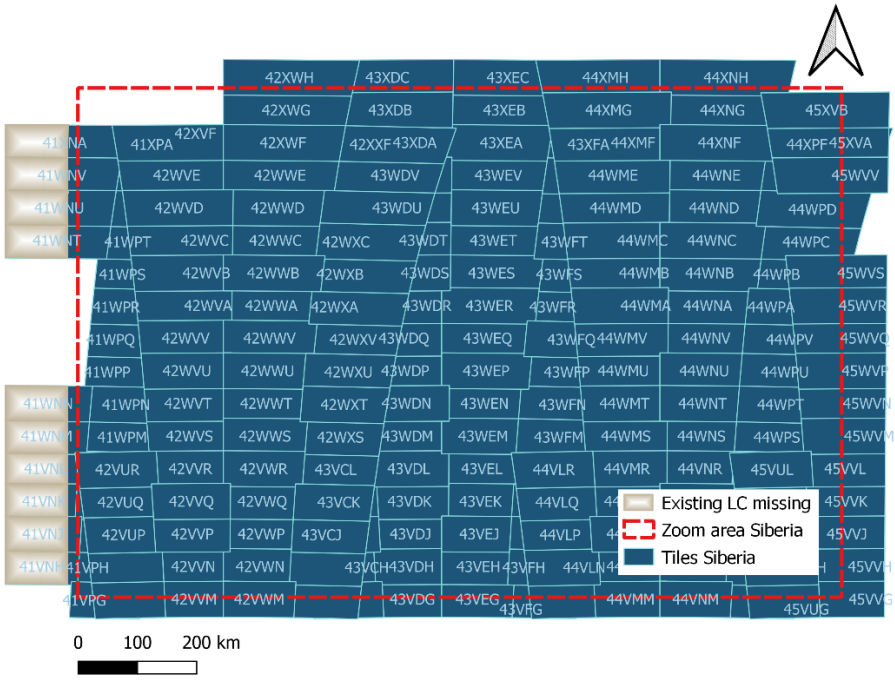

Figure 3. Tiles of static map in zoom area of Siberia

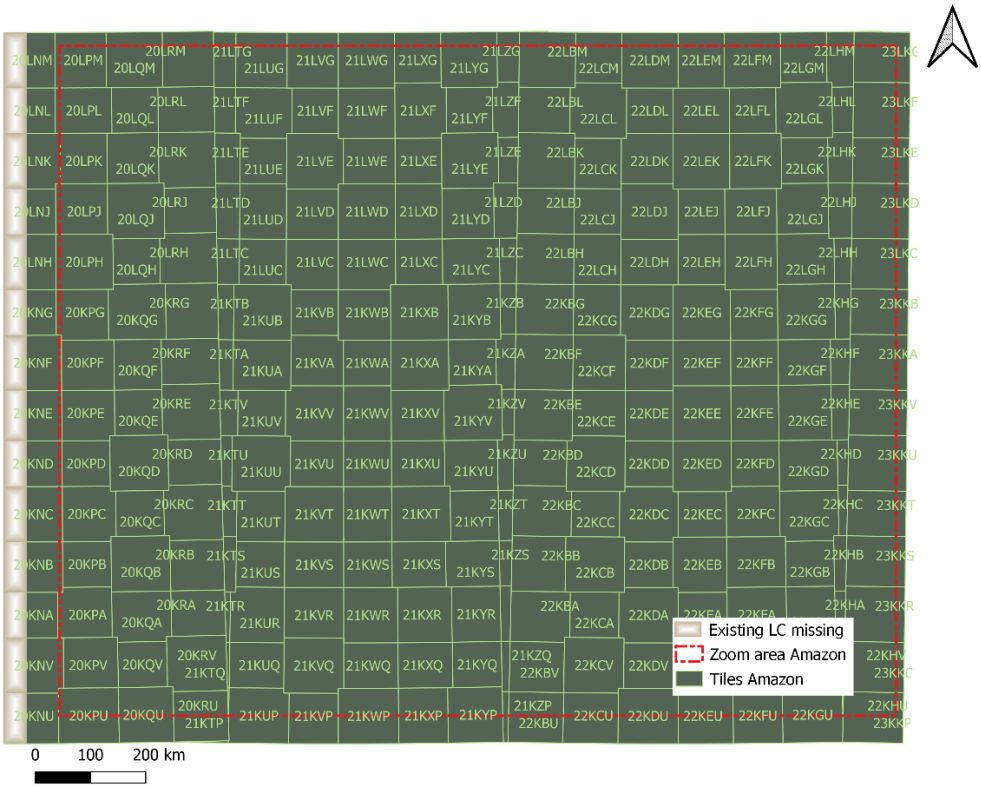

Figure 4. Tiles of static map in zoom area in Amazon

Inter-comparison results will be shown per tile and per whole region of interest. In case of per-tile results the tiles in which existing data are partially missing will not be considered as they are not comparable to the tiles where existing data are available. On the opposite, results for whole region will take into account also partially covered tiles.

OA_b was computed for each tile the existing dataset available in a region. Moreover, all error matrices per region were summed up in order to derive error matrix based on which OA_b was computed for a region as a whole. Please note that with summation of all error matrices in a region some pixels are accounted more than once due to the overlapping of the tiles. Depending on the classification outcome of the overlapping tiles same pixels might have different values. This approach was selected in order to avoid selecting specific mosaicking method that may produce different outcomes with respect to the mosaicking method on the project level that is to be decided in future. Nevertheless, it gives general idea of the agreement of the static maps with existing LC maps in a region.

The results of OA_b do not take into account binary maps: FNF, GHS BU S1, GSW seasonality, GSW_v1_2, AUE. OA_b for these maps is very high due to the presence of the class that represent all the other classes but the one of interest for the map and therefore can be misleading.

3.2.1 Siberia

3.2.1.1 Overall benchmark accuracy

In Siberia there are 3 existing multiple-class land cover maps with which static product for Siberia region was compared: ESA DUE GlobPermafrost, FROM-GLC and GL30. During inter-comparison it was observed that GL30 contains some classes which are not included in the official product legend. We requested more details about classes from the map producer, however we did not receive reply by the day of conclusion of processing of static products of the first production. Thus, results of inter-comparison with GL30 in Siberia were not reported for the first production.

Table 24. Overall benchmark accuracy for whole Siberia

Existing dataset	OA_b
ESA DUE GlobPermafrost	46%

FROM-GLC	50%

Given that there are many tiles the results of OA_b per tile will be displayed in the form of maps of tiles with associated values of OA_b. There are 2 OA_b maps, one for inter-comparison with FROM GLC (Figure 5) and one with ESA DUE Permafrost (Figure 6). Some of the tiles have more than one value displayed. The second value is for the tile that is underneath the displayed one. For most of the tiles the OA_b values for overlapping tiles is similar.

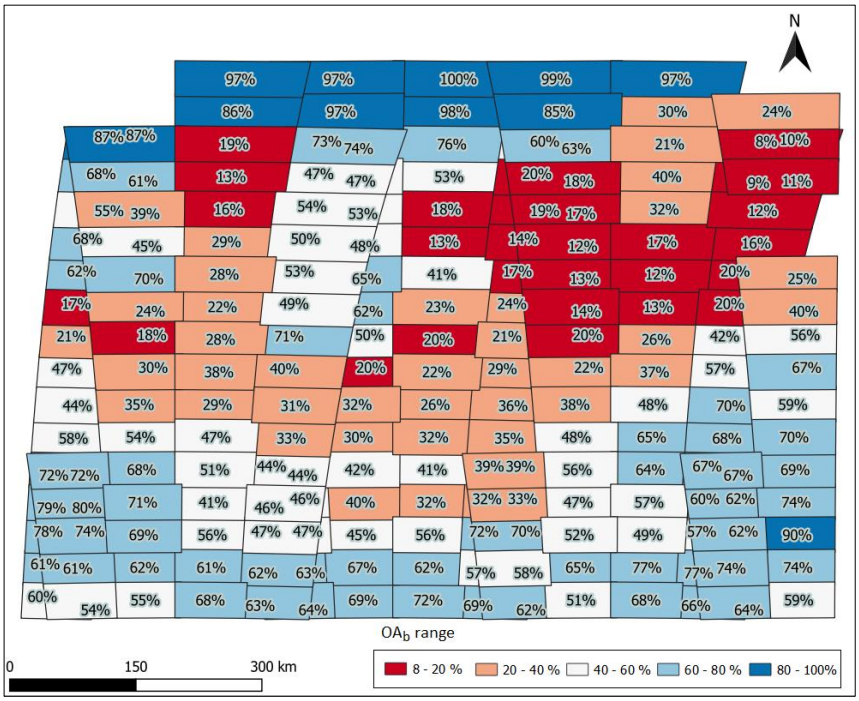

Figure 5. OA_b for each tile of static map in Siberia based on FROM GLC

The ESA DUE Permafrost size is smaller than the zoom area in Siberia therefore the appearance of the map is different with respect to the previous map.

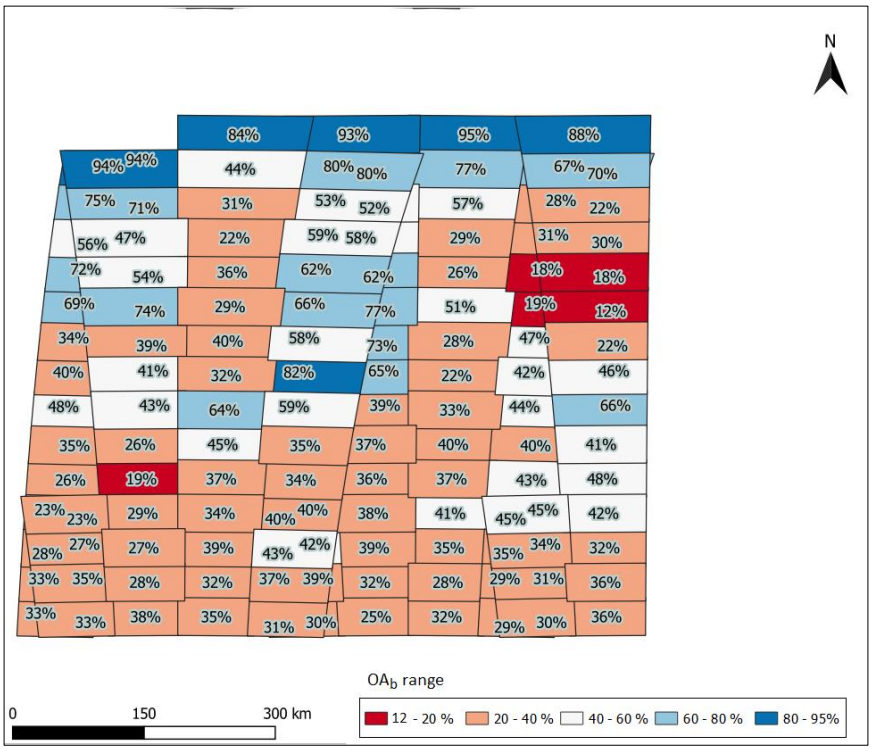

Figure 6. OA$_b$ for each tile of static map in Siberia based on ESA DUE Permafrost

3.2.1.2 Per class benchmark accuracy

Table 25. UA_b and PA_b for whole Siberia

Existing LC	Index	Bareland	Built-up	Cropland	Forest	Forest deciduous broadleaf	Forest evergreen needleleaf	Grassland	Lichens and Mosses	Permanent ice and snow	Shrubland	Shrubland evergreen	Water	Water permanent	Water seasonal	Wetland
ESA DUE GlobPermafrost	PA_b	32%				39%	1%	48%	16%			23%		92%	44%	46%
FROM-GLC		41%	53%	0%	87%			19%	7%	0%	15%		97%			50%
FNF					83%								90%			
GHS BU S1			54%													
GSW seasonality														86%	26%	
GSW_v1_2														88%	24%	
ESA DUE GlobPermafrost	UA_b	25%				21%	17%	20%	10%			74%		99%	37%	7%
FROM-GLC		5%	11%	0%	77%			43%	64%	0%	0%		91%			6%
FNF					67%								83%			
GHS BU S1			9%													
GSW seasonality														96%	19%	
GSW_v1_2														52%	17%	

3.2.2 Amazon

3.2.2.1 Overall benchmark accuracy

In Amazon there are 3 existing multiple-class land cover maps with which static product for Amazon region was compared: FROM-GLC, GL30 and MapBiomas. Table 26 is showing the consistency between static map in Amazon and each of the existing land cover maps.

Table 26. Overall benchmark accuracy for whole Amazon

Existing dataset	OA_b
FROM-GLC	62%
GL30	48%
MapBiomas	62%

As in the case of Siberia, also for Amazon results of OA_b will be shown in form of maps for OA_b with each of the three existing land cover available in the region. OA_b with respect to FROM-GLC is shown in Figure 7, with respect to GL30 Figure 8 in and with respect to MapBiomas in Figure 9.

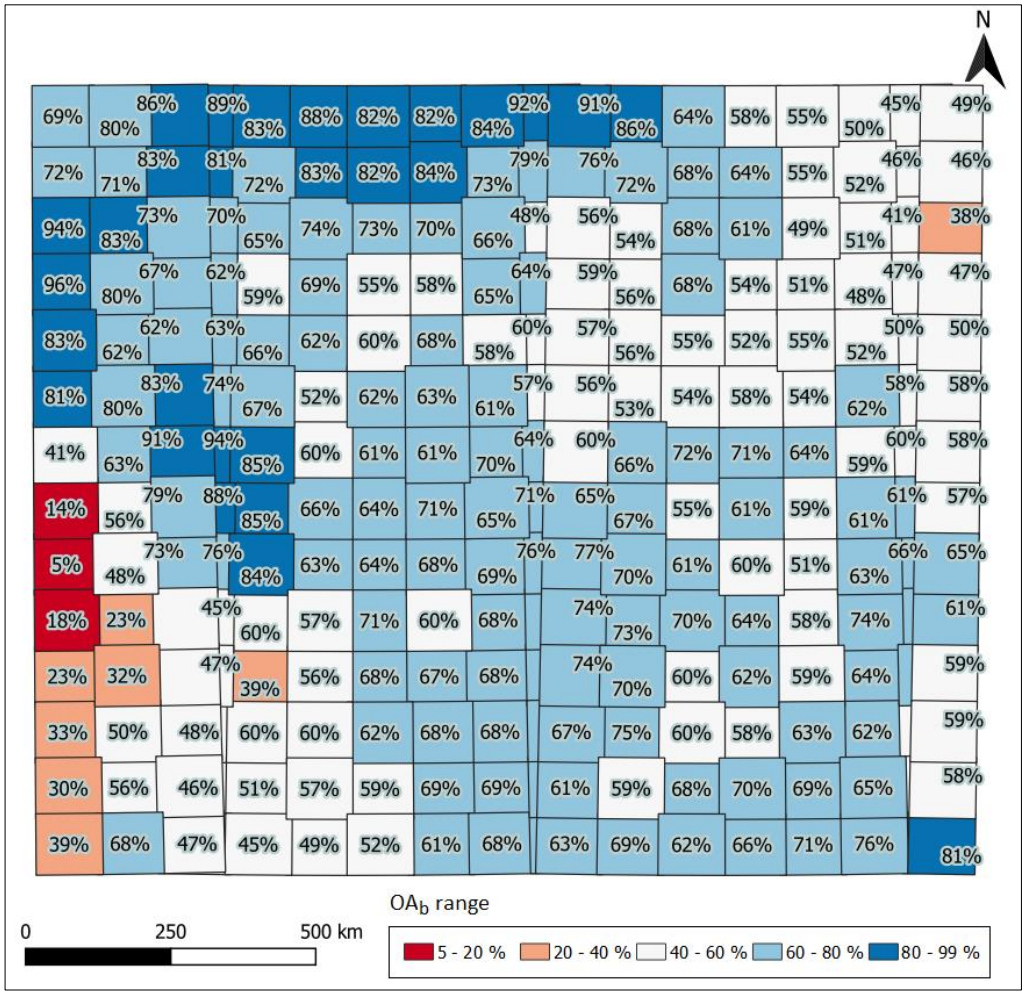

Figure 7. OA_b for each tile of static map in Amazon based on FROM GLC

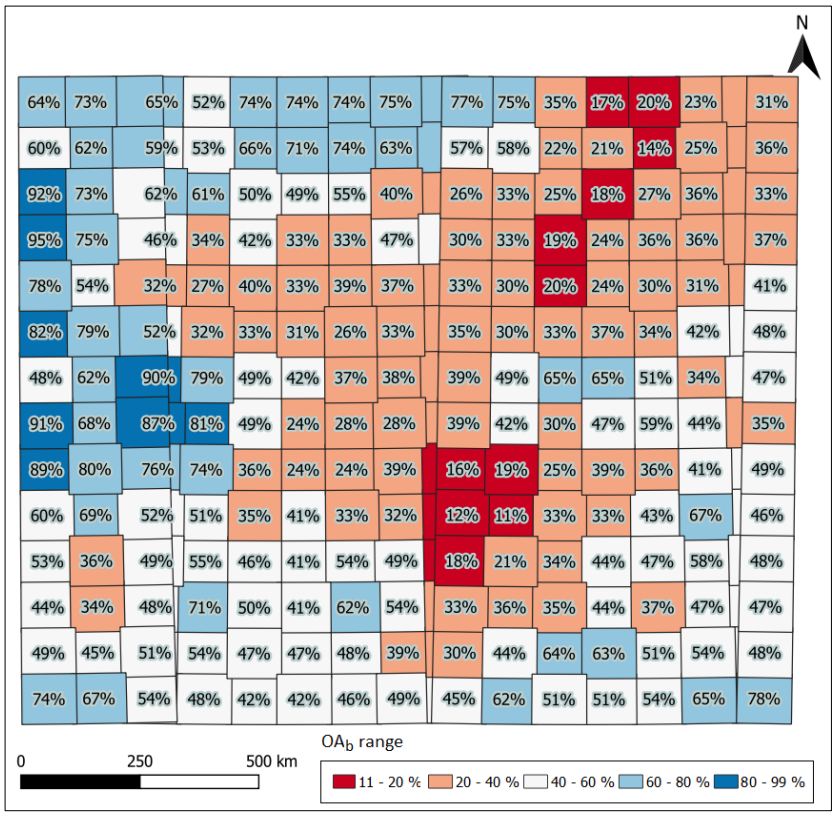

Figure 8. OA_b for each tile of static map in Amazon based on GL30

The MapBiomas dataset does not completely cover zoom area in Amazon therefore the appearance of the map is different with respect to the previous two maps for Amazonia.

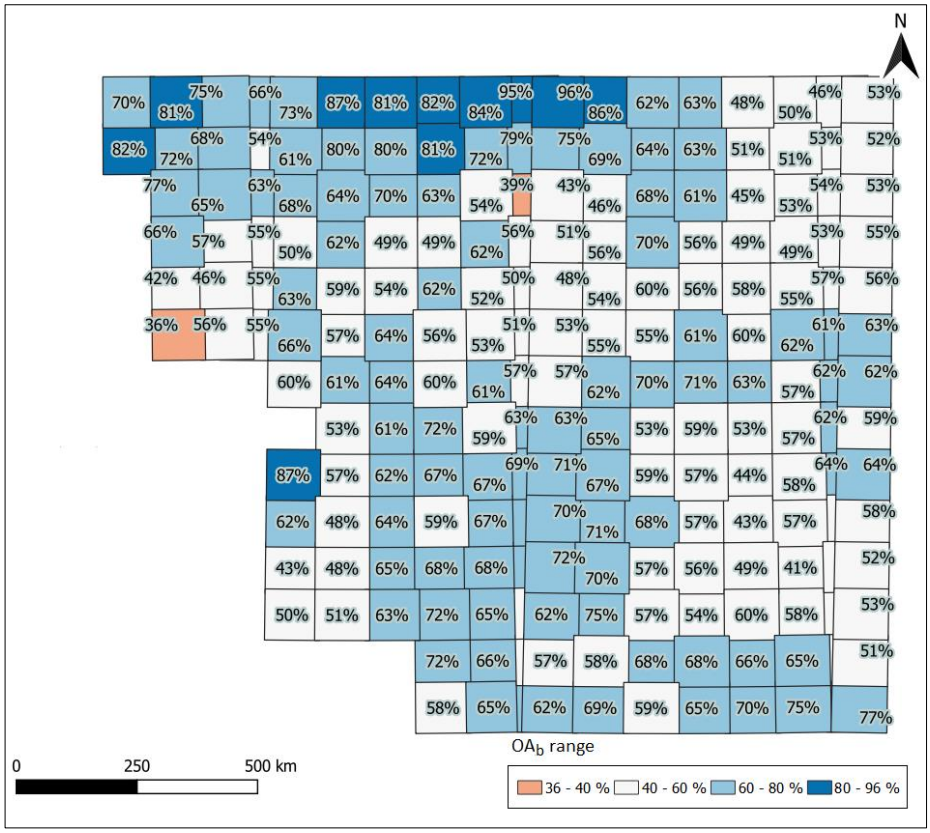

Figure 9. OA_b for each tile of static map in Amazon based on MapBiomas

3.2.2.2 Per class benchmark accuracy

Table 27. UA_b and PA_b for whole Amazon

Dataset	Index	Bareland	Built-up	Cropland	Forest	Grassland	Shrubland	Water	Water permanent	Water seasonal	Wetland	Wetland Herbaceous	Wetland Shrubby
FROM GLC	PA	53%	53%	68%	91%	54%	19%	80%			55%		
GL30		14%	43%	34%	88%	43%	17%	75%			17%		
MapBiomas		36%	59%	65%	88%	59%	21%	74%				40%	0%
FNF					84%			26%					
GHS BU S1			59%										
AUE*			80%					28%					
GSW seasonality									83%	15%			
GSW v1 2									87%	12%			
FROM GLC	UA	0%	36%	67%	69%	74%	25%	67%			19%		
GL30		0%	38%	90%	65%	15%	22%	67%			38%		
MapBiomas		3%	48%	69%	67%	79%	20%	76%				27%	0%
FNF					68%			52%					
GHS BU S1			26%										
AUE*			54%					38%					
GSW seasonality									76%	12%			
GSW v1 2									74%	21%			

*AUE covers only partially 4 tiles out of 266 in Amazon.

3.2.3 Africa

3.2.3.1 Overall benchmark accuracy

In Africa there are 2 existing multiple-class land cover maps with which static product for African region were compared: FROM-GLC and GL30. Table 28 is showing the consistency between static map in Africa and each of the existing land cover maps.

Table 28. Overall benchmark accuracy for whole Africa

Existing dataset	OA_b
FROM-GLC	44%
GL30	33%

Results of OA_b will be shown in form of maps for OA_b with each of the two existing land cover available in the region. OA_b with respect to FROM-GLC is shown in Figure 10, with respect to GL30 in Figure 11.

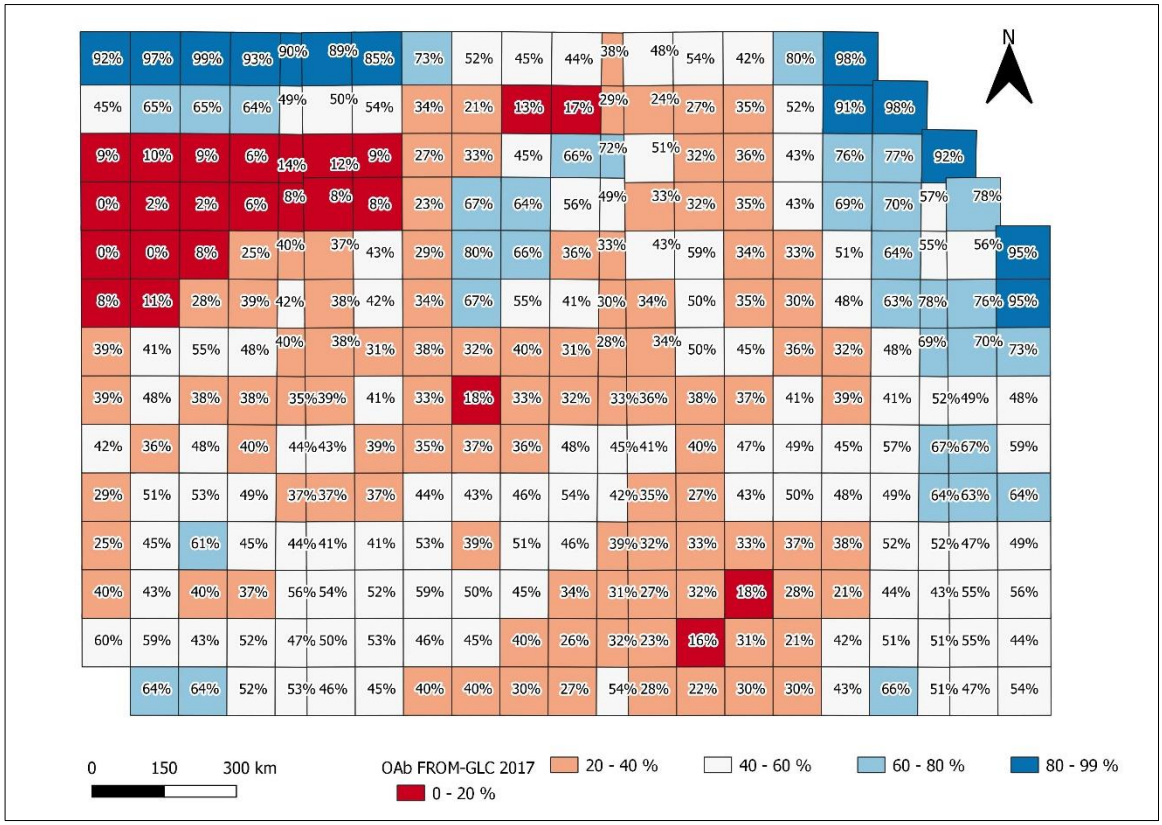

Figure 10. OA_b for each tile of static map in Africa based on FROM GLC

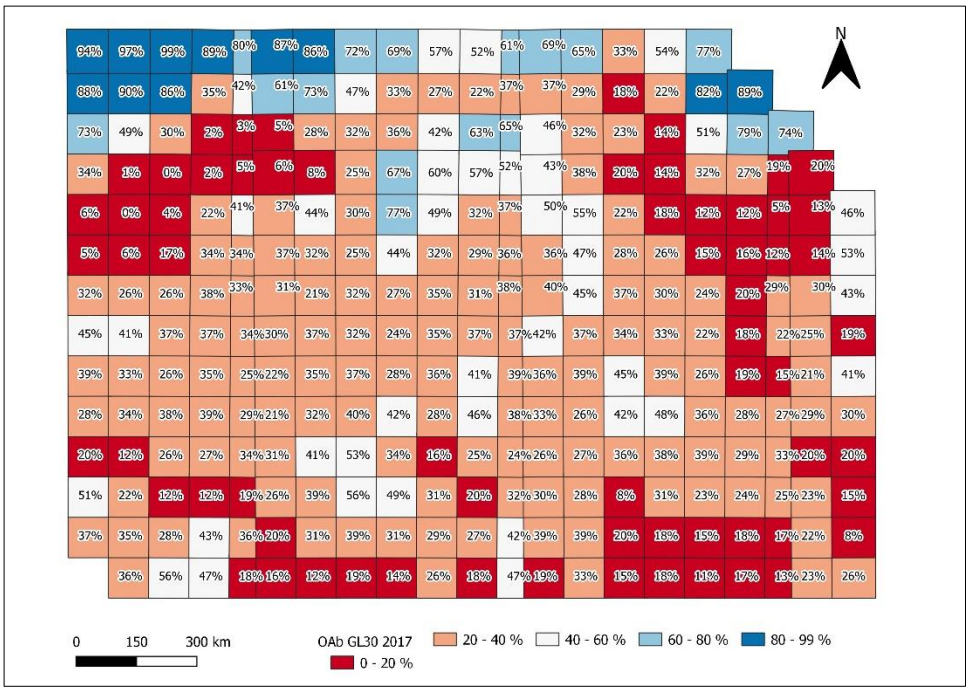

Figure 11. OA_b for each tile of static map in Africa based on GL30

3.2.3.2 Per class benchmark accuracy

Table 29. UA_b and PA_b for whole Africa

Dataset	Index	Bareland	Built-up	Cropland	Forest	Grassland	Shrubland	Water	Water permanent	Water seasonal	Wetland
FROM GLC	PA	85%	12%	46%	70%	19%	44%	84%			8%
GL30		83%	20%	36%	36%	18%	38%	87%			21%
GHS BU S1			28%								
WSF			31%								
FNF					35%			87%			
GSW seasonality									90%	63%	
GSW v1 2									91%	51%	
FROM GLC	UA	48%	1%	43%	19%	34%	56%	92%			1%
GL30		43%	3%	43%	42%	50%	15%	61%			9%
GHS BU S1			1%								
WSF			5%								
FNF					76%			84%			
GSW seasonality									99%	19%	
GSW v1 2									76%	32%	

3.2.4 Conclusions

Overall agreement of the static map with existing land cover maps in Siberia is around 50% (Table 24). The highest agreement is in the northern parts of zoom area due to the dominance of water class which is generally well classified (Figure 5 and Figure 6). Agreement is slightly larger with FROM-GLC then with ESA DUE Permafrost.

Regarding individual accuracy indexes the classification are interpreted as “excellent” if both scores PA_b and UA_b (in the) are above 90%, “well” if the scores are between 70% and 90% and “relatively good” if the scores are between 50% and 70% (For Siberia according to the Table 25 classification of Forest class is relatively good, while for Water and Water permanent class it varies from relatively good to excellent, depending on the existing dataset with which static map is compared with. For other classes the results are low or not possible to interpret.

Agreement of static map in Amazon with existing land cover maps in that region shows higher agreement than in Siberia. OA_b in Amazon is 62% with respect to FROM-GLC and MapBiomas LC, while with respect to GL30 it is 48%. There is couple of patches of tiles where agreement with FROM-GLC (Figure 7) and MapBiomas (Figure 9) exceeds 80%. Visual inspection or these patches showed that it is most probably associated with relatively homogeneous forest landscape. Agreement with GL30 (Figure 8) is generally lower compared to agreement with other two maps in Amazon. Class-wise agreement with existing maps was analysed based on FROM-GLC and MapBiomas because results of inter-comparison with them are similar (Table 27). In case of Permanent water, relatively well to good in case of Water and Forest and relatively well in case of Cropland and Grassland.

According to the AUE dataset Built-up class is relatively well classified, which is not evident from other datasets. Given that AUE dataset is focused on big cities (Ribeirao Preto and partially Sao Paolo) it may indicate that classification of built-up class is more successful in cities with respect to built-up elsewhere. It might be affected by homogeneity of built up class in cities.

For static map in Africa the agreement with existing HRLC is lower than with respect to other two regions. OA_b with respect to FROM-GLC is 44%, and 33% with GL30 (Table 28). UA_b and PA_b (Table 29) are indicating that the Forest class is not classified as good as in Amazon or Siberia, and probably this is the reason behind low overall agreement. Water permanent class has excellent agreement, while the agreement with Water is well. Visual inspection of OA_b for each tile of static map for GL30 and FROM-GLC (Figure 10, Figure 11) do not show any meaningful patterns.

For further conclusions based on inter-comparison it would be important to have information about reliability of the existing products in the regions of interest for the project. The reliability of existing products could be estimated using the validation dataset of the project.

3.3 HRLC historical maps – first production

Historical maps in zoom area for Amazon were provided on 28/12/2020, for Siberia on 15/01/2021, and for Africa on 18/03/2021. Table 30 contains details about the number of tiles per each region and each historical product available so far.

Table 30. Number of tiles for each historical product

Year	Region	Number of tiles	Region	Number of tiles	Region	Number of tiles
2015	Amazon	266	Siberia	212	Africa	291
2010	Amazon	266	Siberia	215	Africa	290
2005	Amazon	266	Siberia	215	Africa	291
2000	Amazon	263	Siberia	213	Africa	291
1995	Amazon	266	Siberia	205	Africa	279
1990	Amazon	262	Siberia	208	Africa	273

3.3.1 Amazon 2015

Following existing land cover maps are used for inter-comparison of historical products for 2015:

- FROM GLC 2015
- MapBiomas 2015

- TerraClass 2014
- GHS BU LDS 2014
- WSF 2015
- FNF 2015
- GSW seasonality 2015
- GSW v1 2 2015
- AUE 2014 (Sao Paolo), 2014 (Ribeirao Preto)

3.3.1.1 Overall benchmark accuracy

There are 3 existing multiple-class land cover maps for year 2015 with which historical product for Amazon region was compared: FROM-GLC, TerraClass and MapBiomas. Table 31 is showing the consistency between historical map in Amazon and each of the existing land cover maps.

Table 31. Overall benchmark accuracy for whole Amazon in 2015

Existing dataset	OA_b
FROM-GLC	57%
MapBiomas	57%
TerraClass	63%

Amazon results of OA_b will be shown in form of maps for OA_b with each of the three existing land cover available in the region. OA_b with respect to FROM-GLC is shown in Figure 12, with respect to MapBiomas Figure 13 in and with respect to TerraClass in Figure 14.

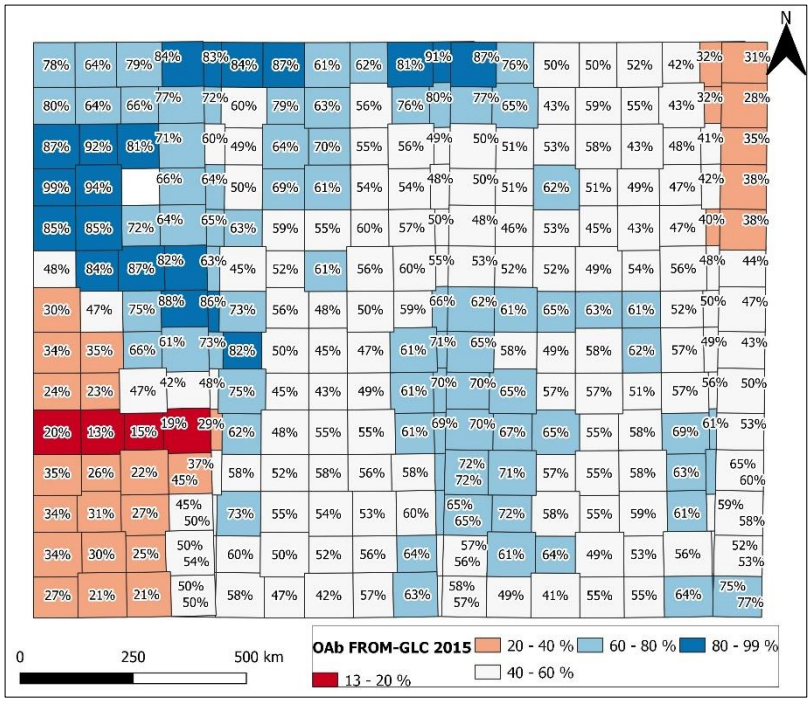

Figure 12. OA_b for each tile of 2015 historical map in Amazon based on FROM GLC

The MapBiomas dataset does not completely cover zoom area in Amazon therefore the appearance of the map is different with respect to the FROM-GLC map for Amazonia.

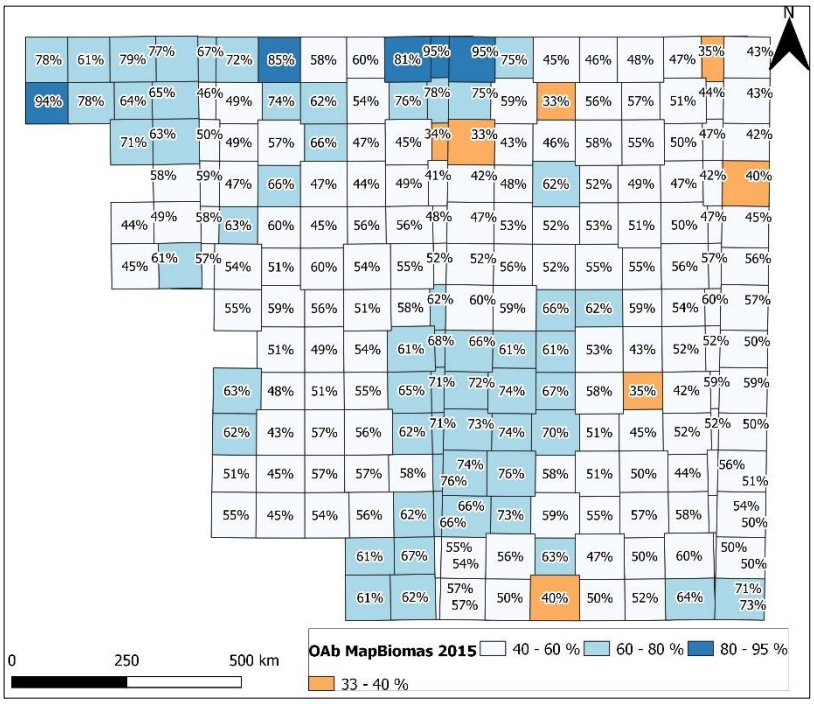

Figure 13. OA_b for each tile of 2015 historical map in Amazon based on MapBiomas

The TerraClass dataset covers only small portion of the zoom area in Amazon therefore the appearance of the map is different with respect to the previous two maps for Amazonia.

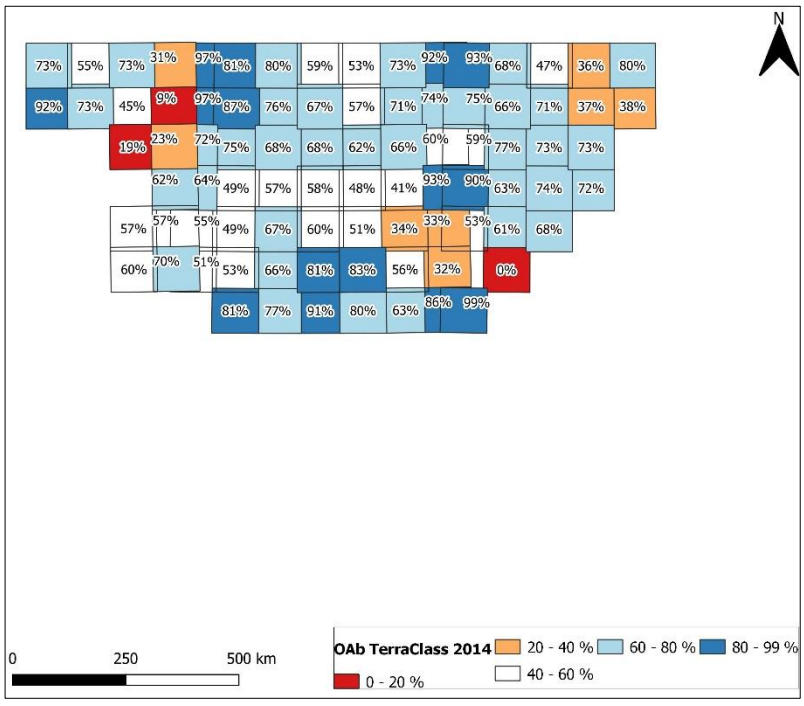

Figure 14. OA_b for each tile of 2015 historical map in Amazon based on TerraClass

3.3.1.2 Per class benchmark accuracy

Table 32. UA_b and PA_b for whole 2015 Amazon

Dataset	Index	Bareland	Built-up	Cropland	Forest	Grassland	Shrubland	Water	Water permanent	Water seasonal	Wetland	Wetland Herbaceous
FROM GLC	PA	48%	75%	53%	91%	44%	7%	90%			19%	
MapBiomas		52%	73%	51%	92%	54%	11%	85%				20%
TerraClass		7%	1%	36%	95%	47%	5%	62%				
GHS BU LDS			83%					96%				
WSF			69%									
FNF					85%			35%				
GSW seasonality									87%	33%		
GSW v1 2									90%	30%		
FROM GLC	UA	0%	30%	52%	67%	66%	18%	67%			12%	
MapBiomas		1%	54%	41%	65%	77%	25%	76%				36%
TerraClass		1%	31%	34%	74%	66%	13%	62%				
GHS BU LDS			27%					40%				
WSF			36%									
FNF					67%			57%				
GSW seasonality									82%	14%		
GSW v1 2									80%	29%		
AUE Ribeirao Preto	PA		70%					42%				
AUE Sao Paulo			66%					85%				
AUE Ribeirao Preto	UA		77%					30%				
AUE Sao Paulo			79%					46%				

3.3.2 Amazon 2010

Following existing land cover maps are used for inter-comparison of historical products for 2010:

- FROM GLC 2010
- GL30 2010
- MapBiomas 2010
- TerraClass 2010
- GUF 2011
- FNF 2010
- GSW seasonality 2010
- GSW v1 2 2010

3.3.2.1 Overall benchmark accuracy

There are 4 existing multiple-class land cover maps for year 2010 with which historical product for Amazon region was compared: FROM-GLC, GL30, TerraClass and MapBiomas. Table 33 is showing the consistency between historical map in Amazon and each of the existing land cover maps.

Table 33. Overall benchmark accuracy for whole Amazon in 2010

Existing dataset	OA_b
FROM-GLC	46%
GL30	44%
MapBiomas	51%
TerraClass	67%

Amazon results of OA_b will be shown in form of maps for OA_b with each of the four existing land cover available in the region. OA_b with respect to FROM-GLC is shown in Figure 15, with respect to GL30 Figure 16, with respect to MapBiomas Figure 17 and with respect in and with respect to TerraClass in Figure 18

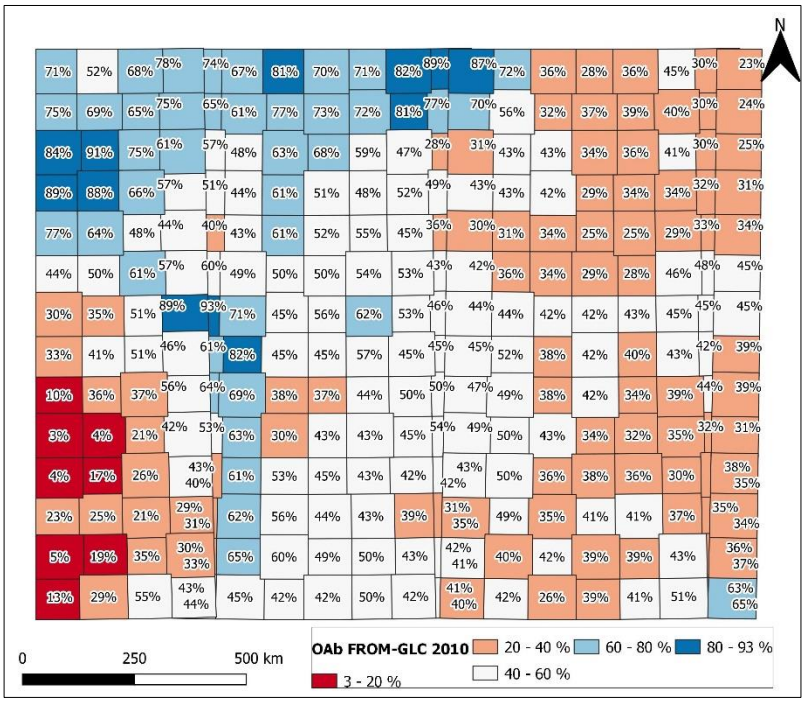

Figure 15. OA_b for each tile of 2010 historical map in Amazon based on FROM GLC

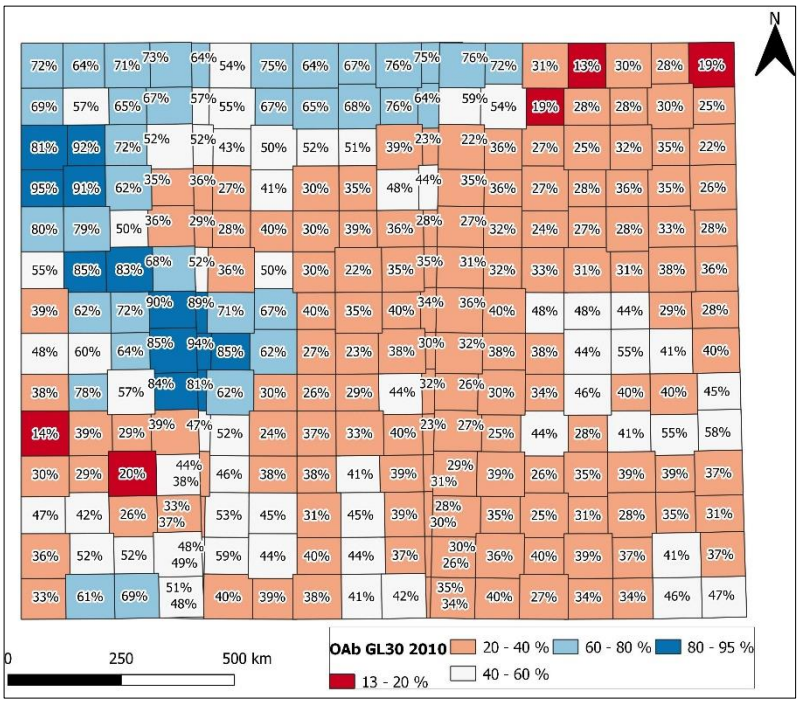

Figure 16. OA_b for each tile of 2010 historical map in Amazon based on GL30

The MapBiomas dataset does not completely cover zoom area in Amazon therefore the appearance of the map is different with respect to the previously displayed maps for Amazonia.

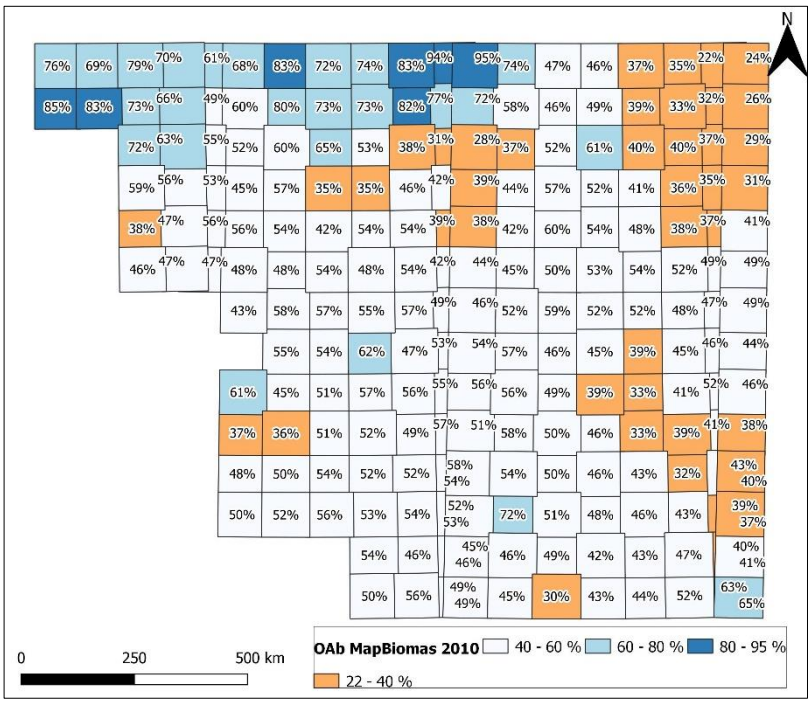

Figure 17. OA_b for each tile of 2010 historical map in Amazon based on MapBiomas

The TerraClass dataset covers only small portion of the zoom area in Amazon therefore the appearance of the map is different with respect to the previous three maps for Amazonia.

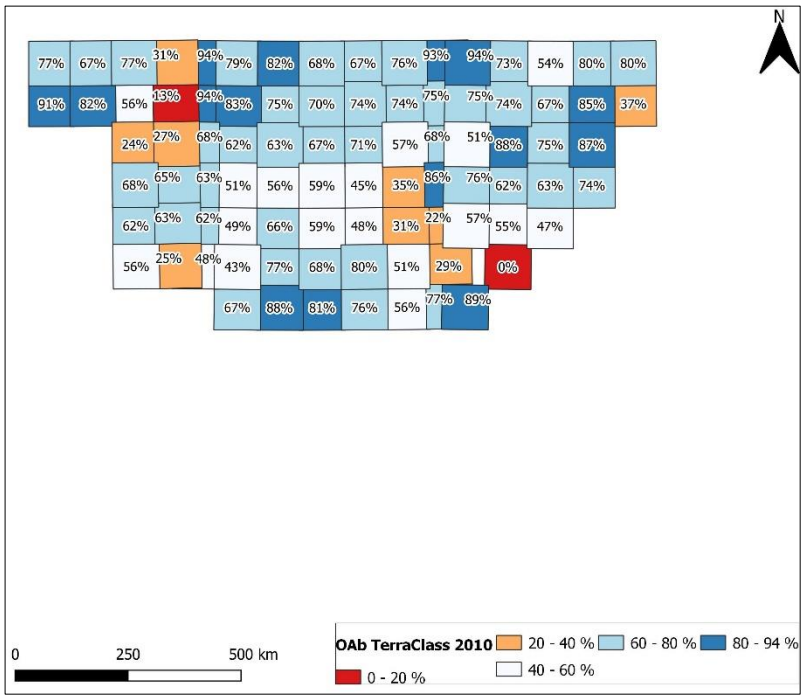

Figure 18. OA_b for each tile of 2010 historical map in Amazon based on TerraClass

3.3.2.2 Per class benchmark accuracy

Table 34. UA_b and PA_b for whole 2010 Amazon

Dataset	Index	Bareland	Built-up	Cropland	Forest	Grassland	Shrubland	Water	Water permanent	Water seasonal	Wetland	Wetland Herbaceous	Wetland Shrubby
FROM GLC	PA	12%	55%	42%	70%	36%	4%	44%					
GL30		22%	58%	35%	78%	34%	6%	79%					
MapBiomas		43%	75%	58%	81%	45%	9%	77%				65%	0%
TerraClass		10%	36%	60%	92%	51%	9%	10%					
GUF			75%										
FNF					77%			20%					
GSW seasonality									85%	15%	55%		
GSW v1 2									88%	14%	4%		
FROM GLC	UA	1%	4%	43%	68%	51%	7%	28%					
GL30		0%	11%	67%	66%	16%	17%	29%					
MapBiomas		1%	19%	38%	62%	82%	18%	32%				16%	0%
TerraClass		0%	10%	55%	77%	77%	12%	40%					
GUF			14%								27%		
FNF					71%			2%			33%		
GSW seasonality									38%	3%			
GSW v1 2									37%	5%			

3.3.3 Amazon 2005

Following existing land cover maps are used for inter-comparison of historical products for 2005:

- MapBiomas 2005
- TerraClass 2004
- FNF 2007
- GSW seasonality 2005
- GSW v1 2 2005

3.3.3.1 Overall benchmark accuracy

There are 2 existing multiple-class land cover maps for year 2005 with which historical product for Amazon region was compared: TerraClass and MapBiomas. Table 35 is showing the consistency between historical map in Amazon and each of the existing land cover maps.

Table 35. Overall benchmark accuracy for whole Amazon in 2005

Existing dataset	OA_b
MapBiomas	55%
TerraClass	75%

Amazon results of OA_b will be shown in form of maps for OA_b with each of existing land cover available in the region. OA_b with respect to MapBiomas is shown in Figure 19, and with respect to TerraClass in Figure 20. As it can be seen from the figures none of the available land cover is as large as the zoom area.

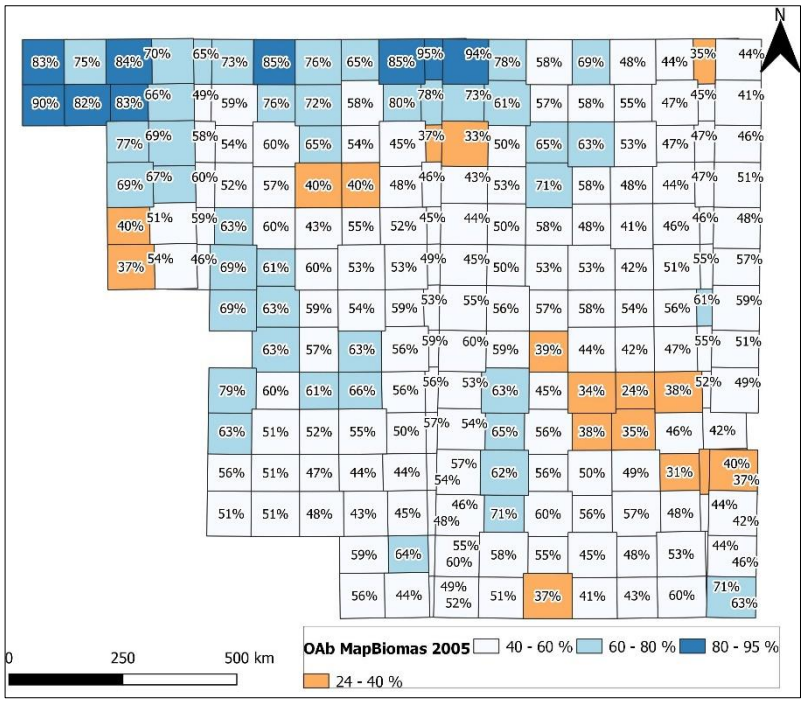

Figure 19. OA_b for each tile of 2005 historical map in Amazon based on MapBiomas

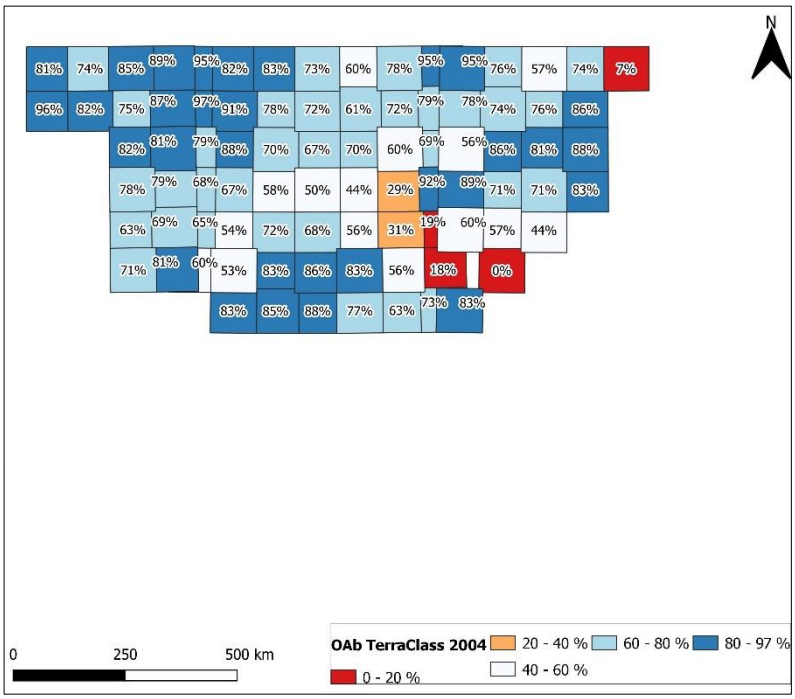

Figure 20. OA_b for each tile of 2005 historical map in Amazon based on TerraClass

3.3.3.2 Per class benchmark accuracy

Table 36. UA_b and PA_b for whole 2005 Amazon

Dataset	Index	Bareland	Built-up	Cropland	Forest	Grassland	Shrubland	Water	Water permanent	Water seasonal	Wetland Herbaceous	Wetland Shrubby
MapBiomas	PA	39%	71%	58%	85%	53%	11%	72%			61%	0%
TerraClass		6%	2%	56%	92%	54%	9%	68%				
FNF					80%			38%				
GSW seasonality									80%	15%		
GSW v1 2									84%	14%		
MapBiomas	UA	1%	27%	41%	68%	78%	17%	46%			14%	0%
TerraClass		0%	12%	38%	86%	75%	7%	50%				
FNF					74%			31%				
GSW seasonality									63%	3%		
GSW v1 2									61%	6%		

3.3.4 Amazon 2000

Following existing land cover maps are used for inter-comparison of historical products for 2000:

- MapBiomas 2000
- GL30 2000
- GHS BU LDS 2000
- TreeCover 2000
- GSW seasonality 2000
- GSW v1 2 2000
- AUE 2000 (Sao Paolo), 2001 (Ribeirao Preto)

3.3.4.1 Overall benchmark accuracy

There are 2 existing multiple-class land cover maps for year 2000 with which historical product for Amazon region was compared: GL30 and MapBiomas. Table 37 is showing the consistency between historical map in Amazon and each of the existing land cover maps.

Table 37. Overall benchmark accuracy for whole Amazon in 2000

Existing dataset	OA_b
GL30	43%
MapBiomas	50%

Amazon results of OA_b will be shown in form of maps for OA_b with each of the four existing land cover available in the region. OA_b with respect to GL30 is shown in Figure 21, and with respect to MapBiomas in Figure 22.

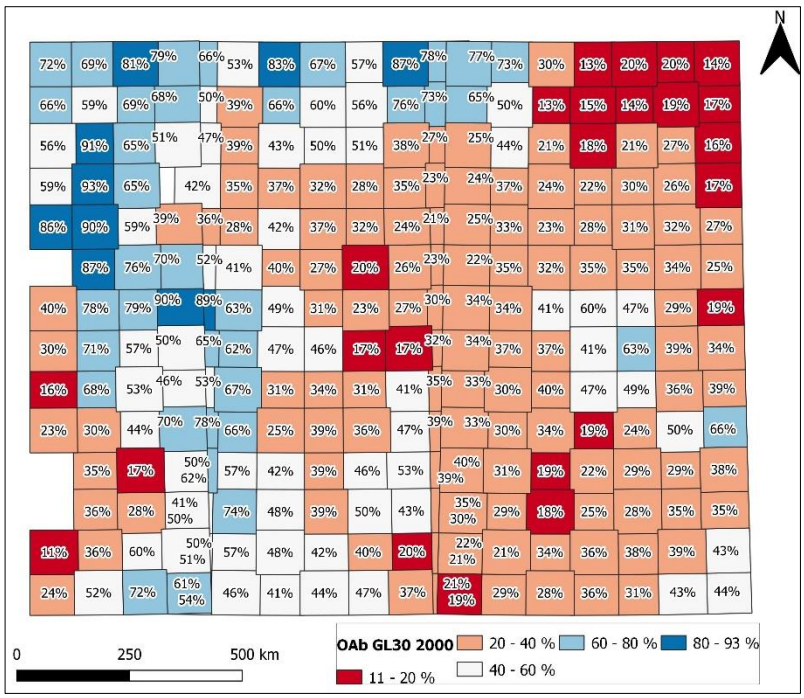

Figure 21. OA_b for each tile of 2000 historical map in Amazon based on GL30

The MapBiomas dataset does not completely cover zoom area in Amazon therefore the appearance of the map is different with respect to the GL30 map for Amazonia.

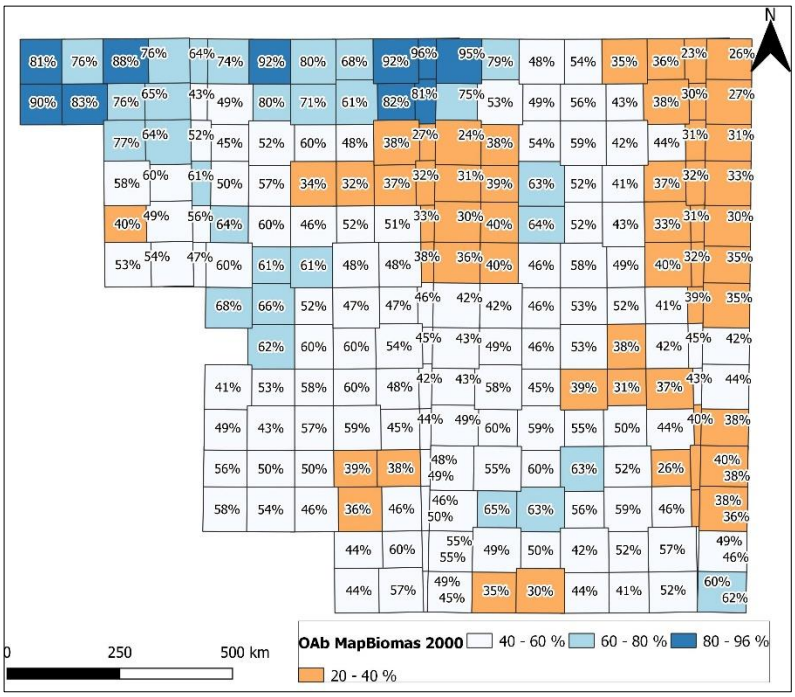

Figure 22. OA_b for each tile of 2000historical map in Amazon based on MapBiomas

3.3.4.2 Per class benchmark accuracy

Table 38. UA_b and PA_b for whole 2000 Amazon

Dataset	Index	Bareland	Built-up	Cropland	Forest	Grassland	Shrubland	Water	Water permanent	Water seasonal	Wetland	Wetland Herbaceous	Wetland Shrubby
MapBiomas	PA	52%	64%	39%	86%	48%	6%	73%				72%	0%
GL30		26%	48%	28%	82%	38%	5%	69%			28%		
GHS BU LDS			65%					92%					
TreeCover					86%								
GSW seasonality									74%	21%			
GSW v1 2									76%	17%			
MapBiomas	UA	1%	13%	27%	64%	78%	15%	36%				14%	0%
GL30		0%	9%	76%	63%	16%	17%	36%			26%		
GHS BU LDS			8%					21%					
TreeCover					82%								
GSW seasonality									43%	4%			
GSW v1 2									42%	7%			
AUE Sao Paulo	PA		51%					45%					
AUE Ribeirao Preto			43%					33%					
AUE Sao Paulo	UA		89%					1%					
AUE Ribeirao Preto			89%					0%					

3.3.5 Amazon 1995

Following existing land cover maps are used for inter-comparison of historical products for 1995:

- MapBiomas 1995
- GSW seasonality 1995
- GSW v1 2 1995

3.3.5.1 Overall benchmark accuracy

There is only 1 existing multiple-class land cover map – MapBiomas – for year 1995 with which historical product for Amazon region was compared. Table 39 is showing the consistency between historical map in Amazon and the existing land cover map.

Table 39. Overall benchmark accuracy for whole Amazon in 1995

Existing dataset	OA_b
MapBiomas	56%

Amazon results of OA_b will be shown in form of maps for OA_b. OA_b with respect to MapBiomas is shown in Figure 23. The MapBiomas dataset does not completely cover zoom area in Amazon.

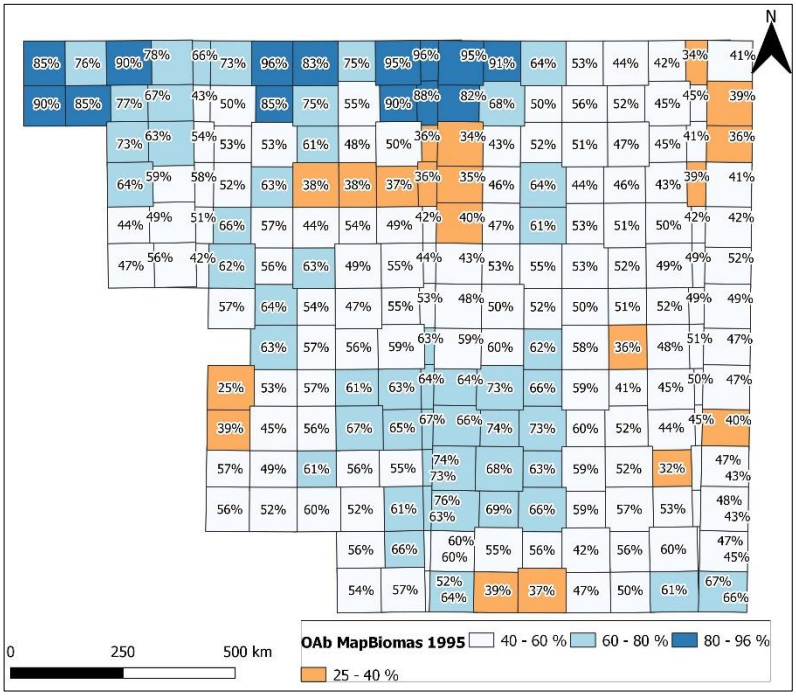

Figure 23. OA_b for each tile of 1995 historical map in Amazon based on MapBiomas

3.3.5.2 Per class benchmark accuracy

Table 40. UA_b and PA_b for whole 1995 Amazon

Dataset	Index	Bareland	Built-up	Cropland	Forest	Grassland	Shrubland	Water	Water permanent	Water seasonal	Wetland Herbaceous	Wetland Shrubby
MapBiomas	PA	39%	70%	39%	91%	58%	7%	63%			52%	0%
GSW seasonality									67%	3%		
GSW v1 2									74%	3%		
MapBiomas	UA	1%	21%	35%	65%	75%	24%	52%			17%	0%
GSW seasonality									45%	4%		
GSW v1 2									42%	10%		

3.3.6 Amazon 1990

Following existing land cover maps are used for inter-comparison of historical products for 1990:

- MapBiomas 1990
- GHS BU LDS 1990
- GSW seasonality 1990
- GSW v1 2 1990
- AUE 1988 (Sao Paolo), 1990 (Ribeirao Preto)

3.3.6.1 Overall benchmark accuracy

There is only 1 existing multiple-class land cover map – MapBiomas – for year 1990 with which historical product for Amazon region was compared. Table 41 is showing the consistency between historical map in Amazon and the existing land cover map.

Table 41. Overall benchmark accuracy for whole Amazon in 1990

Existing dataset	OA_b
MapBiomas	56%

Amazon results of OA_b will be shown in form of maps for OA_b . OA_b with respect to MapBiomas is shown in Figure 24. The MapBiomas dataset does not completely cover zoom area in Amazon.

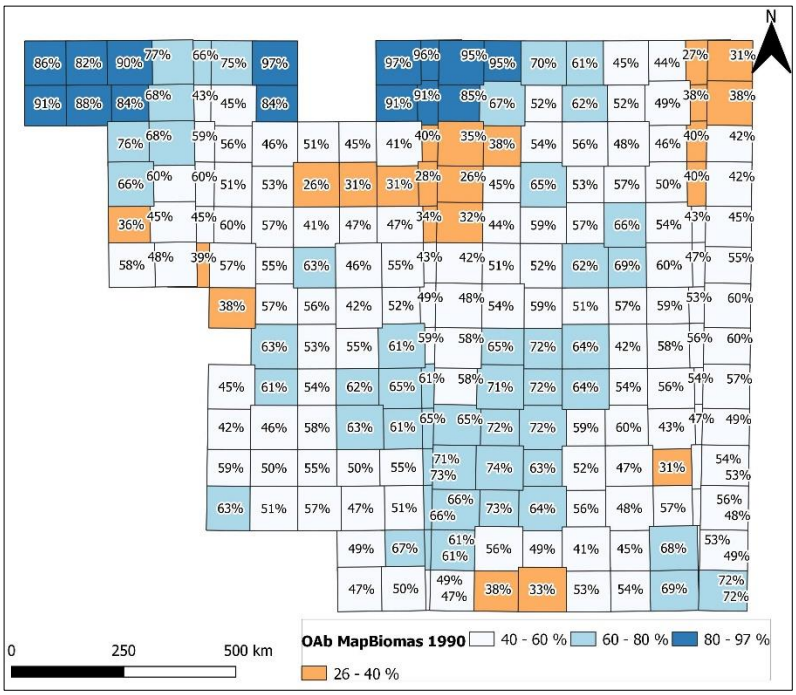

Figure 24. OA_b for each tile of 1990 historical map in Amazon based on MapBiomas

3.3.6.2 Per class benchmark accuracy

Table 42. UA_b and PA_b for whole 1990 Amazon

Dataset	Index	Bareland	Built-up	Cropland	Forest	Grassland	Shrubland	Water	Water permanent	Water seasonal	Wetland Herbaceous	Wetland Shrubby
MapBiomas	PA	31%	68%	39%	87%	66%	3%	57%			45%	0%
GHS BU LDS			67%					66%				
GSW v1 2									63%	14%		
GSW seasonality									60%	16%		
MapBiomas	UA	1%	12%	32%	72%	66%	25%	49%			16%	0%
GHS BU LDS			7%					33%				
GSW v1 2									66%	12%		
GSW seasonality									70%	5%		
AUE Sao Paulo	PA		54%					57%				
AUE Ribeirao Preto			57%					0%				
AUE Sao Paulo	UA		84%					8%				
AUE Ribeirao Preto			95%					0%				

3.3.7 Siberia 2015

Following existing land cover maps are used for inter-comparison of historical products for 2015:

- FROM GLC 2015
- GHS BU LDS 2014
- GSW seasonality 2015
- GSW v1 2 2015
- FNF 2015
- WSF 2015

3.3.7.1 Overall benchmark accuracy

There is single existing multiple-class land cover maps for year 2015 - FROM-GLC - with which historical product for Siberia region was compared. Table 43 is showing the consistency between historical map in Siberia and each of the existing land cover maps.

Table 43. Overall benchmark accuracy for whole Siberia in 2015

Existing dataset	OA_b
FROM-GLC	53%

Siberia results of OA_b will be shown in form of maps for OA_b with existing land cover available in the region. OA_b with respect to FROM-GLC is shown in Figure 25.

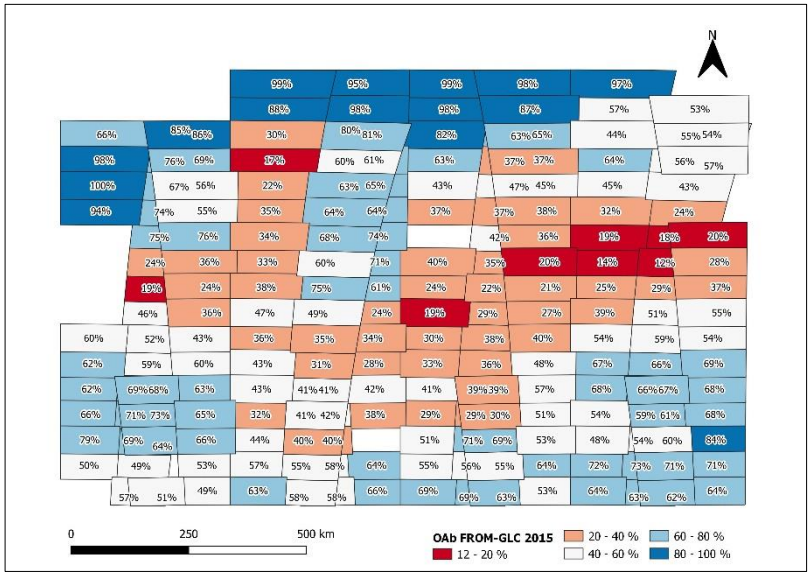

Figure 25. OA_b for each tile of 2015 historical map in Siberia based on FROM GLC

3.3.7.2 Per class benchmark accuracy

Table 44. UA_b and PA_b for whole 2015 Siberia

Dataset	Index	Bareland	Built-up	Cropland	Forest	Grassland	Ice and snow	Shrubland	Tundra	Water	Water permanent	Water seasonal	Wetland
FROM GLC	PA	25%	82%	0%	75%	16%	0%	11%	2%	97%			55%
GHS BU LDS			81%							99%			
WSF			79%										
FNF					78%					91%			
GSW seasonality											81%	36%	
GSW v1 2											84%	37%	
FROM GLC	UA	2%	2%	0%	75%	28%	0%	1%	44%	83%			0%
GHS BU LDS			6%							77%			
WSF			9%										
FNF					56%					75%			
GSW seasonality											96%	15%	
GSW v1 2											53%	17%	

3.3.8 Siberia 2010

Following existing land cover maps are used for inter-comparison of historical products for 2010:

- FROM GLC 2010
- GL30 2010
- GUF 2011
- GSW seasonality 2010
- GSW v1 2 2010
- FNF 2010

3.3.8.1 Overall benchmark accuracy

There are 2 existing multiple-class land cover maps for year 2010 with which historical product for Siberia region was compared: FROM-GLC and GL30. Table 45 is showing the consistency between historical map in Siberia and each of the existing land cover maps.

Table 45. Overall benchmark accuracy for whole Siberia in 2010

Existing dataset	OA_b
FROM-GLC	53%
GL30	53%

Siberia results of OA_b will be shown in form of maps for OA_b with each of the two existing land cover available in the region. OA_b with respect to FROM-GLC is shown in Figure 26, and with respect to GL30 Figure 27.

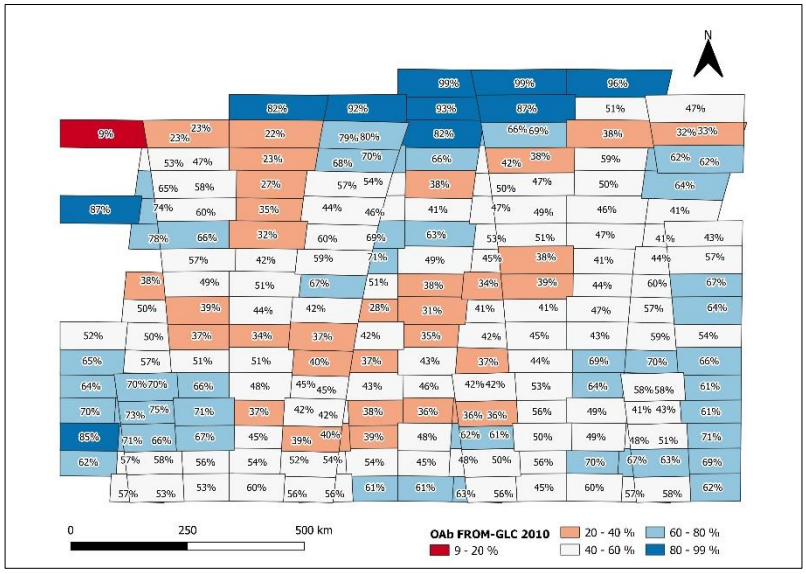

Figure 26. OA_b for each tile of 2010 historical map in Siberia based on FROM GLC

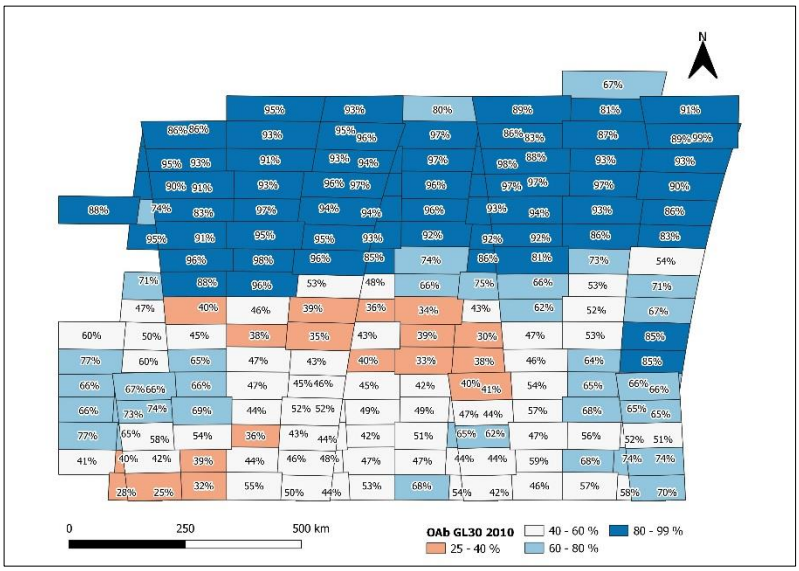

Figure 27. OA_b for each tile of 2010 historical map in Siberia based on GL30

3.3.8.2 Per class benchmark accuracy

Table 46. UA_b and PA_b for whole 2010 Siberia

Dataset	Index	Bareland	Built-up	Cropland	Forest	Grassland	Ice and snow	Shrubland	Water	Water permanent	Water seasonal	Wetland
FROM GLC	PA	15%	16%	0%	73%	31%	0%	32%	86%			44%
GL30		82%	51%	0%	77%	13%		0%	89%			21%
GUF 2011			82%									
FNF					87%				87%			
GSW seasonality										86%	32%	
GSW v1 2										86%	29%	
FROM GLC	UA	21%	17%	0%	65%	82%	0%	3%	79%			1%
GL30		0%	31%	0%	72%	8%		0%	77%			66%
GUF 2011			10%									
FNF					53%				81%			
GSW seasonality										95%	11%	
GSW v1 2										51%	8%	

3.3.9 Siberia 2005

Following existing land cover maps are used for inter-comparison of historical products for 2005:

- FNF 2007
- GSW seasonality 2005
- GSW v1 2 2005

3.3.9.1 Overall benchmark accuracy

For year 2005 other multiple-class land cover do not exist, therefore OA_b cannot be reported.

3.3.9.2 Per class benchmark accuracy

Table 47. UA_b and PA_b for whole 2005 Siberia

Dataset	Index	Forest	Water	Water permanent	Water seasonal
FNF	PA	86%	88%		
GSW seasonality				89%	32%
GSW v1 2				88%	31%
FNF	UA	55%	77%		
GSW seasonality				92%	13%
GSW v1 2				52%	10%

3.3.10 Siberia 2000

Following existing land cover maps are used for inter-comparison of historical products for 2000:

- GL30 2000
- GHS BU LDS 2000
- TreeCover 2000
- GSW seasonality 2000
- GSW v1 2 2000

3.3.10.1 Overall benchmark accuracy

There is single existing multiple-class land cover maps for year 2000 – GL30 - with which historical product for Siberia region was compared. Table 48 is showing the consistency between historical map in Siberia and each of the existing land cover maps.

Table 48. Overall benchmark accuracy for whole Siberia in 2000

Existing dataset	OA_b
GL30	50%

Siberia results of OA_b will be shown in form of maps for OA_b with existing land cover available in the region. OA_b with respect to GL30 is shown in Figure 2.

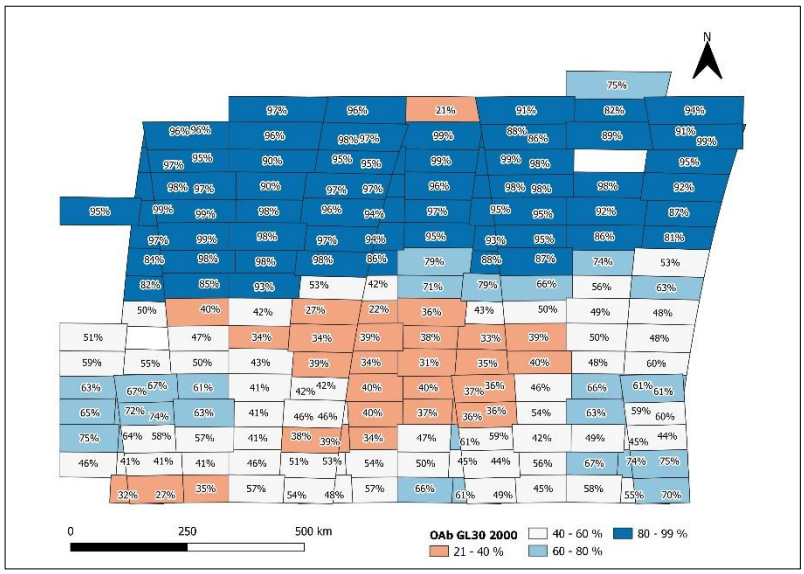

Figure 28. OA_b for each tile of 2000 historical map in Siberia based on GL30

3.3.10.2 Per class benchmark accuracy

Table 49. UA_b and PA_b for whole 2000 Siberia

Dataset	Index	Bareland	Built-up	Cropland	Forest	Grassland	Shrubland	Water	Water permanent	Water seasonal	Wetland
GL30	PA	84%	54%	0%	68%	20%	6%	94%			21%
GHS			83%					99%			
TreeCover					83%						
GSW seasonality									88%	46%	
GSW v1 2									86%	39%	
GL30	UA	0%	20%	0%	71%	7%	0%	63%			55%
GHS			3%					76%			
TreeCover					68%						
GSW seasonality									96%	15%	
GSW v1 2									52%	13%	

3.3.11 Siberia 1995

Following existing land cover maps are used for inter-comparison of historical products for 1995:

- GSW seasonality 1994
- GSW v1 2 1994

3.3.11.1 Overall benchmark accuracy

For year 1995 other multiple-class land cover do not exist, therefore OA_b cannot be reported.

3.3.11.2 Per class benchmark accuracy

Table 50. UA_b and PA_b for whole 1995 Siberia

Dataset	Index	Water permanent	Water seasonal
GSW seasonality	PA	84%	36%
GSW v1 2		84%	36%
GSW seasonality	UA	95%	16%
GSW v1 2		51%	14%

3.3.12 Siberia 1990

Following existing land cover maps are used for inter-comparison of historical products for 1990:

- GHS BU LDS 1990
- GSW seasonality 1990
- GSW v1 2 1990

3.3.12.1 Overall benchmark accuracy

For year 1990 other multiple-class land cover do not exist, therefore OA_b cannot be reported.

3.3.12.2 Per class benchmark accuracy

Table 51. UA_b and PA_b for whole 1990 Siberia

Dataset	Index	Built-up	Water	Water permanent	Water seasonal
GHS	PA	86%	97%		
GSW seasonality				85%	35%
GSW v1 2				84%	33%
GHS	UA	2%	77%		
GSW seasonality				95%	18%
GSW v1 2				53%	15%

3.3.13 Africa 2015

Following existing land cover maps are used for inter-comparison of historical products for 2015:

- FROM GLC 2015
- WSF 2015
- GSW v1 2 2015
- GSW seasonality 2015
- GHS 2014
- FNF 2015

3.3.13.1 Overall benchmark accuracy

There is single existing multiple-class land cover maps for year 2015 - FROM-GLC - with which historical product for Africa region was compared. Table 52 is showing the consistency between historical map in Africa and the existing land cover map.

Table 52. Overall benchmark accuracy for whole Africa in 2015

Existing dataset	OA_b
FROM_GLC	46%

Africa results of OA_b will be shown in form of maps for OA_b with existing land cover available in the region. OA_b with respect to FROM-GLC is shown in Figure 29.

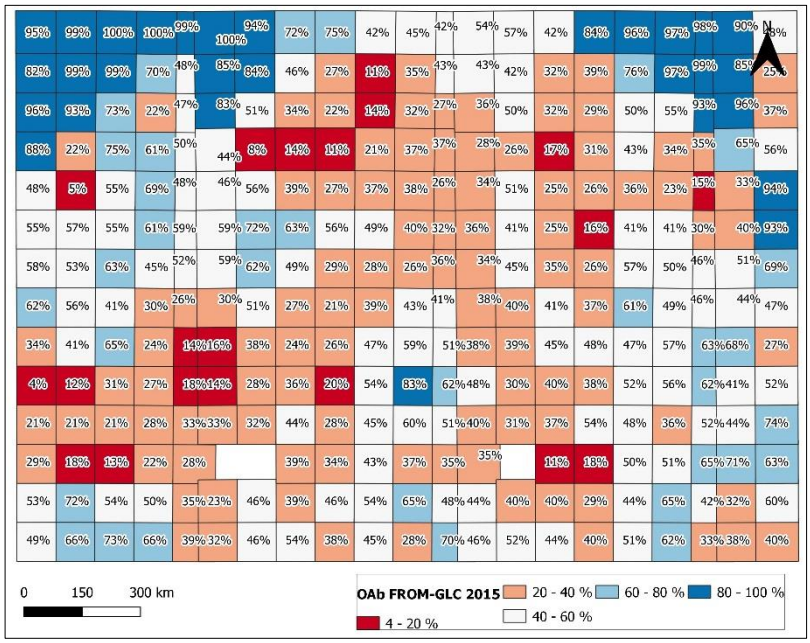

Figure 29. OA_b for each tile of 2015 historical map in Africa based on FROM GLC

3.3.13.2 Per class benchmark accuracy

Table 53. UA_b and PA_b for whole 2015 Africa

Dataset	Index	Bareland	Built-up	Cropland	Forest	Grassland	Shrubland	Water	Water permanent	Water seasonal	Wetland
FROM GLC	PA	61%	21%	23%	85%	20%	44%	86%			45%
GHS			42%					99%			
WSF			33%								

FNF					46%			78%			
GSW seasonality									92%	47%	
GSW v1 2									93%	38%	
FROM GLC	UA	52%	2%	37%	25%	21%	62%	94%			5%
GHS			1%					89%			
WSF			2%								
FNF					68%			85%			
GSW seasonality									100%	8%	
GSW v1 2									61%	12%	

3.3.14 Africa 2010

Following existing land cover maps are used for inter-comparison of historical products for 2010:

- FROM GLC 2010
- GL30 2010
- GUF 2011
- GSW v1 2 2010
- GSW seasonality 2010
- FNF 2010

3.3.14.1 Overall benchmark accuracy

There are 2 existing multiple-class land cover maps for year 2010 with which historical product for Africa region was compared: FROM-GLC and GL30. Table 54 is showing the consistency between historical map in Africa and each of the existing land cover maps.

Table 54. Overall benchmark accuracy for whole Africa in 2010

Existing dataset	OA_b
FROM_GLC	53%
GL30	28%

Africa results of OA_b will be shown in form of maps for OA_b with each of the two existing land cover available in the region. OA_b with respect to FROM-GLC is shown in Figure 30, and with respect to GL30 Figure 31.

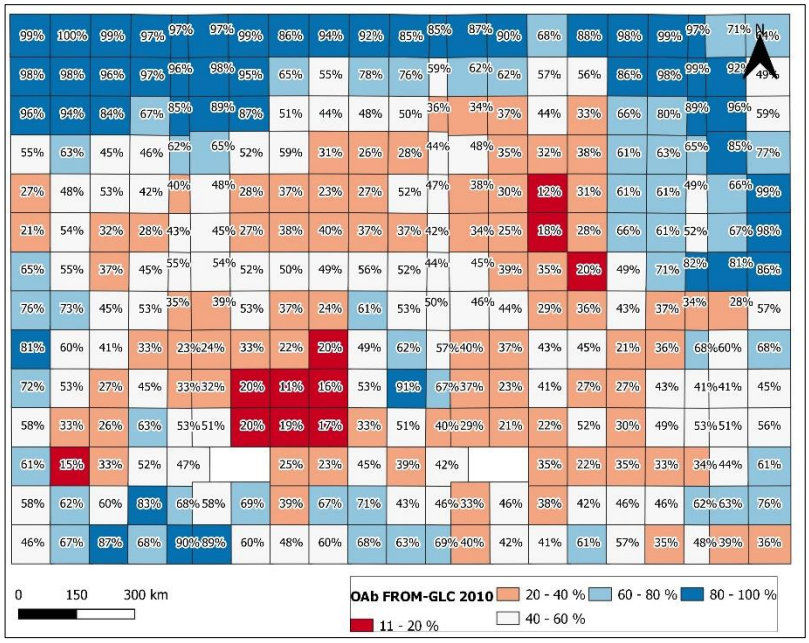

Figure 30. OA_b for each tile of 2010 historical map in Africa based on FROM GLC

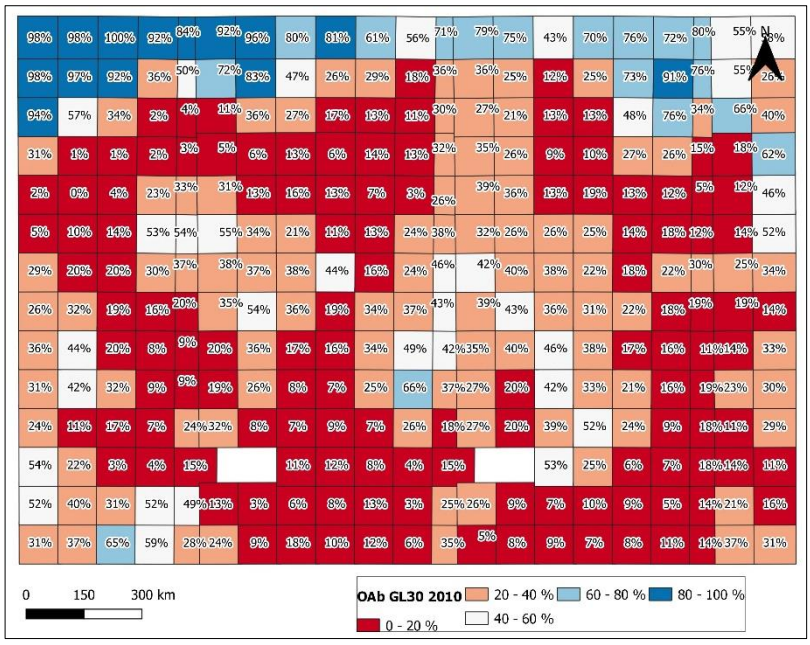

Figure 31. OA_b for each tile of 2010 historical map in Africa based on GL30

3.3.14.2 Per class benchmark accuracy

Table 55. UA_b and PA_b for whole 2010 Africa

Dataset	Index	Bareland	Built-up	Cropland	Forest	Grassland	Permanent ice and snow	Shrubland	Water	Water permanent	Water seasonal	Wetland
FROM GLC	PA	60%	6%	17%	80%	4%	0%	62%	76%			9%
GL30		92%	13%	15%	78%	2%		56%	89%			19%
GUF			23%									
FNF					57%				94%			
GSW seasonality										97%	47%	
GSW v1 2										98%	45%	
FROM GLC	UA	90%	1%	33%	39%	19%	0%	39%	95%			1%
GL30		39%	2%	42%	30%	42%		18%	63%			11%
GUF			2%									
FNF					57%				88%			
GSW seasonality										95%	26%	
GSW v1 2										66%	47%	

3.3.15 Africa 2005

Following existing land cover maps are used for inter-comparison of historical products for 2005:

- GSW seasonality 2005
- GSW v1 2 2005
- FNF 2007

3.3.15.1 Overall benchmark accuracy

For year 2005 other multiple-class land cover do not exist, therefore OA_b cannot be reported.

3.3.15.2 Per class benchmark accuracy

Table 56. UA_b and PA_b for whole 2005 Africa

Dataset	Index	Forest	Water	Water permanent	Water seasonal
FNF	PA	43%	75%		
GSW seasonality				92%	51%
GSW v1 2				93%	54%
FNF	UA	58%	84%		
GSW seasonality				96%	8%
GSW v1 2				65%	18%

3.3.16 Africa 2000

Following existing land cover maps are used for inter-comparison of historical products for 2000:

- GL30 2000
- GSW seasonality 2000
- GSW v1 2 2000
- GHS 2000
- TreeCover 2000

3.3.16.1 Overall benchmark accuracy

There is single existing multiple-class land cover maps for year 2000 – GL30 - with which historical product for Africa region was compared. Table 57 is showing the consistency between historical map in Africa and the existing land cover map.

Table 57. Overall benchmark accuracy for whole Africa in 2000

Existing dataset	OA_b
GL30	26%

Africa results of OA_b will be shown in form of maps for OA_b with existing land cover available in the region. OA_b with respect to GL30 is shown in Figure 32.

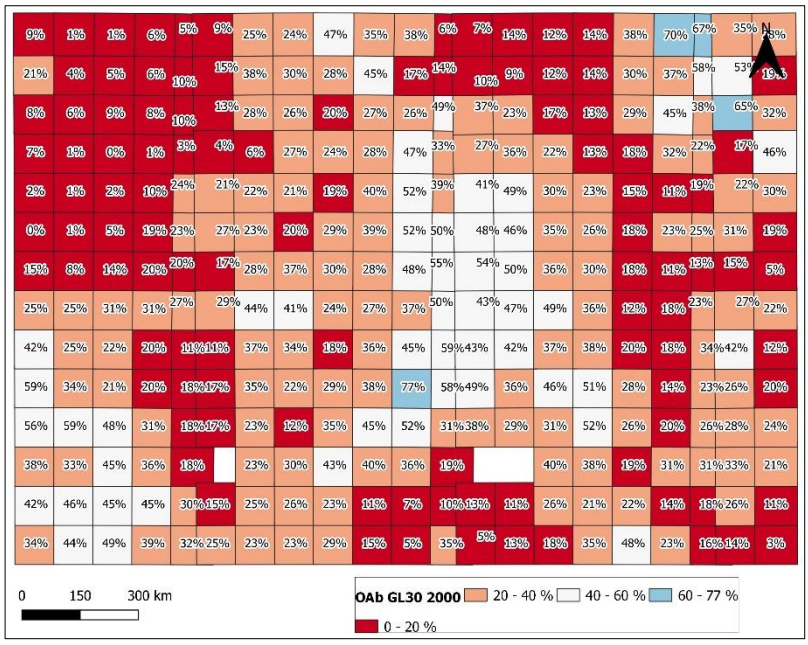

Figure 32. OA_b for each tile of 2000 historical map in Africa based on GL30

3.3.16.2 Per class benchmark accuracy

Table 58. UA_b and PA_b for whole 2000 Africa

Dataset	Index	Bareland	Built-up	Cropland	Forest	Grassland	Shrubland	Water	Water permanent	Water seasonal	Wetland

GL30	PA	28%	31%	26%	39%	19%	22%	78%			39%
GHS			53%					99%			
TreeCover					65%						
GSW seasonality									89%	39%	
GSW v1 2									90%	37%	
GL30	UA	20%	1%	33%	46%	41%	10%	69%			10%
GHS			0%					93%			
TreeCover					21%						
GSW seasonality									100%	7%	
GSW v1 2									68%	11%	

3.3.17 Africa 1995

Following existing land cover maps are used for inter-comparison of historical products for 1995:

- GSW seasonality 1995
- GSW v1 2 1995

3.3.17.1 Overall benchmark accuracy

For year 1995 other multiple-class land cover do not exist, therefore OA_b cannot be reported.

3.3.17.2 Per class benchmark accuracy

Table 59. UA_b and PA_b for whole 1995 Africa

Dataset	Index	Water permanent	Water seasonal
GSW seasonality	PA	93%	23%
GSW v1 2		95%	42%
GSW seasonality	UA	98%	6%
GSW v1 2		68%	13%

3.3.18 Africa 1990

Following existing land cover maps are used for inter-comparison of historical products for 1990:

- GHS 1990
- GSW seasonality 1990 (available only for 27 out of 279 tiles)
- GSW v1 2 1990

3.3.18.1 Overall benchmark accuracy

For year 1990 other multiple-class land cover do not exist, therefore OA_b cannot be reported.

3.3.18.2 Per class benchmark accuracy

Table 60. UA_b and PA_b for whole 1990 Africa

Dataset	Index	Built-up	Water	Water permanent	Water seasonal

GHS	PA	24%	95%		
GSW seasonality				97%	0%
GSW v1 2				97%	7%
GHS	UA	0%	73%		
GSW seasonality				99%	0%
GSW v1 2				27%	0%

3.3.19 Conclusions

From the point of view of benchmark accuracy, for binary maps that are specifically derived for certain class – FNF, GHS BU S1, GHS BU LDS, GSW seasonality, GSW_v1_2, Tree Cover, and WSF - OA_b is very high due to the presence of the class that represent all the other classes but the one of interest for the map. Therefore OA_b for these maps is not informative, and only PA_b and UA_b were taken into consideration for the following conclusions.

Regarding individual accuracy indexes the classification are interpreted as "excellent" if both scores PA_b and UA_b are above 90%, "well" if the scores are between 70% and 90% and "relatively good" if the scores are between 50% and 70%. The classes for which individual accuracy indexes are less than 50% for the majority of the compared datasets are not considered in the conclusions.

GSW datasets – seasonality and v1_2 – are the same datasets with different water permanence threshold. GSW v1 2 is dataset produced by JRC, while GSW seasonality is computed form JRC monthly water dataset to take into account seasonality thresholds as defined by CCI HRLC legend. GSW v1 2 defines Seasonal water as a surface that is underwater for less than 12 months of the year and Permanent water as a surface that is underwater throughout the year. In case of GSW seasonality Seasonal water is defined as a surface that is underwater between 4 and 8 months, and Permanent water as a surface that is underwater for 9 or more months. Both datasets are kept for the inter-comparison in order to see if CCI HRLC products are more similar to GSW seasonality which would confirm that water seasonality is captured well. Since in majority of cases the commission error was reduced for few percent in case of GSW seasonality, for the second production only this version of product is considered in the inter-comparison.

3.3.19.1 Amazon

Overall agreement of the historical map with existing land cover maps in Amazon varying from 43% to 75%. The best agreement is with the TerraClass dataset, which shows values definitely higher than other datasets.

The agreement with each dataset was relatively homogeneous for different years. The agreement with MapBiomas – the only map available for all years concerned in the project - was around 54% for all the years. The agreement with TerraClass on average for all the years was around 68%, with FROM-GLC around 52% and for GL30 around 44%.

There is no significant difference between results for GSW v1 2 and GSW seasonality so no particular comments were made regarding that.

3.3.19.1.1 Amazon 2015

For year 2015 OA_b was 57% for FROM-GLC and MapBiomas, and 63% for TerraClass (Table 31). The per tile OA_b for FROM-GLC and MapBiomas are relatively homogeneous too (Figure 12 and Figure 13)

Regarding the class accuracy (Table 32) Forest and Water are considered as relatively good classified, while Permanent water is classified well. From class accuracy it is evident that TerraClass has slightly better records for Forest than the other two datasets and this is probably the reason why OA_b is higher for this map.

According to the AUE dataset Built-up class is relatively well classified, which is not evident from other datasets. Given that AUE dataset is focused on big cities (Ribeirao Preto and Sao Paolo), it may indicate that classification of built-up class is more successful in cities with respect to built-up elsewhere. It might be due to homogeneity of built-up class in cities.

3.3.19.1.2 Amazon 2010

For year 2010 OA_b was 46% for FROM-GLC, 44% for GL30, 51% for MapBiomas, and 67% for TerraClass (Table 33). The per tile OA_b for FROM-GLC and MapBiomas are relatively homogeneous (Figure 15 and Figure 17), while per tile OA_b of GL30 shows lower agreement in the central part of the region (Figure 16).

Regarding the class accuracy (Table 34), Forest is the only class considered as relatively good classified. It is surprising that UA_b is lower than 50% for classes Water and Permanent water since this class is relatively easy to classify due to specific spectral signature. Given that the PA_b is larger than 70%, it might indicate that water is overestimated. From class accuracy it is evident that TerraClass has slightly better records for Forest than the other two datasets, therefore this is probably the reason why OA_b is higher for this map.

3.3.19.1.3 Amazon 2005

For year 2005 OA_b OA_b was 55% for MapBiomas, and 75% for TerraClass (Table 35). The per tile OA_b for these two maps are not homogeneous (Figure 19 and Figure 20)

Regarding the class accuracy (Table 36) Forest is considered as well classified, while Grassland and Permanent water are considered as relatively good. From class accuracy it is evident that TerraClass has slightly better records for Forest than the other two datasets, therefore this is probably the reason why OA_b is higher for this map.

3.3.19.1.4 Amazon 2000

For year 2000 OA_b was 50% for MapBiomas, and 43% for GL30 (Table 37). The per tile OA_b for these two maps are not homogeneous (Figure 21 and Figure 22).

Regarding the class accuracy (Table 38), Forest is the only class considered as relatively good classified. As for the year 2010 UA_b is lower than 50% for classes Water and Permanent water, but PA_b is larger than 70%. It might indicate that water is overestimated.

According to the AUE dataset in Sao Paulo and Ribeirao Preto Built-up class might be underestimated as PA_b is below 50% and much lower than UA_b.

3.3.19.1.5 Amazon 1995

The only existing multiple-class land cover map for 1995 is MapBiomas (Table 39). It is showing 56% of consistency with historical map for 1995 in Amazon. It shows relatively good agreement for Forest, Grassland and Water classes. Second existing land cover map is GSW. It is specialized for water and it is indicating overestimation of Permanent water class given that UA_b is below 50% and smaller than PA_b (Table 40).

3.3.19.1.6 Amazon 1990

The only existing multiple-class land cover map for 1990 is MapBiomas (Table 41). It is showing 56% of consistency with historical map for 1990 in Amazon. It shows relatively good agreement for Forest and Grassland classes. Other available existing land cover maps are GSW and GHS BU LDS. The former one is specialized for water and it is indicating relatively good classification of Permanent water class. Later one is specialized for built-up areas and in combination with MapBiomas it is showing overestimation of Built-up class. Regarding Built-up class AUE dataset is suggesting relatively good agreement in the big cities (Table 42).

3.3.19.2 Siberia

In Siberia there are only two existing land cover maps with multiple-classes available for 3 year 2015, 2010, 2000. This means that OA_b was estimated only in this years. OA_b was around 52 % according to the GL30 dataset and around 53% according to the FROM-GLC.

3.3.19.2.1 Siberia 2015

According to FROM-GLC consistency with historical map for 2015 is 53% (Table 43). Classes Forest, Water and Permanent Water have UA_b and PA_b above 70 % thus the classification of these classes is well (Table 44). UA_b of Permanent water in case of GSW v1 2 is significantly lower than of GSW seasonality. This indicate that seasonality of Permanent water class is captured well. Per tile OA_b (Figure 22) is showing high values for areas on the north of the Siberia zoom region which coincide with a sea surface. There are also some areas with very low values of OA_b (below 20%).

3.3.19.2.2 Siberia 2010

According to FROM-GLC consistency with historical map for 2010 is 53%, and according to GL30 it is 53% (Table 45). Per tile OA_b (Figure 22) with FROM-GLC is showing high values for areas on the north of the Siberia zoom region which coincide with a sea surface. Per tile OA_b with GL30 has very high values in the northern half of the zoom area. This is because Tundra class was removed. This class consists of grass, shrub, bareland and wetland in ecosystem of tundra. After Tundra removal there are very few classes left. The remaining classes are Water, Cropland, Forest, Built-up and Permanent ice and snow. Out of these classes Water, is predominant as other classes are rarely found in the tundra ecosystems. Classes Forest, Water and Permanent Water have UA_b and PA_b above 70 % thus the classification of these classes is well (Table 46). UA_b of Permanent water in case of GSW v1 2 is significantly lower than of GSW seasonality. This indicate that seasonality of Permanent water class is captured well.

3.3.19.2.3 Siberia 2005

There are no multiple class land cover maps for 2005, thus overall agreement can not be reported. On the opposite binary datasets are showing agreement of some classes (Table 47). In particular there is well agreement for class of Water and Permanent water and relatively good for Forest. UA_b of Permanent water in case of GSW v1 2 is significantly lower than of GSW seasonality. This indicate that seasonality of Permanent water class is captured well.

3.3.19.2.4 Siberia 2000

Consistency of GL30 (the only multi-class existing land cover available) with historical map for 2000 is 50% Table 48. Per tile OA_b with GL30 has very high values in the northern half of the zoom area. This is because Tundra class was removed. This class consists of grass, shrub, bareland and wetland in ecosystem of tundra. After Tundra removal there are very few classes left. The remaining classes are Water, Cropland, Forest, Built-up and Permanent ice and snow. Out of these classes Water, is predominant as other classes are rarely found in the tundra ecosystems. When individual classes are concerned there is relatively good agreement in case of Forest, and well agreement in case of Water and Permanent Water Table 49. UA_b of Permanent water in case of GSW v1 2 is significantly lower than of GSW seasonality. This indicate that seasonality of Permanent water class is captured well.

3.3.19.2.5 Siberia 1995

There are no multiple class land cover maps for 1995, thus overall agreement can not be reported. For the class agreement, GSW seasonality is showing high scores for Water permanent class thus this class can be considered as well classified Table 50. UA_b of Permanent water in case of GSW v1 2 is significantly lower than of GSW seasonality. This indicate that seasonality of Permanent water class is captured well.

3.3.19.2.6 Siberia 1990

There are no multiple class land cover maps for 1990, thus overall agreement can not be reported. For the class agreement, GSW seasonality is showing high scores for Water permanent and GHS BU LDS for Water class thus class thus these classes can be considered as well classified (Table 51). UA_b of Permanent water in case of GSW v1 2 is significantly lower than of GSW seasonality. This indicate that seasonality of Permanent water class is captured well.

3.3.19.3 Africa

3.3.19.3.1 Africa 2015

According to FROM-GLC consistency with historical map for 2015 is 46% (Table 52). There is no other non binary existing HRLC in 2015. Per tile OA_b (Figure 29) with FROM-GLC is showing high values for areas on the north-west corner of the African zoom region which coincide with a desertic/sandy area. Similarly, in the north-east corner of the zoom region there are high-values which are most probably related to the homogeneous water surface of the Red Sea. When individual classes are concerned there is Excellent agreement for Water permanent, and well agreement for Water class (Table 53). Bareland class has relatively good agreement, with respect to FROM-GLC, but in absence of another existing HRLC to confirm it is not possible to have solid conclusion on this matter.

3.3.19.3.2 Africa 2010

50% of information of historical map for 2010 coincides with the information of FROM GLC for the same year, on the opposite amount of shared information with GL30 is 28% (Table 54). Per tile OA_b (Figure 30) with FROM-GLC is showing high values in the northern part of the zoom area, which are most probably due to homogeneous landscape in this area where sand is present in the north-west, and water in the north-east. High values of agreement are evident even the case of GL30 in the north-west (Figure 31). From the class agreement (Table 55) it is possible to see that Water and Permanent water are classified well in 2010. Bareland seems to be relatively good classified according to the FROM-GLC, but not according to the GL30, and this is probably the reason why agreement with GL30 is lower than the agreement with FROM-GLC.

3.3.19.3.3 Africa 2005

There are no multiple class land cover maps for 2005, thus overall agreement can not be reported. On the opposite binary datasets are showing agreement of some classes (Table 56). In particular there is well agreement for class of Water and Permanent water.

3.3.19.3.4 Africa 2000

In 2000 the only multiple class existing HRLC available is GL30. It has 26% of agreement (Table 57) with CCI HRLC products for this year, which is very low. Per tile OA_b (Figure 32) does not show any meaningful pattern. The classes that can be considered as well classified are Water and Permanent water (Table 58).

3.3.19.3.5 Africa 1995

There are no multiple class land cover maps for 1995, thus overall agreement can not be reported. For the class agreement, GSW seasonality is showing high scores for Water permanent class thus this class can be considered as well classified (Table 59). UA_b of Permanent water in case of GSW v1 2 is significantly lower than of GSW seasonality. This indicate that seasonality of Permanent water class is captured well.

3.3.19.3.6 Africa 1990

There are no multiple class land cover maps for 1990, thus overall agreement can not be reported. For the class agreement, GSW seasonality is showing high scores for Water permanent and GHS BU LDS for Water class thus class thus these classes can be considered as well classified (Table 60). UA_b of Permanent water in case of GSW v1 2 is significantly lower than of GSW seasonality. This indicate that seasonality of Permanent water class is captured well.

3.4 Reliability of existing HRLC in RR regions

To understand how reliable the existing CCI HRLCs are in the regions of interest for the CCI HRLC project, we computed the accuracy of the existing datasets in Round Robin tiles. The accuracy was estimated based on validation samples prepared and provided by UCLouvain. The samples were created for validation of Round Robin tiles.

For computing accuracy metrics of the existing HRLC, it was necessary to harmonize classes from the RR validation dataset with the existing HRLC. Moreover, the CCI HRLC RR tiles legend was adjusted to the legends of different existing HRLCs, and the accuracy of adjusted versions of CCI HRLC RR tiles was estimated so that it is directly comparable with the accuracy of existing HRLC. OA was computed for RR tiles in each region individually, as well as for all tiles at once. The result of OA for existing HRLC compared with results of OA of CCI HRLC when its legend is adjusted to existing HRLC is displayed in Figure 33. The accuracy of GL30 is significantly lower than the accuracy of CCI HRLC products, but regional maps MapBiomas and ESA DUE Permafrost are more accurate than CCI HRLC products.

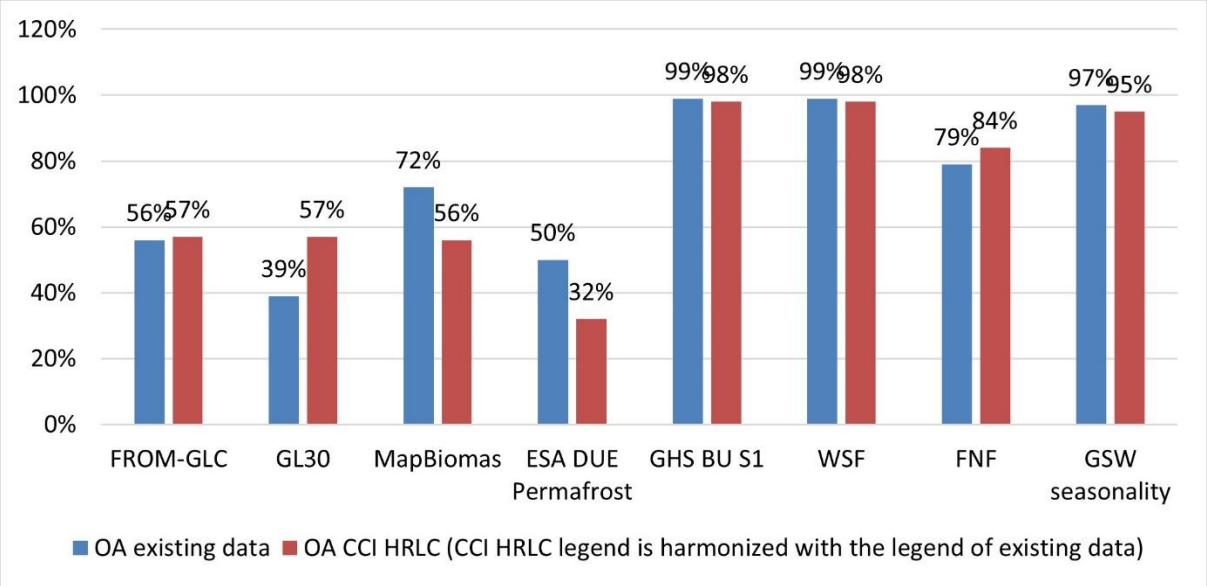

Figure 33. Comparison of OA of existing data and CCI HRLC for all RR tiles

Figure 34 shows the result for RR tiles in Siberia. CCI HRLC is more accurate than GL30 and FROM-GLC, but less accurate than the regional map - ESA DUE Permafrost. Other existing HRLCs have OA comparable to the OA of CCI HRLC.

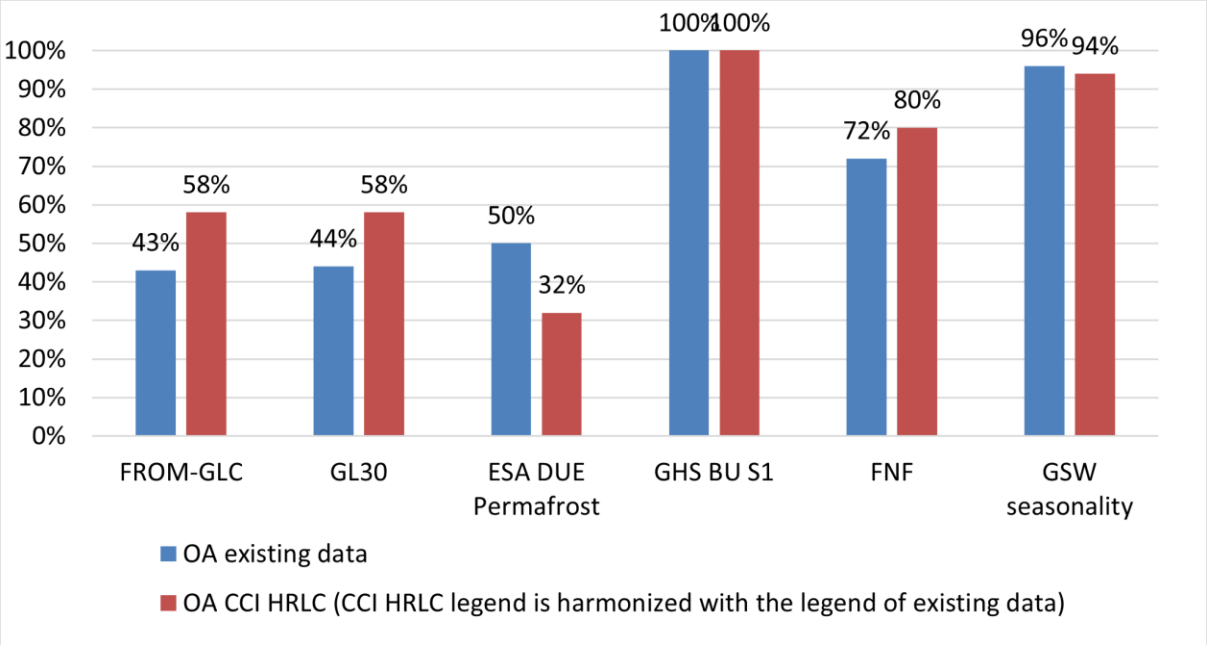

Figure 34. Comparison of OA of existing data and CCI HRLC for Siberia (42WXS)

Figure 35 shows that most of the existing HRLCs have comparable accuracy to the accuracy of CCI HRLC RR in Africa. However, there is an exception in the case of GL30 that has an accuracy lower than the one of CCI HRLC RR.

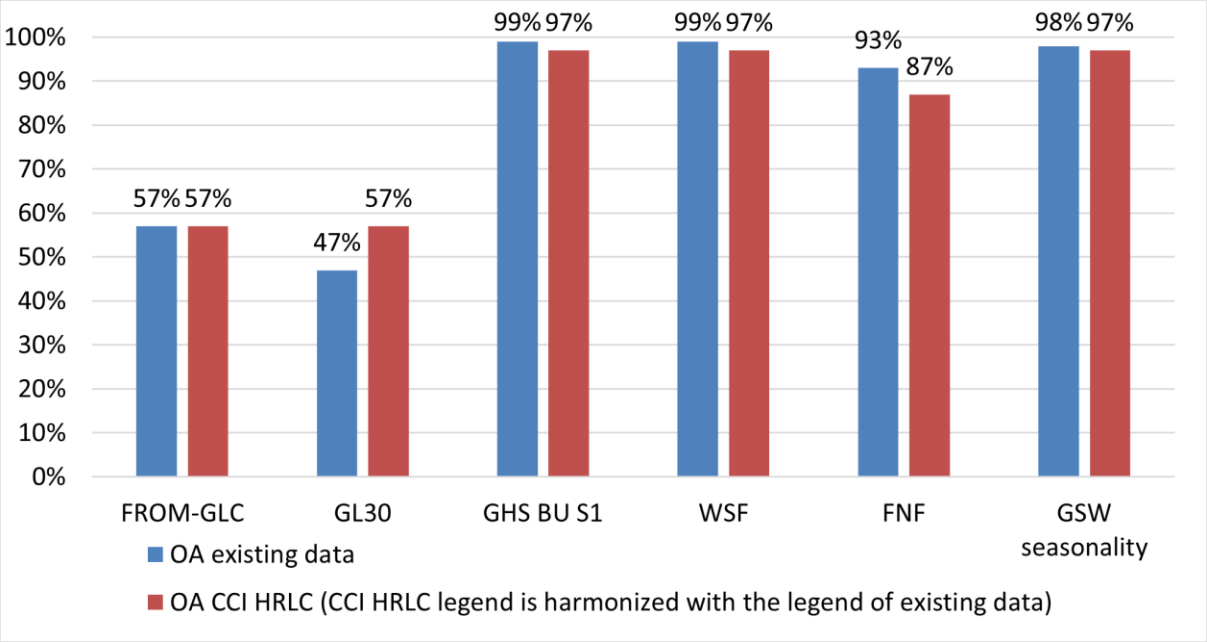

Figure 35. Comparison of OA of existing data and CCI HRLC for Africa (37PCP)

Figure 36 shows the result of OA for existing datasets and CCI HRLC in the RR regions in Amazon. It is evident that CCI HRLC is more accurate than GL30 but less accurate than MapBiomas.

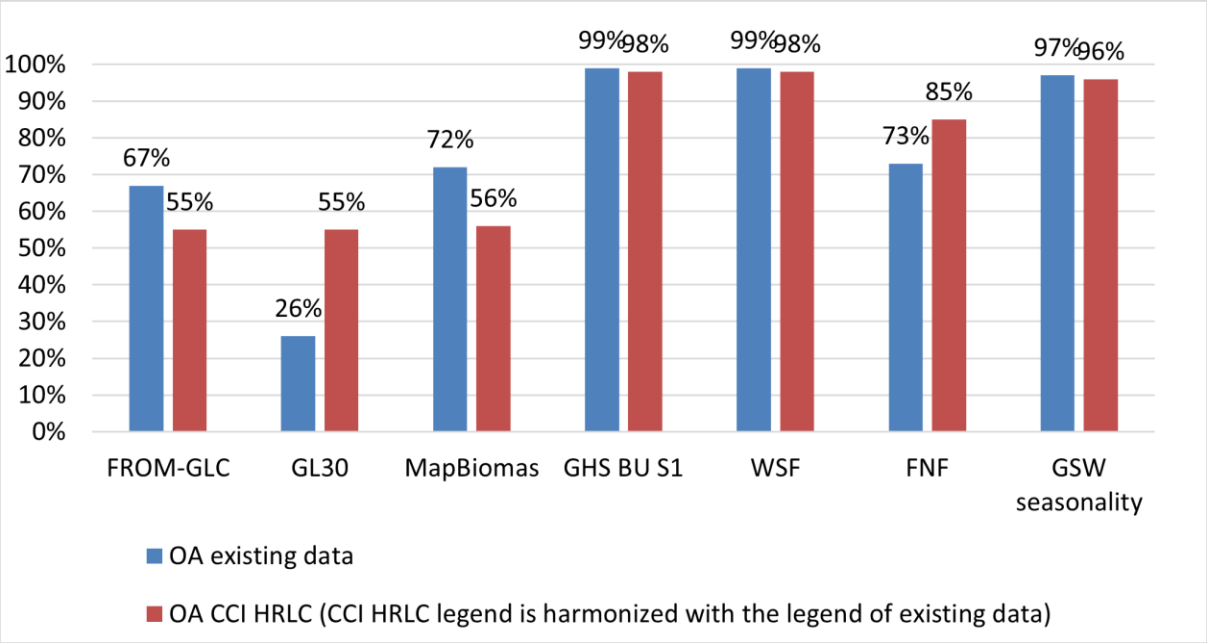

Figure 36. Comparison of OA of existing data and CCI HRLC for Amazon (21KXT and 21KUQ)

Starting from validation data we also analyzed class accuracy and focused on User's accuracy (UA), especially because that is of interest to us in the existing datasets (Table 61).

Each odd row of Table 61 shows the UA of CCI HRLC products, and each even row is showing the difference in UA with respect to an existing dataset.

It is evident that the accuracy of Bareland and Built-up is higher in the existing datasets, and it is relatively low in CCI HRLC products. It is an indicator that these are the most critical classes that could be improved given that they were more successfully classified in the existing datasets.

From this table, it is also evident why the agreement with GL30 is very low.

Table 61. Comparison of UA of existing data and CCI HRLC for all RR tiles

	Forest	Water	Bareland	Built-up	Cropland	Grassland	Shrubland	Wetland	Water permanent	Water seasonal	Wetland Herbaceous	Deciduous broadleaf	Evergreen needleleaf	Lichens and mosses
CCI HRLC UA			55%			92%	0%	31%	100%	0%		0%	100%	33%
Difference with ESA DUE			43%			1%	0%	19%	0%	-7%		0%	7%	33%
CCI HRLC UA	76%	73%												
Difference with FNF	3%	11%												
CCI HRLC UA	76%	73%	26%	24%	64%	65%	43%	21%						
Difference with FROM-GLC	-13%	-5%	-43%	-31%	8%	21%	-2%	3%						
CCI HRLC UA				24%										
Difference with GHS BU S1				-43%										
CCI HRLC UA	76%	73%	26%	24%	64%	65%	43%	21%						
Difference with GL30	11%	6%	-56%	-13%	32%	42%	34%	10%						
CCI HRLC UA									94%	0%				
Difference with GSW seasonality									4%	-6%				
CCI HRLC UA	84%	82%	11%	30%	6%	87%	20%				57%			
Difference with MapBiomas	-3%	26%	11%	-16%	6%	13%	-9%				26%			
CCI HRLC UA				24%										
Difference with WSF				-35%										

The accuracy analyses of the existing HRLC showed that in the majority of cases the accuracy of the existing HRLC is comparable to the accuracy of the CCI HRLC products. The only existing HRLC that has lower accuracy than CCI HRLC is GL30, and therefore this dataset is not suitable for inter-comparison and will be excluded from inter-comparison in the second phase of the project. When classes are concerned, the accuracy analyses showed that the accuracy of Bareland and Built-up classes could be improved.

3.5 HRLC static maps – the second production

3.5.1 Siberia

The static map in Siberia is provided as a set of 392 tiles.

3.5.1.1 Inter-comparison with the map of agreement Siberia

Inter-comparison based on the map of agreement and CCI HRLC is presented in Table 62. The map of agreement covers 39% of the Siberian static region. The overall agreement between the two maps is 93%. UA_b and PA_b of many classes are very high (more than 80%) including Cropland, Forest, Grassland, and Water. On the opposite, Built-up appears to be overestimated (high PA_b, but low UA_b), while the accuracy of Shrubland is low. The accuracy of Wetland is not extremely low, but it is not sufficient either. The accuracy of Bareland is "Relatively good" with a PA_b of 83% and a UA_b of 58%. There were no pixels classified as Permanent ice and snow in the CCI HRLC, so the accuracy of this class is 0. Cells highlighted in green show the number of correctly classified pixels according to the map of agreement. Cells highlighted in orange show commission errors larger than a class's agreement. The highest error is in the case of Shrubland. Many pixels that belong to Forest, Grassland, Wetland, Water, and Cropland were classified as Shrubland. Cells highlighted in red show omission errors larger than a class's agreement. An omission error larger than the agreement is present in the case of the Shrubland class for which pixels were prevalently wrongly classified as Grassland, and somewhat less frequently as Wetland. Even though some classes are affected by the error, OA_b is still high because the affected classes are smaller than the classes with high accuracy.

Table 62. Error matrix of map of agreement and CCI HRLC

	Bareland	Built-up	Cropland	Forest	Grassland	Permanent ice and snow	Shrubland	Water	Wetland	PA_b	OA_b	UA_b
Bareland	38,229,051	116,720	527,000	2,455,367	11,436,445	166,265	24,705	10,045,394	2,878,512	83%	58%	93%
Built-up	211,846	4,772,152	4,231,271	3,035,469	4,521,810	16,749	388	543,745	302,232	94%	27%	
Cropland	44,042	111,024	2,254,735,814	19,258,902	253,191,695	1,256	454	277,969	11,311,459	90%	89%	
Forest	77,114	20,621	10,544,805	10,371,033,084	190,862,239	1,397	40,943	23,006,729	40,931,103	98%	98%	
Grassland	3,609,465	55,531	205,728,265	150,380,287	2,726,292,501	36,758	1,064,423	7,418,645	39,809,757	81%	87%	
Permanent ice and snow	0	0	0	0	0	0	0	0	0	0%	0%	
Shrubland	14,305	311	660,845	18,352,834	18,320,267	90	168,608	411,075	5,587,492	11%	0%	
Water	3,718,508	9,669	579,775	9,808,035	8,071,793	134,380	3,711	3,905,829,243	53,008,950	99%	98%	
Wetland	225,633	1,745	19,710,393	60,665,072	164,721,975	317	199,881	14,597,915	194,082,255	56%	43%	

Besides OA_b for the whole of Siberia, OA_b for each tile of CCI HRLC is computed to observe spatial variation (Figure 37). Spatial variation does not appear to be strong. There are only several tiles with an accuracy smaller than 80%

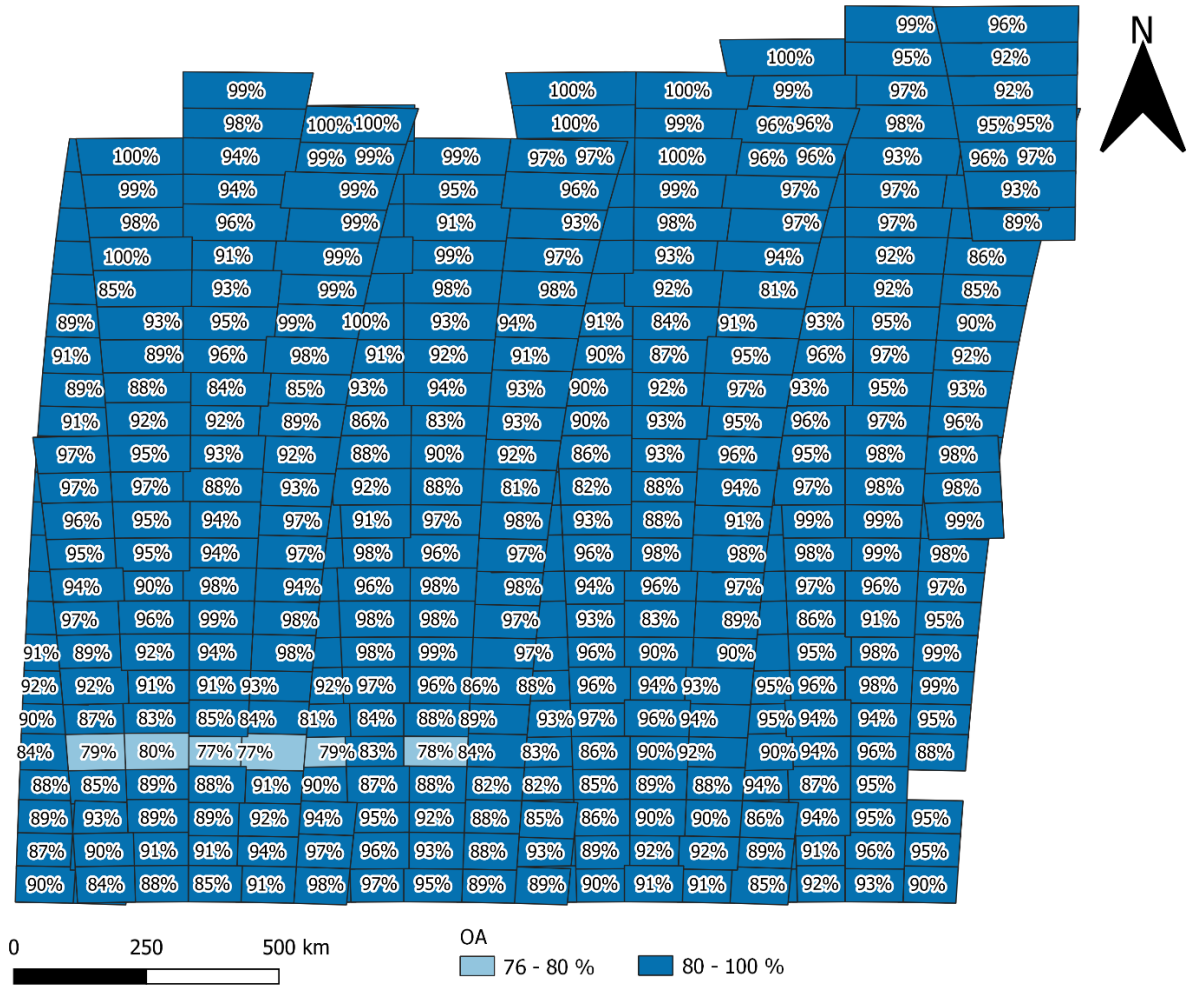

Figure 37. OA_b of each tile in Siberia based on the map of agreement

To understand better if there is a pattern in disagreement, we analyzed the correlation of OA_b with landscape indices of diversity and fragmentation. In particular, we analyzed the correlation of the Shannon index, Diversity index, Shape index, and Edge density index.

3.5.1.2 Correlation of benchmark accuracy with landscape structure indexes

Benchmark accuracy patterns were analyzed by means of the correlation of OA_b with landscape structure indices and class proportion of CCI HRLC. The values of each variable were collected for each tile in a region. The correlation of the considered variables for Siberian tiles is displayed in correlation matrices (Figure 38). The figure consists of three subplots, one for overall correlation for all tiles, one for tiles with OA_b in the range from 0% to 80%, and one for tiles with OA_b greater than 80%. In general, OA_b in Siberia is above 77% which is high. There is no strong correlation of OA_b with landscape structure indices in all tiles concerned, as well as in the case of OA_b interval 80% - 100%. An increase of correlation is evident in the case of OA_b interval 0-80%, however, it was based on 6 tiles only, and therefore it is not enough representative.

To support correlation matrix analyses, box plots were created to better describe the distribution of the variables considered for correlation analyses (Figure 39). They were created for the same OA_b intervals as correlation matrices. For this purpose, the landscape structure indices were normalized so that they can be displayed with other variables that are in the range of 0 - 1. From the boxplot for all tiles, it can be seen that the Forest is the most dominant class in Siberia, which is probably the reason for the overall high OA_b in Siberia.

Figure 38. Correlation of landscape structure indices with OAb, landscape structure indices, and class proportion.

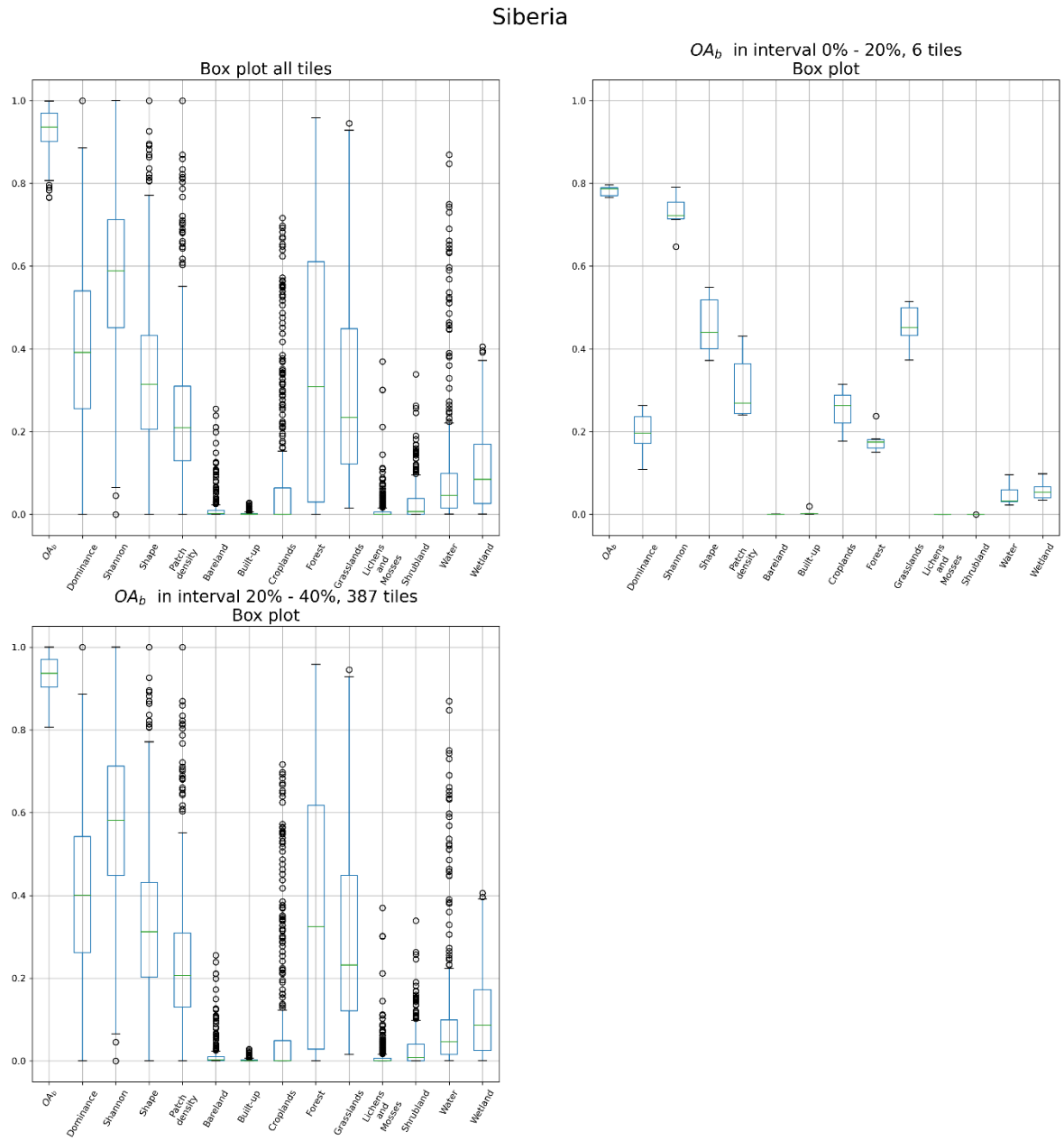

Figure 39. Box plot of OA_b, normalized landscape structure indices, and class proportions

3.5.1.3 Overall benchmark accuracy with existing HRLCs

In Siberia, there are 2 existing multiple-class land cover maps with which static product for the Siberia region was compared one by one: ESA DUE GlobPermafrost, and FROM-GLC. Table 63 is showing the consistency between the static map in Siberia and each of the existing land cover maps.

Table 63. Overall benchmark accuracy for the whole Siberia v2

Existing dataset	OA_b
FROM-GLC 2017	60%
ESA DUE GlobPermafrost 2016	43%

Given that there are many tiles the results of OA_b per tile will be displayed in the form of maps of tiles with associated values of OA_b. There are two OA_b maps, one for inter-comparison with FROM GLC (Figure 40), and one with ESA DUE GlobPermafrost (Figure 41). Some of the tiles have more than one value displayed. The second

value is for the tile that is underneath the displayed one. For most of the tiles, the OA_b values for overlapping tiles are similar.

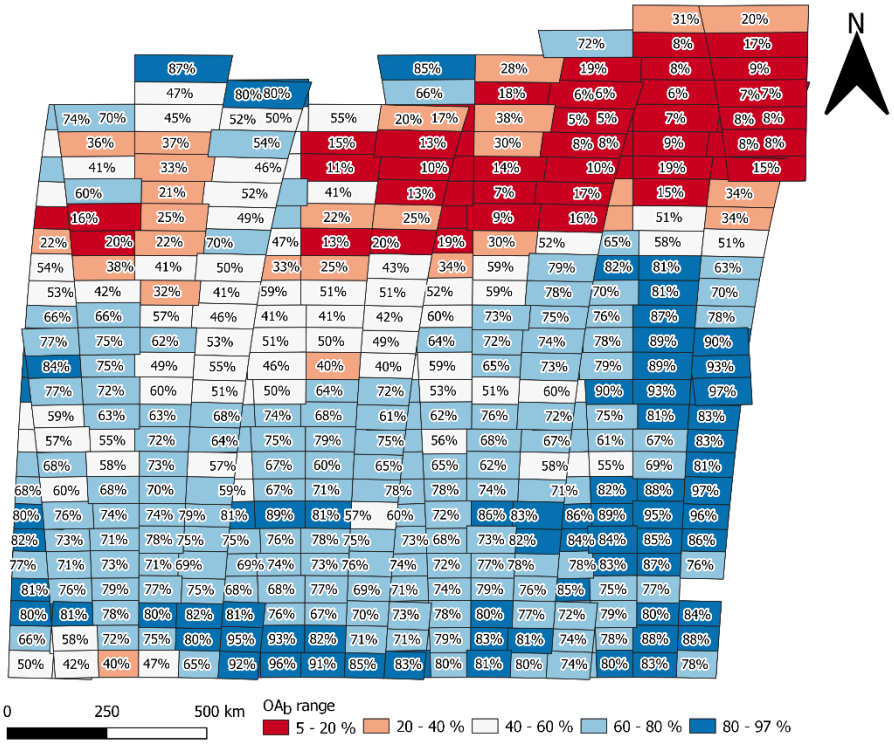

Figure 40. OAb for each tile of the static map in Siberia based on FROM GLC

The ESA DUE GlobPermafrost size is smaller than the static area in Siberia therefore the appearance of the map is different from the previous two maps.

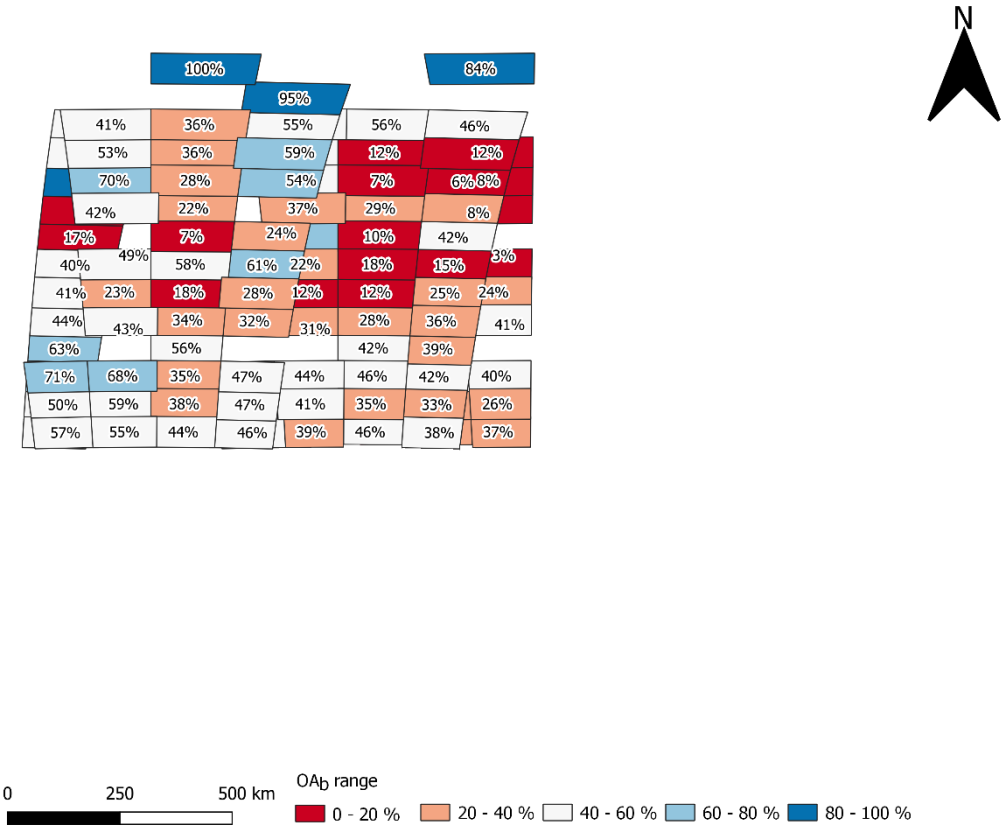

Figure 41. OAb for each tile of the static map in Siberia based on ESA DUE GlobPermafrost

The overall agreement of the static map in Siberia is 60% with FROM-GLC and 43% with ESA DUE GlobPermafrost (Table 63). The agreement with FROM-GLC increased by 10% compared to the first production, but the agreement with ESA DUE GlobPermafrost decreased by 3%. In the case of comparison with FROM-GLC, there are very low values in the North-East of the static region (Figure 40). Some error matrices in the region with low OA_b were verified (44XPF, 45WVV, 44WPE). They are showing that the most important confusion is between Lichens and mosses in FROM-GLC and Grassland in CCI HRLC. Probably this is the reason for having low OA_b values in the North-West side of the static region.

Comparison of CCI HRLC with ESA DUE GlobPermafrost shows an area in the eastern part with a very low agreement. Analyses of tiles in the critical region (44WMV, 43WFT, and 43WET) show that the greatest discrepancies are related to the confusion of Grassland in CCI HRLC with Shrub cover evergreen and Bareland in ESA DUE GlobPermafrost.

3.5.1.4 Per class benchmark accuracy with existing HRLCs

For Siberia according to Table 64 classification of Forest, and Water is “Well”, and the classification of Cropland and Forest evergreen needleleaf is “Relatively good”. For other classes, no conclusions can be made because computed accuracy indexes are showing very different values for the same class depending on the existing HRLC used for computation. Agreement concerning Cropland and Forest evergreen needleleaf classes notably increased in the second production. A slight increase in agreement for the Forest class is also evident.

Table 64. UA_b and PA_b for the whole of Siberia

Existing LC	Index	Bareland	Built-up	Cropland	Forest	Forest deciduous broadleaf	Forest evergreen needleleaf	Grassland	Lichens and Mosses	Permanent ice and snow	Shrubland	Shrubland evergreen	Water	Wetland
FROM GLC	PA_b	38%	66%	88%	93%			50%	5%	0%	5%		96%	38%
ESA DUE GlobPermafrost		16%				22%	75%	63%	64%			0%	93%	49%
FNF					83%								86%	
GSW seasonality													86%	
GHS BU S1			40%											
WSF			66%											
FROM GLC	UA_b	21%	18%	56%	84%			53%	77%	0%	0%		86%	6%
ESA DUE GlobPermafrost		34%				26%	64%	16%	43%			78%	98%	10%
FNF					68%								76%	
GSW seasonality													88%	
GHS BU S1			38%											
WSF			23%											

3.5.2 Amazon

The static map in Amazon was provided as a set of 568 tiles.

3.5.2.1 Inter-comparison with the map of agreement Amazon

Inter-comparison based on the map of agreement and CCI HRLC is presented in Table 65. The map of the agreement covers 51% of the Amazon static region. The overall agreement between the two maps is 91%. UA_b and PA_b of many classes are very high (more than 80%) including Cropland, Forest, and Water. On the opposite, Bareland, Built-up, and Grassland appear to be overestimated (high PA, but low UA_b), while Shrubland is underestimated. The accuracy of Wetland is low overall. Cells highlighted in green show the number of pixels that are correctly classified according to the map of agreement. Cells highlighted in orange show commission errors that are larger than the agreement of a class. Many pixels were classified as Bareland even if they are Cropland, Forest, Grassland, Shrubland, and Water. Many pixels were classified as Wetland even if they are Water. Cells highlighted in red show omission errors that are larger than the agreement of a class. An omission error larger than the agreement is present in the case of the Shrubland class for which pixels were wrongly classified as Grassland. Even though some classes are affected by the error, OA_b is still high because the affected classes are smaller than the classes with high accuracy

Table 65. Error matrix of map of agreement and CCI HRLC

	Bareland	Built-up	Cropland	Forest	Grassland	Shrubland	Water	Wetland	PA	UA	OA
Bareland	1,670,300	655,006	7,439,805	5,784,313	30,286,067	9,239,906	3,603,364	87,103	74%	3%	91%
Built-up	38,269	47,836,157	6,533,948	2,369,430	13,244,959	3,204,729	408,407	8,192	95%	65%	
Cropland	2,908	70,988	3,915,693,850	61,061,557	174,372,847	48,351,865	323,559	183,765	93%	93%	
Forest	84,815	101,248	18,432,202	21,766,498,693	122,436,396	492,175,616	1,399,969	12,063,027	99%	97%	
Grassland	29,935	1,488,477	282,375,675	156,676,397	4,237,088,072	1,502,379,678	3,933,475	20,067,813	92%	68%	
Shrubland	30	10,977	1,409,067	76,731,072	23,351,676	1,238,674,304	16,323	139,965	38%	92%	
Water	433,760	29,742	77,850	1,613,290	1,581,432	336,533	1,307,331,621	1,074,713	96%	100%	
Wetland	3,152	18,067	422,643	4,915,821	3,251,670	1,657,966	44,332,724	22,589,036	40%	29%	

Besides OA_b for the whole of Amazon, OA_b for each tile of CCI HRLC is computed to observe spatial variation (Figure 42). Spatial variation does not appear to be strong. There are only several tiles with an accuracy smaller than 80%

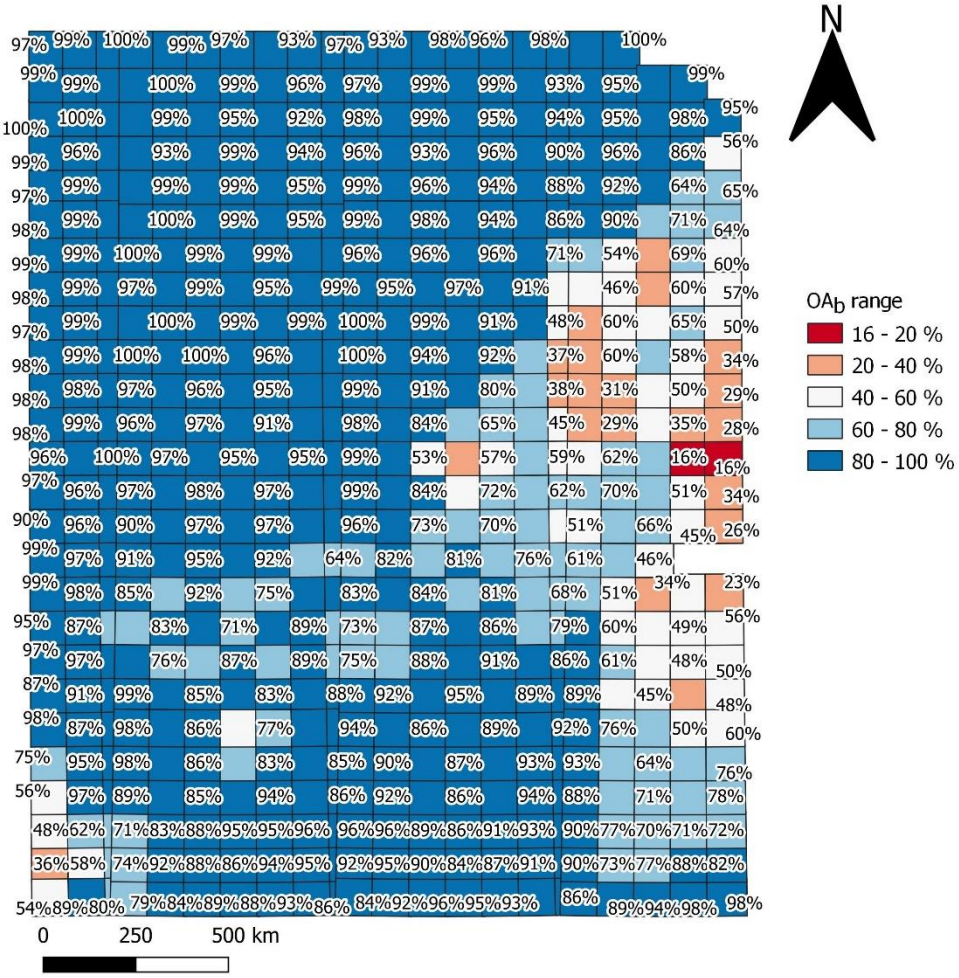

Figure 42. OA_b of each tile in Amazon based on the map of agreement

3.5.2.2 Correlation of benchmark accuracy with landscape structure indexes

Benchmark accuracy patterns were analyzed by means of the correlation of OA_b with landscape structure indices and class proportion of CCI HRLC. The values of each variable were collected for each tile in a region. The correlation of the considered variables for Amazonian tiles is displayed in correlation matrices (Figure 43). The figure consists of three subplots, one for overall correlation for all tiles, one for 0 - 80% interval of OA_b, and one for OA_b values above 80%. The overall correlation matrix shows a moderate positive correlation of OA_b with the Dominance index and a moderate negative correlation with the Shannon index. This indicates that the landscape tends to be dominated by a class. From the correlation of these two indices with pixel counts of each class, it is evident that the Dominance is strongly positively correlated with the Forest class, and moderately negatively correlated with Grasslands, Croplands, and Shrubland classes. In other words, the dominance of the Forest class leads to higher OA_b, while lower OA_b is associated with a higher number of Grassland, Cropland, and Shrubland classes. Fragmentation indices, Shape, and Patch density are strongly negatively correlated with OA_b. The indices are moderately positively correlated with the number of pixels in the Grassland, and Shrubland classes, and negatively moderately correlated with the Forest class. This indicates that fragmentation of landscape (more patches or longer borders among different classes) is more intense in the case of the Grassland, and Shrubland classes, and that higher fragmentation leads to lower OA_b. The results in the OA_b 80% - 100% interval are consistent with the overall correlation matrix, except for the correlation of Shrubland with landscape structure

indexes which is lower for this interval. The correlation matrix for the 0% - 80% interval does not show an important correlation OA_b with landscape indices. A more detailed analysis of the correlation can be done by splitting further 0% - 80% interval into 4 intervals with a 20% step (Figure 44), however due to the high variation of the number of tiles per interval and the very low number of tiles in an interval the results should be interpreted prudently. For example, we can see that in the OA_b 0% - 20% the correlation is computed based on the variables for 4 tiles only, thus even if there is a strong correlation, the number of tiles is rather small to make relevant conclusions. In other intervals, the correlation does not appear to be strong.

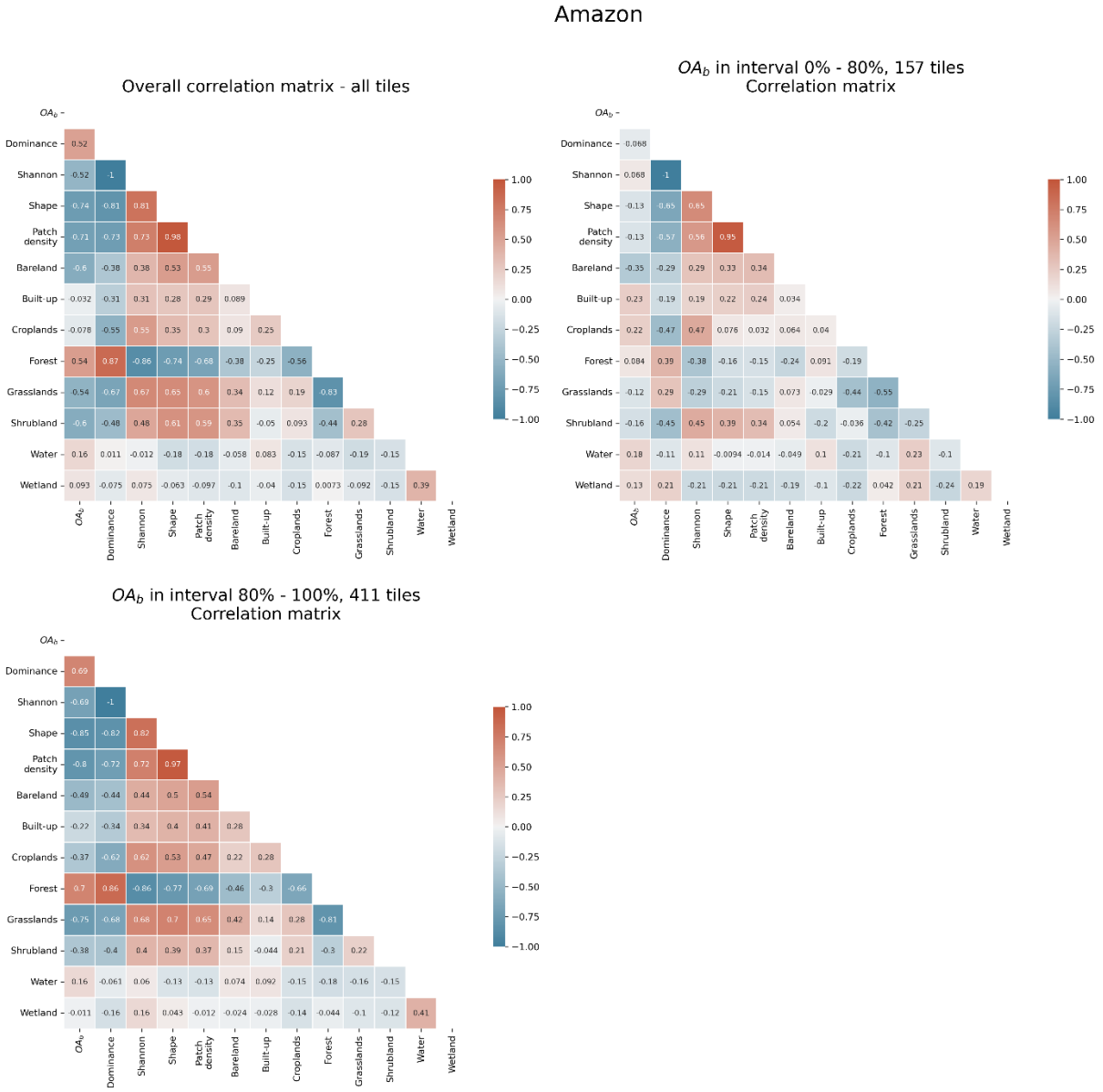

Figure 43. Correlation of landscape structure indices with OA_b, landscape structure indices, and class proportion for different OA_b intervals. The subplot in the upper left corner refers to all OA_b values, the one in the upper right corner refers to the subset of OA_b values in the 0% - 80% interval, and the one in the lower left corner refers to OA_b subset with values above 80%

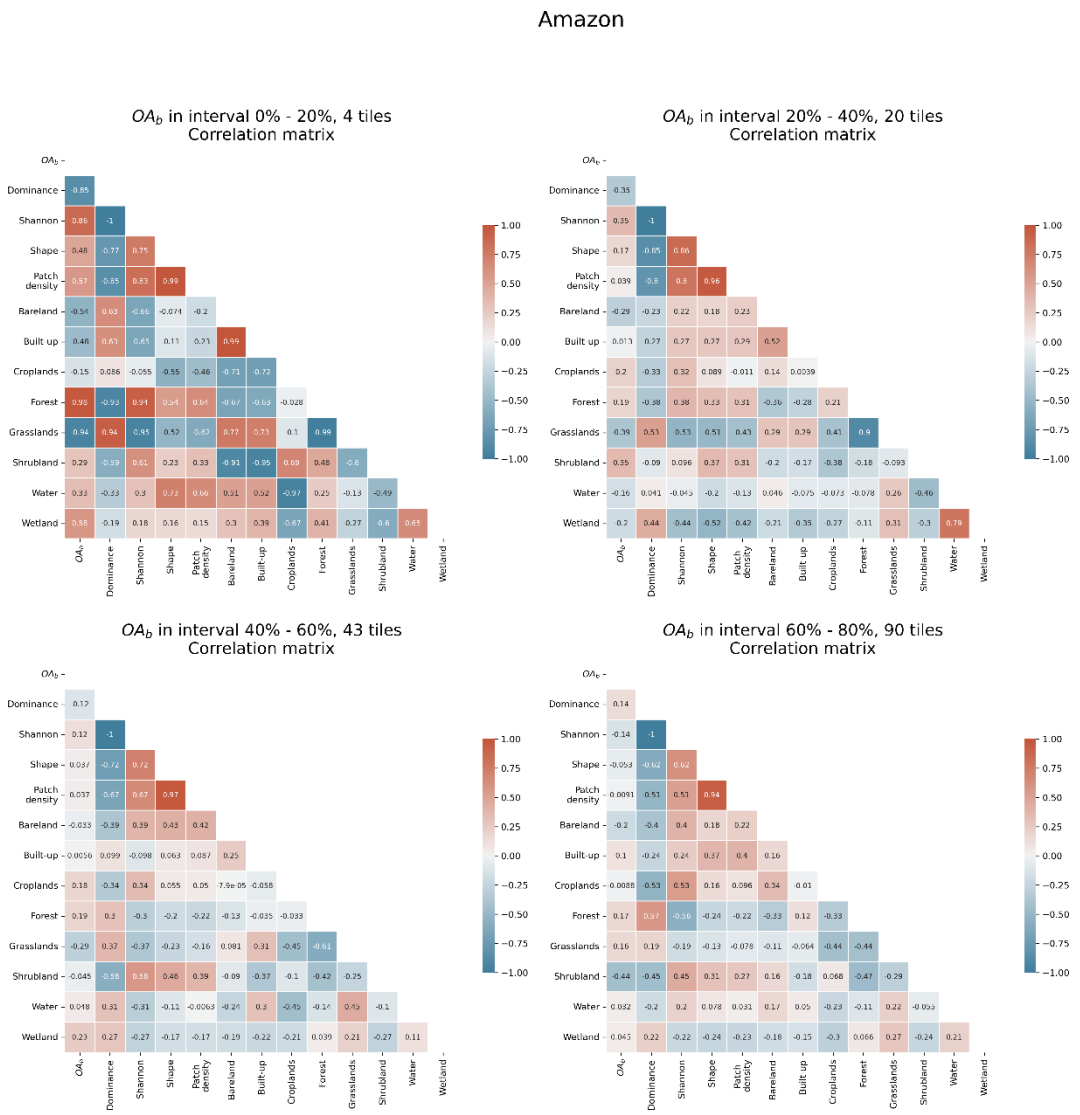

Figure 44. Correlation of landscape structure indices with OA_b, landscape structure indices, and class proportion for different OA_b intervals. The subplot in the upper left corner refers to the subset of OA_b values in the 0% - 20% interval, the subplot in the upper right corner refers to the subset of OA_b values in the 20% - 40% interval, Subplot in the upper left corner refers to the subset of OA_b values in the 40% - 60% interval, Subplot in the upper left corner refers to the subset of OA_b values in 60% - 80% interval.

To support correlation matrix analyses, box plots were created to better describe the distribution of the variables considered for correlation analyses (Figure 45, Figure 46). They were created for the same OA_b intervals as correlation matrices. For this purpose, the landscape structure indices were normalized so that they can be displayed with other variables that are in the 0 – 1 range. From the boxplots for all tiles, the Forest is the most dominant class in the Amazon, which is probably the reason for the overall high OA_b in Amazon. Furthermore, it can be observed that the proportion of the Grassland class is higher than the proportion of the Forest class in the OA_b 0% - 80% interval, and it is the opposite in the 80% - 100%. The proportion of the Shrubland and Cropland classes is lower in the 80% - 100% interval. The dominance index is higher, and Shannon, Shape, and Patch density indices are lower for the 80% - 100% interval than for the 0% - 80% interval.

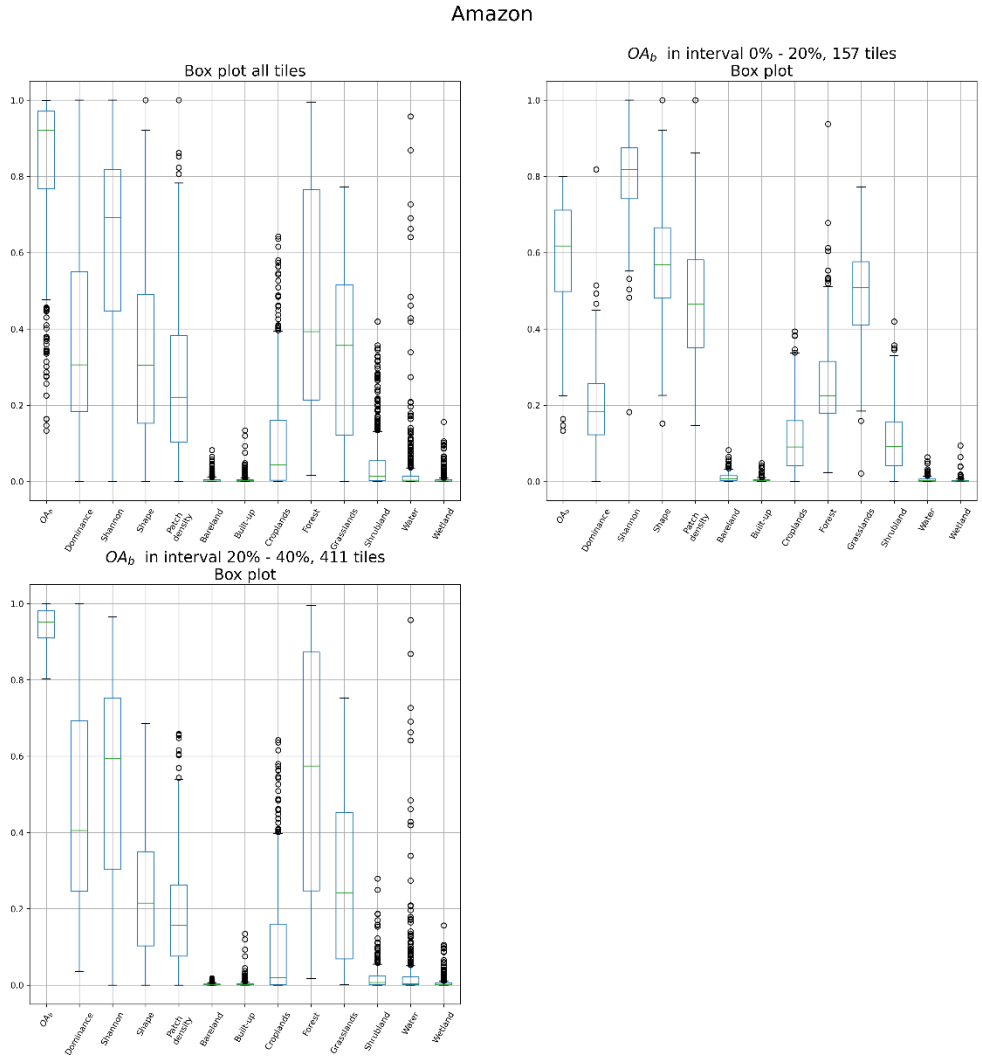

Figure 45. Box plot of OA, normalized landscape structure indices, and class proportions. The subplot in the upper left corner refers to all OA_b values, the one in the upper right corner refers to the subset of OA_b values in the 0% - 80% interval, and the one in the lower left corner refers to OA_b subset with values above 80%.

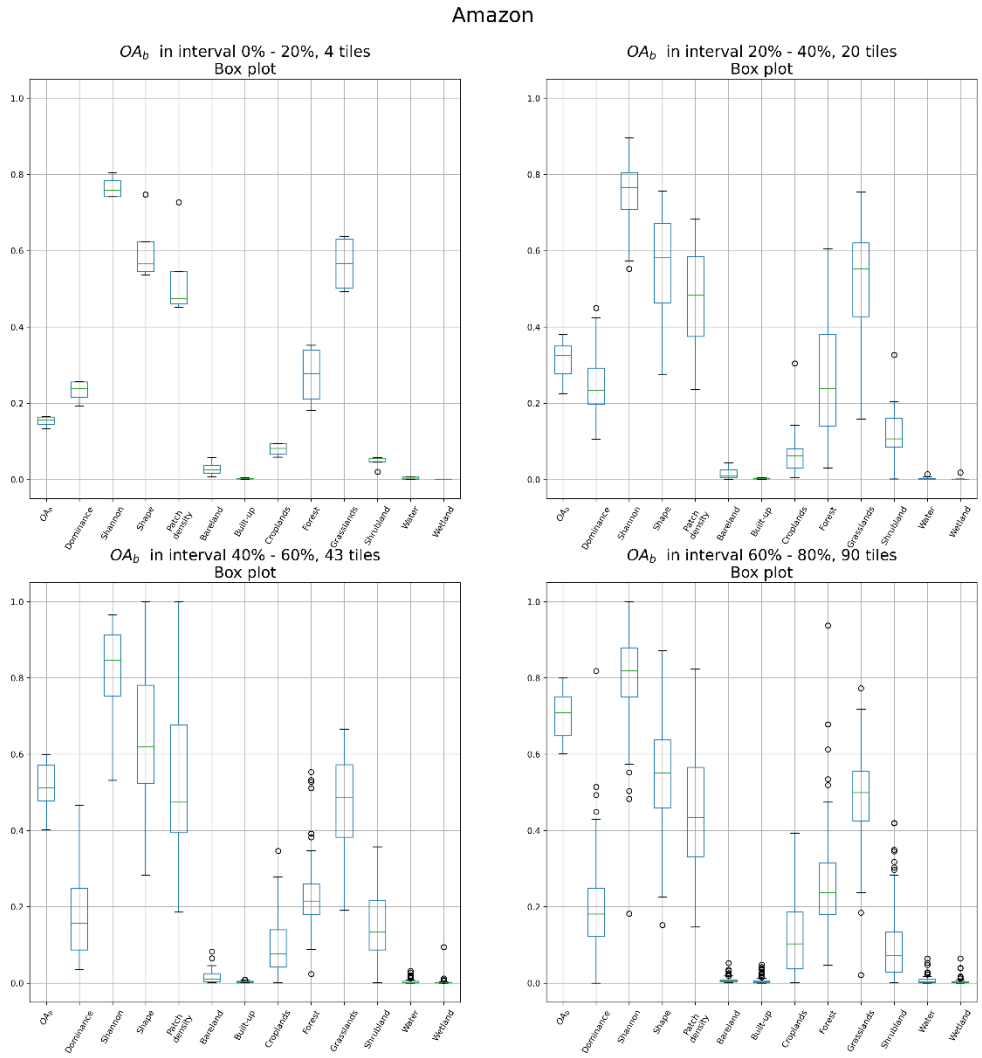

Figure 46. Box plot of OA_b, normalized landscape structure indices, and class proportions. The subplot in the upper left corner refers to the subset of OA_b values in the 0% - 20% interval, the subplot in the upper right corner refers to the subset of OA_b values in the 20% - 40% interval, Subplot in the upper left corner refers to the subset of OA_b values in the 40% - 60% interval, Subplot in the upper left corner refers to subset of OA_b values in 60% - 80% interval.

3.5.2.3 Overall benchmark accuracy with existing HRLCs

In Amazon, there are two existing multiple-class land cover maps with which static product for the Amazonian region was compared one by one: MapBiomas, and FROM-GLC. Table 66 is showing consistency between the static map in Amazon and each of the existing land cover maps.

Table 66. Overall benchmark accuracy for the whole Amazon v2

Existing dataset	OA_b
FROM-GLC 2017	76%
MapBiomas 2019	75%

Given that there are many tiles the results of OA_b per tile will be displayed in the form of maps of tiles with associated values of OA_b. There are 3 OA_b maps, one for inter-comparison with FROM GLC (Figure 47), and one for CCI Prototype (Figure 48). Some of the tiles have more than one value displayed. The second value is for the tile that is underneath the displayed one. For most of the tiles, the OA_b values for overlapping tiles are similar.

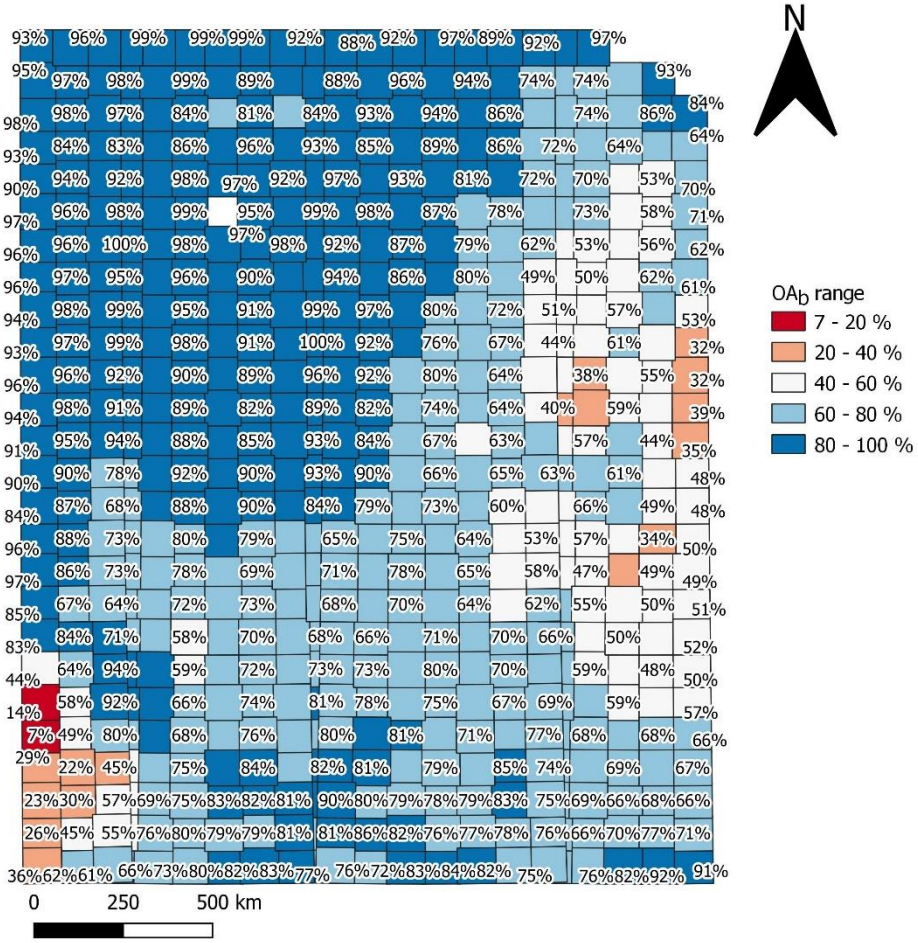

Figure 47. OA$_b$ for each tile of the static map in Amazon based on FROM GLC

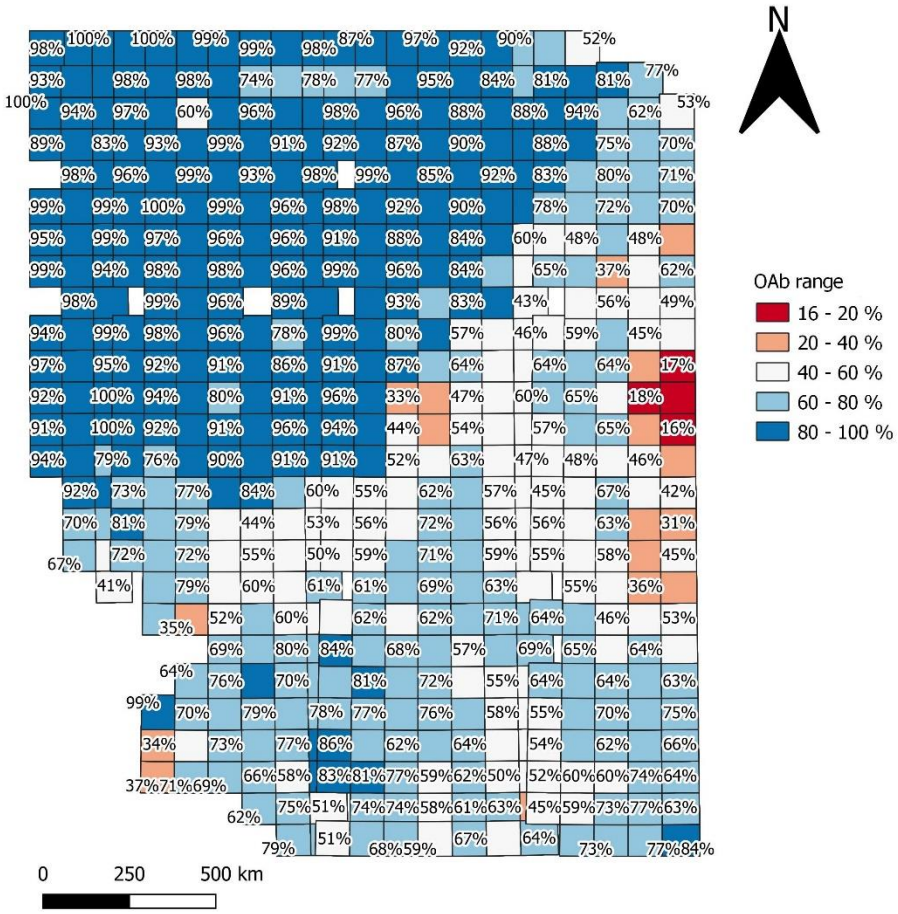

Figure 48. OA_b for each tile of the static map in Amazon based on MapBiomas

The overall agreement of the static map with existing land cover maps in Amazon is around 75% (Table 66), which is almost 15% more with respect to the first production. The agreement with FROM-GLC and MapBiomas is similar. The agreement is the highest in the North-West area of the region of interest and the lowest in the east. This pattern seems to follow the homogeneity of the landscape which according to Google Satellite base map is a dense rainforest in the North-West and becomes a mix of classes towards the South-East.

3.5.2.4 Per class benchmark accuracy with existing HRLCs

Regarding individual classes in Amazon according to Table 67 classification of Permanent Water is “Excellent”, the classification of Forest, and Water is “Well”, and the classification of Grassland is “Relatively good”. For other classes, no conclusions can be made because computed accuracy indexes are showing very different values for the same class depending on the existing HRLC used for computation.

Table 67. UA_b and PA_b for the whole Amazon

Existing LC	Index	Bareland	Built-up	Cropland	Forest	Grassland	Shrubland	Water	Water permanent	Water seasonal	Wetland	Wetland Herbaceous	Wetland Shrubby
FROM GLC	PA_b	71%	49%	77%	92%	80%	21%	93%			38%		
MapBiomas		25%	67%	21%	95%	84%	27%	80%				3%	31%
GHS BU S1			75%										

WSF			83%										
FNF					89%			56%					
GSW seasonality									93%	13%			
FROM GLC	UA_b	3%	50%	65%	89%	64%	68%	95%			22%		
MapBiomas		11%	66%	30%	84%	67%	80%	96%				14%	40%
GHS BU S1			37%										
WSF			41%										
FNF					79%			81%					
GSW seasonality									95%	27%			

3.5.3 Africa

The static map for Africa was provided as a set of 768 tiles.

3.5.3.1 Inter-comparison with the map of agreement Africa

Inter-comparison based on the map of agreement and CCI HRLC is presented in Table 68. The map of agreement covers 4% of the African static region. The overall agreement between the two maps is 92%. UA_b and PA_b of many classes are very high (more than 80%) including Bareland, Cropland, Forest, and Water. On the opposite, Cropland and Grassland appear to be overestimated (high PA_b, but low UA_b). Wetland leans towards overestimation, however, PA_b is below 80% and UA_b is very low - 12%. Shrubland seems to be underestimated, with UA_b slightly lower than 80% and PA_b 26%. Cells highlighted in green show the number of pixels that are correctly classified according to the map of agreement. Cells highlighted in orange show commission errors that are larger than the agreement of a class. Many pixels were classified as Wetland even if they are Grassland. Cells highlighted in red show omission errors that are larger than the agreement of a class. An omission error larger than the agreement is present in the case of the Shrubland class for which pixels were wrongly classified as Grassland. Even though some classes are affected by the error, OA_b is still high because the affected classes are smaller than the classes with high accuracy.

Table 68. Error matrix of map of agreement and CCI HRLC

	Bareland	Built-up	Cropland	Forest	Grassland	Shrubland	Water	Wetland	PA_b	UA_b	OA_b
Bareland	11,971,483,363	144,037	6,736,325	557,390	376,294,279	45,817,379	4,043,103	159,750	98%	97%	92%
Built-up	1,644,322	6,753,141	3,946,849	1,046,413	2,294,678	462,481	23,639	72	93%	42%	
Cropland	6,083,026	49,125	3,166,384,629	50,019,516	186,148,981	50,598,225	391,316	74,765	85%	92%	
Forest	618,352	3,431	38,353,820	12,023,706,462	12,687,065	2,677,869	442,437	39,596	99%	100%	
Grassland	271,083,115	235,101	457,060,284	50,813,001	3,516,612,498	944,208,557	705,792	680,945	84%	67%	
Shrubland	1,242,318	45,417	34,832,891	20,248,452	81,240,542	371,342,820	20,771	9,370	26%	73%	
Water	572,102	1,908	1,607,841	981,932	1,307,175	64,236	1,901,736,758	442,512	100%	100%	
Wetland	96,828	421	2,067,300	2,481,880	16,882,822	958,259	3,365,187	3,436,121	71%	12%	

Besides OA_b for the whole of Africa, OA_b for each tile of CCI HRLC is computed to observe spatial variation (Figure 49). Spatial variation does not appear to be strong. There are only several tiles with an accuracy smaller than 80%

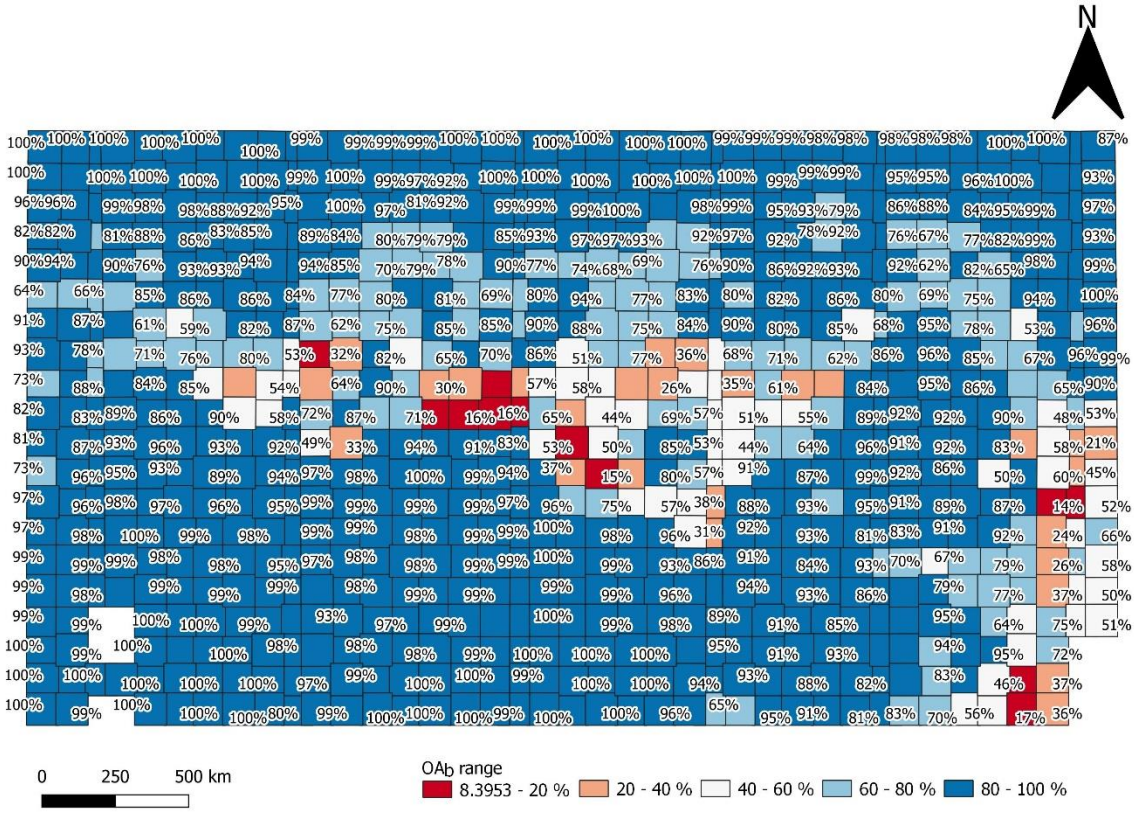

Figure 49. OA_b of each tile in Africa based on the map of agreement

3.5.3.2 Correlation of benchmark accuracy with landscape structure indexes

Benchmark accuracy patterns were analyzed by means of the correlation of OA_b with landscape structure indices and class proportion of CCI HRLC. The values of each variable were collected for each tile in a region. The correlation of the considered variables for African tiles is displayed in correlation matrices (Figure 50). The figure consists of three subplots, one for overall correlation for all tiles, one for 0 - 80% interval of OA_b, and one for OA_b values above 80%. Overall correlation matrix does not show a significant correlation of OA_b with Dominance, Shannon, or Patch density indices, while the correlation with the Shape index is moderate. There is no strong correlation between any of the indices and with classes' pixel counts. This indicates that there is no intense class dominance or landscape fragmentation overall.

The results in the OA_b 80% - 100% interval show a somewhat higher correlation of different variables than the overall correlation matrix. Landscape indices are more correlated with some classes, however, the correlation is not strong. Week correlation is evident between Shannon, Shape, and Patch density with Croplands, Grassland, and Shrubland in the positive direction, and with Bareland in the negative direction. A more detailed analysis of the correlation can be done by splitting further the 0% - 80% interval of OA_b into 4 intervals with a 20% step (Figure 51). In the first interval (OA_b 0% - 20%) the correlation of OA_b with Patch density is moderate. Patch density and Dominance indices are correlated with Cropland pixel counts. This indicates that the Grassland class is dominant and fragmented in the tiles with low OA_b. Even though there is a correlation, the number of tiles is rather small concerning the total number of tiles to make relevant conclusions. In other intervals, the correlation does not appear to be strong.

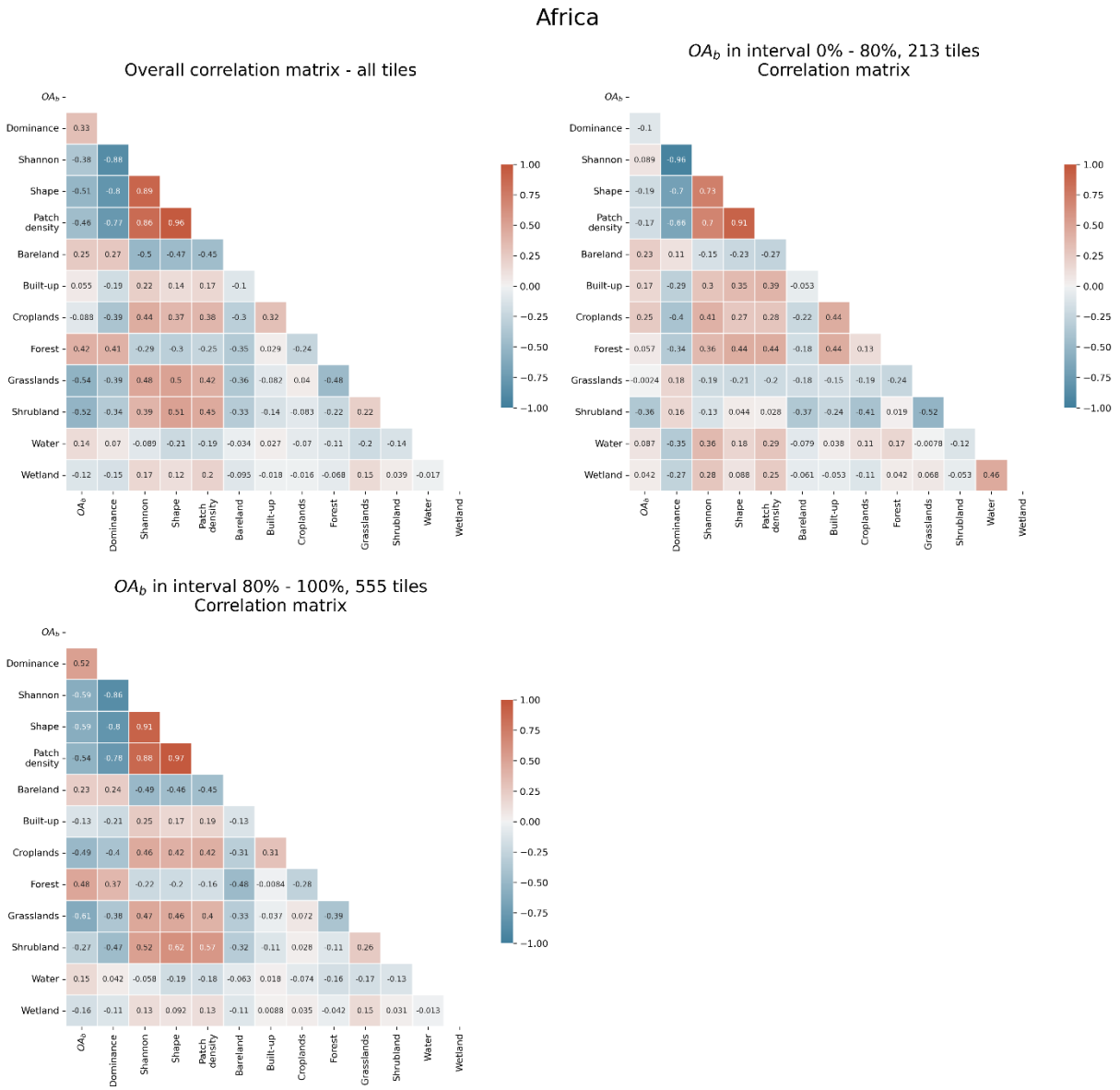

Figure 50. Correlation of landscape structure indices with OA_b, landscape structure indices, and class proportion for different OA_b intervals. The subplot in the upper left corner refers to all OA_b values, the one in the upper right corner refers to the subset of OA_b values in the 0% - 80% interval, and the one in the lower left corner refers to OA_b subset with values above 80%

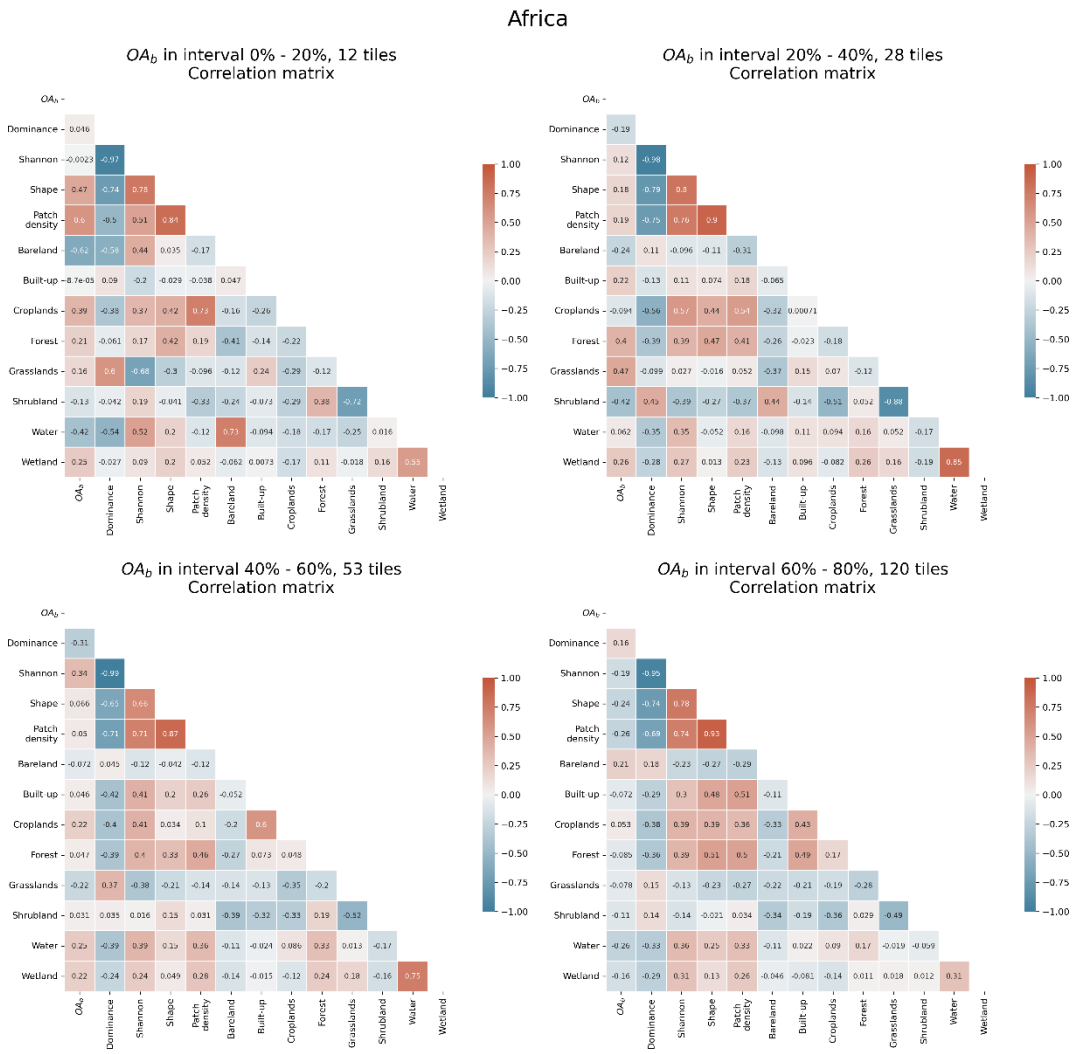

Figure 51. Correlation of landscape structure indices with OA_b, landscape structure indices, and class proportion for different OA_b intervals. The subplot in the upper left corner refers to the subset of OA_b values in 0% - 20% interval, the subplot in the upper right corner refers to the subset of OA_b values in the 20% - 40% interval, Subplot in the upper left corner refers to the subset of OA_b values in the 40% - 60% interval, Subplot in the upper left corner refers to the subset of OA_b values in the 60% - 80% interval.

To support correlation matrix analyses, box plots were created to better describe the distribution of the variables considered for correlation analyses (Figure 52, Figure 53). They were created for the same OA_b intervals as correlation matrices. For this purpose, the landscape structure indices were normalized so that they can be displayed with other variables that are in the 0 – 1 range. From the boxplots for all tiles, the Grassland is the most dominant class in Africa, which is probably the reason for the overall high OA_b in Africa. Furthermore, it can be observed that the proportion of Grassland and Shrubland classes is significantly higher in the OA_b 0% - 80% interval than in the 80% - 100%, while the proportion of the Forest class increased slightly in the second interval. The dominance index is higher, and Shannon, Shape, and Patch density indices are lower for the 80% - 100% interval than for the 0% - 80% interval.

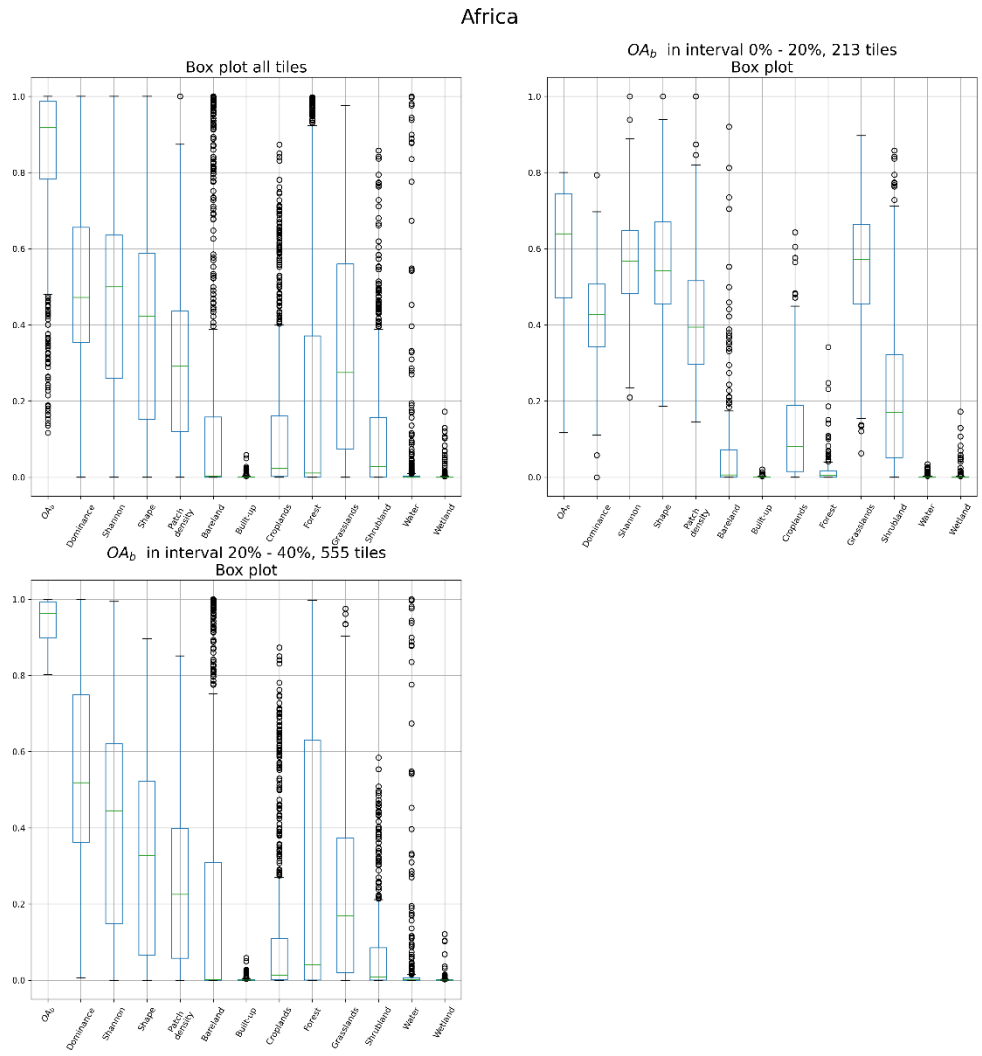

Figure 52. Box plot of OA_b, normalized landscape structure indices, and class proportions. The subplot in the upper left corner refers to all OA_b values, the one in the upper right corner refers to the subset of OA_b values in the 0% - 80% interval, and the one in the lower left corner refers to OA_b subset with values above 80%.

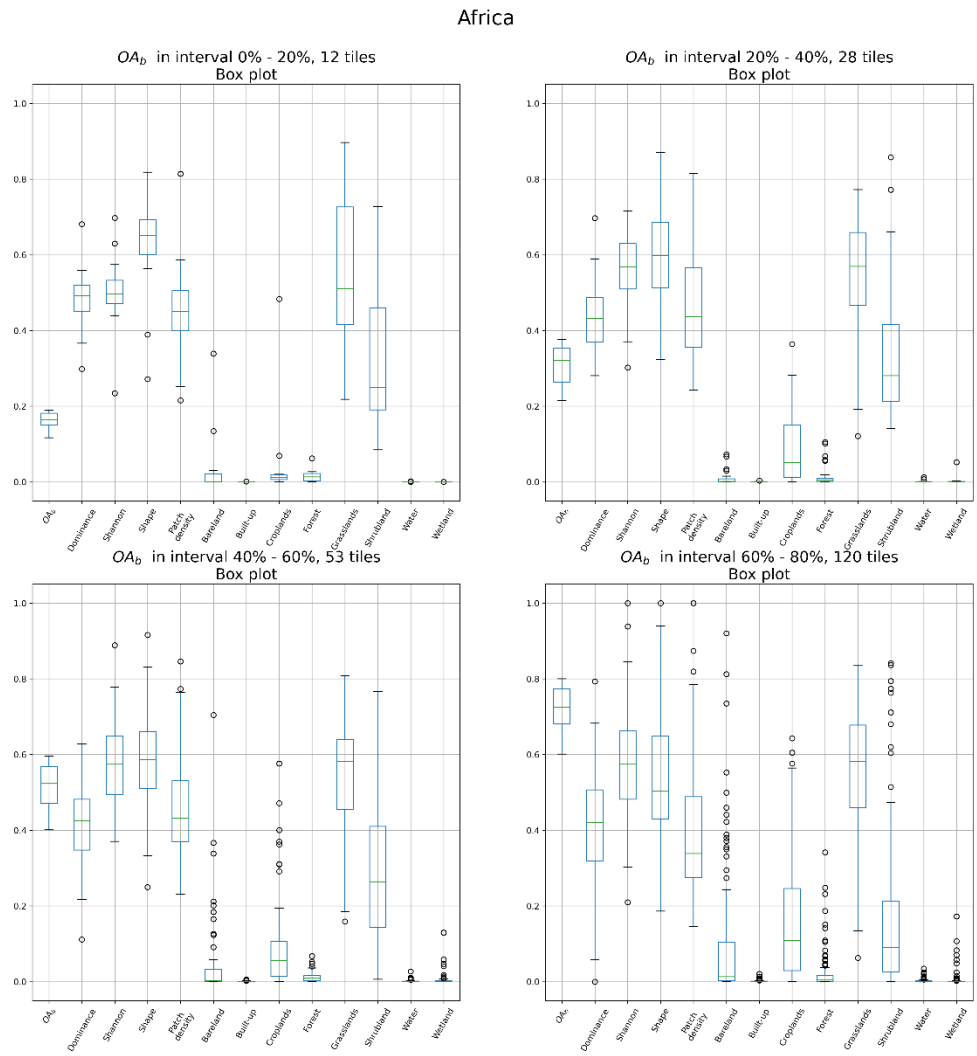

Figure 53. Box plot of OA_b, normalized landscape structure indices, and class proportions. The subplot in the upper left corner refers to the subset of OA_b values in the 0% - 20% interval, the subplot in the upper right corner refers to the subset of OA_b values in the 20% - 40% interval, Subplot in the upper left corner refers to the subset of OA_b values in the 40% - 60% interval, Subplot in the upper left corner refers to the subset of OA_b values in the 60% - 80% interval.

3.5.3.3 Overall benchmark accuracy with existing HRLCs

In Africa, there are two existing multiple-class land cover maps with which static product for the African region was compared one by one: ESA DUE GlobPermafrost, and FROM-GLC. Table 69 is showing the consistency between the static map in Africa and each of the existing land cover maps.

Table 69. Overall benchmark accuracy for whole Africa v2

Existing dataset	OA_b
FROM GLC 2017	66%
CCI Prototype 2016	57%

Given that there are many tiles the results of OA_b per tile will be displayed in the form of maps of tiles with associated values of OA_b. There are 3 OA_b maps, one for inter-comparison with FROM GLC (Figure 54), and one for CCI Prototype (Figure 55). Some of the tiles have more than one value displayed. The second value is for the tile that is underneath the displayed one. For most of the tiles, the OA_b values for overlapping tiles are similar.

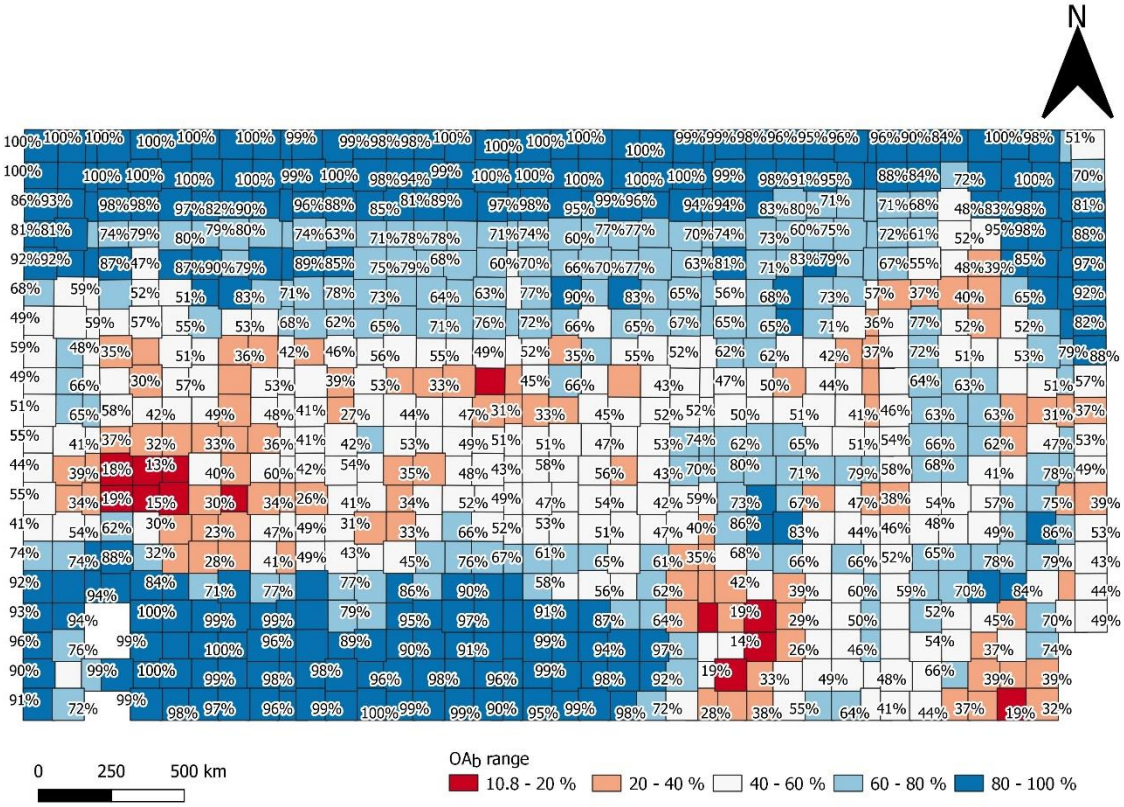

Figure 54. OA_b for each tile of the static map in Africa based on FROM GLC

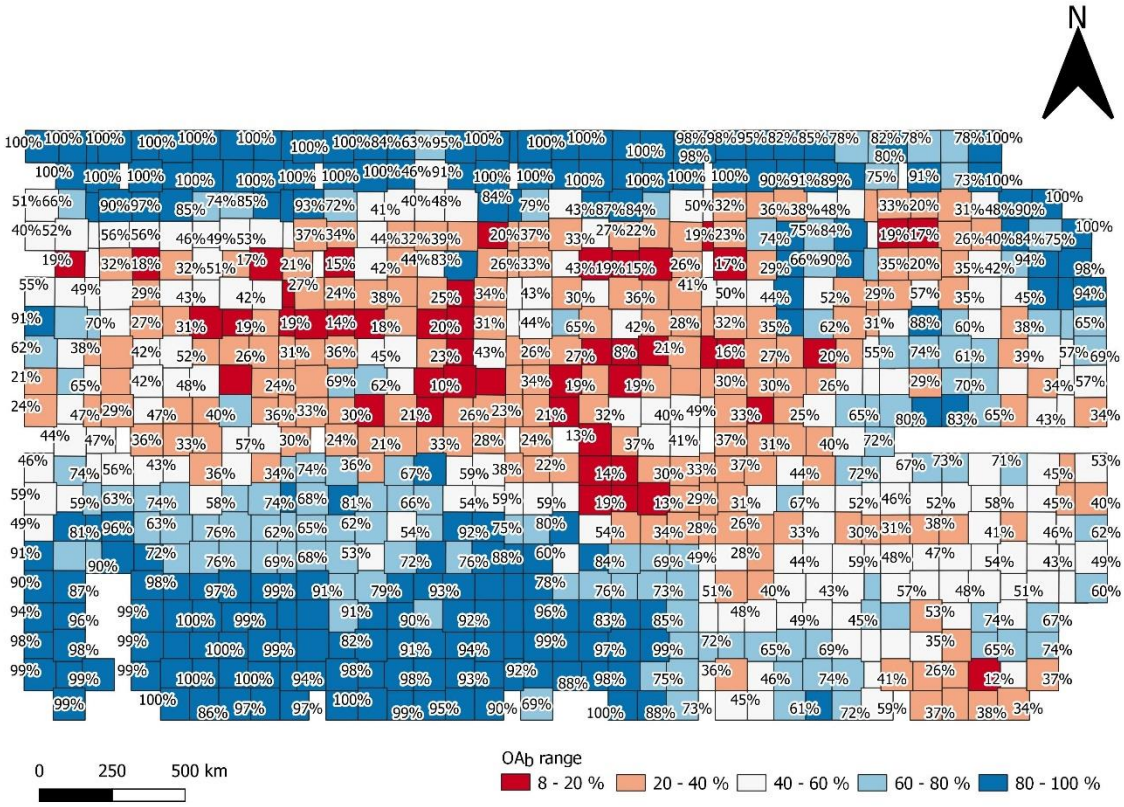

Figure 55 OA_b for each tile of the static map in Africa based on the CCI Prototype

The overall agreement of the static map in Africa is 66% with FROM-GLC and 57% with CCI Prototype (Table 69). The agreement with FROM-GLC increased by 22%. CCI Prototype was not used for inter-comparison in the first production, therefore it is not possible to compare the agreement of the first and second production. OA_b for individual tiles is showing higher agreement in the north and south of the region of interest (Figure 54 and Figure 55). This is probably due to the homogeneous Bareland landscape in the north, and the homogeneous Forest landscape in the south.

3.5.3.4 Per class benchmark accuracy with existing HRLCs

According to the agreement on the level of individual classes (Table 70), the classification of Water and Permanent water is "Excellent", and the classification of Bareland and Forest is "Well". Substantial improvement of agreement is achieved for Bareland and Forest classes.

Table 70. UA_b and PA_b for the whole of Africa

Existing LC	Index	Bareland	Built-up	Cropland	Forest	Grassland	Permanent ice and snow	Shrubland	Water	Water permanent	Water seasonal	Wetland
FROM GLC	PA_b	94%	22%	70%	98%	69%		31%	90%			39%
CCIPrototype		90%	61%	44%	60%	60%		24%	94%			13%
GSW seasonality										99%	20%	
FNF					57%				88%			
GHS BU S1			50%									
WSF			29%									
FROM GLC	UA_b	85%	19%	44%	73%	48%		91%	98%			9%
CCIPrototype		70%	38%	65%	92%	35%		21%	93%			6%
GSW seasonality										97%	47%	
FNF					97%				93%			
GHS BU S1			21%									
WSF			54%									

3.6 HRLC historical maps – the second production

Historical maps in each region were delivered as a set of tiles. Table 71 contains details about the number of tiles per region for each historical product.

Table 71. Number of tiles for each historical product

Year	Region	Number of tiles	Region	Number of tiles	Region	Number of tiles
2019	Siberia	186	Amazon	234	Africa	280
2015	Siberia	186	Amazon	234	Africa	280
2010	Siberia	186	Amazon	234	Africa	280
2005	Siberia	186	Amazon	234	Africa	280
2000	Siberia	183	Amazon	234	Africa	280
1995	Siberia	174	Amazon	234	Africa	266
1990	Siberia	175	Amazon	234	Africa	263

From the point of view of benchmark accuracy, for binary maps that are specifically derived for a certain class – FNF, GHS BU S1, GHS BU LDS, GSW seasonality, Tree Cover, and WSF - OA_b is very high due to the presence of the

class that represents all the other classes but the one of interest for the map. Therefore, OA_b for these maps is not informative, and only PA_b and UA_b were taken into consideration for the following conclusions.

Unlike in the first production, in the second production, there were no two versions of GSW. The reason for this is explained in section 3.3.19. Furthermore, the GL30 map was not used for inter-comparison as explained in section 3.4.

In Siberia, there are only two existing land cover maps with multiple classes – FROM-GLC and ESA DUE GlobPermafrost. They are available for 3 inter-comparison years 2010, 2015, and 2019. This means that OA_b was estimated only in these years. OA_b was ranging from 45% to 69% depending on the year and dataset compared. On average, the agreement with FROM-GLC was around 62% for the 3 years in which this existing dataset is available, while with ESA DUE GlobPermafrost it is 45% for the 2019 comparison for which ESA DUE GlobPermafrost is available. The UA_b and PA_b of the Grassland class increased the most compared to the first production.

The overall agreement of the historical map with existing land cover maps in Amazon is varying from 57% to 74% depending on the year and dataset involved in inter-comparison. The best agreement is with the TerraClass dataset, whose values are higher on average than other datasets.

The agreement with each dataset was relatively homogeneous for different years. The agreement with MapBiomas – the only map available for all years concerned in the project - was around 63% for all the years. The agreement with TerraClass on average for all the years in which this dataset is available was around 73%, and with FROM-GLC around 64%. Agreement of CCI HRLC historical products with existing products for corresponding years increased compared to the first production. The classes for which the agreement increased the most are Built-up, Water, Water Permanent, and Cropland. The agreement for Grassland increased only in the period from 2010 onwards.

In the African region of interest, there are two multiple-class existing land cover maps – FROM-GLC and CCI Prototype. They are available for 3 inter-comparison years 2010, 2015, and 2019. Maximum OA_b was with FROM-GLC for the 2019 comparison and it was 66%. The lowest OA_b was with CCI Prototype for 2019 comparison – 46%. On average, agreement with FROM-GLC in 3 different years was 57%, while with CCI Prototype is only available for 2019 comparison and OA_b is 46%. In comparison to the first production, increased UA_b and PA_b were observed for some years for classes Cropland and Bareland.

3.6.1 Siberia 2019

Following existing land cover maps are used for inter-comparison of historical products for 2019:

- FROM GLC 2017
- ESA DUE GlobPermafrost 2016
- WSF 2019
- GHS BU S1 2016
- FNF 2017
- GSW seasonality 2019

3.6.1.1 Overall benchmark accuracy

There are two existing multiple-class land cover maps for the year 2019 - FROM-GLC and ESA DUE GlobPermafrost- with which historical product for the Siberia region was compared. Table 72 is showing the consistency between the historical map in Siberia and each of the existing land cover maps.

Table 72. Overall benchmark accuracy for the whole of Siberia in 2019

Existing dataset		OA_b
FROM GLC		53%
ESA DUE GlobPermafrost		45%

Siberia results of OA_b will be shown in form of maps for OA_b with existing land cover available in the region. OA_b concerning FROM-GLC is shown in Figure 56, and concerning ESA DUE GlobPermafrost in Figure 57.

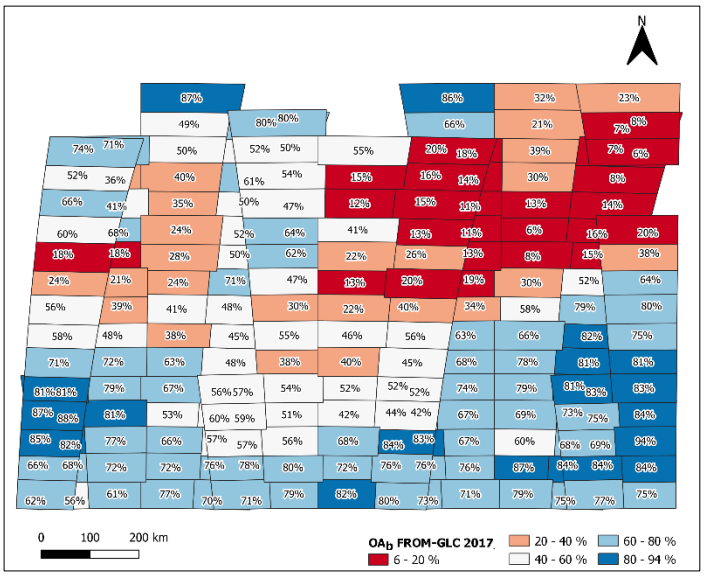

Figure 56. OA$_b$ for each tile of the 2019 historical map in Siberia based on FROM GLC

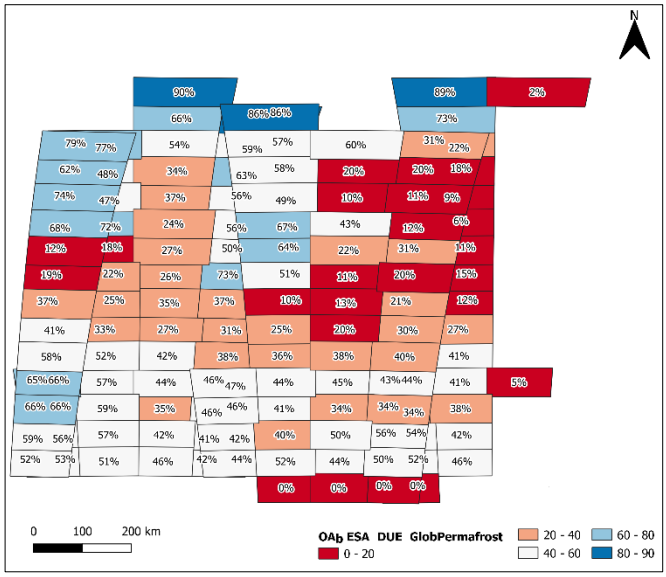

Figure 57. OA$_b$ for each tile of the 2019 historical map in Siberia based on ESA DUE GlobPermafrost

According to FROM-GLC consistency with the historical map for 2019 is 53%, and according to ESA DUE GlobPermafrost is 45% (Table 72). Per tile OA_b (Figure 56, Figure 57) is showing very low values of OA_b (below 20%) in the North-East part of the region for both datasets – FROM-GLC and ESA DUE GlobPermafrost. According to the base map, the North-East landscape is similar to the North-West landscape. There is plenty of lakes/ponds surrounded by vegetation. However, in the North-East of the CCI HRLC vegetation is classified prevalently as Grassland, while in the North-West vegetation is detected as Lichens and Mosses. Therefore, probably Lichens and Mosses in the North-East regions were misclassified as Grassland in the historical product for 2019.

3.6.1.2 Per class benchmark accuracy

Classes Forest, and Water have UA_b and PA_b above 70 % thus the classification of these classes is "Well" (Table 73).

Table 73. UA_b and PA_b for the whole of 2019 Siberia

Dataset	Index	Bareland	Built-up	Cropland	Forest	Forest deciduous broadleaf	Forest evergreen needleleaf	Grassland	Lichens and Mosses	Permanent ice and snow	Shrubland	Shrubland evergreen	Water	Wetland
FROM GLC	PA_b	56%	64%	1%	92%			44%	6%	0%	7%		97%	39%
ESA DUE GlobPermafrost		28%				22%	75%	77%	69%			0%	94%	38%
GHS BU S1			0%											
WSF			85%											
FNF					86%								87%	
GSW seasonality													90%	
FROM GLC	UA_b	13%	14%	0%	80%			33%	86%	0%	0%		83%	7%
ESA DUE GlobPermafrost		36%				24%	65%	15%	45%			68%	95%	12%
GHS BU S1			100%											
WSF			6%											
FNF					68%								73%	
GSW seasonality													84%	

3.6.2 Siberia 2015

Following existing land cover maps are used for inter-comparison of historical products for 2015:

- FROM GLC 2015
- GHS BU LDS 2014
- GSW seasonality 2015
- FNF 2015
- WSF 2015

3.6.2.1 Overall benchmark accuracy

There is a single existing multiple-class land cover map for the year 2015 - FROM-GLC - with which historical product for the Siberia region was compared. Table 74 is showing the consistency between the historical map in Siberia and each of the existing land cover maps.

Table 74. Overall benchmark accuracy for the whole of Siberia in 2015

Existing dataset	OA_b
FROM-GLC	69%

Siberia results of OA_b will be shown in form of maps for OA_b with existing land cover available in the region. OA_b concerning FROM-GLC is shown in Figure 58.

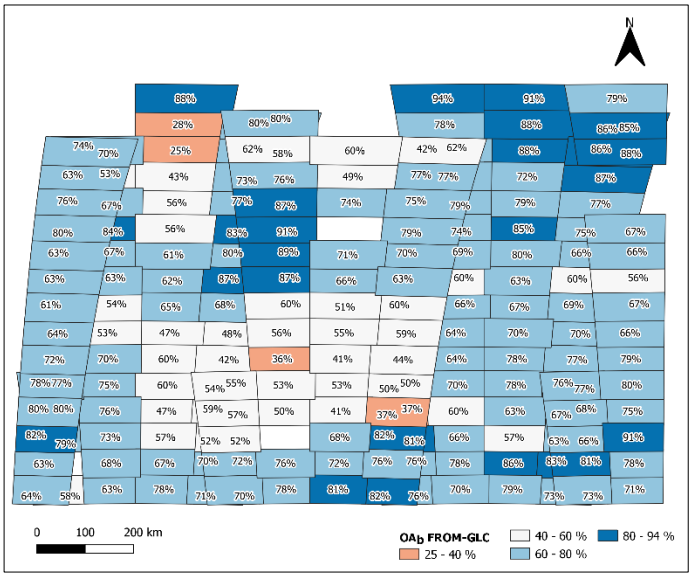

Figure 58. OA_b for each tile of the 2015 historical map in Siberia based on FROM-GLC

According to FROM-GLC consistency with the historical map for 2015 is 69% (Table 74) which is 16% more compared to the first production. In the second production, the most obvious improvement is in class Grassland for which UA_b and PA_b are more than 50%, which makes Grassland classification "Relatively good". There is also an increase of agreement in the class Forest by several percent. Per tile OA_b (Figure 58) does not show very low values, but in the lower central part of the region, there are values from 40-60% that are clustered. In the CCI HRLC, the presence of Wetland classes is evident in this region, while in FROM-GLC it is Grassland. However, the base map is showing that the classification in CCI HRLC is likely to be correct because this area is rich with small water bodies, and thus Wetland is expected to be found.

3.6.2.2 Per class benchmark accuracy

Classes Forest, and Water have UA_b and PA_b above 70 % thus the classification of these classes is "Well" (Table 75).

Table 75. UA_b and PA_b for the whole of 2015 Siberia

Dataset	Index	Bareland	Built-up	Cropland	Forest	Grassland	Permanent ice and snow	Shrubland	Water	Wetland
FROM GLC	PA_b	69%	86%	0%	79%	55%	0%	12%	95%	53%

GHS			73%						99%	
WSF			73%							
FNF					85%				91%	
GSW seasonality									88%	
FROM GLC		5%	3%	0%	79%	91%	0%	2%	82%	1%
GHS			11%						74%	
WSF	UA_b		19%							
FNF					60%				71%	
GSW seasonality									84%	

3.6.3 Siberia 2010

Following existing land cover maps are used for inter-comparison of historical products for 2010:

- FROM GLC 2010
- GUF 2011
- GSW seasonality 2010
- FNF 2010

3.6.3.1 Overall benchmark accuracy

There is a single existing multiple-class land cover map for the year 2010 with which the historical product for the Siberia region was compared: FROM-GLC. Table 76 is showing the consistency between the historical map in Siberia and each of the existing land cover maps.

Table 76. Overall benchmark accuracy for the whole of Siberia in 2010

Existing dataset	OA_b
FROM-GLC	63%

Siberia results of OA_b will be shown in form of maps for OA_b with each of the two existing land covers available in the region. OA_b concerning FROM-GLC is shown in Figure 59.

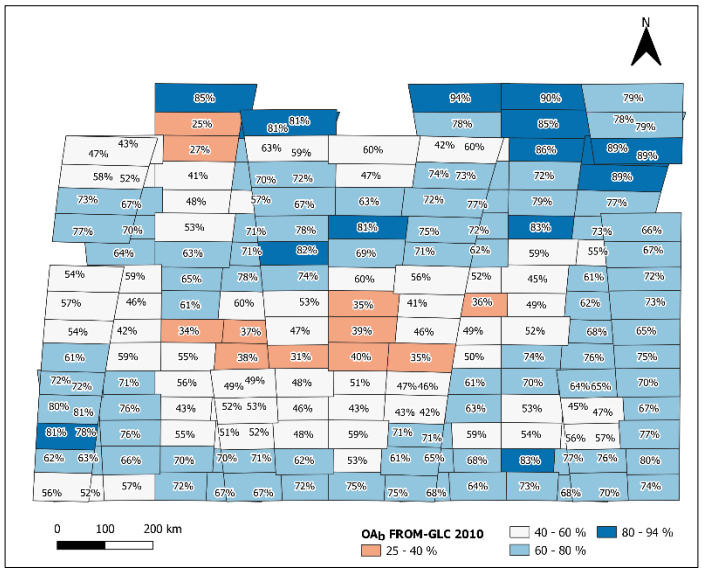

Figure 59. OA_b for each tile of the 2010 historical map in Siberia based on FROM GLC

According to FROM-GLC consistency with the historical map for 2010 is 63%, which is a 10% increase in agreement compared to the first production (Table 76). Per tile OA_b (Figure 59) is relatively consistent with per

tile OA_b for 2015. Therefore, the lower agreement is probably because Wetland is classified as Grassland in FROM -GLC.

3.6.3.2 Per class benchmark accuracy

Classes Forest, and Water have UA_b and PA_b above 70 % thus the classification of these classes is "Well" (Table 77). In the second production, UA_b and PA_b increased by over 50%, which makes the Grassland classification "Relatively good", but there is also a small improvement in the agreement for the Forest class as well.

Table 77. UA_b and PA_b for the whole of 2010 Siberia

Dataset	Index	Bareland	Built-up	Cropland	Forest	Grassland	Permanent ice and snow	Shrubland	Water	Wetland
FROM GLC	PA_b	6%	13%	0%	74%	57%	0%	12%	86%	36%
GUF			77%							
FNF					91%				89%	
GSW seasonality									95%	
FROM GLC	UA_b	14%	25%	1%	73%	77%	0%	2%	79%	1%
GUF			17%							
FNF					63%				75%	
GSW seasonality									80%	

3.6.4 Siberia 2005

Following existing land cover maps are used for inter-comparison of historical products for 2005:

- FNF 2007
- GSW seasonality 2005

3.6.4.1 Overall benchmark accuracy

For the year 2005 other multiple-class land covers do not exist, therefore OA_b cannot be reported.

3.6.4.2 Per class benchmark accuracy

When the agreement of individual classes is concerned, there is a "Well" agreement for the class of Water and "Relatively good" for Forest (Table 78).

Table 78. UA_b and PA_b for the whole of 2005 Siberia

Dataset	Index	Forest	Water
FNF	PA_b	91%	94%
GSW seasonality			94%
FNF	UA_b	63%	72%
GSW seasonality			79%

3.6.5 Siberia 2000

Following existing land cover maps are used for inter-comparison of historical products for 2000:

- GHS BU LDS 2000
- TreeCover 2000
- GSW seasonality 2000

3.6.5.1 Overall benchmark accuracy

For the year 2005 other multiple-class land covers do not exist, therefore OA_b cannot be reported.

3.6.5.2 Per class benchmark accuracy

Binary datasets show the agreement of some classes. There is a well agreement for classes of Water, and Forest (Table 79).

Table 79. UA_b and PA_b for the whole of 2000 Siberia

Dataset	Index	Built-up	Forest	Water
GHS	PA_b	75%		99%
GSW seasonality				93%
TreeCover			92%	
GHS	UA_b	15%		74%
GSW seasonality				81%
TreeCover			70%	

3.6.6 Siberia 1995

Following existing land cover maps are used for inter-comparison of historical products for 1995:

- GSW seasonality 1994

3.6.6.1 Overall benchmark accuracy

For the year 1995 other multiple-class land covers do not exist, therefore OA_b cannot be reported.

3.6.6.2 Per class benchmark accuracy

For the class agreement, GSW seasonality is showing high scores for the Water class thus this class can be considered as “Well” classified (Table 80).

Table 80. UA_b and PA_b for the whole of 1995 Siberia

Existing LC	Index	Water
GSW seasonality	PA_b	89%
GSW seasonality	UA_b	84%

3.6.7 Siberia 1990

Following existing land cover maps are used for inter-comparison of historical products for 1990:

- GHS BU LDS 1990
- GSW seasonality 1990

3.6.7.1 Overall benchmark accuracy

For the year 1990 other multiple-class land covers do not exist, therefore OA_b cannot be reported.

3.6.7.2 Per class benchmark accuracy

For the class agreement, GSW seasonality and GHS BU LDS are showing high scores Water class thus this class can be considered as "Well" classified (Table 81).

Table 81. UA_b and PA_b for the whole of 1990 Siberia

Dataset	Index	Built-up	Water
GHS	PA_b	74%	99%
GSW seasonality			88%
GHS	UA_b	17%	74%
GSW seasonality			84%

3.6.8 Amazon 2019

Following existing land cover maps are used for inter-comparison of historical products for 2019:

- FROM GLC 2017
- MapBiomas 2019
- GHS BU S1 2016
- WSF 2019
- FNF 2017
- GSW seasonality 2019

3.6.8.1 Overall benchmark accuracy

There are two existing multiple-class land cover maps for the year 2019 - FROM-GLC, and MapBiomas - with which historical product for the Amazon region was compared. Table 82 is showing the consistency between the historical map for the Amazon and each of the existing land cover maps.

Table 82. Overall benchmark accuracy for the whole of Amazon in 2019

Existing dataset	OA_b
FROM GLC	71%
MapBiomas	63%

Amazon results of OA_b will be shown in form of maps for OA_b with existing land cover available in the region. OA_b concerning FROM-GLC is shown in Figure 60, and concerning MapBiomas in Figure 61.

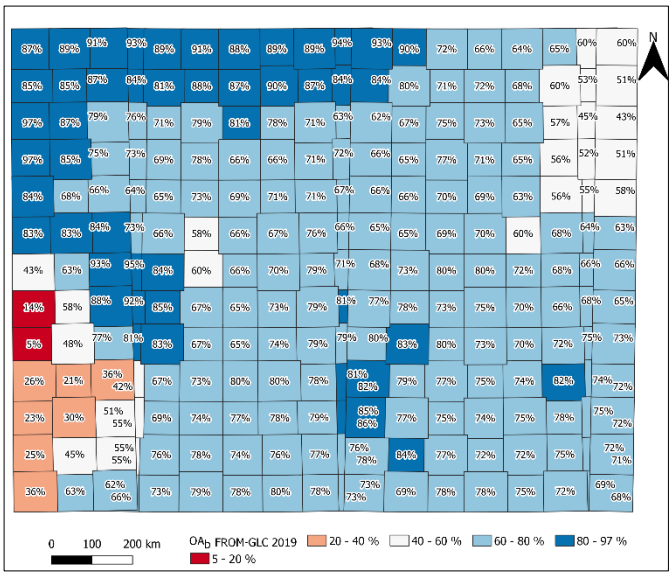

Figure 60. OA_b for each tile of the 2019 historical map in Amazon based on FROM GLC

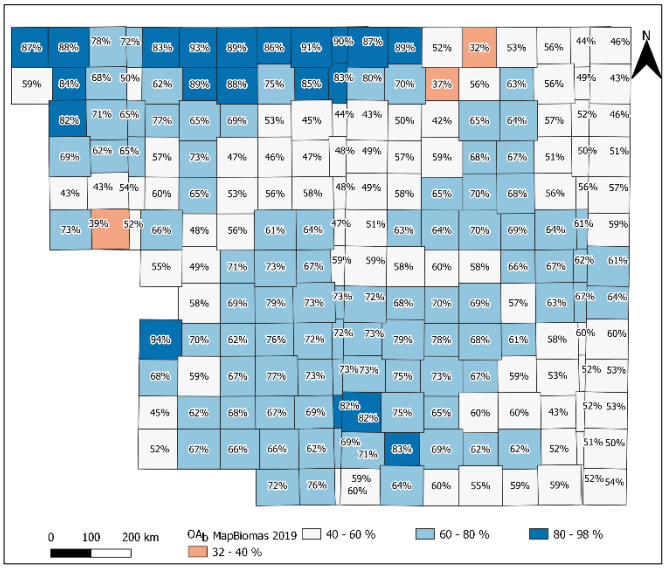

Figure 61. OA_b for each tile of the 2019 historical map in Amazon based on MapBiomas

According to FROM-GLC consistency with a historical map for 2019 is 71%, and according to MapBiomas is 63% (Table 82). Per tile OA_b (Figure 60, Figure 61) is not showing any specific pattern of OA_b except higher values in the northern area of the region of interest where homogeneous areas of forest are present.

3.6.8.2 Per class benchmark accuracy

When classes are concerned, the Permanent Water classification is “Excellent”. Forest, Water, and Grassland have UA_b and PA_b above 70 %, thus the classification of these classes is “Well”. The Built-up class has PA_b above 50 % with all existing HRLCs, and UA_b above 50 % with the majority of existing HRLCs therefore it can be considered “Relatively good” (Table 83).

Table 83. UA_b and PA_b for the whole of 2019 Amazon

Dataset	Index	Bareland	Built-up	Cropland	Forest	Grassland	Shrubland	Water	Water permanent	Water seasonal	Wetland	Wetland Herbaceous	Wetland Shrubby
FROM GLC	PA_b	61%	68%	81%	90%	76%	14%	83%			50%		
MapBiomas		19%	71%	23%	91%	84%	16%	69%				11%	0%
GHS BU S1			80%										
WSF			84%										
FNF					82%			25%					
GSW seasonality									89%	9%			
FROM GLC	UA_b	2%	54%	68%	76%	72%	44%	89%			36%		
MapBiomas		10%	69%	37%	64%	68%	46%	94%				34%	0%
GHS BU S1			41%										
WSF			39%										
FNF					74%			66%					
GSW seasonality									91%	21%			

3.6.9 Amazon 2015

Following existing land cover maps are used for inter-comparison of historical products for 2015:

- FROM GLC 2015
- MapBiomas 2015
- TerraClass 2014
- GHS 2014
- WSF 2015
- FNF 2015
- AUE - Sao Paulo 2014, Ribeirao Preto 2014

3.6.9.1 Overall benchmark accuracy

There are three existing multiple-class land cover maps for the year 2015 - FROM-GLC, MapBiomas, and TerraClass - with which historical product for the Amazon region was compared. Table 84 is showing the consistency between the historical map for Amazon and each of the existing land cover maps.

Table 84. Overall benchmark accuracy for the whole of Amazon in 2015

Existing dataset	OA_b
FROM GLC	66%
MapBiomas	71%
TerraClass	73%

Amazon results of OA_b will be shown in form of maps for OA_b with existing land cover available in the region. OA_b concerning FROM-GLC is shown in Figure 62, concerning the MapBiomas in Figure 63, and concerning the TerraClass in Figure 64.

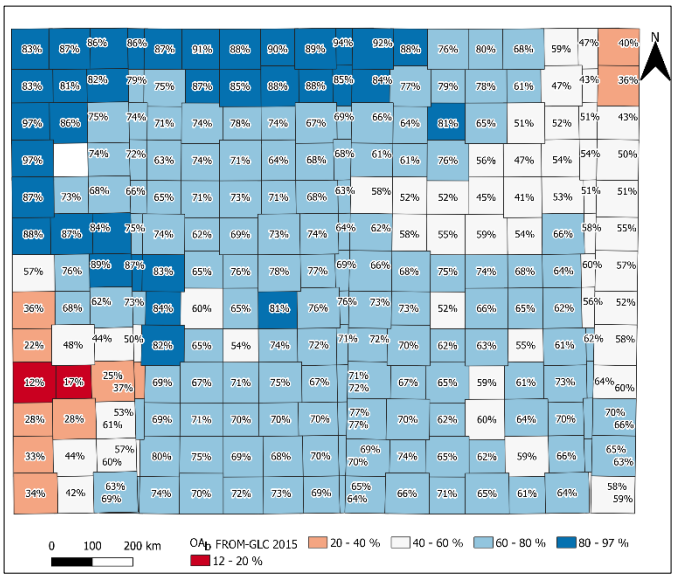

Figure 62. OA_b for each tile of the 2015 historical map in Amazon based on FROM-GLC

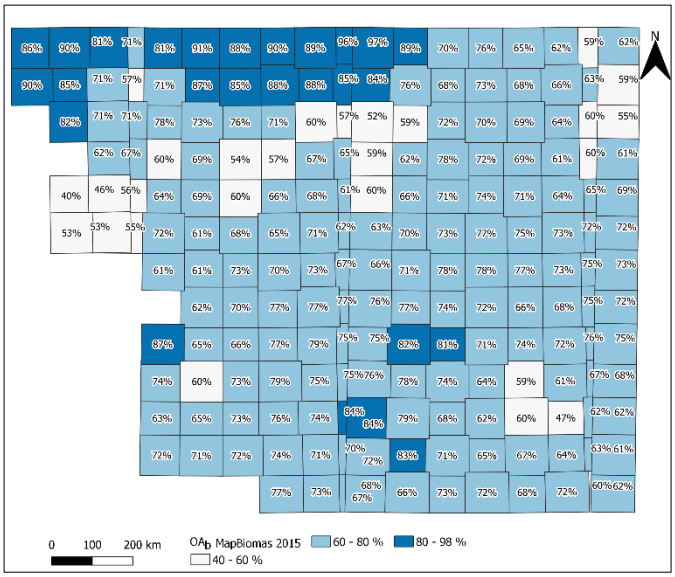

Figure 63. OA_b for each tile of the 2015 historical map in Amazon based on MapBiomas

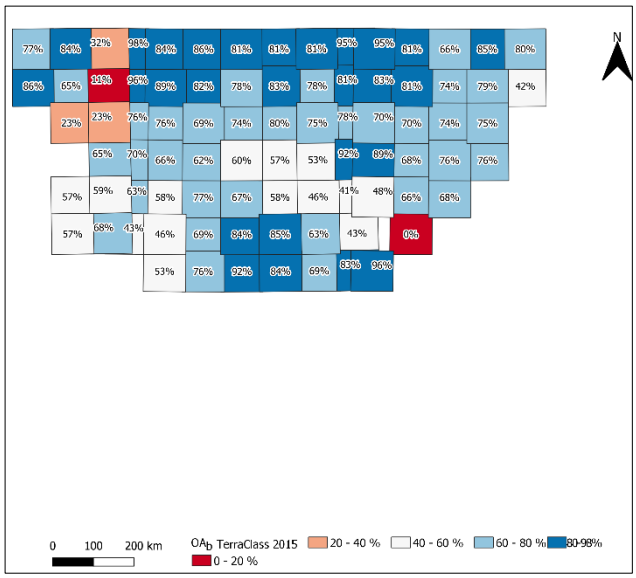

Figure 64. OA_b for each tile of the 2015 historical map in Amazon based on TerraClass

For the year 2015 OA_b was 66% for FROM-GLC, 71% for MapBiomas, and 73% for TerraClass (Table 84). Compared to the first production, this is an increase of agreement of 9% for inter-comparison with FROM-GLC, 14% with MapBiomas, and 10% with Terra Class. The per tile OA_b for FROM-GLC, MapBiomas, and TerraClass are relatively homogeneous (Figure 62, Figure 63, Figure 64). Higher values are evident in the northern part of the area of interest where a homogeneous forest landscape is present. OA_b with FROM-GLC has some lower values in the south-west part where CCI HRLC detected Cropland surrounded by deciduous broadleaf forest, while this is Grassland in FROM-GLC. Basemap is showing that the CCI HRLC classification is correct.

3.6.9.2 Per class benchmark accuracy

Regarding the class accuracy (Table 85) Forest, Water, Permanent water, and Grassland are considered as "Well" classified, while Built-up is classified as "Relatively good". Compared to the first production, improvements are evident for Grassland, Cropland, and Built-up classes. Agreement with the AUE dataset is consistent with the agreement with other existing datasets regarding the Built-up class.

Table 85. UA_b and PA_b for the whole of 2015 Amazon

Dataset	Index	Bareland	Built-up	Cropland	Forest	Grassland	Shrubland	Water	Water permanent	Water seasonal	Wetland	Wetland Herbaceous
FROM GLC	PA_b	30%	77%	63%	89%	69%	12%	79%			50%	
MapBiomas		21%	77%	76%	90%	79%	18%	73%				42%
TerraClass		0%	2%	82%	95%	63%	7%	59%				
GHS			87%					92%				
WSF			73%									
FNF					83%			30%				
GSW seasonality									87%	9%		
FROM GLC	UA_b	5%	59%	68%	71%	68%	30%	89%			14%	
MapBiomas		10%	77%	66%	69%	79%	44%	91%				37%
TerraClass		2%	69%	63%	75%	83%	16%	73%				
GHS			45%					53%				

WSF			72%									
FNF					72%			72%				
GSW seasonality									89%	19%		
AUE Ribeirao Preto	PA_b		83%					29%				
AUE Sao Paulo			83%					61%				
AUE Ribeirao Preto	UA_b		68%					26%				
AUE Sao Paulo			72%					56%				

3.6.10 Amazon 2010

Following existing land cover maps are used for inter-comparison of historical products for 2010:

- FROM GLC 2010
- MapBiomas 2010
- TerraClass 2010
- GUF 2011
- FNF 2010
- GSW seasonality 2010

3.6.10.1 Overall benchmark accuracy

There are three existing multiple-class land cover maps for the year 2010 with which the historical product for the Amazon region was compared: FROM-GLC, MapBiomas, and TerraClass. Table 86 is showing the consistency between the historical map for the Amazon and each of the existing land cover maps.

Table 86. Overall benchmark accuracy for the whole of Amazon in 2010

Existing dataset	OA_b
FROM GLC	57%
MapBiomas	67%
TerraClass	71%

Amazon results of OA_b will be shown in form of maps for OA_b with each of the two existing land covers available in the region. OA_b concerning FROM-GLC is shown in Figure 65, Mapbiomas in Figure 66, and concerning TerraClass in Figure 67.

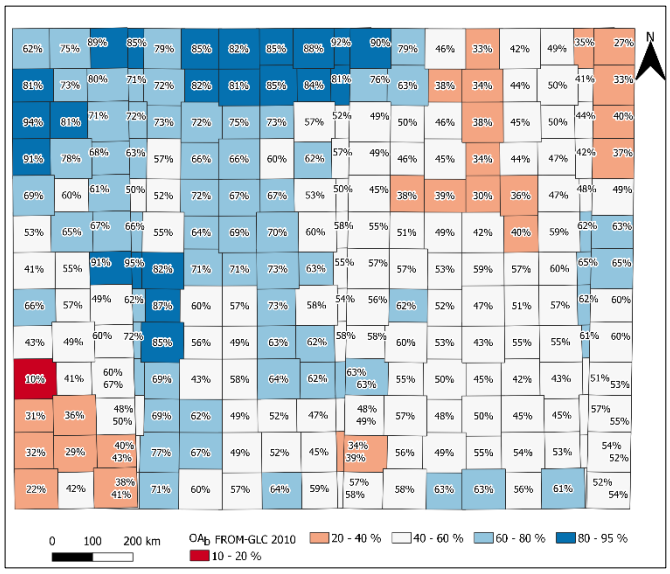

Figure 65. OA_b for each tile of the 2010 historical map in Amazon based on FROM GLC

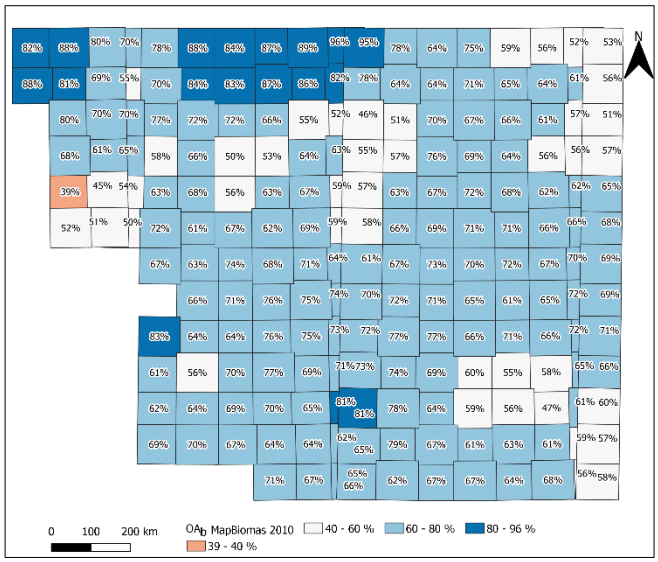

Figure 66. OA_b for each tile of the 2010 historical map in Amazon based on MapBiomas

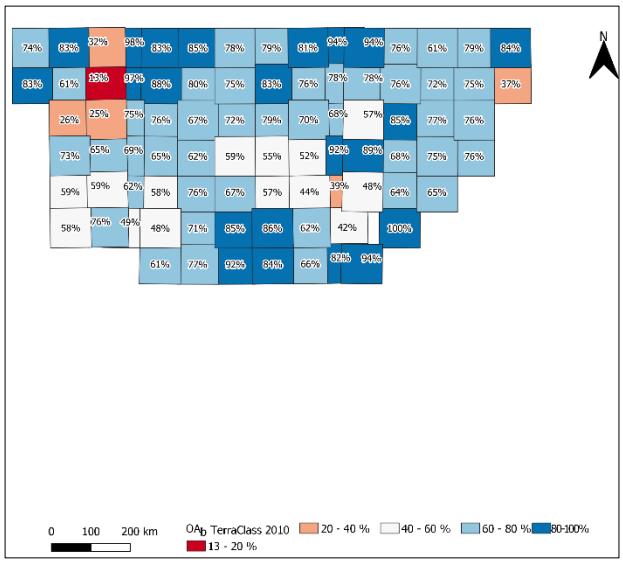

Figure 67. OA_b for each tile of the 2010 historical map in Amazon based on TerraClass

For the year 2010 OA_b was 57% for FROM-GLC, 67% for MapBiomas, and 71% for TerraClass (Table 86). Compared to the first production, this is an increase of 11% for inter-comparison with FROM-GLC, 16% with MapBiomas, and 4% with Terra Class. The per-tile OA_b does not show a particular pattern for MapBiomas and TerraClass (Figure 66 and Figure 67). OA_b with FROM-GLC has some lower values in the south-west part where CCI HRLC detected Cropland surrounded by deciduous broadleaf forest, while this is Grassland in FROM-GLC. Basemap is showing that the CCI HRLC classification is correct.

3.6.10.2 Per class benchmark accuracy

Regarding class accuracy (Table 87), Forest and Water permanent are "Well" classified, and Cropland, Grassland, and Built-up are "Relatively good" classified. Unlike for other years, many PA_b values for the Water class are below 50% which indicates an underestimation of the Water class for this year. The most significant agreement increase concerning the first production is for the Built-up, Cropland, Grassland, Water, and Water permanent classes.

Table 87. UA_b and PA_b for the whole of 2010 Amazon

Dataset	Index	Bareland	Built-up	Cropland	Forest	Grassland	Shrubland	Water	Water permanent	Water seasonal	Wetland	Wetland Herbaceous
FROM GLC	PA_b	2%	57%	48%	77%	58%	8%	41%			38%	
MapBiomas		21%	77%	75%	91%	72%	15%	70%				48%
TerraClass		1%	40%	76%	96%	56%	9%	9%				
GUF			76%									
FNF					87%			20%				
GSW seasonality									84%	5%		
FROM GLC	UA_b	6%	22%	57%	70%	52%	13%	87%			9%	
MapBiomas		6%	77%	52%	67%	79%	38%	91%				37%
TerraClass		1%	67%	59%	74%	81%	16%	75%				
GUF			65%									
FNF					75%			7%				

GSW seasonality									89%	15%		

3.6.11 Amazon 2005

Following existing land cover maps are used for inter-comparison of historical products for 2005:

- MapBiomas 2005
- TerraClass 2004
- FNF 2007
- GSW seasonality 2005

3.6.11.1 Overall benchmark accuracy

There are 2 existing multiple-class land cover maps for the year 2005 with which the historical product for the Amazon region was compared: MapBiomas and TerraClass. Table 88 is showing the consistency between the historical map for the Amazon and each of the existing land cover maps.

Table 88. Overall benchmark accuracy for the whole of Amazon in 2005

Existing dataset	OA_b
MapBiomas	65%
TerraClass	74%

Amazon results of OA_b will be shown in form of maps for OA_b with each of the two existing land covers available in the region. OA_b concerning MapBiomas is shown in Figure 68, and concerning TerraClass in Figure 69.

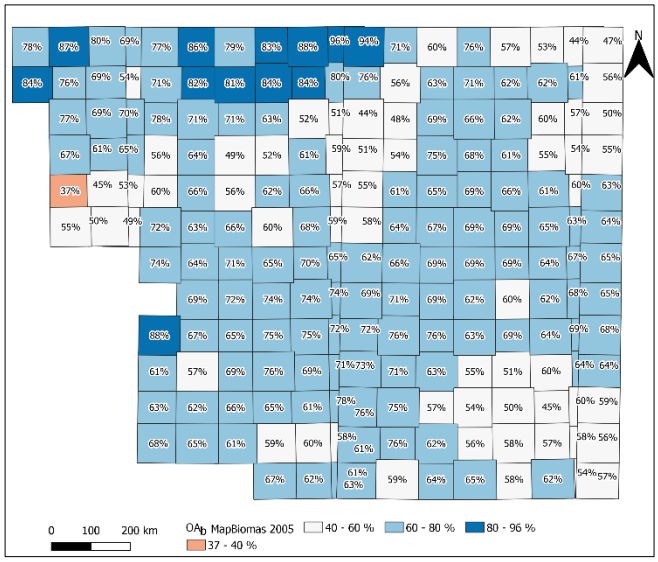

Figure 68. OA_b for each tile of the 2005 historical map in Amazon based on MapBiomas

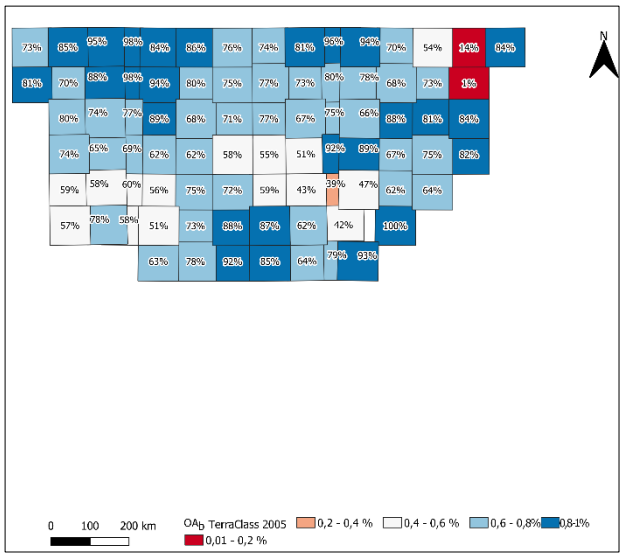

Figure 69. OA_b for each tile of the 2005 historical map in Amazon based on TerraClass

For the year 2005 OA_b OA_b was 65% for MapBiomas, and 74% for TerraClass (Table 88). Compared to the first production, this is an increase of agreement of 10% for inter-comparison with MapBiomas and a decrease of the agreement by 1% with Terra Class. The per-tile OA_b does not show a particular pattern for MapBiomas and TerraClass (Figure 68 and Figure 69).

3.6.11.2 Per class benchmark accuracy

Regarding class accuracy (Table 89) Forest and Permanent water are "Well" classified, while Grassland and Water are considered "Relatively good". In comparison to the first production, improvement in agreement for Water is significant.

Table 89. UA_b and PA_b for the whole of 2005 Amazon

Dataset	Index	Bareland	Built-up	Cropland	Forest	Grassland	Shrubland	Water	Water permanent	Water seasonal	Wetland Herbaceous
MapBiomas	PA_b	17%	77%	74%	91%	68%	14%	71%			55%
TerraClass		1%	2%	81%	95%	48%	9%	60%			
FNF					88%			38%			
GSW seasonality									82%	7%	
MapBiomas	UA_b	7%	77%	47%	66%	79%	33%	90%			41%
TerraClass		2%	76%	38%	84%	79%	8%	71%			
FNF					73%			66%			
GSW seasonality									89%	14%	

3.6.12 Amazon 2000

Following existing land cover maps are used for inter-comparison of historical products for 2000:

- MapBiomas 2000
- GHS 2000
- GSW seasonality 2000
- TreeCover 2000

- AUE - Sao Paulo 2000, Ribeirao Preto 2001

3.6.12.1 Overall benchmark accuracy

There is a single multiple-class land cover map for the year 2000 – MapBiomas - with which the historical product for the Amazon region was compared. Table 90 is showing the consistency between the historical map of the Amazon and each of the existing land cover maps.

Table 90. Overall benchmark accuracy for the whole of Amazon in 2000

Existing dataset	OA_b
MapBiomas	62%

Amazon results of OA_b will be shown in form of maps for OA_b with existing land cover available in the region. OA_b concerning MapBiomas in Figure 70.

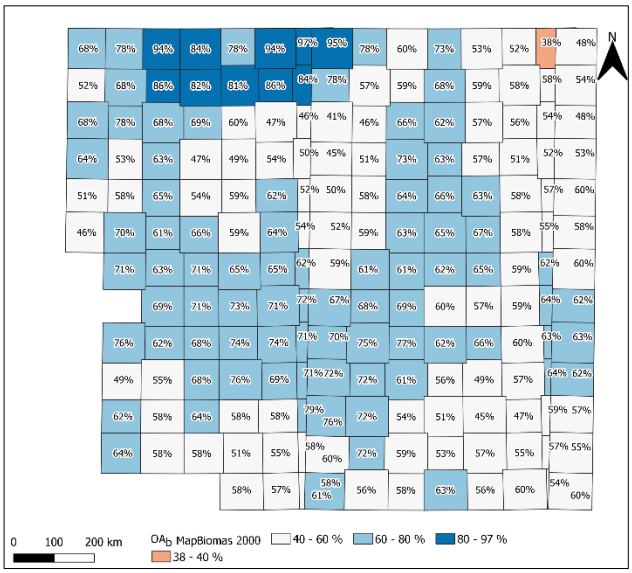

Figure 70. OA_b for each tile of the 2000 historical map in Amazon based on MapBiomas

The only existing multiple-class land cover map for 2000 is MapBiomas. OA_b for this map for this year was 62% (Table 90) which is a 12% of improvement in agreement compared to the first production. The per-tile OA_b is not subject to a distinct pattern (Figure 70).

3.6.12.2 Per class benchmark accuracy

Regarding class accuracy (Table 91), Built-up, Forest, Grassland, Water, and Water permanent are "Well" classified. The most significant improvements in the agreement are for the classes Built-up, Water, Permanent Water, and Cropland. Agreement of AUE increased compared to the first production, and it can be considered "Well". It is consistent with the agreement of other datasets related to the Built-up class.

Table 91. UA_b and PA_b for the whole 2000 Amazon

Dataset	Index	Bareland	Built-up	Cropland	Forest	Grassland	Shrubland	Water	Water permanent	Water seasonal	Wetland	Wetland Herbaceous
MapBiomas	PA_b	16%	72%	73%	93%	65%	11%	72%				54%
GHS			77%					93%				
GSW seasonality									85%	6%		
TreeCover					93%							

MapBiomas	UA_b	10%	82%	37%	62%	79%	34%	88%				42%
GHS			58%					59%				
GSW seasonality									86%	14%		
TreeCover					78%							
AUE Ribeirao Preto	PA_b		91%					0%				
AUE Sao Paulo			93%					41%				
AUE Ribeirao Preto	UA_b		70%					6%				
AUE Sao Paulo			70%					44%				

3.6.13 Amazon 1995

Following existing land cover maps are used for inter-comparison of historical products for 1995:

- MapBiomas 1995
- GSW seasonality 1995

3.6.13.1 Overall benchmark accuracy

There is a single existing multiple-class land cover map for the year 1995 – MapBiomas - with which historical product for the Amazon region was compared. Table 92 is showing the consistency between the historical map of the Amazon and the existing land cover map.

Table 92. Overall benchmark accuracy for the whole of Amazon in 1995

Existing dataset	OA_b
MapBiomas	61%

Amazon results of OA_b will be shown in form of maps for OA_b with existing land cover available in the region. OA_b concerning MapBiomas is shown in Figure 71.

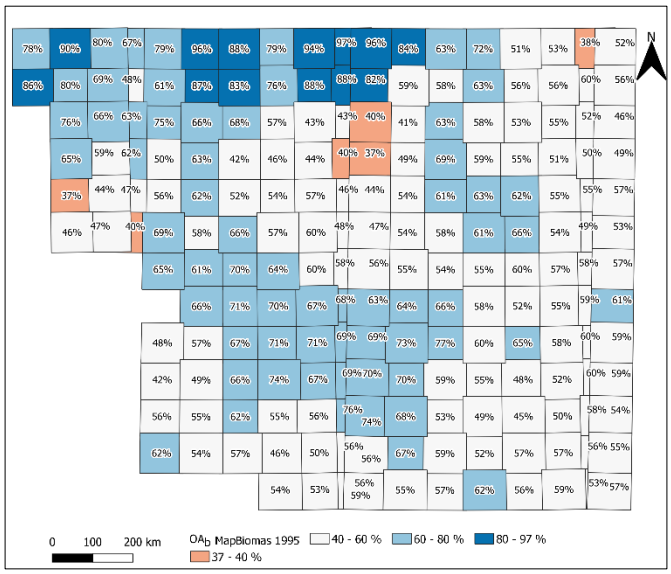

Figure 71. OA_b for each tile of the 1995 historical map in Amazon based on MapBiomas

The only existing multiple-class land cover map for 1995 is MapBiomas (Table 92). It is showing 61% of consistency with the historical map for 1995 in Amazon. It is a 5% of improvement in consistency concerning the first production. The per-tile OA_b does not show a particular pattern for MapBiomas (Figure 71).

3.6.13.2 Per class benchmark accuracy

It shows “Well” agreement for Built-up, Forest, Water, and Permanent water classes. The Grassland class is “Relatively good” classified (Table 93). In comparison to the first production, significant improvements in agreement for Built-up, Water, and Permanent Water are visible.

Table 93. UA_b and PA_b for the whole of 1995 Amazon

Dataset	Index	Bareland	Built-up	Cropland	Forest	Grassland	Shrubland	Water	Water permanent	Water seasonal	Wetland Herbaceous
MapBiomas	PA_b	11%	67%	68%	93%	62%	12%	65%			47%
GSW seasonality									70%	3%	
MapBiomas	UA_b	9%	83%	31%	63%	76%	38%	86%			39%
GSW seasonality									86%	10%	

3.6.14 Amazon 1990

Following existing land cover maps are used for inter-comparison of historical products for 1990:

- MapBiomas 1990
- GHS 1990
- GSW seasonality 1990
- AUE - Sao Paulo 1988, Ribeirao Preto 1990

3.6.14.1 Overall benchmark accuracy

There is a single existing multiple-class land cover map for the year 1990 – MapBiomas - with which historical product for the Amazon region was compared. Table 94 is showing the consistency between the historical map of the Amazon and the existing land cover map.

Table 94. Overall benchmark accuracy for the whole of Amazon in 1990

Existing dataset	OA_b
MapBiomas	58%

Amazon results of OA_b will be shown in form of maps for OA_b with existing land cover available in the region. OA_b concerning MapBiomas is shown in Figure 72.

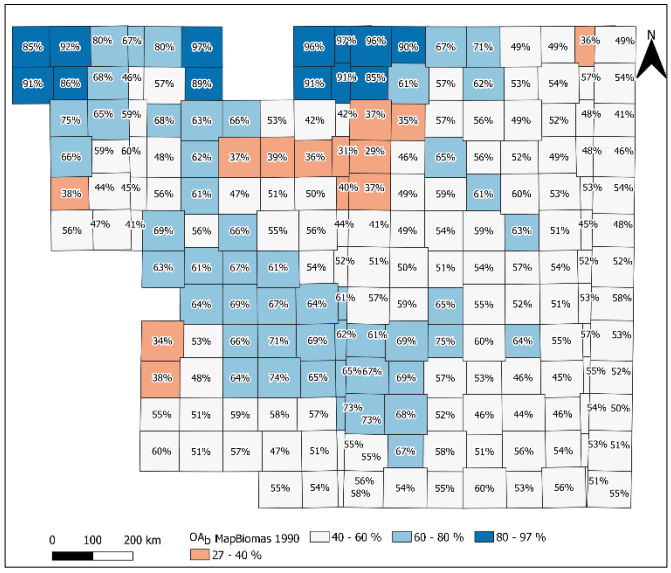

Figure 72. OA_b for each tile of the 1990 historical map in Amazon based on MapBiomas

The only existing multiple-class land cover map for 1990 is MapBiomas (Table 94). It is showing 58% of consistency with the historical map for 1990 in Amazon, which is a 2% of improvement in consistency compared to the first production.

3.6.14.2 Per class benchmark accuracy

The per-tile OA_b does not show a particular pattern for MapBiomas (Figure 72). It shows "Well" agreement for Forest, Water, and Permanent Water classes, and "Relatively good" agreement for Built-up and Grassland classes (Table 95). In comparison to the first production, improvements in agreement for Built-up, Water, and Permanent Water classes are significant. Agreement with AUE increased compared to the first production, and it can be considered "Well". It is a bit higher than agreement with other existing datasets related to the Built-up class. Given that the AUE dataset is focused on big cities (Ribeirao Preto and Sao Paolo), it may indicate that classification of the Built-up class is more successful in cities than Built-up elsewhere. It might be due to the homogeneity of Built-up classes in cities.

Table 95. UA_b and PA_b for the whole 1990 Amazon

Dataset	Index	Bareland	Built-up	Cropland	Forest	Grassland	Shrubland	Water	Water permanent	Water seasonal	Wetland Herbaceous
MapBiomas	PA_b	9%	68%	66%	93%	60%	10%	61%			46%
GHS			73%					88%			
GSW seasonality									70%	5%	
MapBiomas	UA_b	7%	73%	28%	60%	73%	39%	84%			39%
GHS			51%					69%			
GSW seasonality									85%	11%	
AUE Ribeirao Preto	PA_b		92%					0%			
AUE Sao Paulo			77%					5%			
AUE Ribeirao Preto	UA_b		72%					4%			
AUE Sao Paulo			74%					2%			

3.6.15 Africa 2019

Following existing land cover maps are used for inter-comparison of historical products for 2019:

- FROM GLC 2017
- CCI Prototype 2016
- GHS BU S1 2016
- WSF 2019
- FNF 2017
- GSW seasonality 2019

3.6.15.1 Overall benchmark accuracy

There are two existing multiple-class land cover maps for the year 2019 - FROM-GLC, and CCI Prototype - with which historical product for the African region was compared. Table 96 is showing the consistency between the historical map in Africa and each of the existing land cover maps.

Table 96. Overall benchmark accuracy for the whole of Africa in 2019

Existing dataset	OA_b
FROM GLC	66%

CCI Prototype	46%

Africa results of OA_b will be shown in form of maps for OA_b with existing land cover available in the region. OA_b concerning FROM-GLC is shown in Figure 73, and concerning CCI Prototype in Figure 74.

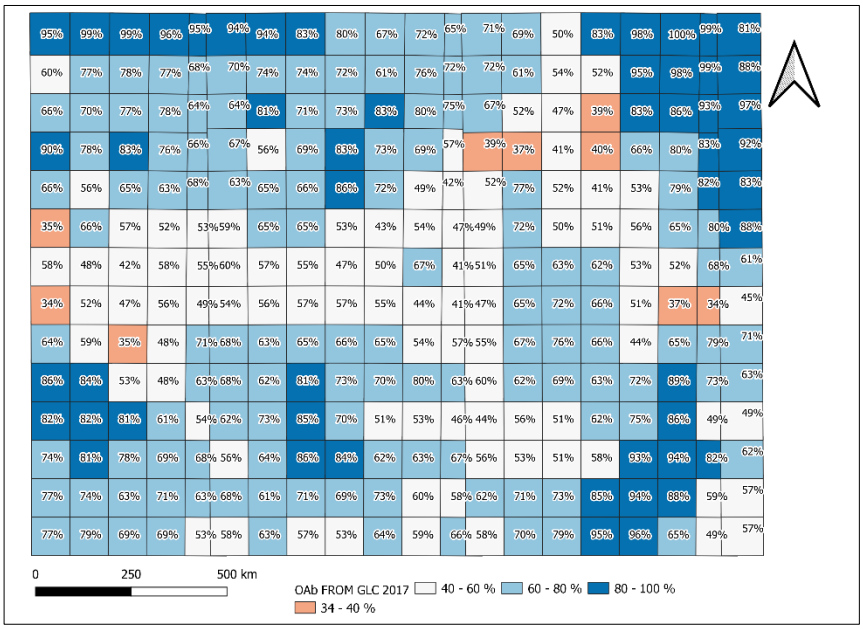

Figure 73. OA_b for each tile of the 2019 historical map in Africa based on FROM GLC

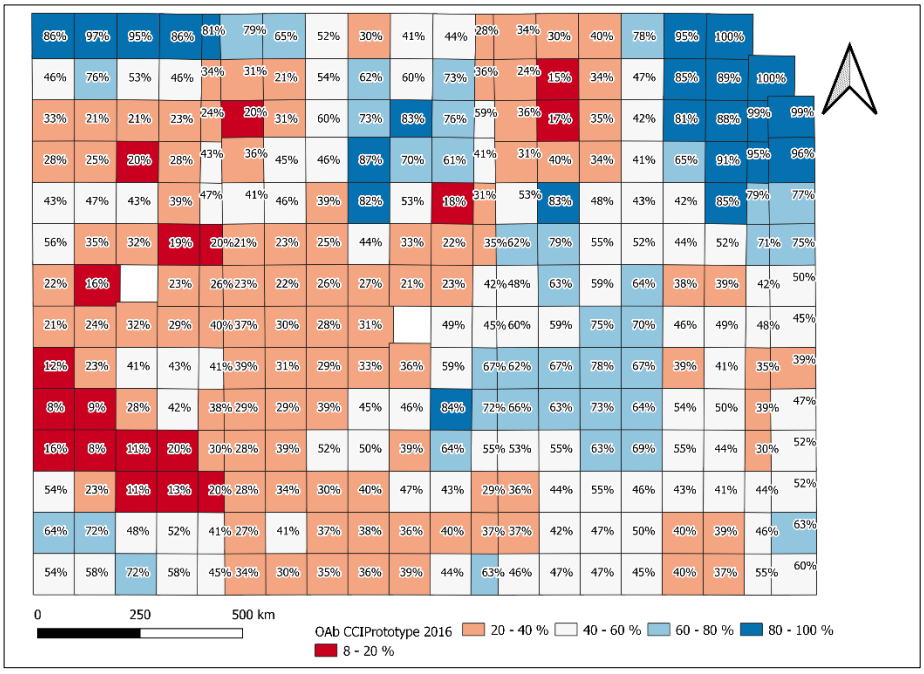

Figure 74. OA_b for each tile of the 2019 historical map in Africa based on the CCI Prototype

According to FROM-GLC consistency with the historical map for 2019 is 66%, and according to CCI Prototype is 46% (Table 96). Per tile OA_b with FROM-GLC (Figure 60) is not showing any specific pattern of OA_b except higher values in the northern area of the region of interest where homogeneous areas of Bareland are present. On the opposite, per tile OA_b with CCI Prototype Figure 61 shows a small number of grouped tiles with low OA_b values. In those areas, confusion is between Forest in CCI Prototype and Shrubland in CCI HRLC. From a base map, the area seems to be prevalently covered with shrubs.

3.6.15.2 Per class benchmark accuracy

When classes are concerned, Permanent Water and Water classifications are "Excellent". Bareland and Cropland are "Relatively good" classified. It is surprising to observe that agreement with the Forest class is not high, since it was typically high in other regions.

Table 97. UA_b and PA_b for the whole of 2019 Africa

Dataset	Index	Bareland	Built-up	Cropland	Forest	Grassland	Shrubland	Water	Water permanent	Water seasonal	Wetland
FROM GLC	PA_b	91%	15%	71%	93%	66%	53%	87%			49%
CCIPrototype		92%	58%	48%	28%	45%	39%	97%			29%
GHS BU S1			50%								
WSF			27%								
FNF					23%			92%			
GSW seasonality									99%	24%	
FROM GLC	UA_b	73%	17%	57%	47%	53%	89%	98%			10%
CCIPrototype		54%	45%	73%	80%	35%	24%	95%			12%
GHS BU S1			99%								
WSF			57%								
FNF					88%			93%			
GSW seasonality									98%	46%	

3.6.16 Africa 2015

Following existing land cover maps are used for inter-comparison of historical products for 2015:

- FROM GLC 2015
- GHS 2014
- WSF 2015
- FNF 2015
- GSW seasonality 2015

3.6.16.1 Overall benchmark accuracy

There is one existing multiple-class land cover map for the year 2015 - FROM-GLC - with which historical product for the African region was compared. Table 98 is showing the consistency between the historical map in Africa and the existing land cover map.

Table 98. Overall benchmark accuracy for the whole of Africa in 2015

Existing dataset	OA_b
FROM GLC	57%

Africa results of OA_b will be shown in form of maps for OA_b with existing land cover available in the region. OA_b concerning FROM-GLC is shown in Figure 75.

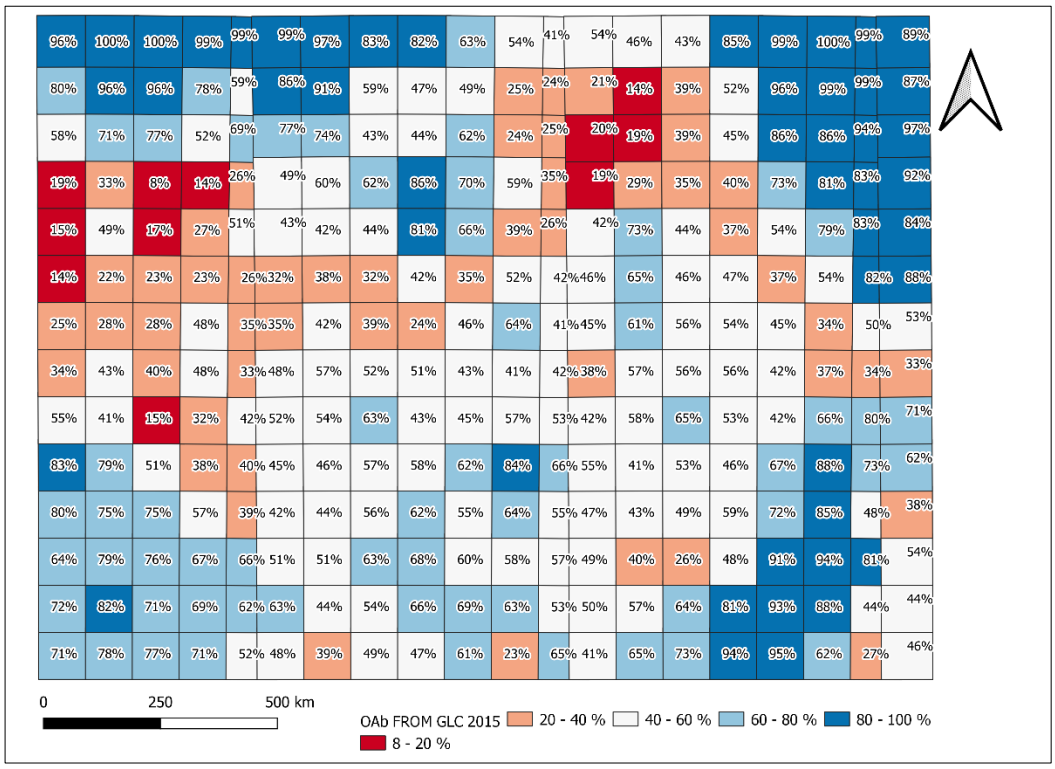

Figure 75. OA_b for each tile of the 2015 historical map in Africa based on FROM-GLC

Compared to the first production, OA_b increased by 11% for intercomparison with FROM-GLC. OA_b with FROM-GLC has higher values in the northern part of the area of interest where a homogeneous Bareland or Water landscape is present (Figure 75).

3.6.16.2 Per class benchmark accuracy

Regarding the class accuracy (Table 99) Water classification is "Excellent", while for the other classes the agreement is low, or there is just one dataset with a class used for inter-comparison, thus the conclusions cannot be made. However, the agreement regarding Bareland and Cropland of FROM-GLC increased compared to the first production.

Table 99. UA_b and PA_b for the whole of 2015 Africa

Dataset	Index	Bareland	Built-up	Cropland	Forest	Grassland	Shrubland	Water	Water permanent	Water seasonal	Wetland
FROM GLC	PA_b	90%	28%	61%	75%	54%	45%	83%			28%
GHS			74%					100%			
WSF			40%								
FNF					22%			78%			
GSW seasonality									96%	40%	
FROM GLC	UA_b	79%	53%	50%	55%	21%	84%	99%			11%
GHS			36%					95%			

WSF			70%								
FNF					86%			92%			
GSW seasonality									99%	27%	

3.6.17 Africa 2010

Following existing land cover maps are used for inter-comparison of historical products for 2010:

- FROM GLC 2010
- GUF 2011
- FNF 2010
- GSW seasonality 2010

3.6.17.1 Overall benchmark accuracy

There is one existing multiple-class land cover map for the year 2010 with which historical product for Africa region was compared - FROM-GLC. Table 100 is showing the consistency between the historical map in Africa and the existing land cover map.

Table 100. Overall benchmark accuracy for the whole of Africa in 2010

Existing dataset	OA_b
FROM GLC	48%

Africa results of OA_b will be shown in form of maps for OA_b with existing land cover available in the region. OA_b concerning FROM-GLC is shown in Figure 76.

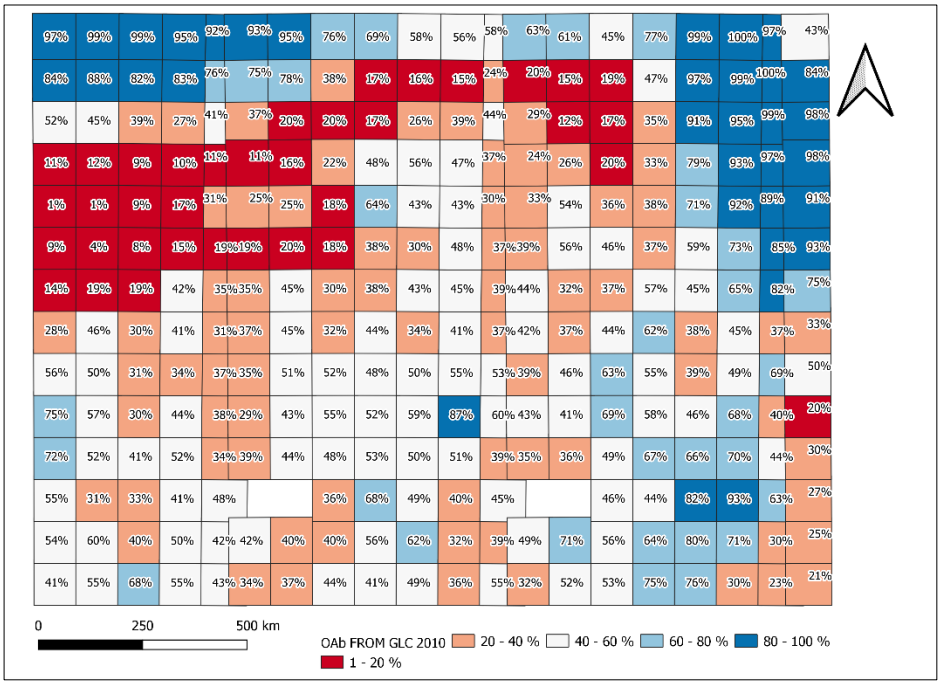

Figure 76. OA_b for each tile of the 2010 historical map in Africa based on FROM GLC

For the year 2010 OA_b was 48% for FROM-GLC (Table 100). Compared to the first production, this is a decrease of 5% for inter-comparison with FROM-GLC. OA_b with FROM-GLC has some very low values in the North-West part where Cropland and Grassland of CCI are mostly confused with Bareland of FROM-GLC. This is probably due to the overestimation of Bareland in the FROM-GLC because base map imagery shows some crop fields and sparse vegetation.

3.6.17.2 Per class benchmark accuracy

Regarding the class accuracy (Table 101), Water classification is "Excellent", while for the other classes the agreement is low, or there is just one dataset with a class used for inter-comparison, thus the conclusions cannot be made. However, the agreement regarding Cropland of FROM-GLC increased compared to the first production, while the agreement with Bareland decreased.

Table 101. UA_b and PA_b for the whole of 2010 Africa

Dataset	Index	Bareland	Built-up	Cropland	Forest	Grassland	Shrubland	Water	Water permanent	Water seasonal	Wetland
FROM GLC	PA_b	39%	13%	59%	47%	41%	55%	72%			20%
GL30		78%	21%	67%	49%	40%	37%	85%			25%
GUF			36%								
FNF					26%			94%			
GSW seasonality									98%	28%	
FROM GLC	UA_b	97%	39%	38%	69%	14%	55%	97%			2%
GL30		55%	73%	62%	57%	63%	17%	88%			24%
GUF			72%								
FNF					80%			92%			
GSW seasonality									99%	30%	

3.6.18 Africa 2005

Following existing land cover maps are used for inter-comparison of historical products for 2005:

- FNF 2007
- GSW seasonality 2005

3.6.18.1 Overall benchmark accuracy

For the year 2005 other multiple-class land covers do not exist for Africa, therefore OA_b cannot be reported.

3.6.18.2 Per class benchmark accuracy

Regarding the class accuracy (Table 102) it is not possible to make strong conclusions given that for each class there is only one existing LC containing such a class, so the agreement refers to a specific map. According to FNF, the agreement with Water is "Well", and according to GSW seasonality, Permanent water is "Excellent".

Table 102. UA_b and PA_b for the whole of 2005 Africa

Dataset	Index	Forest	Water	Water permanent	Water seasonal
FNF	PA_b	24%	80%		
GSW seasonality				97%	32%
FNF	UA_b	80%	93%		
GSW seasonality				99%	22%

3.6.19 Africa 2000

Following existing land cover maps are used for inter-comparison of historical products for 2000:

- GHS 2000
- GSW seasonality 2000
- TreeCover 2000

3.6.19.1 Overall benchmark accuracy

For the year 2000 other multiple-class land covers do not exist for Africa, therefore OA_b cannot be reported.

3.6.19.2 Per class benchmark accuracy

Regarding the class accuracy (Table 103), it is not possible to make strong conclusions given that for each class there is only one existing LC containing such a class, so the agreement refers to a specific map. According to Tree cover, the agreement with the Forest is “Relatively good”, according to GSW seasonality, Permanent water is "Excellent", and according to GHS Built-up is “Relatively good”, and Water is “Excellent”.

Table 103. UA_b and PA_b for the whole of 2000 Africa

Dataset	Index	Bareland	Built-up	Cropland	Forest	Grassland	Shrubland	Water	Water permanent	Water seasonal	Wetland
GHS			72%					100%			
GSW seasonality									97%	28%	
TreeCover					71%						
GHS			58%					97%			
GSW seasonality									99%	36%	
TreeCover					54%						

3.6.20 Africa 1995

Following existing land cover maps are used for inter-comparison of historical products for 1995:

- GSW seasonality 1995

3.6.20.1 Overall benchmark accuracy

For the year 1995 other multiple-class land covers do not exist for Africa, therefore OA_b cannot be reported.

3.6.20.2 Per class benchmark accuracy

For the class agreement (Table 104), GSW seasonality is showing “Excellent” agreement for the Permanent water class. Agreement of other classes cannot be estimated in absence of existing LC containing other classes.

Table 104. UA_b and PA_b for the whole of 1995 Africa

Dataset	Index	Water permanent	Water seasonal
GSW seasonality	PA_b	97%	6%
GSW seasonality	UA_b	97%	17%

3.6.21 Africa 1990

Following existing land cover maps are used for inter-comparison of historical products for 1990:

- GHS 1990
- GSW seasonality 1990

3.6.21.1 Overall benchmark accuracy

For the year 1990 other multiple-class land covers do not exist for Africa, therefore OA_b cannot be reported.

3.6.21.2 Per class benchmark accuracy

Regarding the class accuracy (Table 105), it is not possible to make strong conclusions given that for each class there is only one existing LC containing such a class, so the agreement refers to a specific map. According to GSW seasonality, and according to GHS Water is “Excellent”.

Table 105. UA_b and PA_b for the whole of 1990 Africa

Dataset	Index	Built-up	Water	Water permanent	Water seasonal
GHS	PA_b	70%	100%		
GSW seasonality				99%	0%
GHS	UA_b	44%	97%		
GSW seasonality				100%	0%

4 ANNEX 1 HRLC legend hierarchical approach

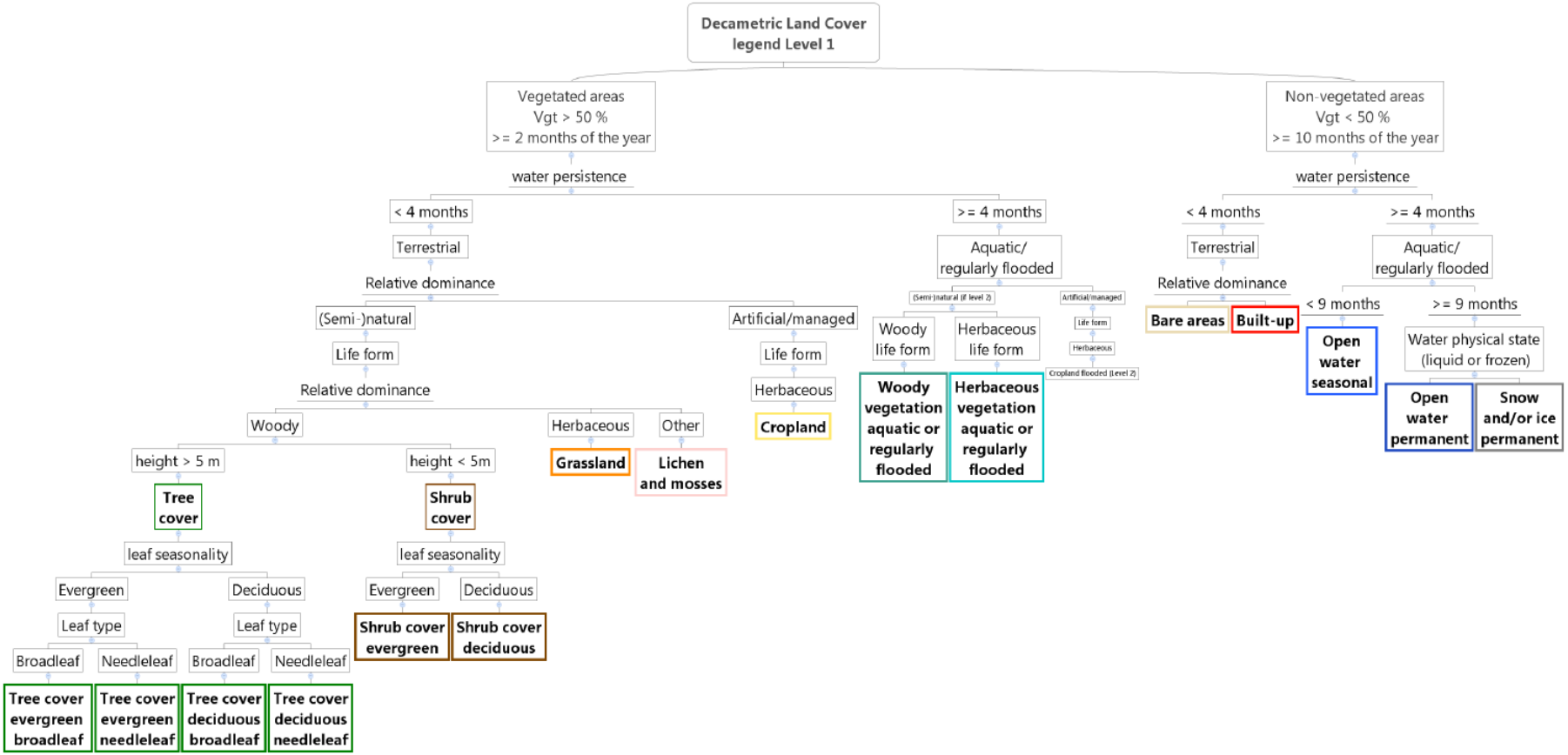

Figure 77. Hierarchical approach to determine the land cover class. The "Herbaceous vegetation aquatic or regularly flooded" corresponds to a vegetation cover more than 2 months per year, and a water persistence of more than 4 months. Finally, an herbaceous life form is present as apposed to a woody life form.