

Integration of the Wall-to-wall Mapping and Statistical Sampling for Landsat-based Land Cover and Land Use Monitoring Using GLAD ARD and Tools

Peter Potapov, UMD GLAD



<https://glad.umd.edu/>



Global Land Analysis and Discovery Lab (GLAD), University of Maryland



Laos (Vientiane) - 2018



Vietnam (Hanoi) - 2017



Madagascar (UMD)
2018



Nepal (Kathmandu) - 2017



Peru
Colombia
Ecuador

Rep. of the Congo
Dem. Rep. of the Congo
Madagascar

Laos
Nepal
Cambodia

Mexico
Guatemala
Indonesia

Vietnam
Cameroon
Bangladesh

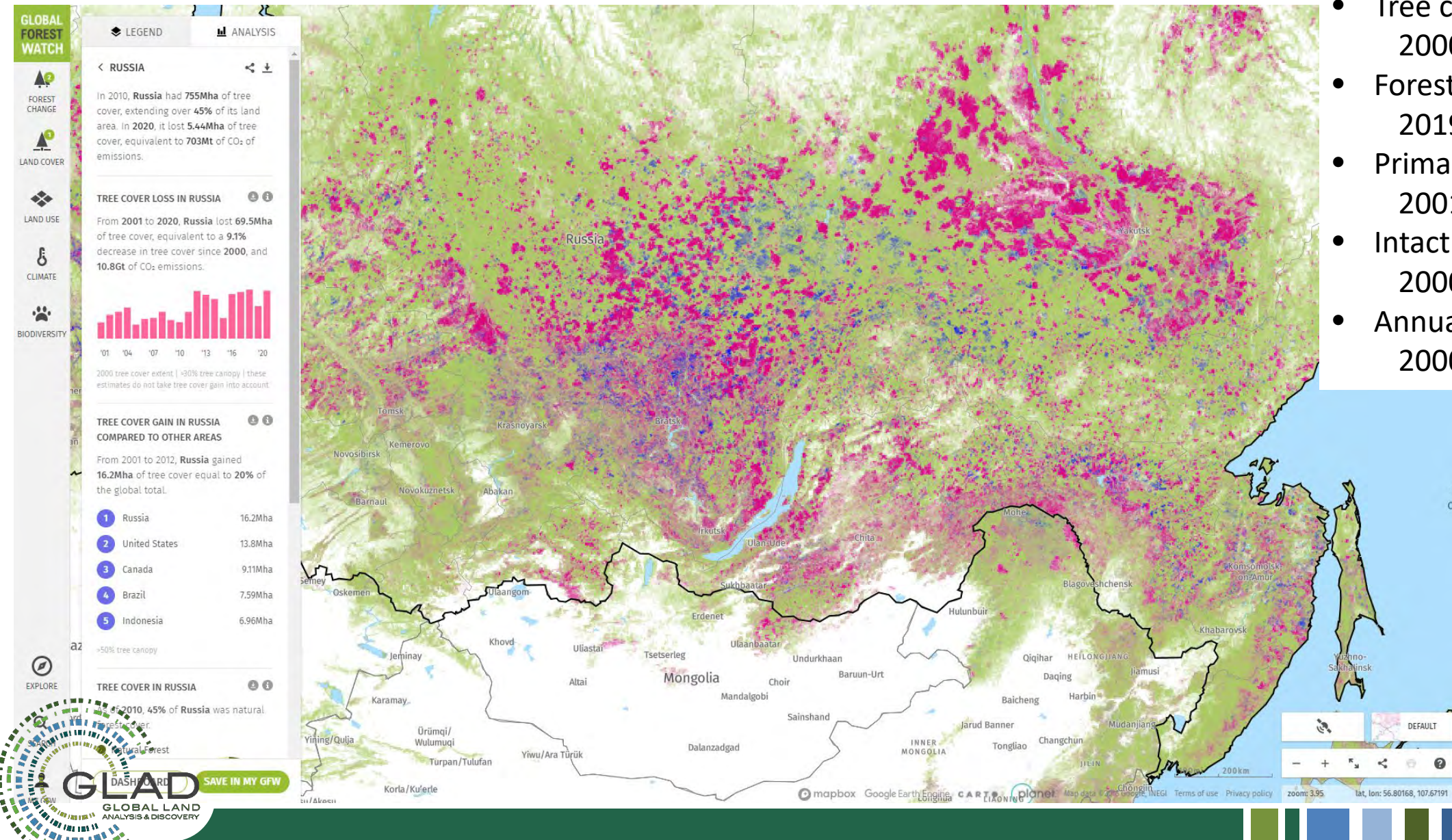
<https://glad.umd.edu/>



Global Forest Monitoring (with GFW/WRI)

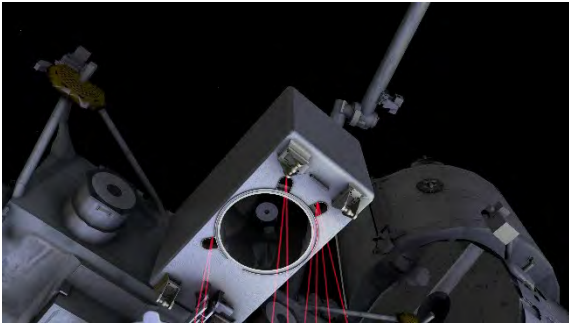
<https://www.globalforestwatch.org/>

- Tree canopy cover 2000, 2010
- Forest height 2019
- Primary tropical forests 2001
- Intact Forest Landscapes 2000, 2013, 2016
- Annual forest cover loss 2000-2020



WORLD
RESOURCES
INSTITUTE

GED I and Landsat Integration for Forest Height Mapping

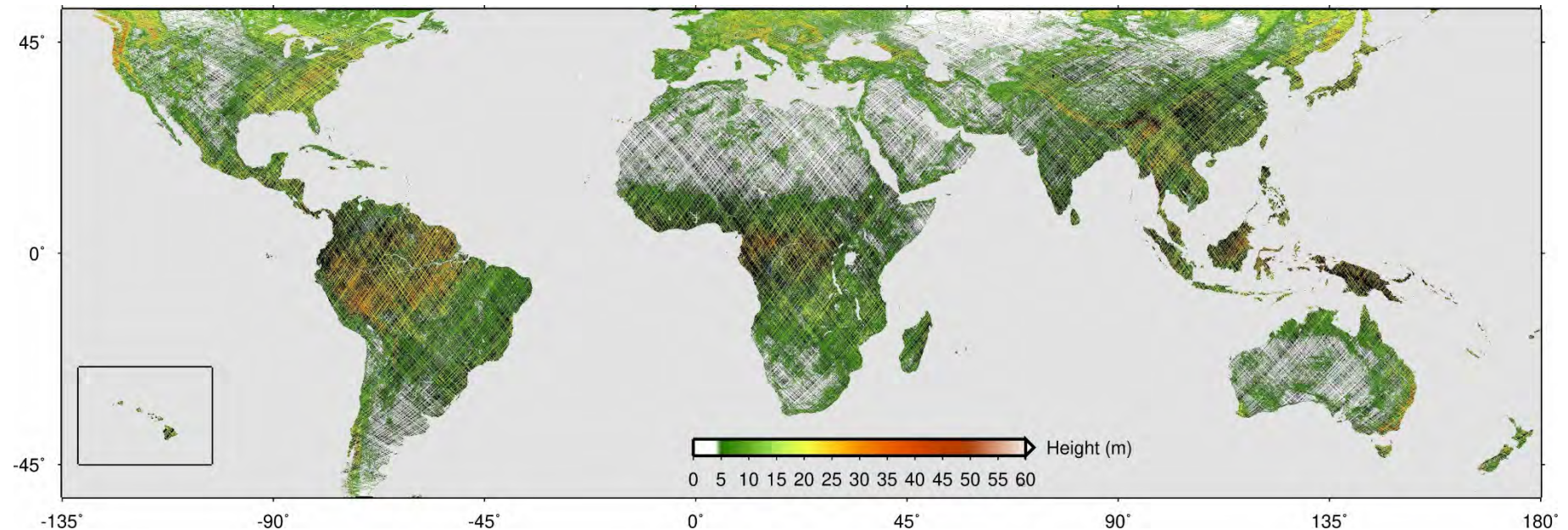


Global Ecosystem Dynamics Investigation (GEDI)

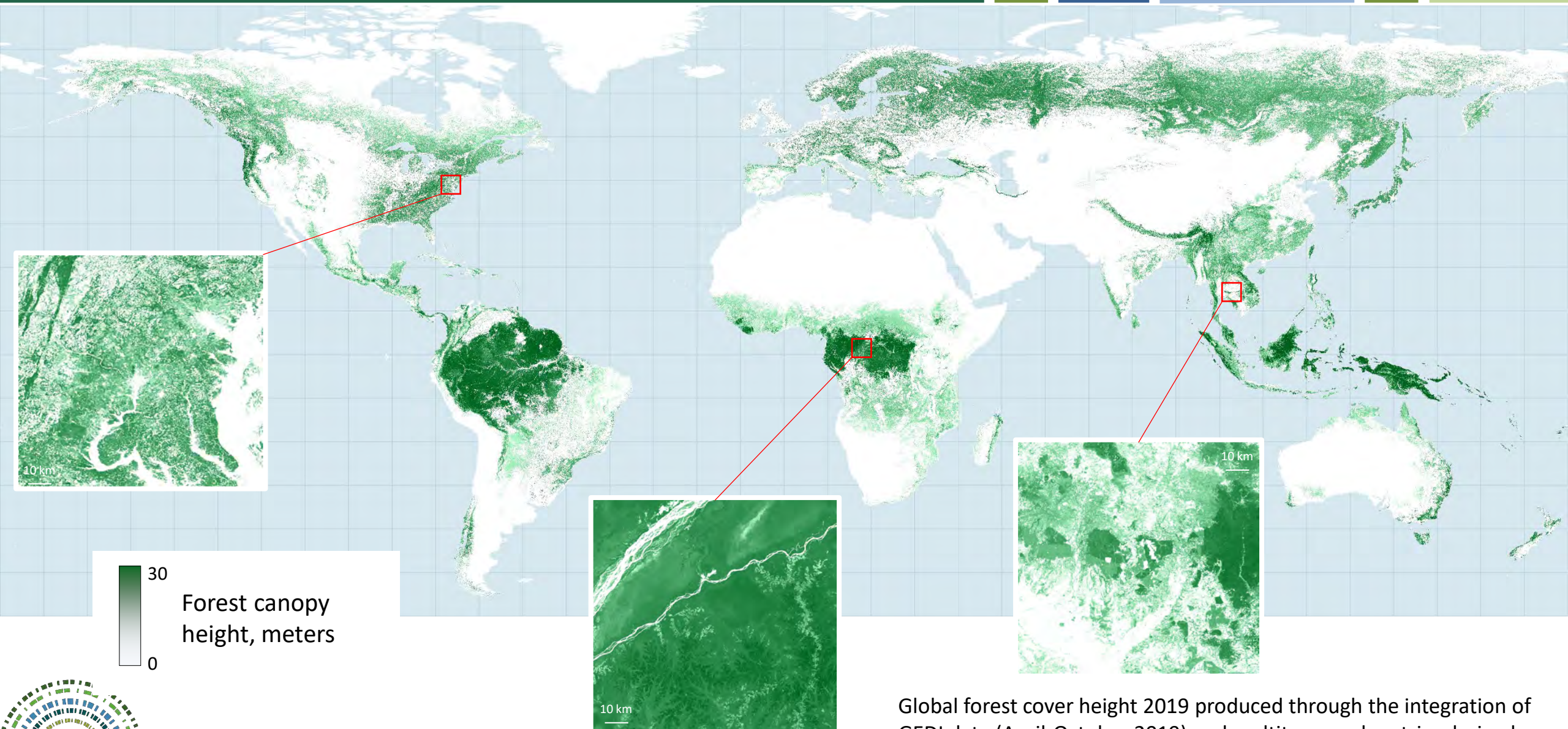
High resolution laser ranging of Earth's forests and topography from the ISS

Product #	Data product	Format
L2A V001	Elevation and Height Metrics Data	Global Footprint Level (25 m diameter)
L2B V001	Canopy Cover and Vertical Profile (RH) Metrics Data	

Canopy height footprint level data (<https://gedi.umd.edu>)



GEDI and Landsat Integration for Forest Height Mapping

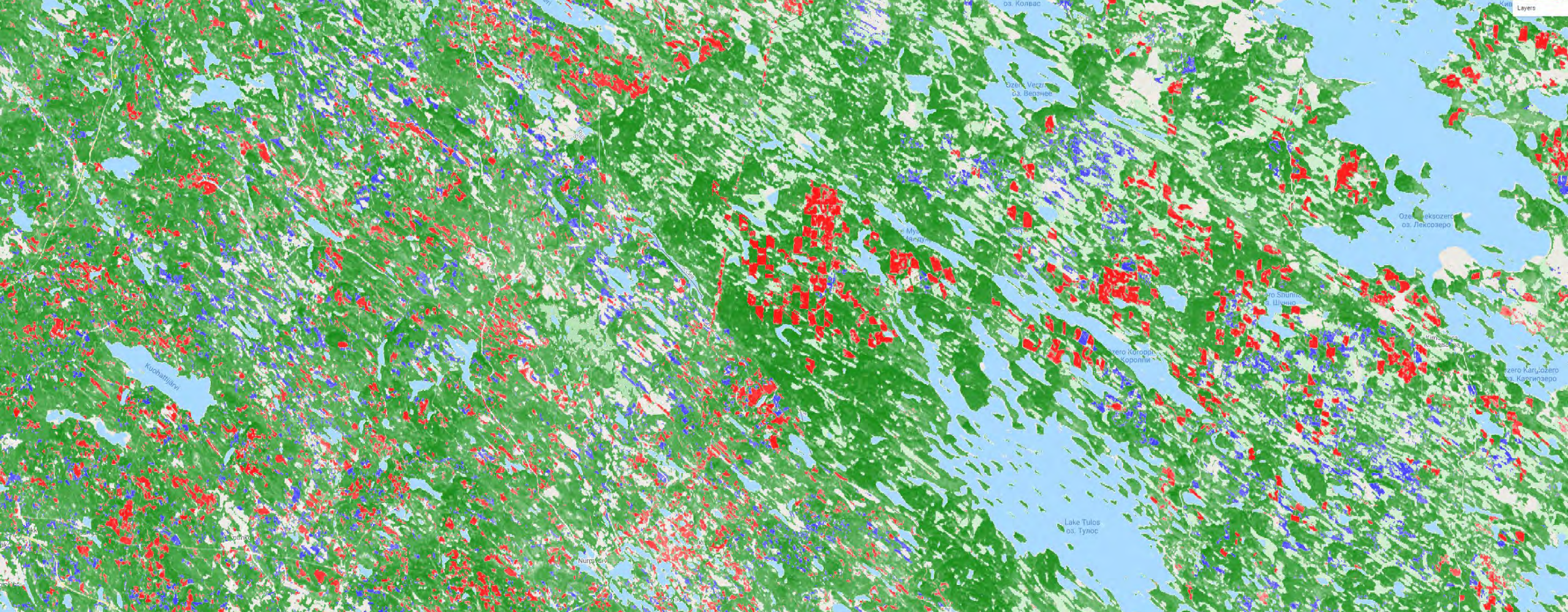


Global forest cover height 2019 produced through the integration of GEDI data (April-October 2019) and multitemporal metrics derived from Landsat GLAD ARD. (Potapov *et al.*, *RSE*, 2020)

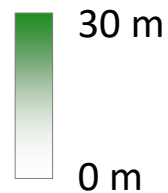
GEDI and Landsat Integration for Forest Height Mapping

Finland

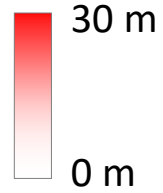
Russia



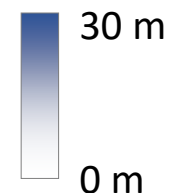
Forest
height
2020



Forest
height loss
2000-2020



Forest
height gain
2000-2020

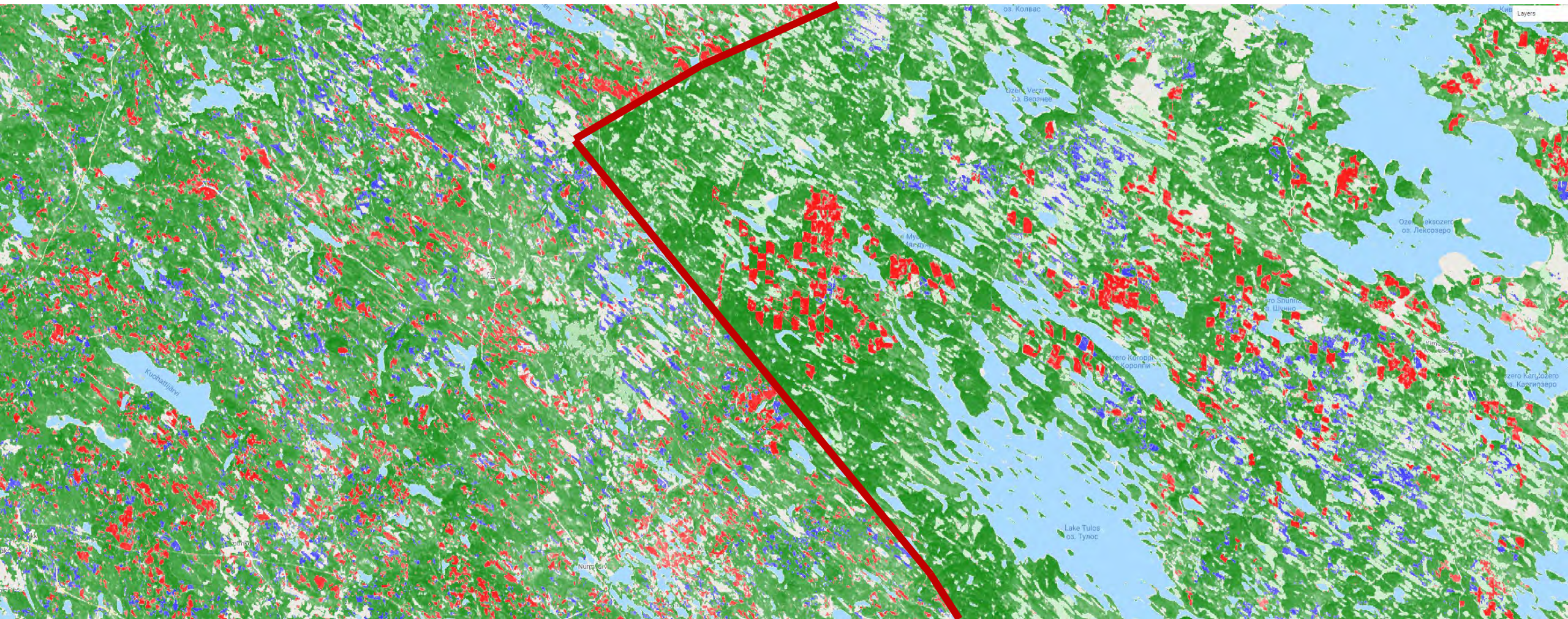


2 km

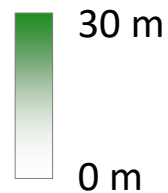
GEDI and Landsat Integration for Forest Height Mapping

Finland

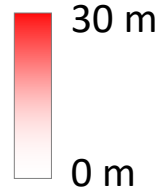
Russia



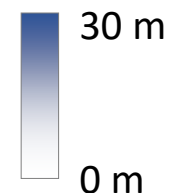
Forest
height
2020



Forest
height loss
2000-2020

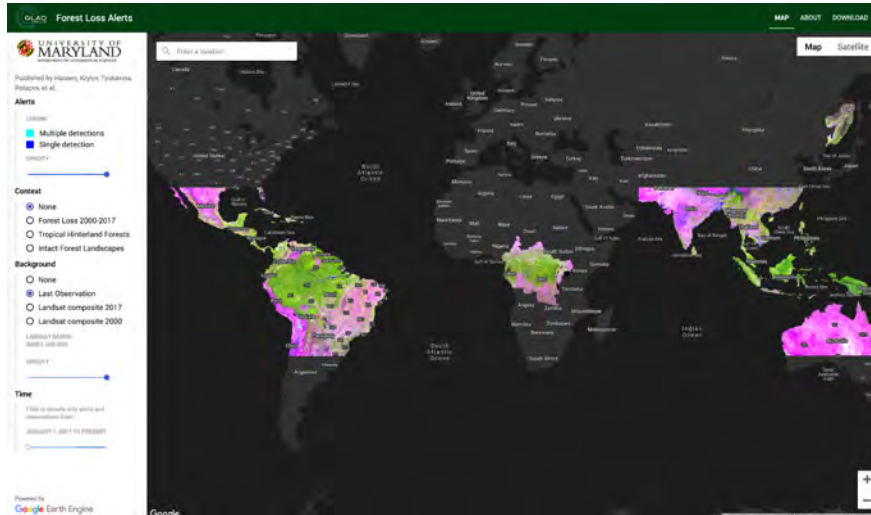


Forest
height gain
2000-2020



2 km

Near-real-time Forest Monitoring (GLAD Forest Loss Alerts)



<https://www.globalforestwatch.org/>
<https://glad.umd.edu/dataset/glad-forest-alerts>

GLAD forest loss alerts
2005-present
Tropical countries
Daily/weekly updates
Landsat and Sentinel-2 data

nature climate change

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nature > nature climate change > analyses > article

Analysis | Published: 04 January 2021

The impact of near-real-time deforestation alerts across the tropics

Fanny Moffette , Jennifer Alix-Garcia, Katherine Shea & Amy H. Pickens

Nature Climate Change **11**, 172–178 (2021) | [Cite this article](#)

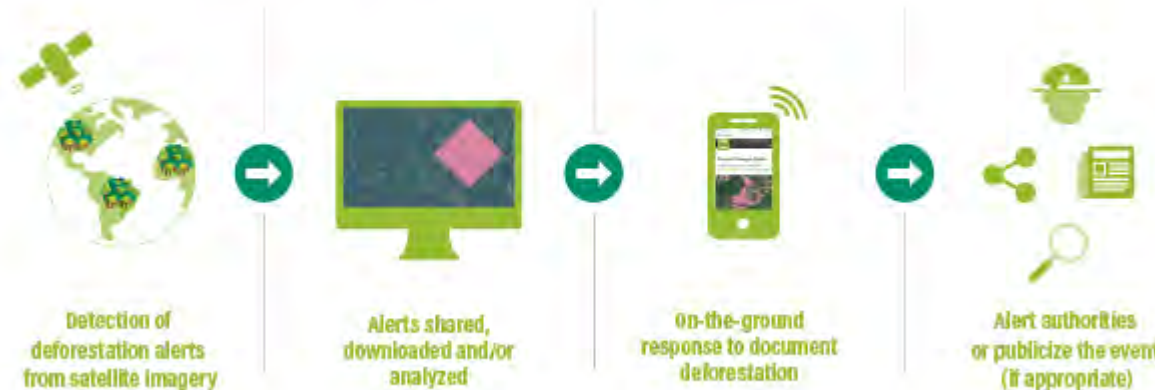
1889 Accesses | **1** Citations | **498** Altmetric | [Metrics](#)

Subscriptions to alerts in 22 tropical countries decrease the probability of deforestation in Africa by 18%.

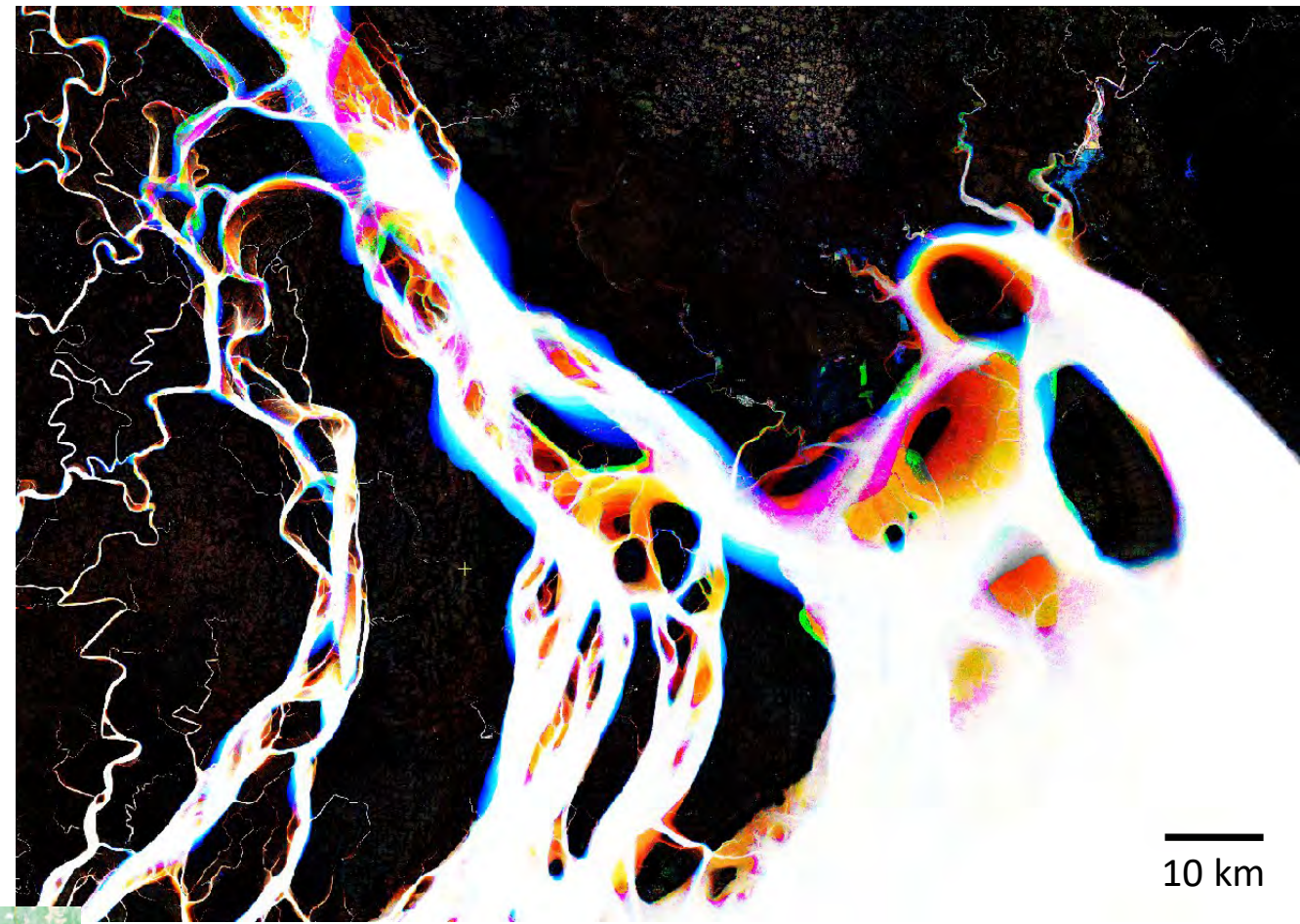
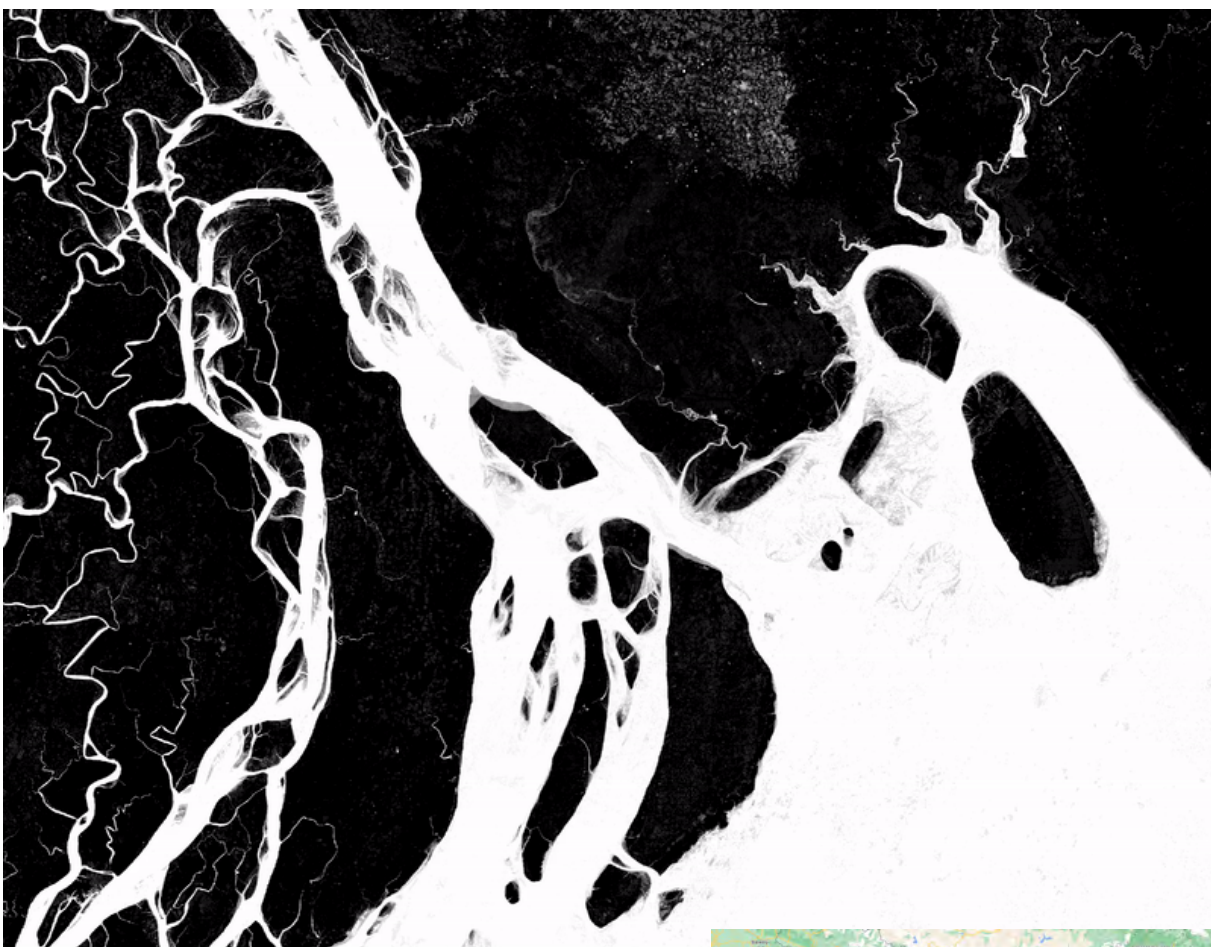
The alert system's value is between US\$149 million and US\$696 million in social cost of carbon for avoided deforestation in Africa.



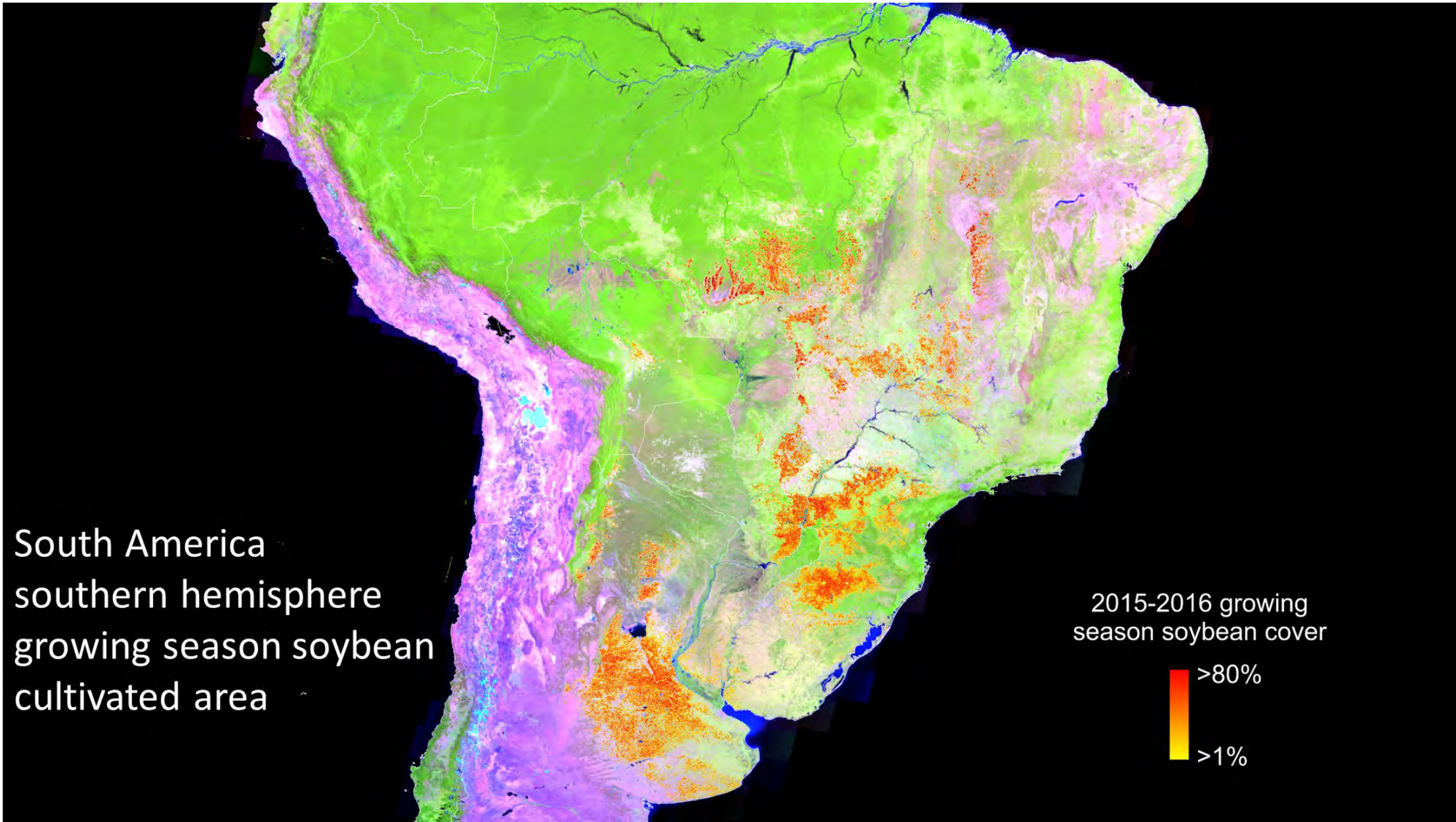
Workflow for Following-up on Deforestation Alerts



Global Surface Water Monitoring



Pre-harvest Soybean Area in South America



Pre-harvest Soybean Area in South America

2019/20



2009/10

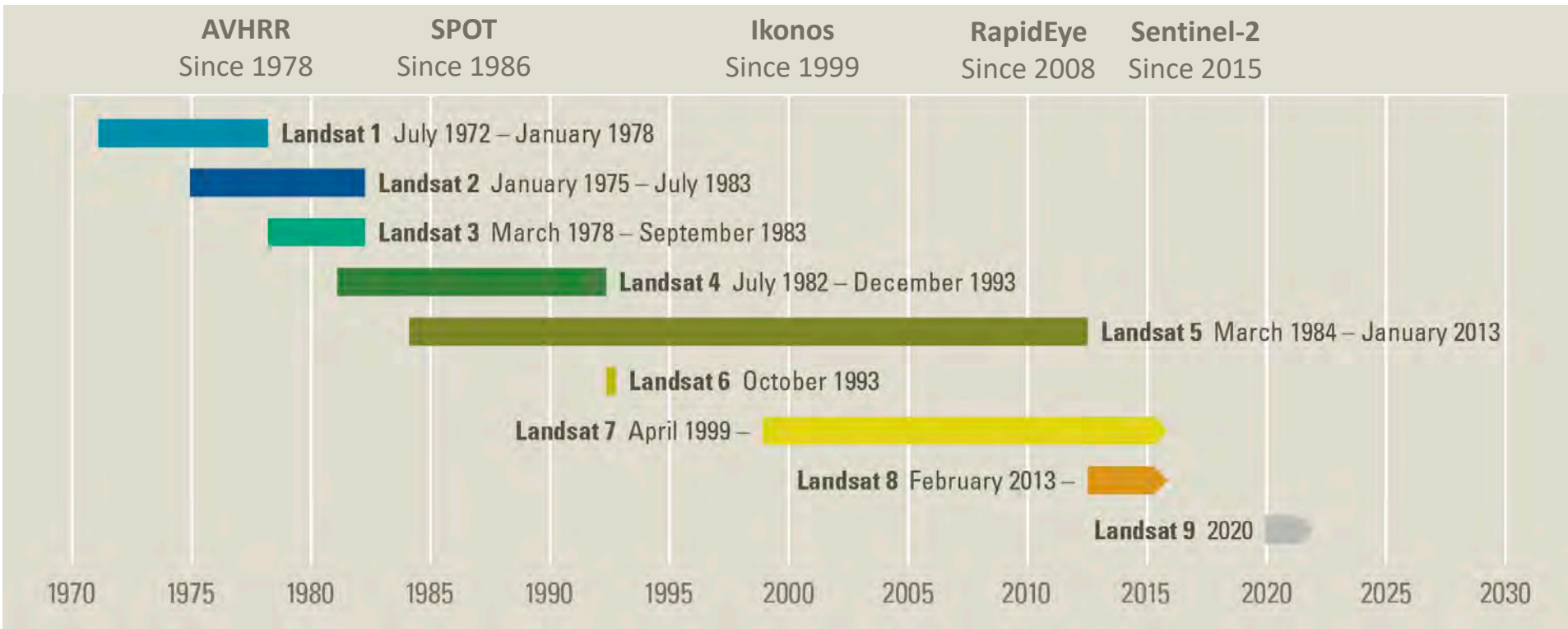


2000/01

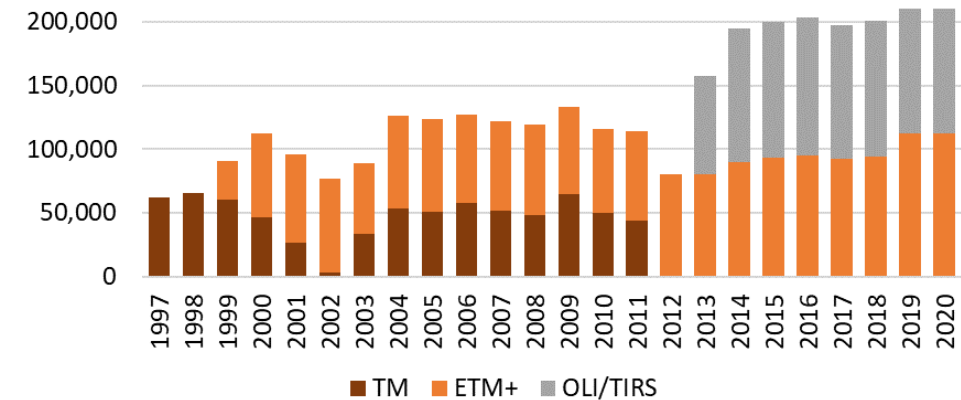


Song, X.-P., Hansen, M.C., Potapov, P.V., Adusei, B., Pickering, J., Adami, M., Lima, A., Zalles, V., Stehman, S.V., Di Bella, C.M., Cecilia, C.M., Copati, E.J., Fernandes, L.B., Hernandez-Serna, A., Jantz, S.M., Pickens, A.H., Turubanova, S., & Tyukavina, A. (In review). Massive soybean expansion in South America since 2000 and implications for conservation. *Nature Sustainability*

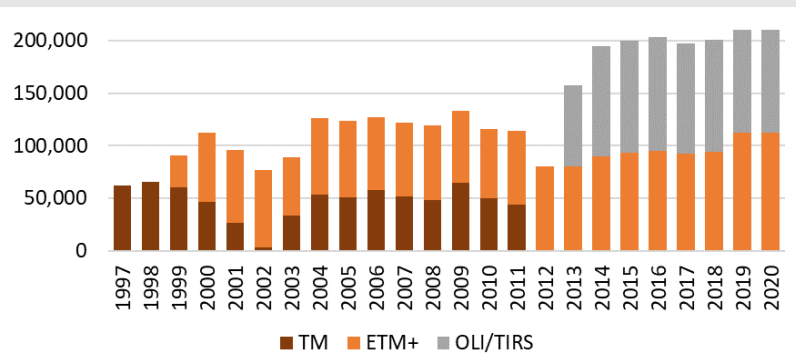
NASA/USGS Landsat program



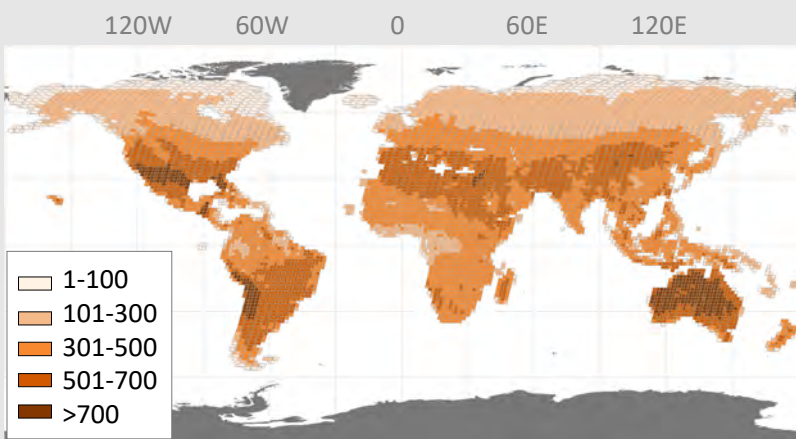
Total scenes since 1982: >6 million
 Total 30x30m data pixels: >200 trillion



Landsat C1 T1 Data (TOA)



Archive @GLAD ~ 4 million scenes

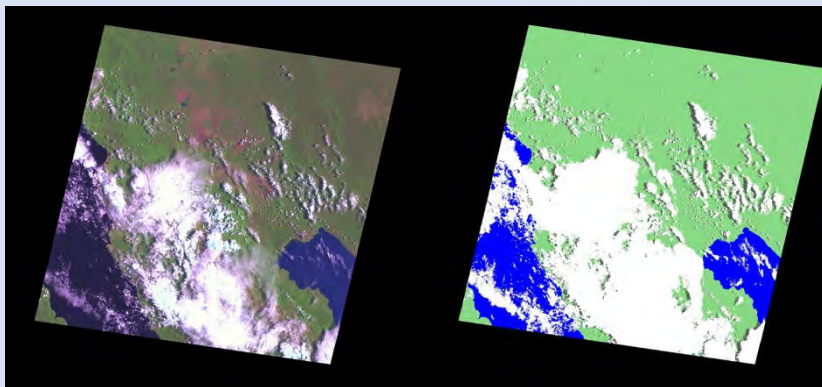


Number of processed images
1997–2019 by WRS path/row



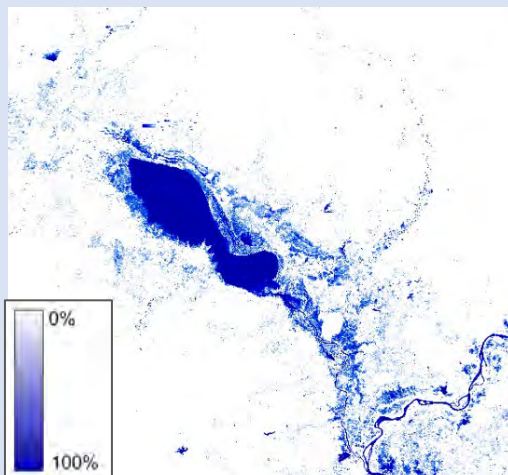
Per-pixel QA

Integration of cfmask and GLAD QA models



QA layer for every Landsat scene

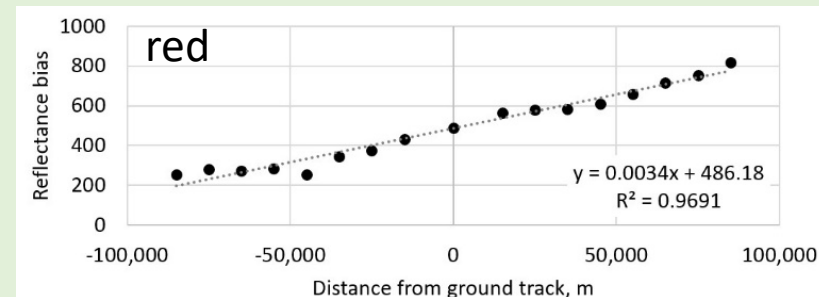
- Clear-sky land, water, snow/ice
- Clouds, cloud shadows, haze
- Cloud/shadow proximity
- Topographic shadows



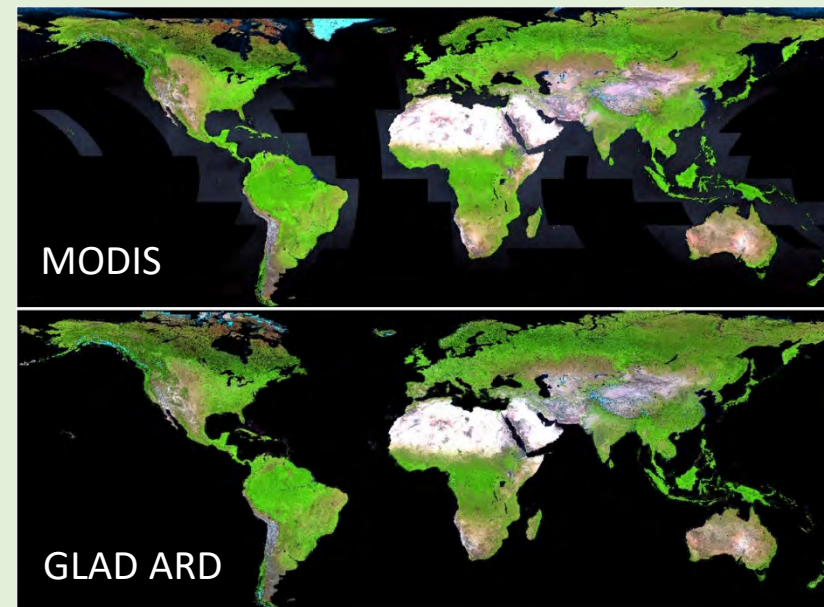
QA-based
products:
Water
permanence
(% time of the
year when the
area was
submerged)

Reflectance Normalization

MODIS growing season surface reflectance used as a normalization target. Bias value calculated for each spectral band within pseudo-invariant object mask.



$$\rho^{\text{NORM}} = \rho^{\text{TOA}} - (G \times d + B)$$



Temporal Integration

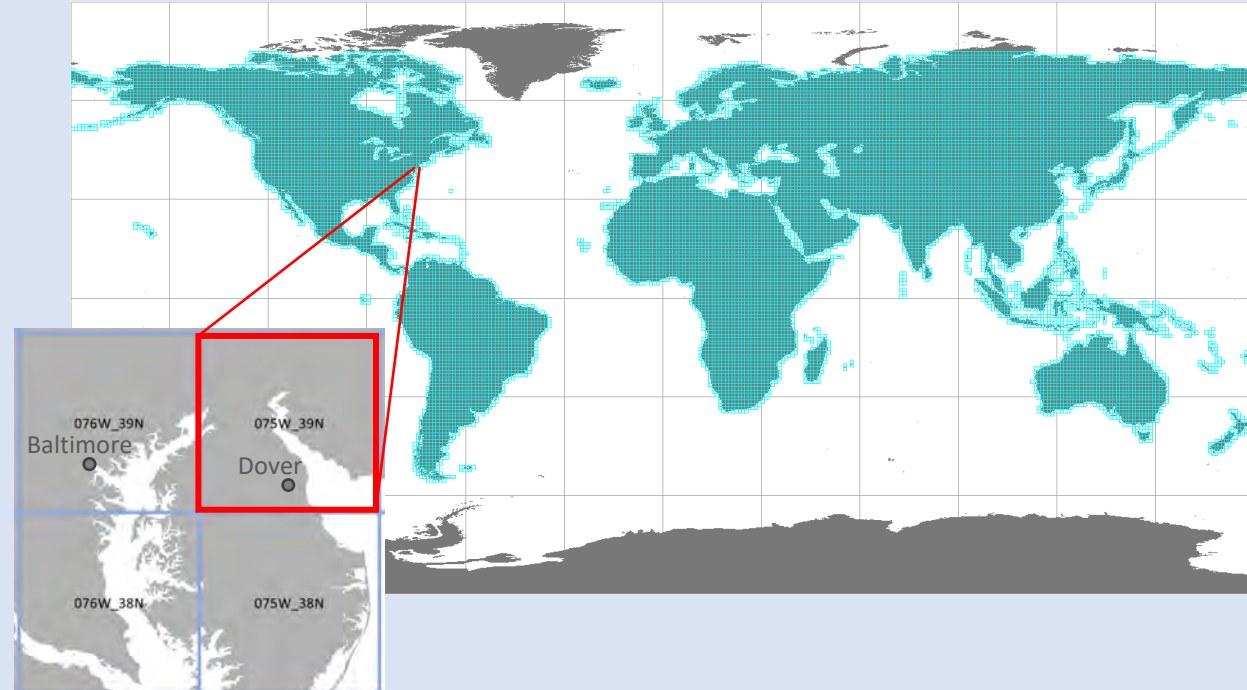
ID	DOY start	DOY end
1	1	16
2	17	32
3	33	48
4	49	64
5	65	80
6	81	96
7	97	112
8	113	128
9	129	144
10	145	160
11	161	176
12	177	192
13	193	208
14	209	224
15	225	240
16	241	256
17	257	272
18	273	288
19	289	304
20	305	320
21	321	336
22	337	352
23	353	366

16-day composites of
normalized surface reflectance
(8-band LZW-compressed GeoTIFF files)

Layer	Image data	Units, data format
1	Blue	Normalized surface reflectance scaled to the range from 1 to 40,000, UInt16
2	Green	
3	Red	
4	NIR	
5	SWIR1	
6	SWIR2	
7	Brightness temperature	K × 100, UInt16
8	QA	QA code, UInt16



Spatial Data Format



Projection

+proj=longlat +ellps=WGS84 +datum=WGS84 +no_defs

Pixel size

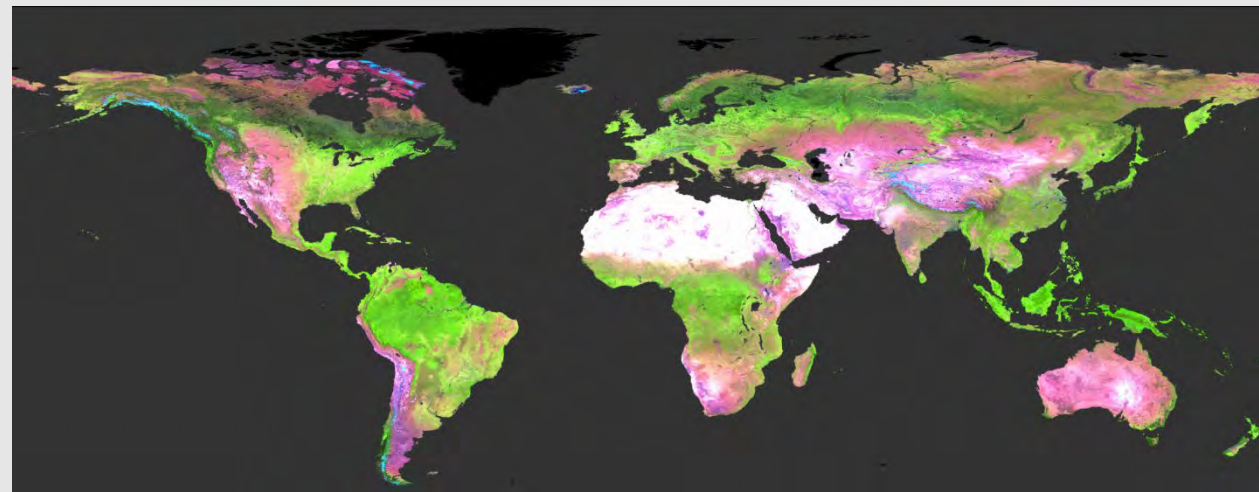
0.00025 x 0.00025 degree

Tile size

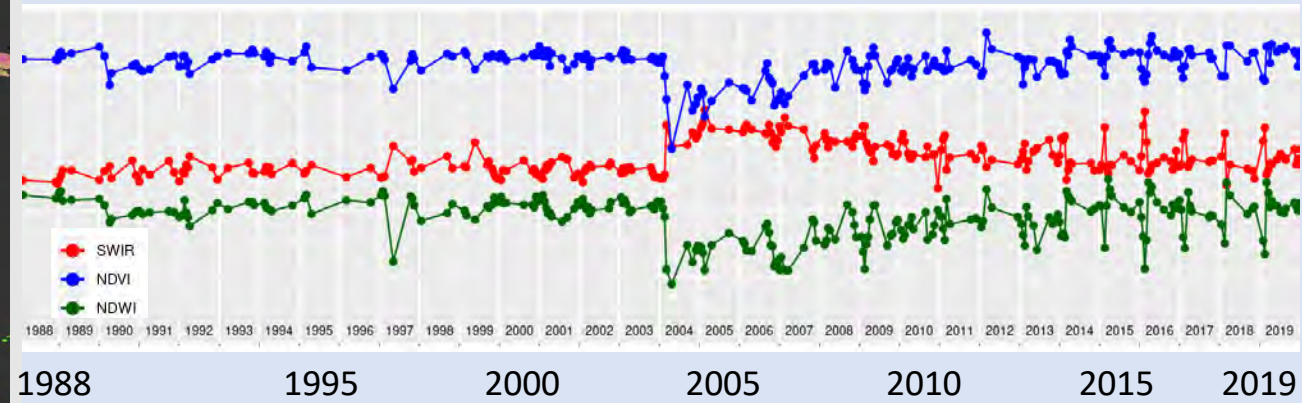
4004 x 4004 pixels (1.0005 by 1.0005 degrees)

The 16-day ARD data are available globally for the 1997-present.

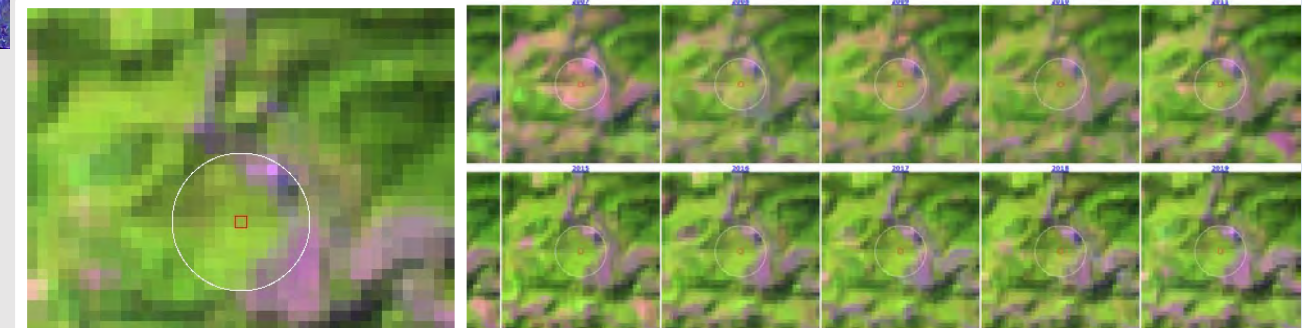
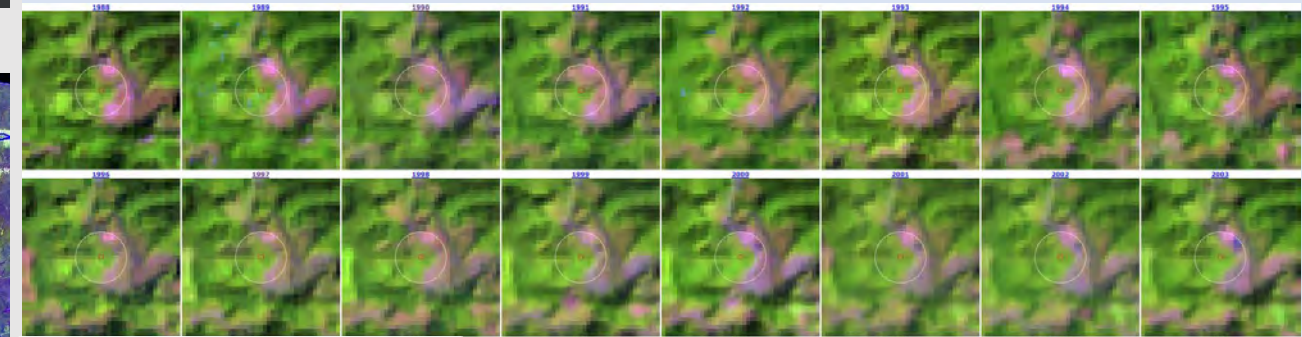
Spatial Consistency



Temporal Consistency

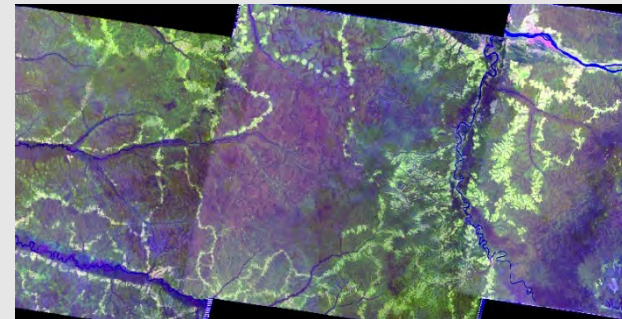


1988

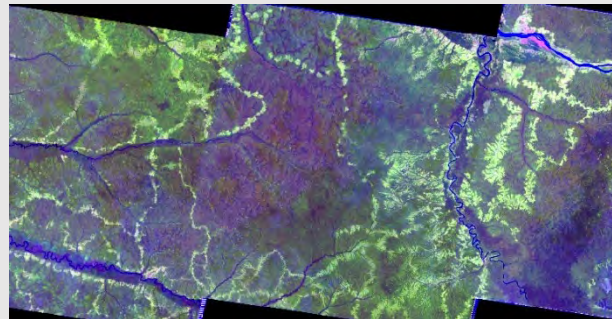


2019

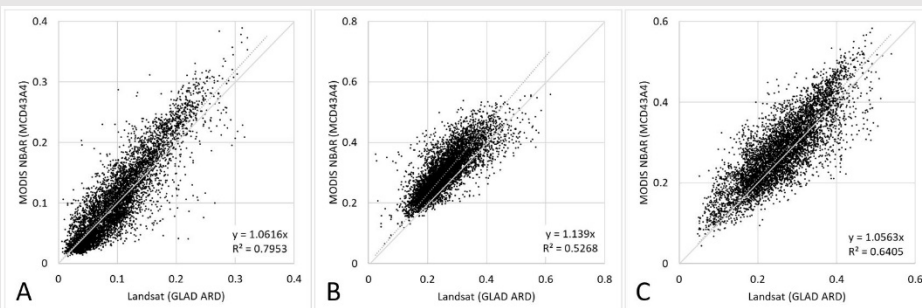
Without anisotropy correction



With anisotropy correction



Comparison of
MODIS NBAR
and GLAD ARD



red

NIR

SWIR (1.6 μm)

ARD API Access

The GLAD ARD API provides access to ~1.5PB of global data.
<https://glad.umd.edu/ard/home/>

CURL

```
>curl -u username:password -X GET https://glad.umd.edu/dataset/landsat_v1.1/26N/086E_26N/920.tif -o D:/Data/086E_26N/920.tif
```

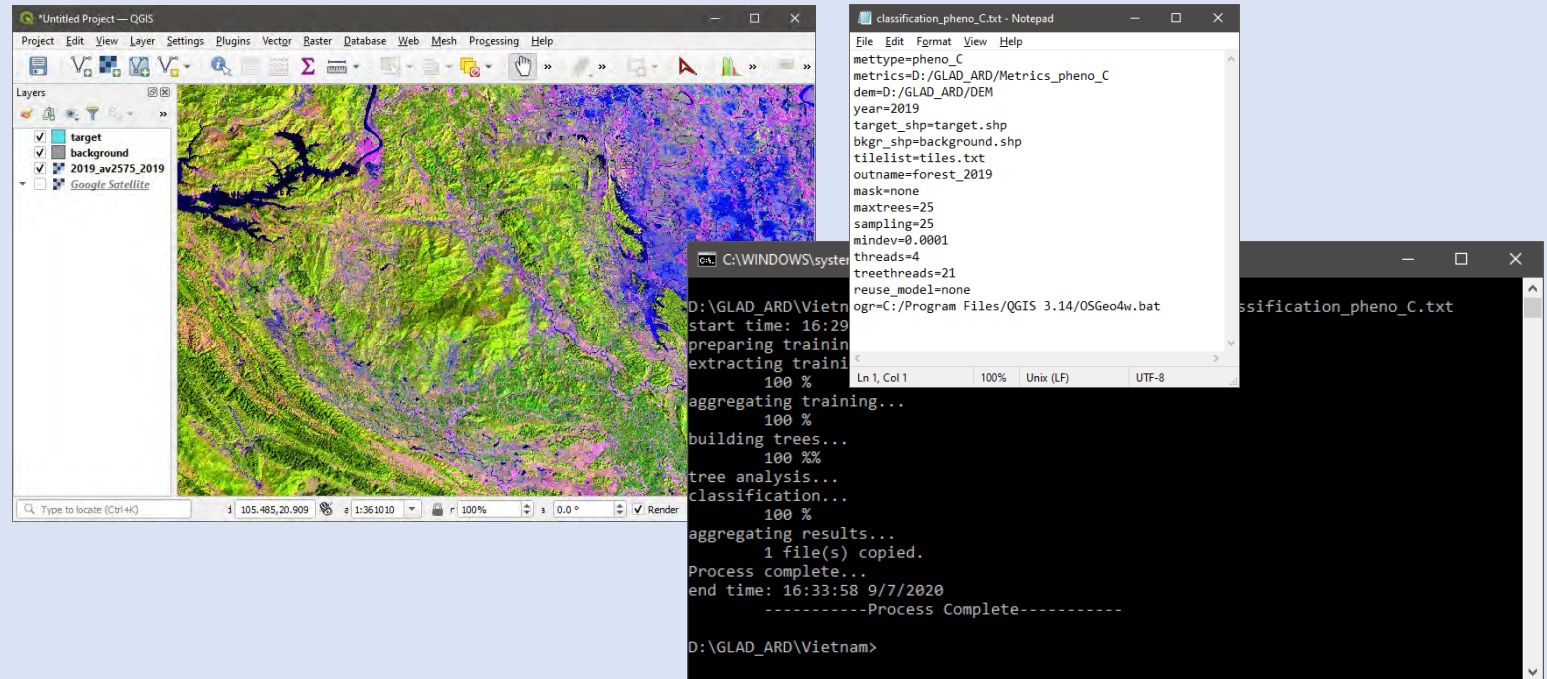
Batch download using PERL scripting

```
>perl C:/GLAD_1.1/download_V1.1.pl <uname> <passwd> <tile list> <start int> <end int> <folder>
```

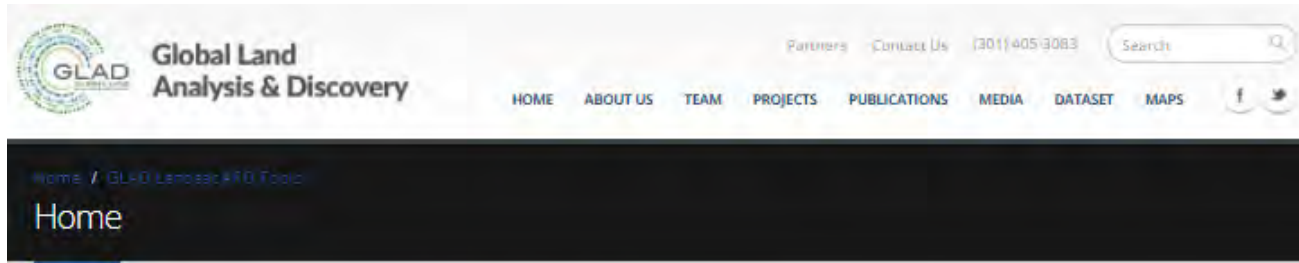
GLAD Tools V1.1

The GLAD Tools V1.1 provides end-to-end capability for land cover mapping, change detection, and sample analysis.

- Open-source software (R, MinGW, QGIS/OSGeo4W, PERL).
- Includes machine-learning tools for image analysis.
- Includes statistical tools for sample interpretation and analysis.

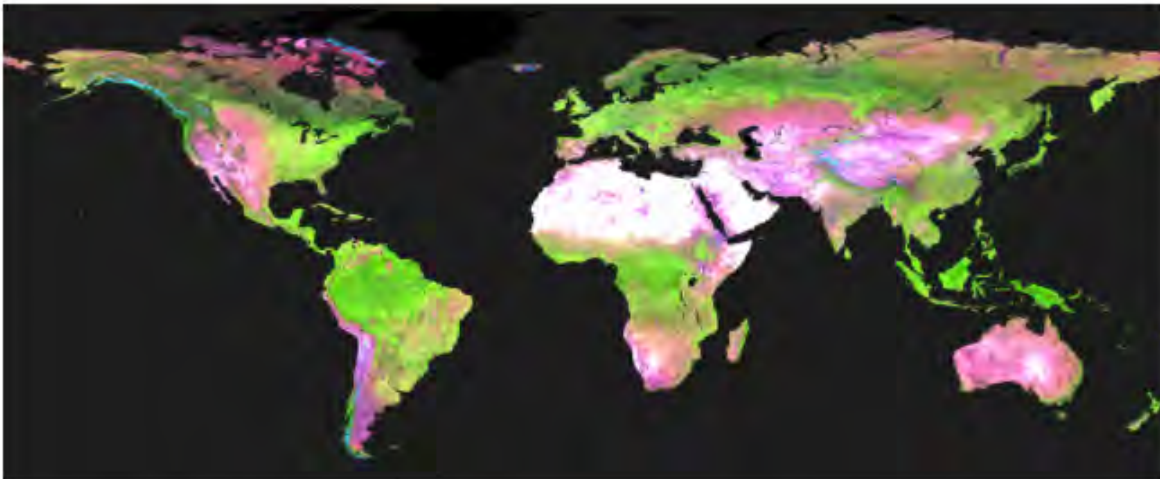


<https://glad.umd.edu/ard/home>



Home [Software Download](#) [User Registration](#) [User Manual](#) [License and Disclaimer](#)

1. GLAD Landsat ARD Tools



The Landsat Analysis Ready Data (ARD) developed by the Global Land Analysis and Discovery team (GLAD) provides spatially and temporally consistent inputs for land cover mapping and change detection. The ARD is available for the ice-free area of continents and large islands between 75N and 56S Latitude. The GLAD Landsat ARD data is available online, with no charges for access and no restrictions on subsequent redistribution or use, as long as the proper citation is provided as specified by the Creative Commons Attribution License (CC BY). See [License and Disclaimer](#) for additional information and citation. To facilitate the ARD application, the GLAD team providing a set of tools for data processing and supervised classification using machine learning. For all questions and comment contact Peter Potapov (potapov@umd.edu).

Potapov, P., Hansen, M.C., Kommareddy, I., Kommareddy, A., Turubanova, S., Pickens, A., Adusei, B., Tyukavina, A., and Ying, Q., 2020. Landsat analysis ready data for global land cover and land cover change mapping. *Remote Sens.* 2020, 12, 426; doi:10.3390/rs12030426 (Potapov_RS_2020.pdf)

GLAD ARD data, tools, and manuals are available at <https://glad.umd.edu/ard/home>

System requirements:

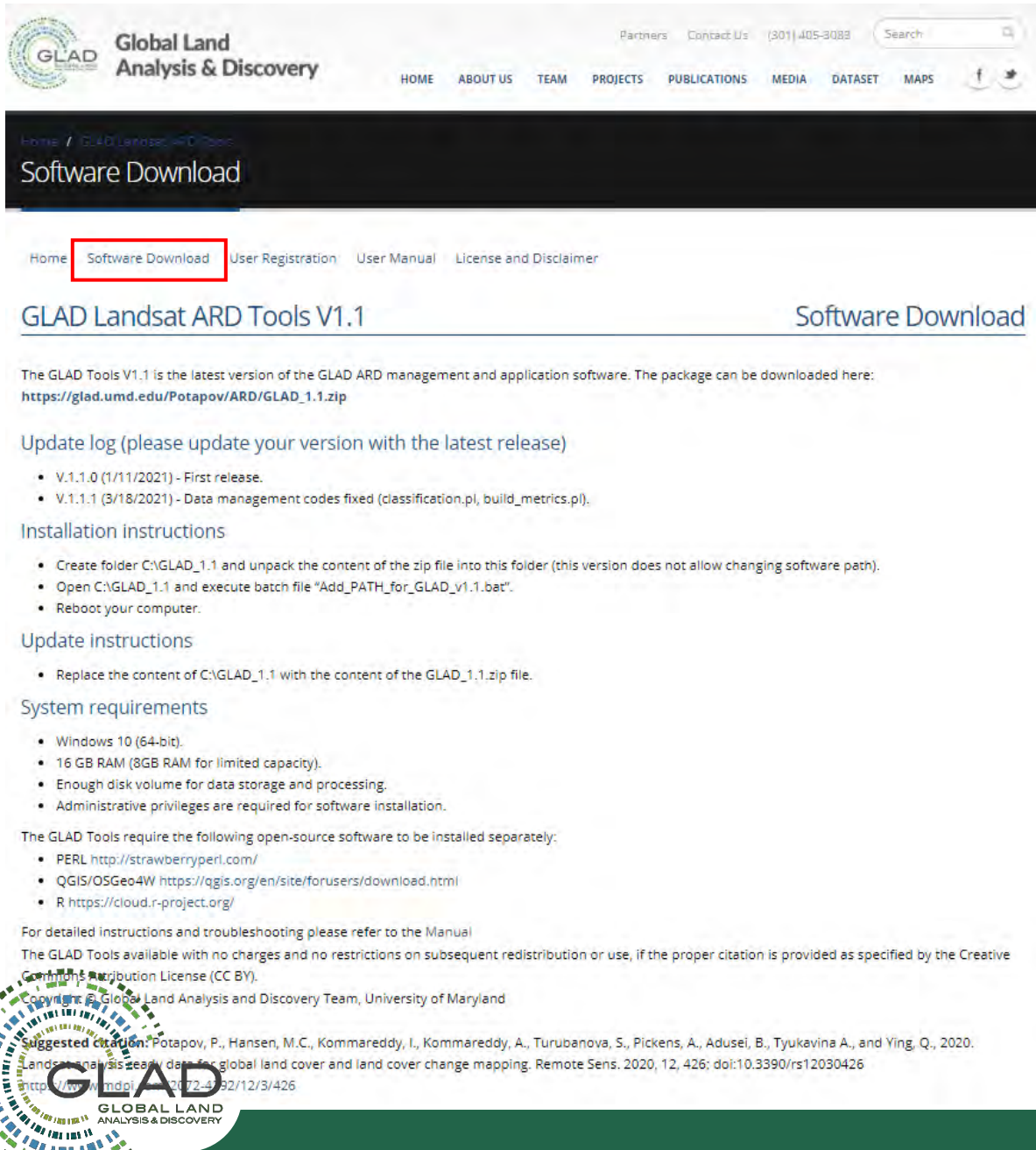
- Windows 10 (64 bit).
- 16 GB RAM (64GB or more for optimal performance).
- Enough disk space for data storage and processing.
- Administrative privileges are required for software installation.

Open source/free software required for GLAD Tools
(must be installed **before** GLAD Tools installation):

- PERL
<http://strawberryperl.com/>
- QGIS/OSGeo4W
<https://qgis.org/en/site/forusers/download.html>
- R
<https://cloud.r-project.org/>



<https://glad.umd.edu/ard/home>



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Software Download

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GLAD Landsat ARD Tools V1.1

The GLAD Tools V1.1 is the latest version of the GLAD ARD management and application software. The package can be downloaded here:
https://glad.umd.edu/Potapov/ARD/GLAD_1.1.zip

Update log (please update your version with the latest release)

- V.1.1.0 (1/11/2021) - First release.
- V.1.1.1 (3/18/2021) - Data management codes fixed (classification.pl, build_metrics.pl).

Installation instructions

- Create folder C:\GLAD_1.1 and unpack the content of the zip file into this folder (this version does not allow changing software path).
- Open C:\GLAD_1.1 and execute batch file "Add_PATH_for_GLAD_v1.1.bat".
- Reboot your computer.

Update instructions

- Replace the content of C:\GLAD_1.1 with the content of the GLAD_1.1.zip file.

System requirements

- Windows 10 (64-bit).
- 16 GB RAM (8GB RAM for limited capacity).
- Enough disk volume for data storage and processing.
- Administrative privileges are required for software installation.

The GLAD Tools require the following open-source software to be installed separately:

- PERL <http://strawberryperl.com/>
- QGIS/QGIS4W <https://qgis.org/en/site/forusers/download.html>
- R <https://cloud.r-project.org/>

For detailed instructions and troubleshooting please refer to the Manual

The GLAD Tools available with no charges and no restrictions on subsequent redistribution or use, if the proper citation is provided as specified by the Creative Commons Attribution License (CC BY).

Copyright © Global Land Analysis and Discovery Team, University of Maryland

Suggested citation: Potapov, P., Hansen, M.C., Kommareddy, I., Kommareddy, A., Turubanova, S., Pickens, A., Adusei, B., Tyukavina, A., and Ying, Q., 2020. Landsat analysis-ready data for global land cover and land cover change mapping. Remote Sens. 2020, 12, 426; doi:10.3390/rs12030426
<http://www.mdpi.com/2072-4292/12/3/426>

GLOBAL LAND ANALYSIS & DISCOVERY

GLAD ARD data, tools, and manuals are available at
<https://glad.umd.edu/ard/home>

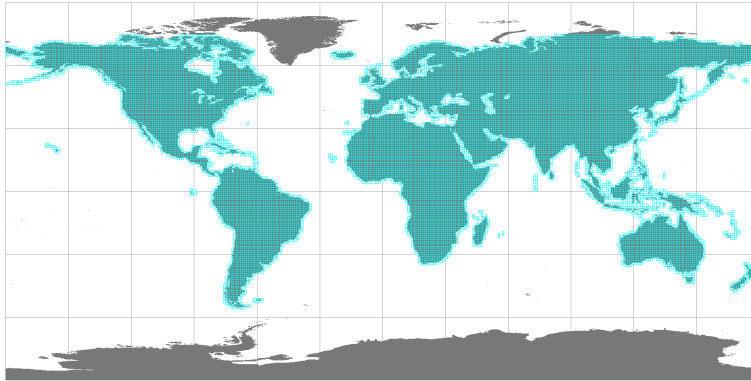
Installation instructions:

- Download the latest version of the package (https://glad.umd.edu/Potapov/ARD/GLAD_1.1.zip)
- Create folder "C:\GLAD_1.1" and unpack the content of the zip file into this folder.
- Open "C:\GLAD_1.1" and execute batch file "Add_PATH_for_GLAD_v1.1.bat" (as administrator).
- Reboot your computer.

Update instructions:

- To update the GLAD Tools, simply download the latest version and unpack to "C:\GLAD_1.1", replacing all old files. The update log provided in "C:\GLAD_1.1\!readme.txt".

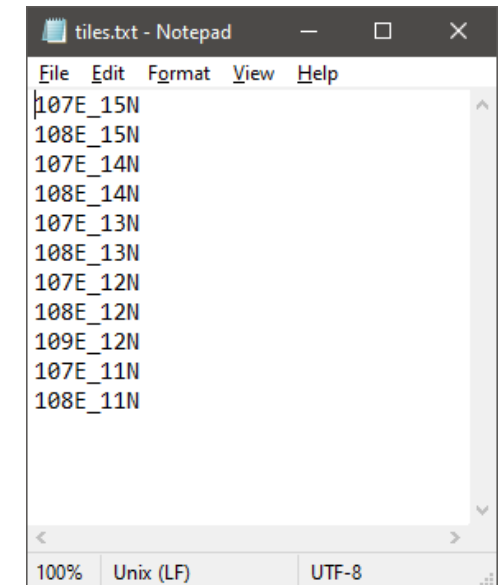
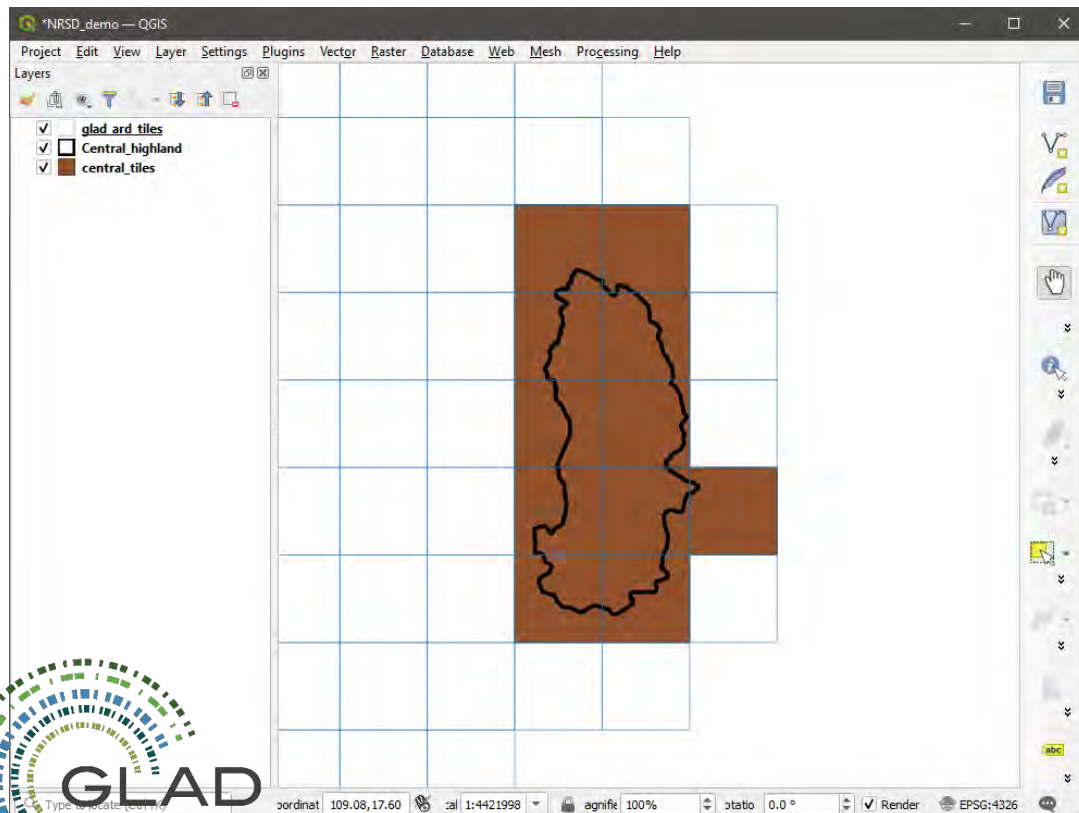
Selecting Tiles



The global Landsat ARD product is provided as a set of 1x1 geographic degrees tiles. To select ARD data tiles for your area of analysis, use the tile boundary shapefile located in C:\GLAD_1.1\Data\Global_tiles\glad_ard_tiles.shp

Load both the project boundary shapefile and the global tiles shapefile to QGIS. Select tiles that intersect with the project boundaries (use QGIS “Select by Location” tool). Save the selection as a separate shapefile.

Open the “*.dbf” file of the selected tiles dataset. Copy the list of tiles and paste them into a new text file (“[tiles.txt](#)”). No header or empty lines are allowed in the list.



Selecting 16-day Composites

The global Landsat ARD data composited in a set of 16-day intervals, 23 composites per year. Each interval has a unique numeric ID, starting from the first interval of the year 1980.

Use 16-day interval ID table

(C:\GLAD_1.1\Documentation\16d_intervals.xlsx) to select intervals for your analysis.

Example:

To create a gap-filled annual data for 2018, we need to select all intervals of the year 2018 (875-897). To implement gap-filling of missing data, it is recommended to download data for four preceding years (2014-2017). The overall ARD time interval 2014-2018 for data download is 783-897.

Year	16-day interval # within a year																						
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
1980	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
1981	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40	41	42	43	44	45	46
1982	47	48	49	50	51	52	53	54	55	56	57	58	59	60	61	62	63	64	65	66	67	68	69
1983	70	71	72	73	74	75	76	77	78	79	80	81	82	83	84	85	86	87	88	89	90	91	92
1984	93	94	95	96	97	98	99	100	101	102	103	104	105	106	107	108	109	110	111	112	113	114	115
1985	116	117	118	119	120	121	122	123	124	125	126	127	128	129	130	131	132	133	134	135	136	137	138
1986	139	140	141	142	143	144	145	146	147	148	149	150	151	152	153	154	155	156	157	158	159	160	161
1987	162	163	164	165	166	167	168	169	170	171	172	173	174	175	176	177	178	179	180	181	182	183	184
1988	185	186	187	188	189	190	191	192	193	194	195	196	197	198	199	200	201	202	203	204	205	206	207
1989	208	209	210	211	212	213	214	215	216	217	218	219	220	221	222	223	224	225	226	227	228	229	230
1990	231	232	233	234	235	236	237	238	239	240	241	242	243	244	245	246	247	248	249	250	251	252	253
1991	254	255	256	257	258	259	260	261	262	263	264	265	266	267	268	269	270	271	272	273	274	275	276
1992	277	278	279	280	281	282	283	284	285	286	287	288	289	290	291	292	293	294	295	296	297	298	299
1993	300	301	302	303	304	305	306	307	308	309	310	311	312	313	314	315	316	317	318	319	320	321	322
1994	323	324	325	326	327	328	329	330	331	332	333	334	335	336	337	338	339	340	341	342	343	344	345
1995	346	347	348	349	350	351	352	353	354	355	356	357	358	359	360	361	362	363	364	365	366	367	368
1996	369	370	371	372	373	374	375	376	377	378	379	380	381	382	383	384	385	386	387	388	389	390	391
1997	392	393	394	395	396	397	398	399	400	401	402	403	404	405	406	407	408	409	410	411	412	413	414
1998	415	416	417	418	419	420	421	422	423	424	425	426	427	428	429	430	431	432	433	434	435	436	437
1999	438	439	440	441	442	443	444	445	446	447	448	449	450	451	452	453	454	455	456	457	458	459	460
2000	461	462	463	464	465	466	467	468	469	470	471	472	473	474	475	476	477	478	479	480	481	482	483
2001	484	485	486	487	488	489	490	491	492	493	494	495	496	497	498	499	500	501	502	503	504	505	506
2002	507	508	509	510	511	512	513	514	515	516	517	518	519	520	521	522	523	524	525	526	527	528	529
2003	530	531	532	533	534	535	536	537	538	539	540	541	542	543	544	545	546	547	548	549	550	551	552
2004	553	554	555	556	557	558	559	560	561	562	563	564	565	566	567	568	569	570	571	572	573	574	575
2005	576	577	578	579	580	581	582	583	584	585	586	587	588	589	590	591	592	593	594	595	596	597	598
2006	599	600	601	602	603	604	605	606	607	608	609	610	611	612	613	614	615	616	617	618	619	620	621
2007	622	623	624	625	626	627	628	629	630	631	632	633	634	635	636	637	638	639	640	641	642	643	644
2008	645	646	647	648	649	650	651	652	653	654	655	656	657	658	659	660	661	662	663	664	665	666	667
2009	668	669	670	671	672	673	674	675	676	677	678	679	680	681	682	683	684	685	686	687	688	689	690
2010	691	692	693	694	695	696	697	698	699	700	701	702	703	704	705	706	707	708	709	710	711	712	713
2011	714	715	716	717	718	719	720	721	722	723	724	725	726	727	728	729	730	731	732	733	734	735	736
2012	737	738	739	740	741	742	743	744	745	746	747	748	749	750	751	752	753	754	755	756	757	758	759
2013	760	761	762	763	764	765	766	767	768	769	770	771	772	773	774	775	776	777	778	779	780	781	782
2014	783	784	785	786	787	788	789	790	791	792	793	794	795	796	797	798	799	800	801	802	803	804	805
2015	806	807	808	809	810	811	812	813	814	815	816	817	818	819	820	821	822	823	824	825	826	827	828
2016	829	830	831	832	833	834	835	836	837	838	839	840	841	842	843	844	845	846	847	848	849	850	851
2017	852	853	854	855	856	857	858	859	860	861	862	863	864	865	866	867	868	869	870	871	872	873	874
2018	875	876	877	878	879	880	881	882	883	884	885	886	887	888	889	890	891	892	893	894	895	896	897
2019	898	899	900	901	902	903	904	905	906	907	908	909	910	911	912	913	914	915	916	917	918	919	920
2020	921	922	923	924	925	926	927	928	929	930	931	932	933	934	935	936	937	938	939	940	941	942	943
2021	944	945	946	947	948	949	950	951	952	953	954	955	956	957	958	959	960	961	962	963	964	965	966
2022	967	968	969	970	971	972	973	974	975	976	977	978	979	980	981	982	983	984	985	986	987	988	989
2023	990	991	992	993	994	995	996	997	998	999	1000	1001	1002	1003	1004	1005	1006	1007	1008	1009	1010	1011	1012
2024	1013	1014	1015	1016	1017	1018	1019	1020	1021	1022	1023	1024	1025	1026	1027	1028	1029	1030	1031	1032	1033	1034	1035



Data Download

User registration.

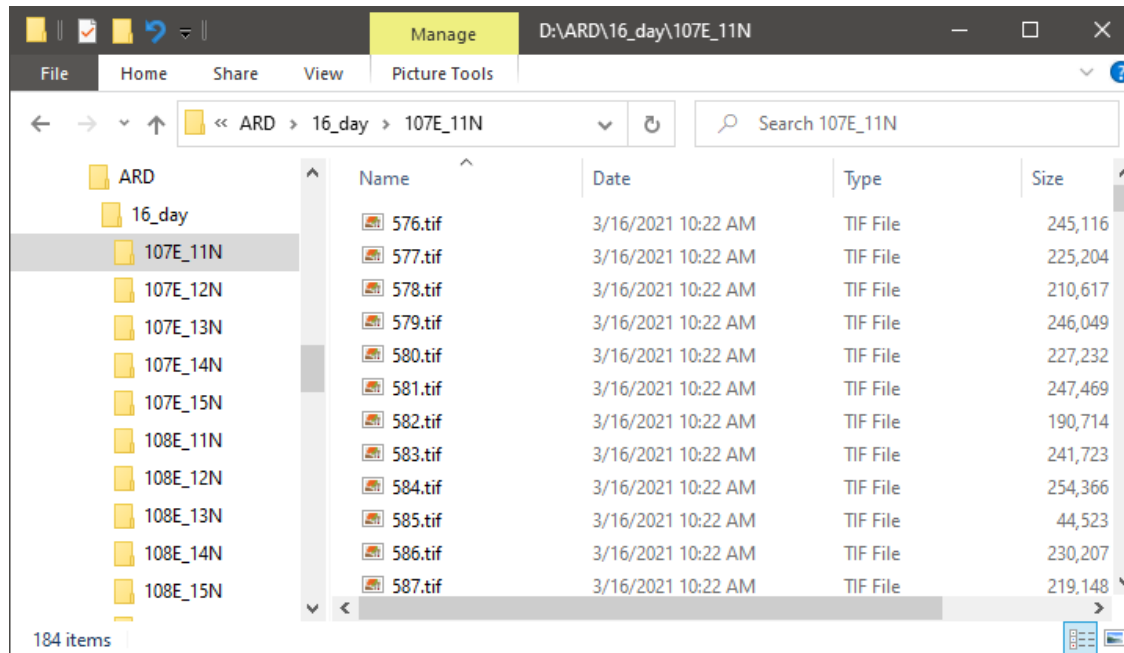
To download the data, please obtain the unique username and password by registering at <https://glad.umd.edu/ard/glad-landsat-ard-tools>. The following section uses username “valdai” and the password “valdaitest”. These username and password are for test purposes only and will be eventually deprecated.

Open CMD in the folder with tiles.txt file. Run the following command to download data:

```
perl C:/GLAD_1.1/download_V1.1.pl valdai valdaitest tiles.txt 806 897 D:/ARD/16_day
```

In the same CMD, run the command to download topography data:

```
perl C:/GLAD_1.1/download_SRTM.pl valdai valdaitest tiles.txt D:/ARD/DEM
```

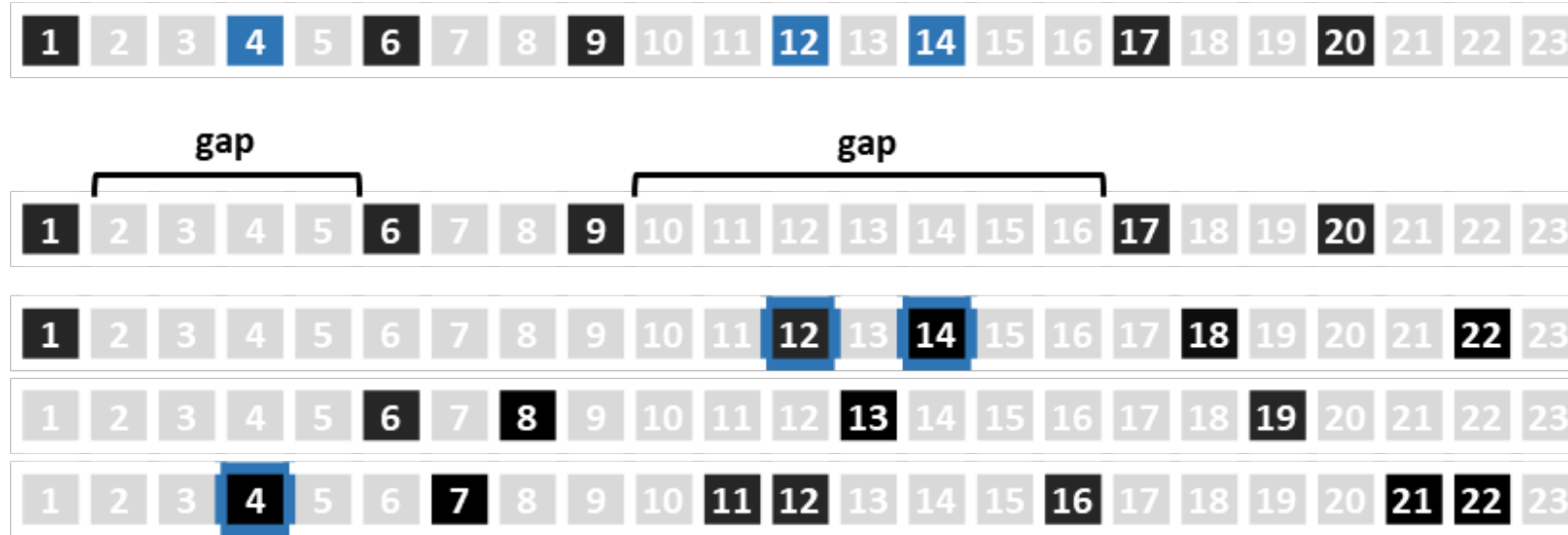


Local ARD data storage.

Each tile should be stored in a separate folder. The DEM data should be stored separately from the ARD data. See section 4.3 of the User Manual for data organization guidelines.

Phenological Metrics

Gap-filled annual time-series data



Pheno_C metrics

- 3-interval gaps filled with data from years Y-1 and Y-2
- 5-interval gaps filled with data from years Y-3 and Y-4
- The number of preceding years used for gap-filling can be defined for a metrics set.
- Missing data interpolated using linear regression.

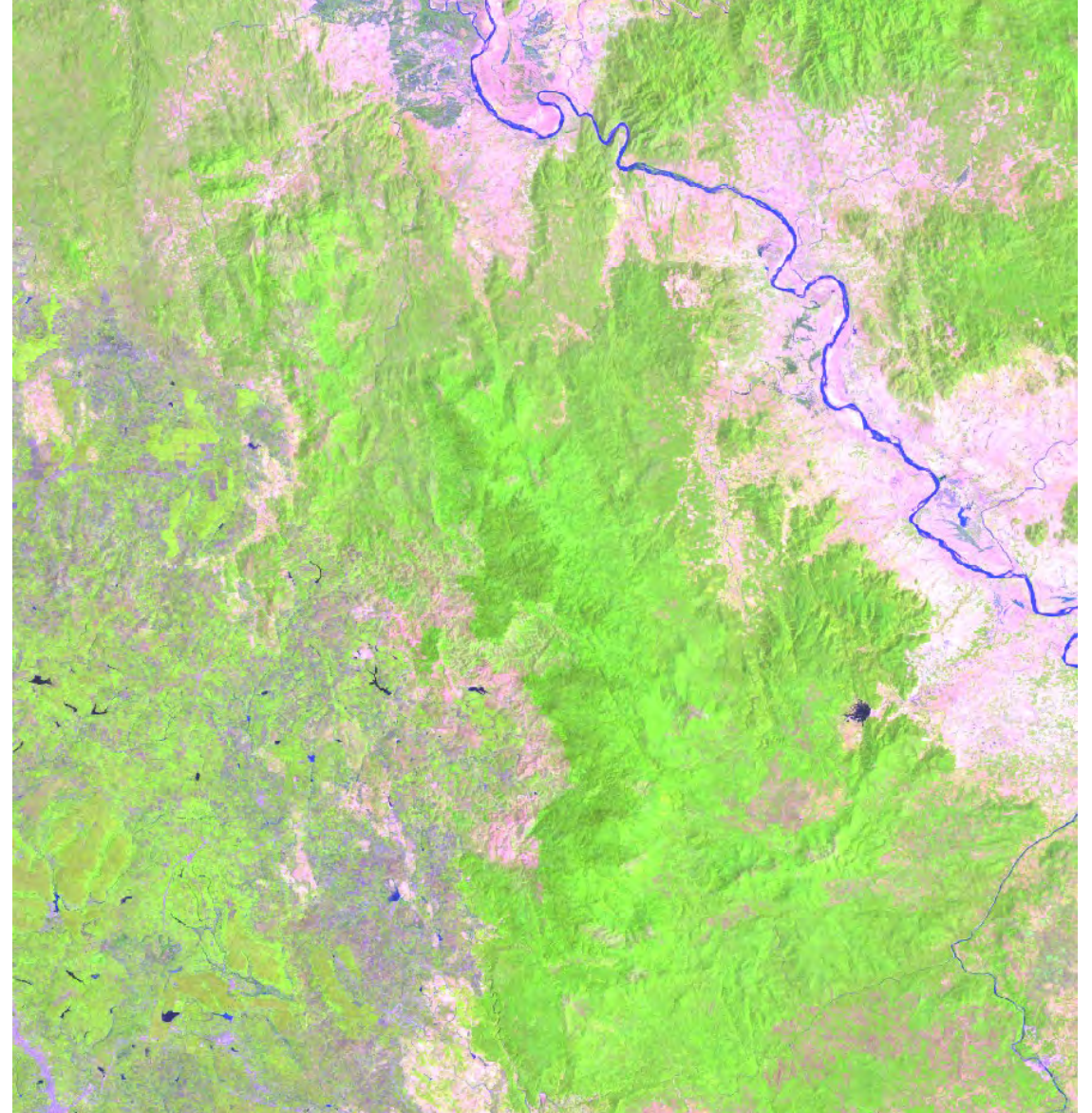
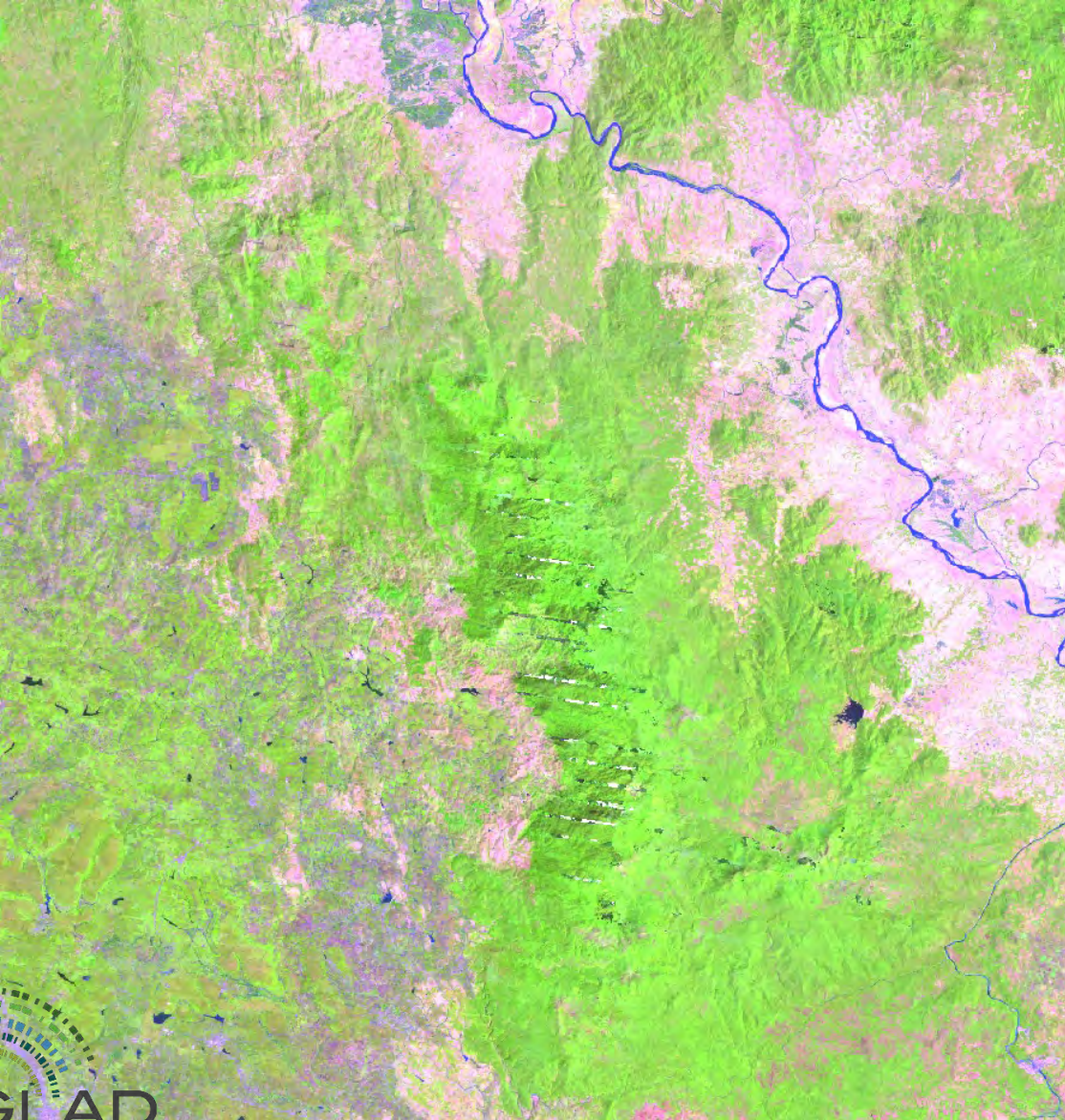
Data selection rules (metrics processing flag, PF)

- All data from the target and selected preceding years are considered.
- PF codes 1-3 indicate clear-free data presence; code 7 – permanent snow/ice.
- Codes 4 indicate presence of topographic shadows or wetlands.
- Codes 5-6 indicate presence of haze/shadow contaminated observations.
- Code 8 indicated cloud/shadow observations only.

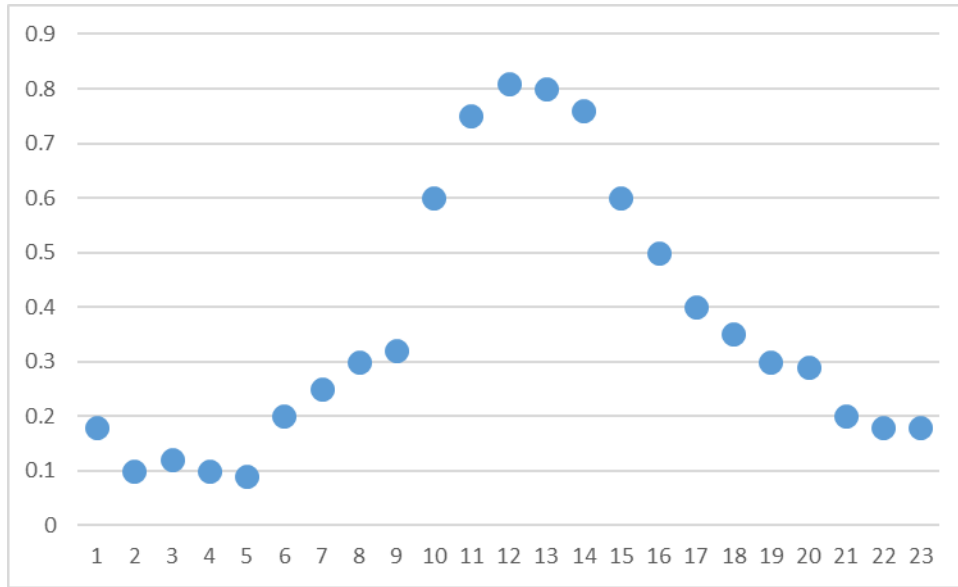
Phenological Metrics

Year 2008 image composite, no gap-filling

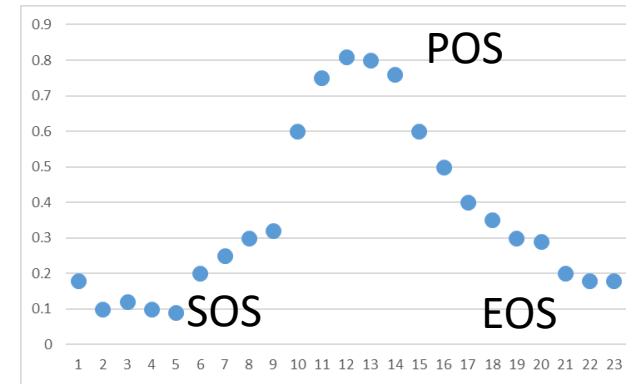
Year 2008 image composite, gap-filling using 3 years of data



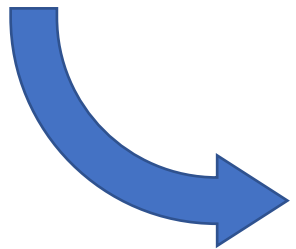
Phenological Metrics



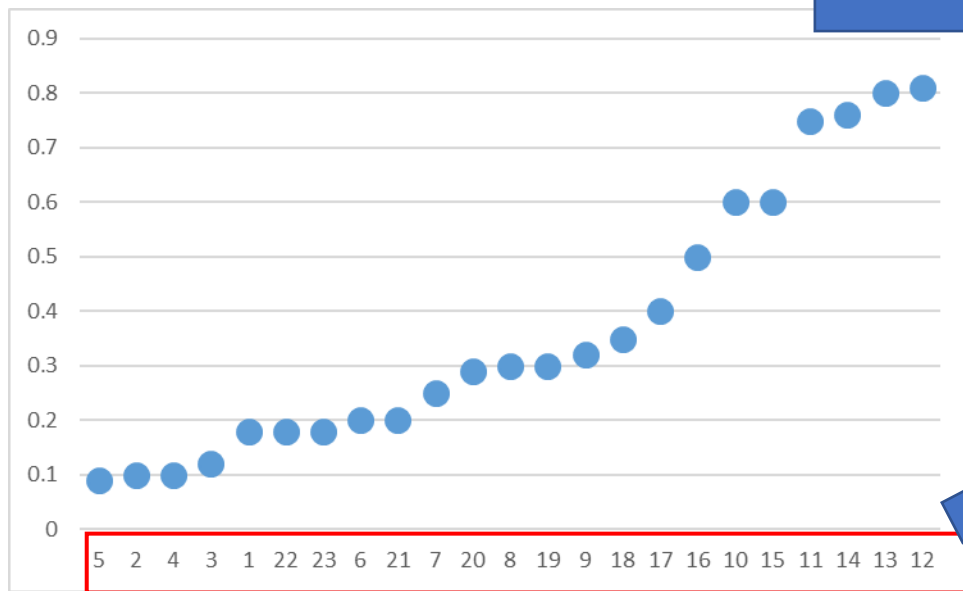
NDVI-based
phenology



- SOS, EOS, POS NDVI values
- NDVI increase/decrease rates and amplitudes



Ranked by value



Based on individual ranks

- Statistics (min, max, median)
- Averages (min-Q1, Q1-Q3, Q3-max, min-max)
- Amplitudes (min-max, Q1-Q3, etc.)

Based on corresponding NDVI, LST, etc. ranks

- Statistics (min, max)
- Averages (min-Q1, Q3-max,)
- Amplitudes (min-max, etc.)

Phenological Metrics

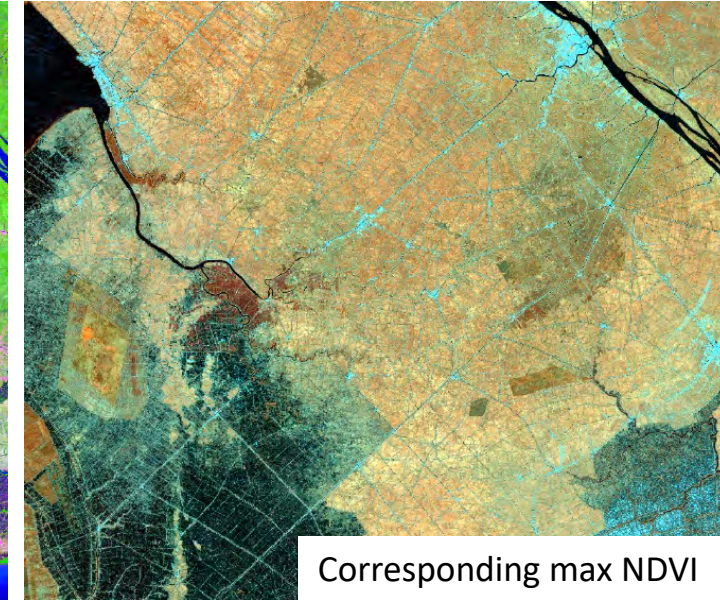
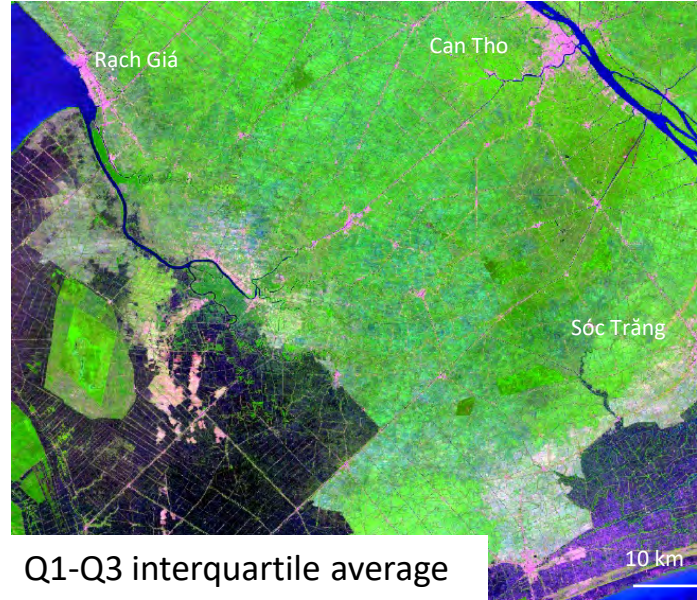
Ranking of 16-day observation time-series by spectral reflectance or index value

Spectral data and indices

Blue (482 nm)
Green (561 nm)
Red (654 nm)
NIR (864 nm)
SWIR1 (1609 nm)
SWIR2 (2201 nm)
$(\text{NIR}-\text{Green})/(\text{NIR}+\text{Green})$
$(\text{NIR}-\text{Red})/(\text{NIR}+\text{Red})$
$(\text{NIR}-\text{SWIR1})/(\text{NIR}+\text{SWIR1})$
$(\text{NIR}-\text{SWIR2})/(\text{NIR}+\text{SWIR2})$
$(\text{SWIR1}-\text{SWIR2})/(\text{SWIR1}+\text{SWIR2})$
Spectral variability index
Tasseled Cap Greenness

Summary statistics

Minimum
Maximum
Median
Average between min and Q1
Average between Q3 and max
Average between Q1 and Q3
Average of all values
Standard deviation
Total absolute difference
Amplitude min to max
Amplitude Q1 to Q3
Amplitude Q2 to max



Ranking of 16-day observation time-series by the value of corresponding variable

Spectral data

Corresponding variable

Summary statistics

Blue
Green
Red
NIR
SWIR1
SWIR2

$(\text{NIR}-\text{Red})/(\text{NIR}+\text{Red})$
$(\text{NIR}-\text{SWIR2})/(\text{NIR}+\text{SWIR2})$
Brightness temperature

Minimum
Maximum
Average between min and Q1
Average between Q3 and max
Amplitude min to max
Amplitude Q1 to Q3

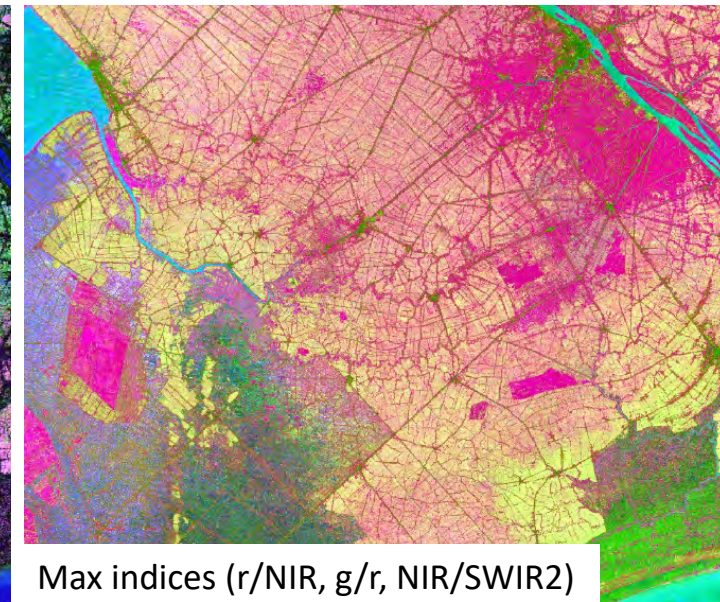
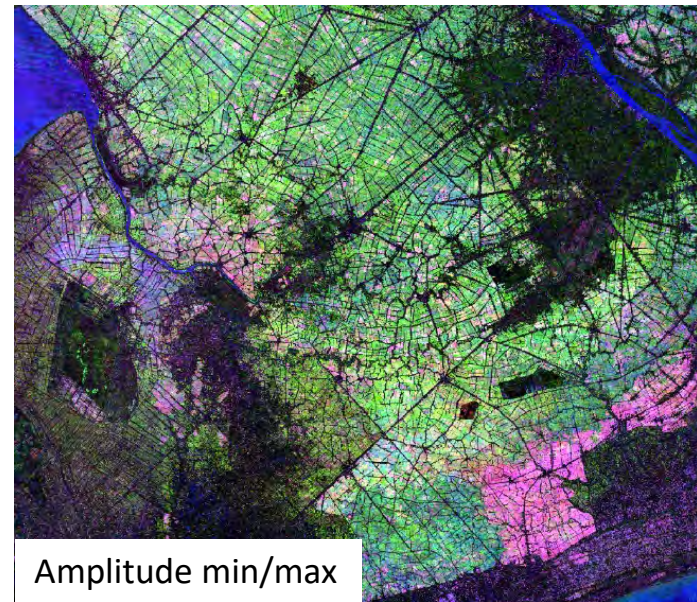
NDVI-based phenology metrics

Vegetation index

$(\text{NIR}-\text{Red})/(\text{NIR}+\text{Red})$

Phenology metrics

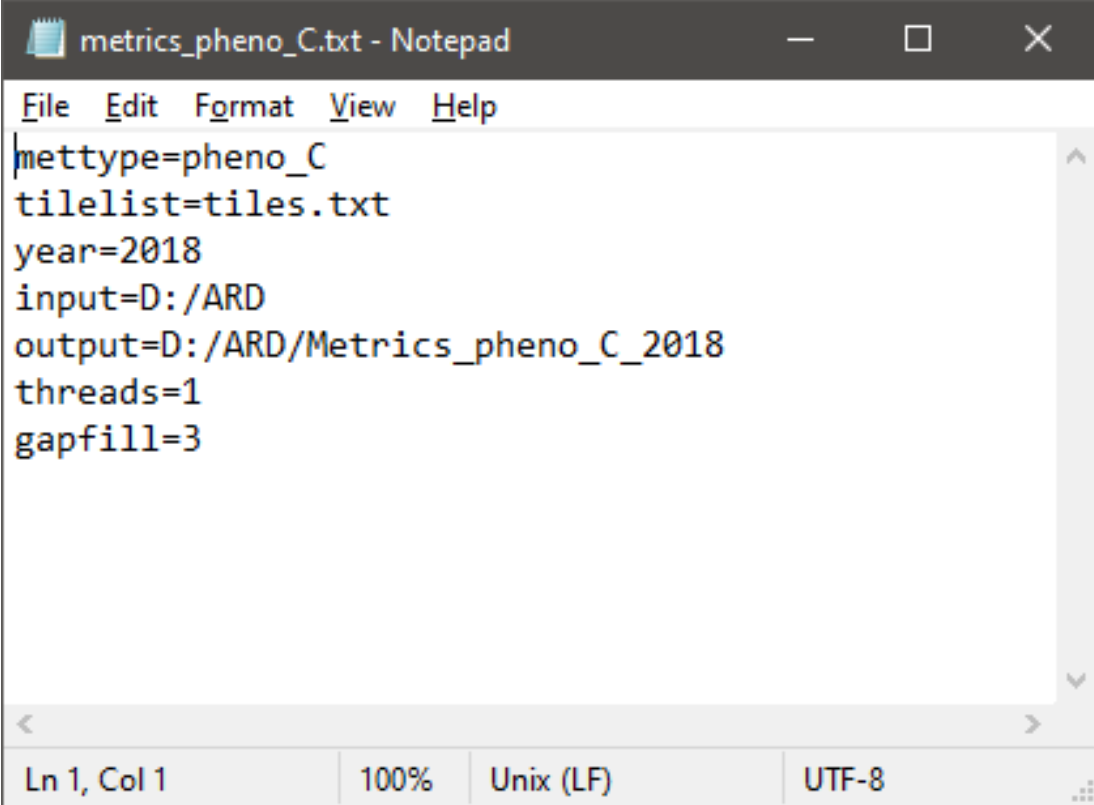
Start of season value	Start of season amplitude
End of season value	End of season amplitude
Start of season slope	Growing season average
End of season slope	Growing season total



Phenological Metrics

The metric generation code requires a parameter file (see User Manual, section 5.6). Make sure that:

- The list of tiles (tiles.txt) is within the same folder as the parameter file.
- The Input folder exists.
- The disk has enough space for the metrics (~5.8GB per tile).
- Use “threads=1” unless running a powerful computer.
- The “gapfill” parameter indicate the number of years used for gap-filling (default 4). If gapfill=0, the gap filling algorithm is disabled.



```
mettype=pheno_C
tilelist=tiles.txt
year=2018
input=D:/ARD
output=D:/ARD/Metrics_pheno_C_2018
threads=1
gapfill=3
```

Open CMD in the folder with parameter file. Run the following command to build metrics:

```
perl C:/GLAD_1.1/build_metrics.pl metrics_pheno_C.txt
```


Image Composites

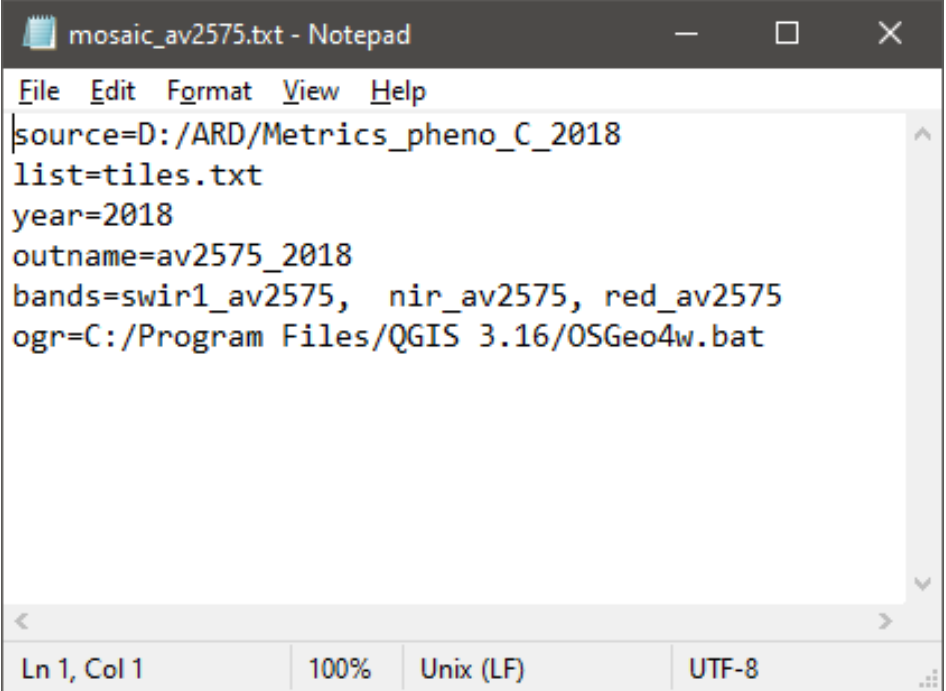
The annual phenological metrics provides several options for data visualization. To create each image composite, use a separate parameter file.

Example: parameter file for interquartile average composite in pseudo-natural band combination (SWIR-NIR-Red).

The “bands” parameter may contain several metrics, comma-separated. Check and correct the path to OSGeo4w.bat file (it depends on your QGIS installation).

Metric names provided in XLS files in

[C:\GLAD_1.1\Documentation](#), e.g. [Metrics_change_C.xlsx](#)

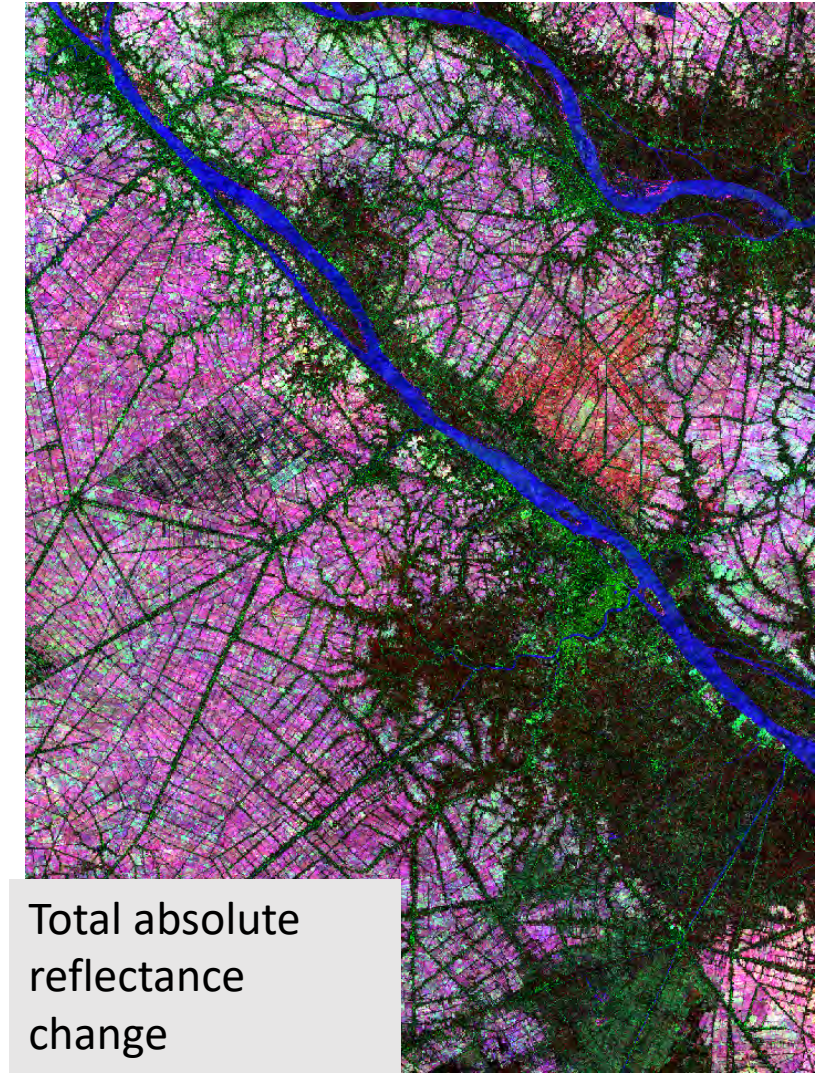
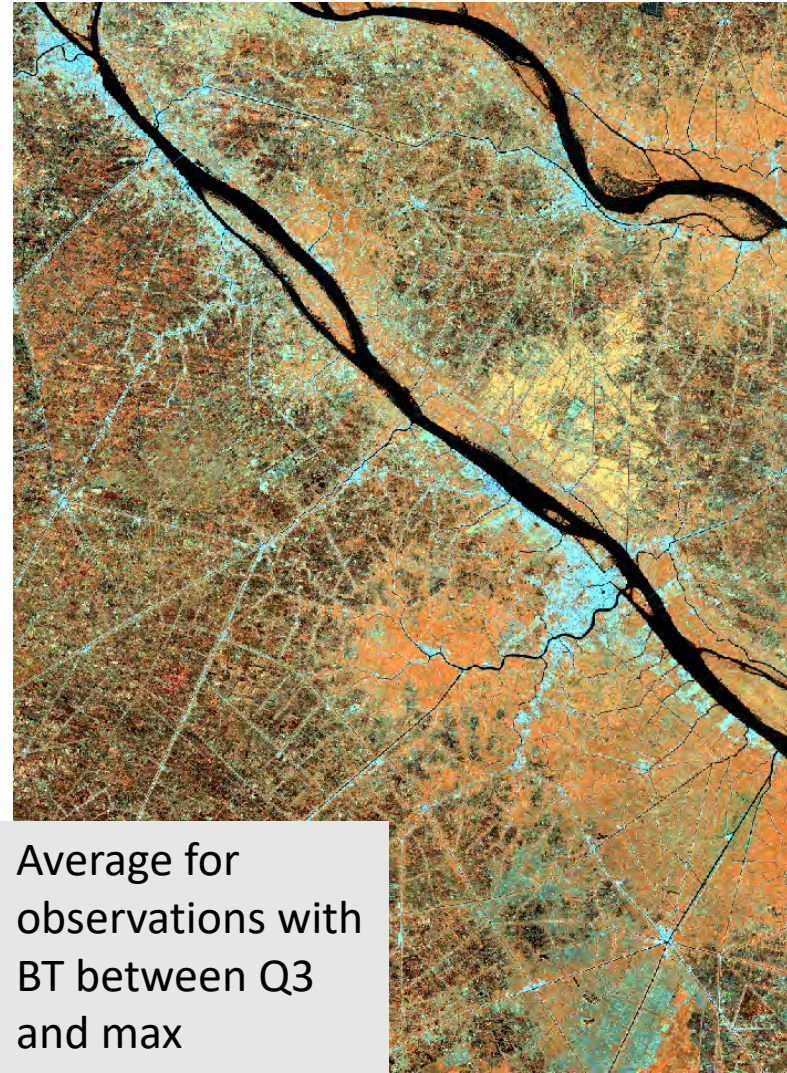
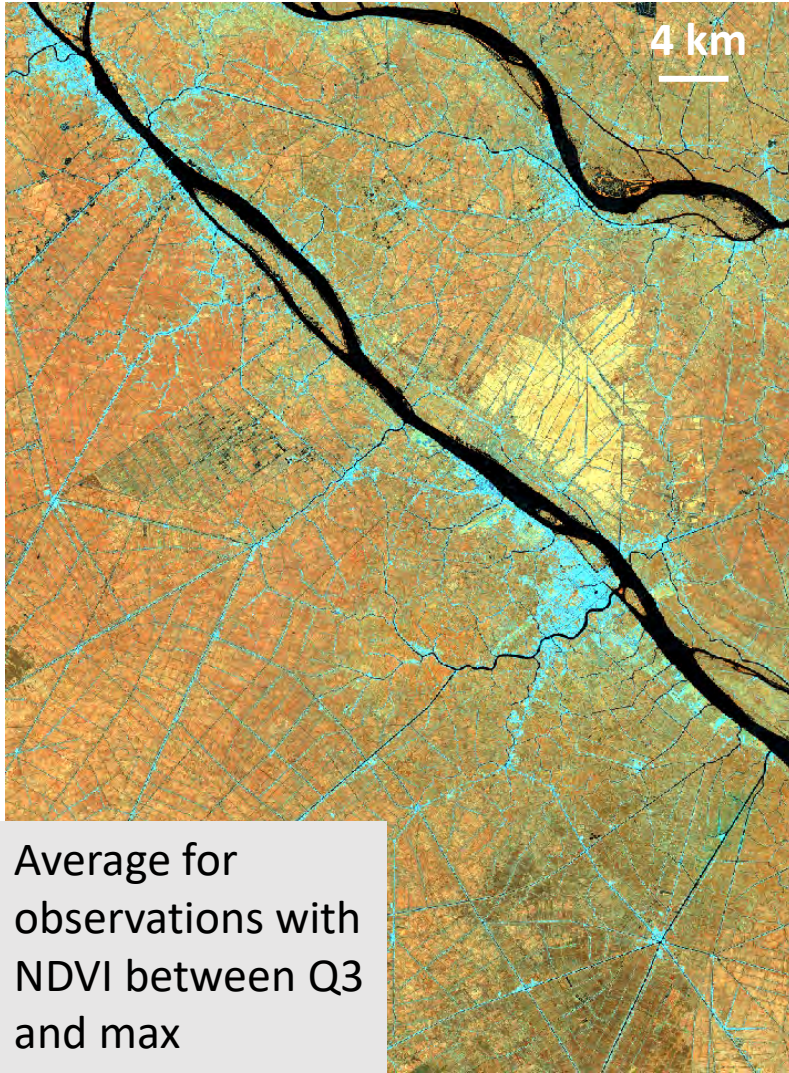


```
File Edit Format View Help
source=D:/ARD/Metrics_pheno_C_2018
list=tiles.txt
year=2018
outname=av2575_2018
bands=swir1_av2575, nir_av2575, red_av2575
ogr=C:/Program Files/QGIS 3.16/OSGeo4w.bat
```

Open CMD in the folder with the parameter file. Run the following command to make image mosaic:

```
perl C:/GLAD_1.1/mosaic_tiles.pl mosaic_av2575.txt
```


Image Composites



2018

Normalized surface reflectance

R – NIR

G – SWIR1

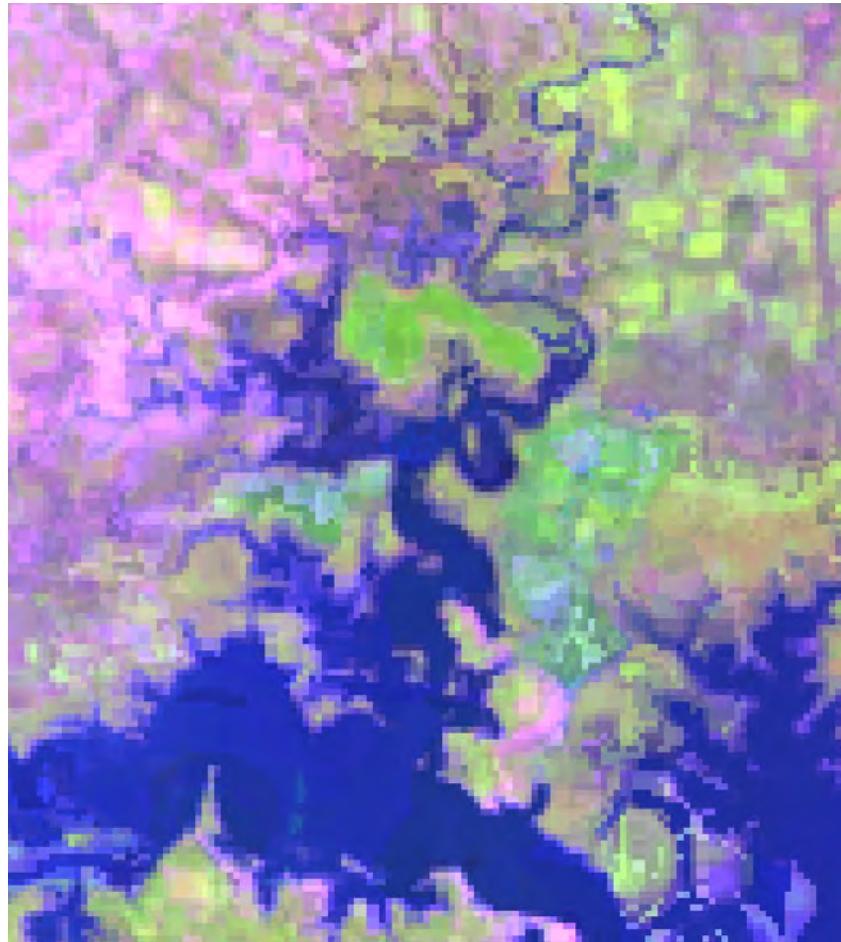
B – SWIR2

Image Composites

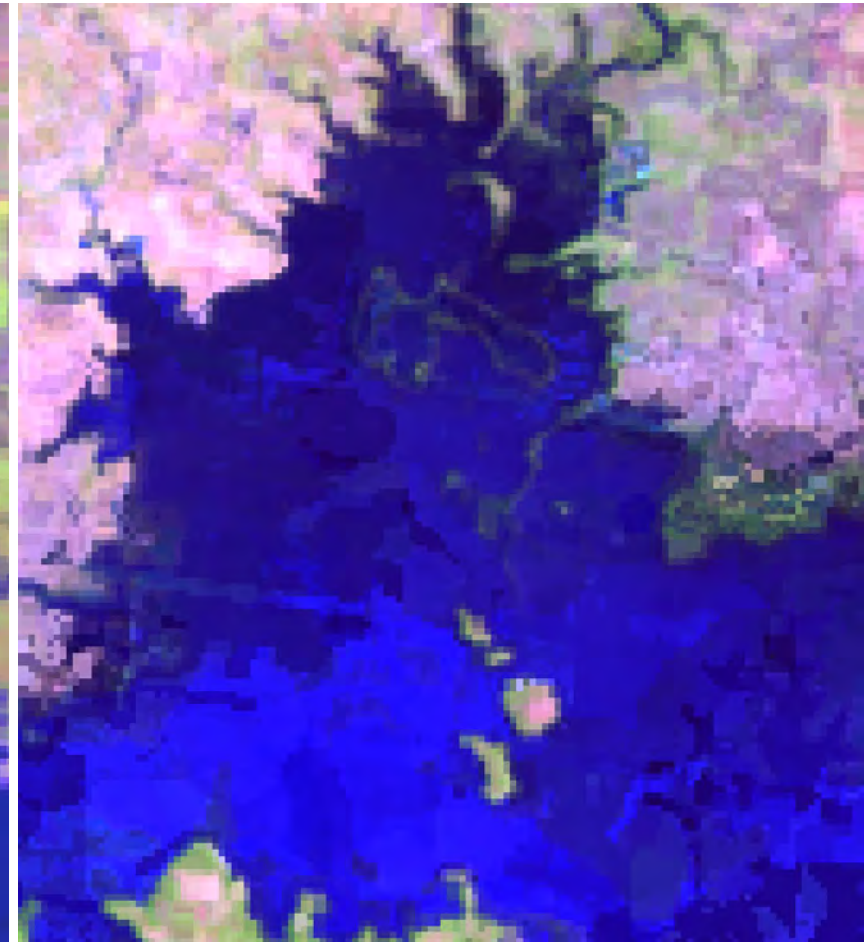
Google Earth Image



High NDVI 2018 composite



Low NDVI 2018 composite

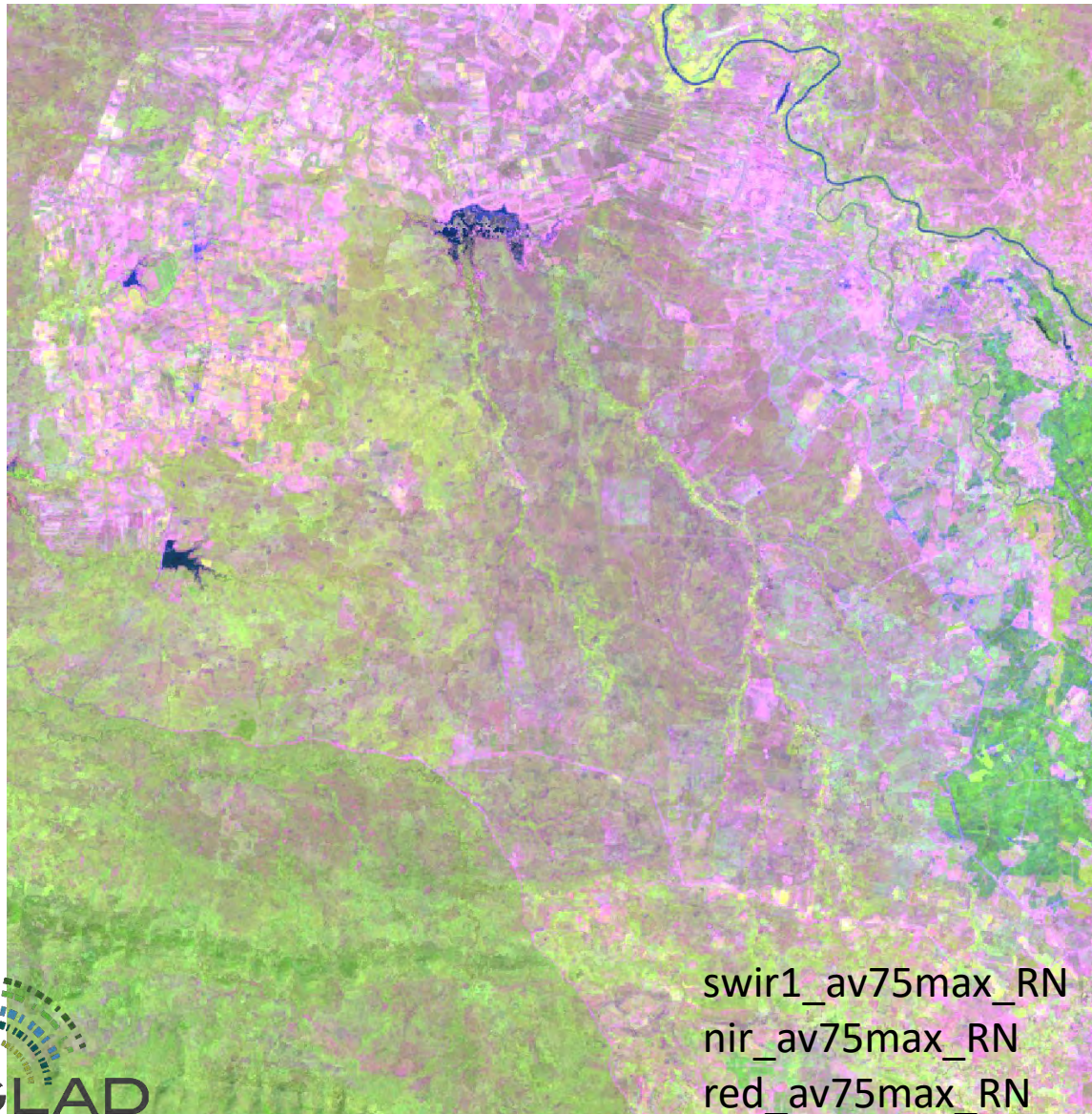


swir1_av75max_RN
nir_av75max_RN
red_av75max_RN

swir1_avmin25_RN
nir_avmin25_RN
red_avmin25_RN

Image Composites

High NDVI 2018 composite



Low NDVI 2018 composite

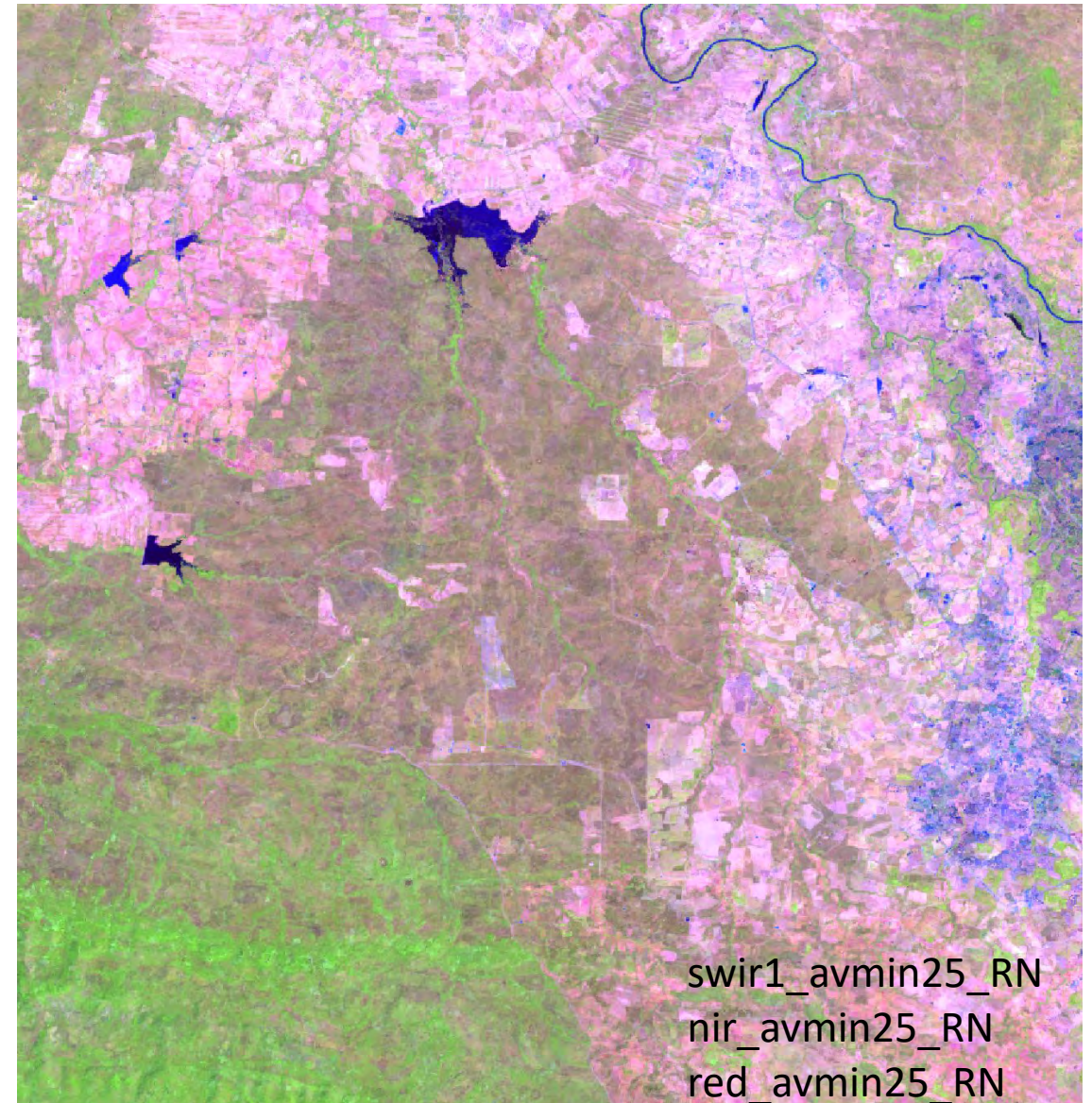
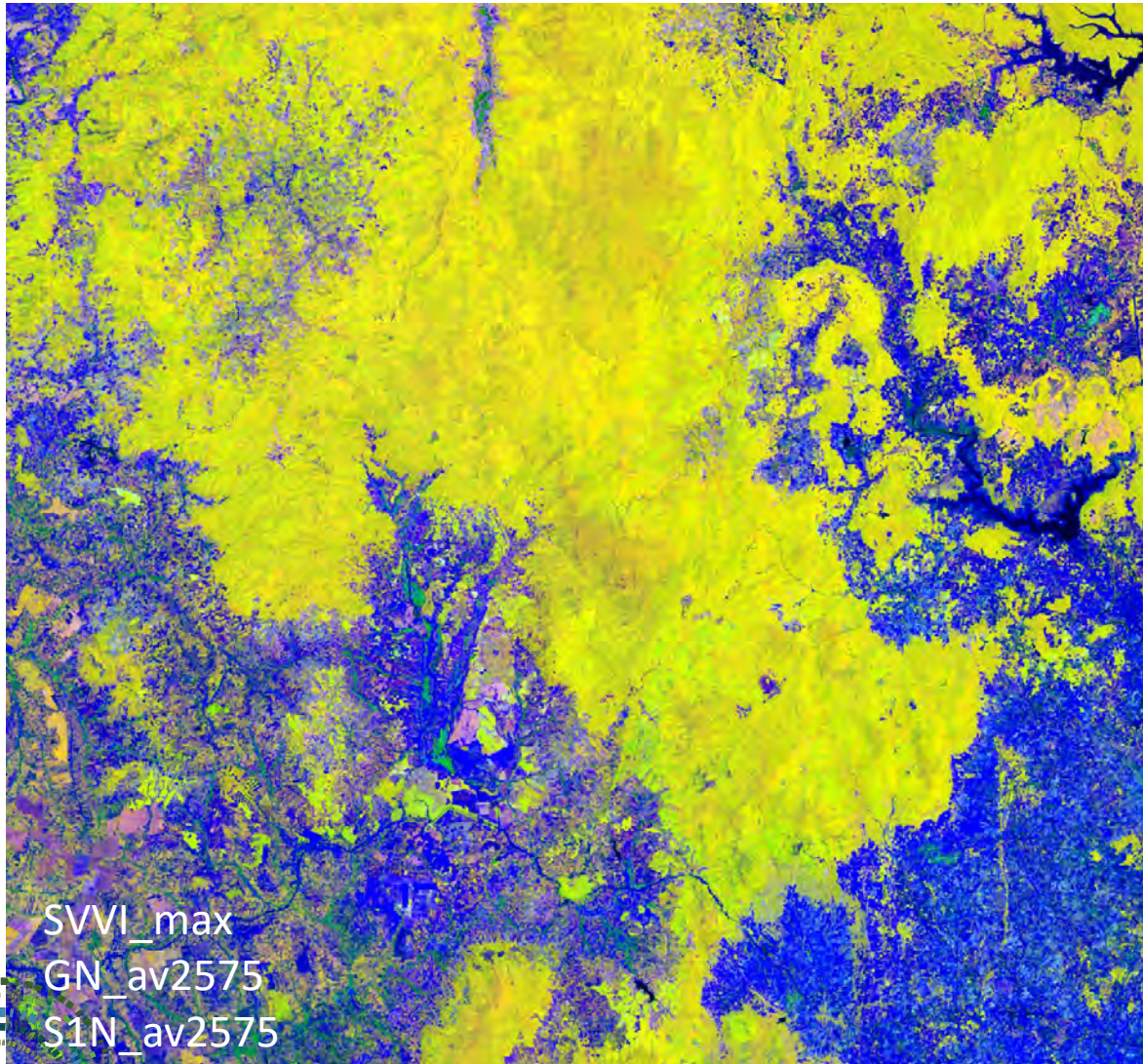
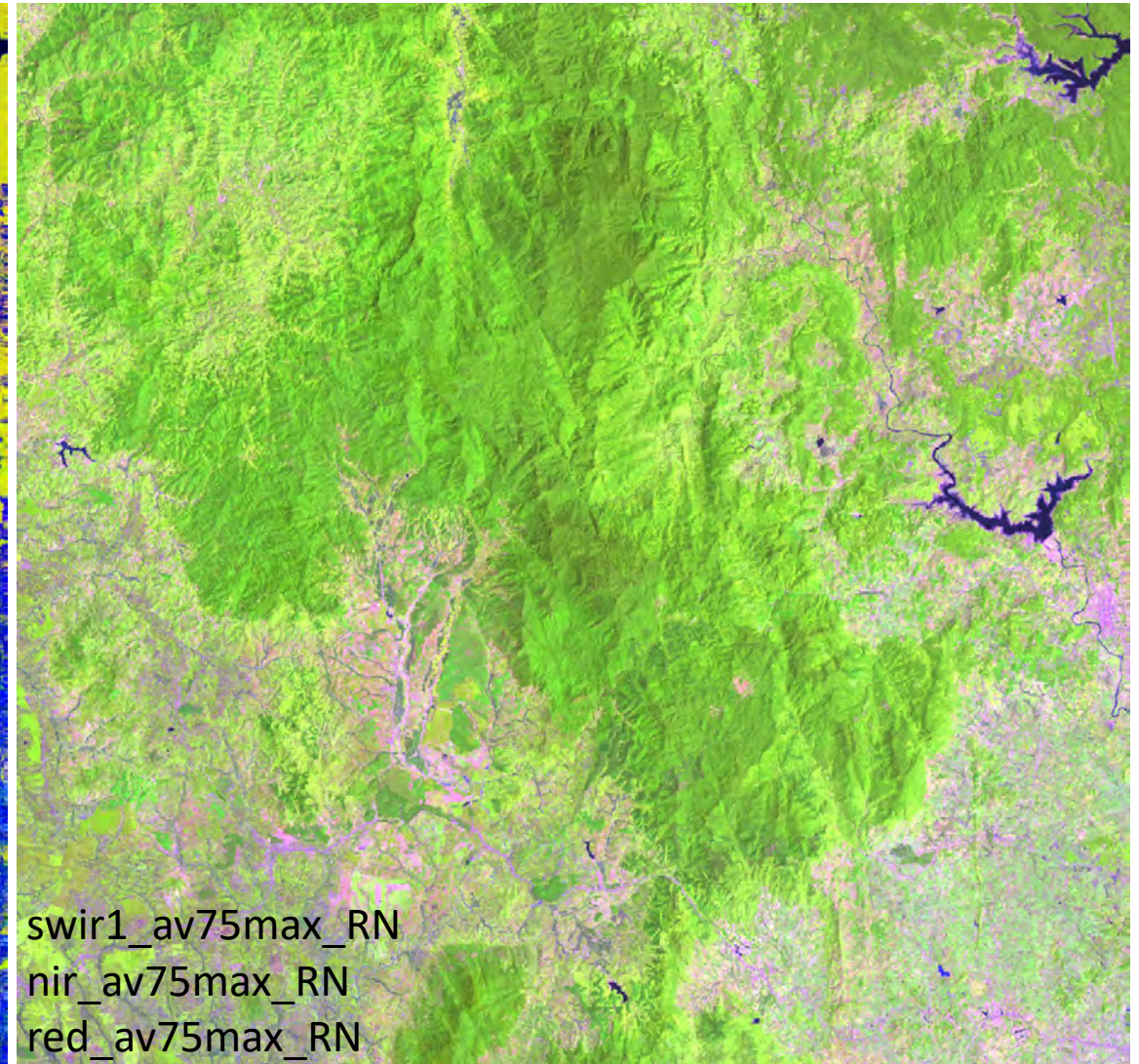


Image Composites

SVVI index, SWIR/NIR, and Green/NIR ratio composite

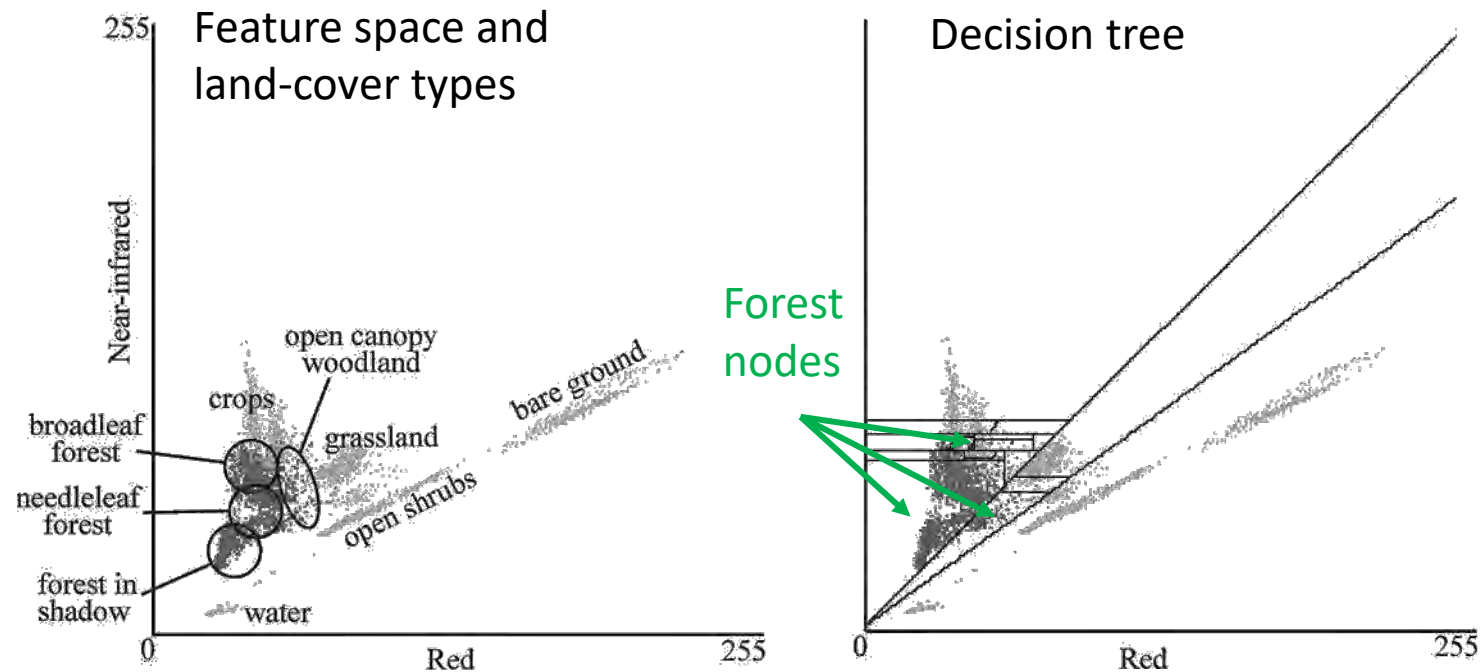


SWIR-NIR-Red high NDVI composite



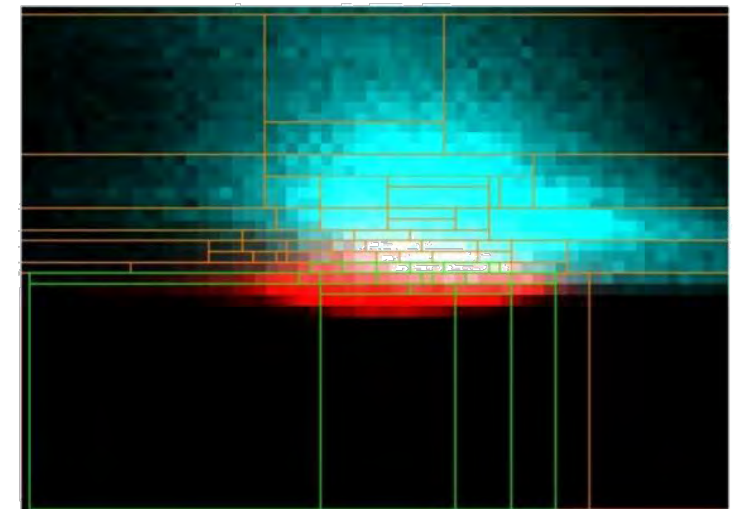
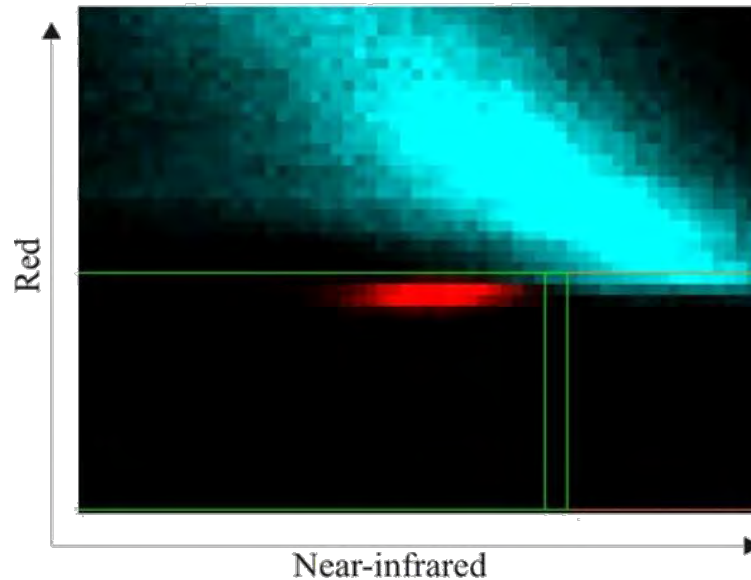
Land Cover Mapping

Decision tree (“Classification and regression trees” – CART; Breiman *et al.*, 1984) is hierarchical classifier that predicts class membership by recursively partitioning a data set into more homogeneous subsets (“nodes”). This splitting procedure is followed until a perfect tree (one in which every pixel is discriminated from pixels of other classes, if possible) is created with all pure terminal nodes or until preset conditions are met for terminating the tree’s growth.



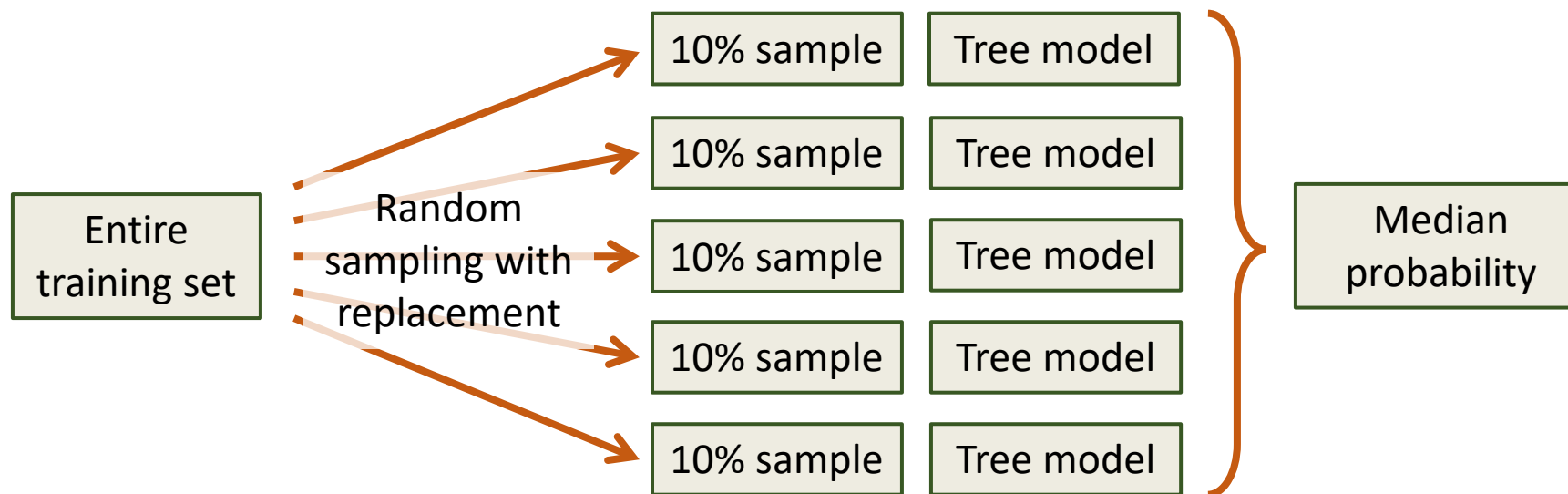
Land Cover Mapping

Training data for the CART model should be collected with the emphasis to the class boundaries. Large, uniform training areas are useless.



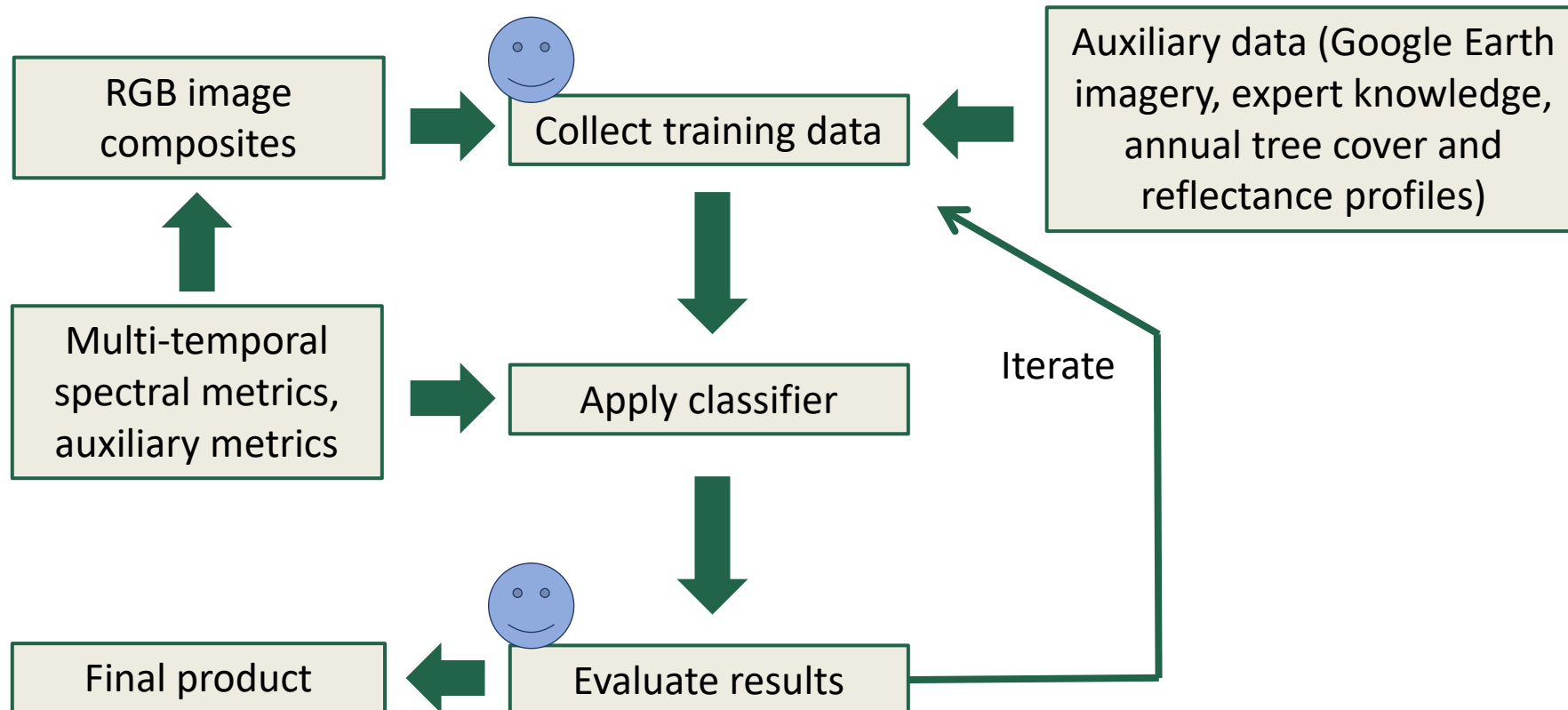
Land Cover Mapping

Bagging (**b**ootstrap **a**ggregation) - an ensemble learning method, builds multiple decision trees by repeatedly resampling training data with replacement, and voting the trees for a consensus prediction. Bagging can dramatically reduce the variance of unstable procedures like trees, leading to improved prediction.

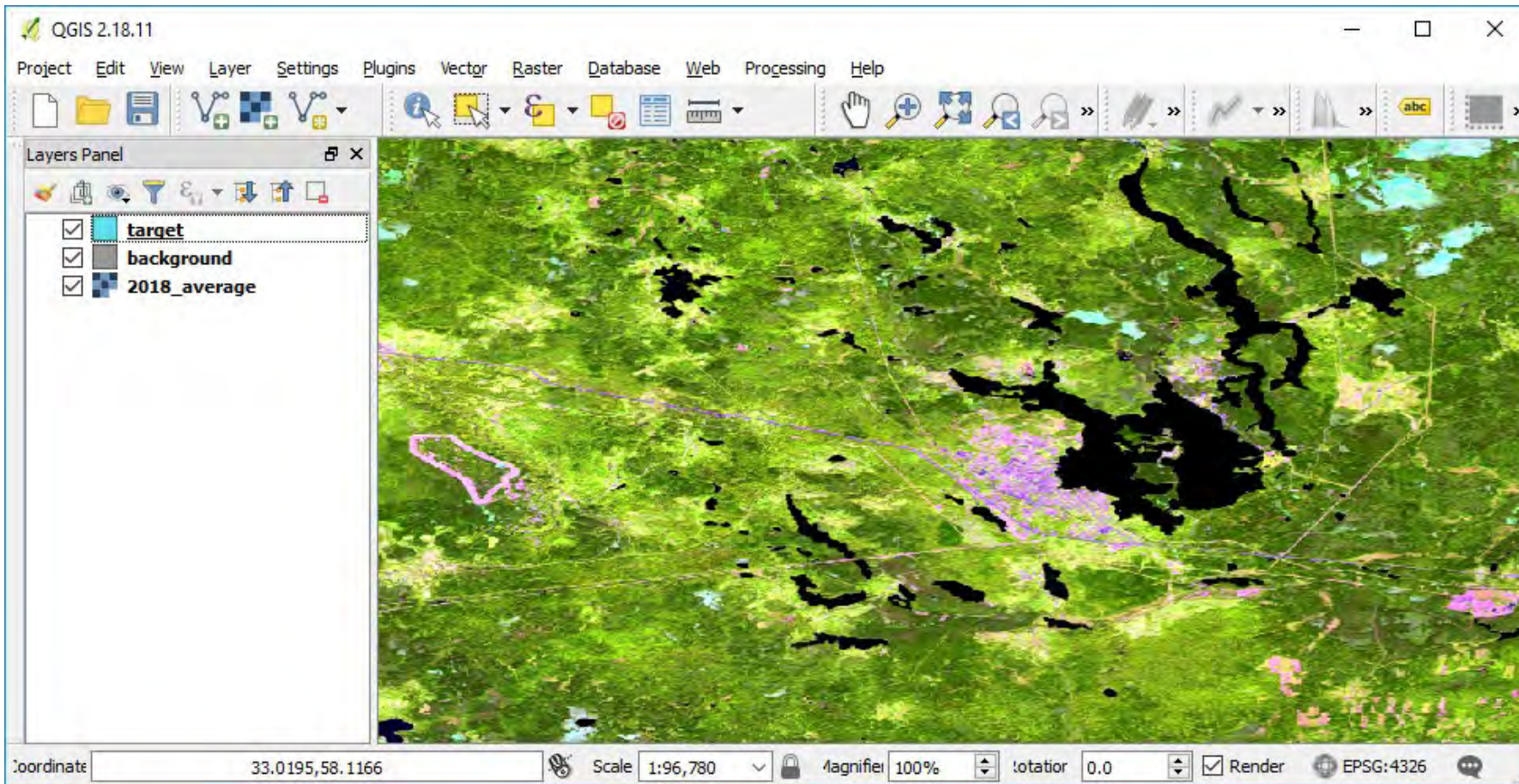


Land Cover Mapping

Analyst-driven supervised change classification is based on “**active learning**” method. Active learning focuses on the interaction between the analyst (or some other information source) and the classifier. The model returns to the analyst the classification outcome and helps to highlight the most uncertain areas. After accurate labeling by the analyst, these areas are added to the training set in order to reinforce the model. In this way, the model is optimized on well-chosen difficult examples, maximizing its generalization capabilities.



Land Cover Mapping

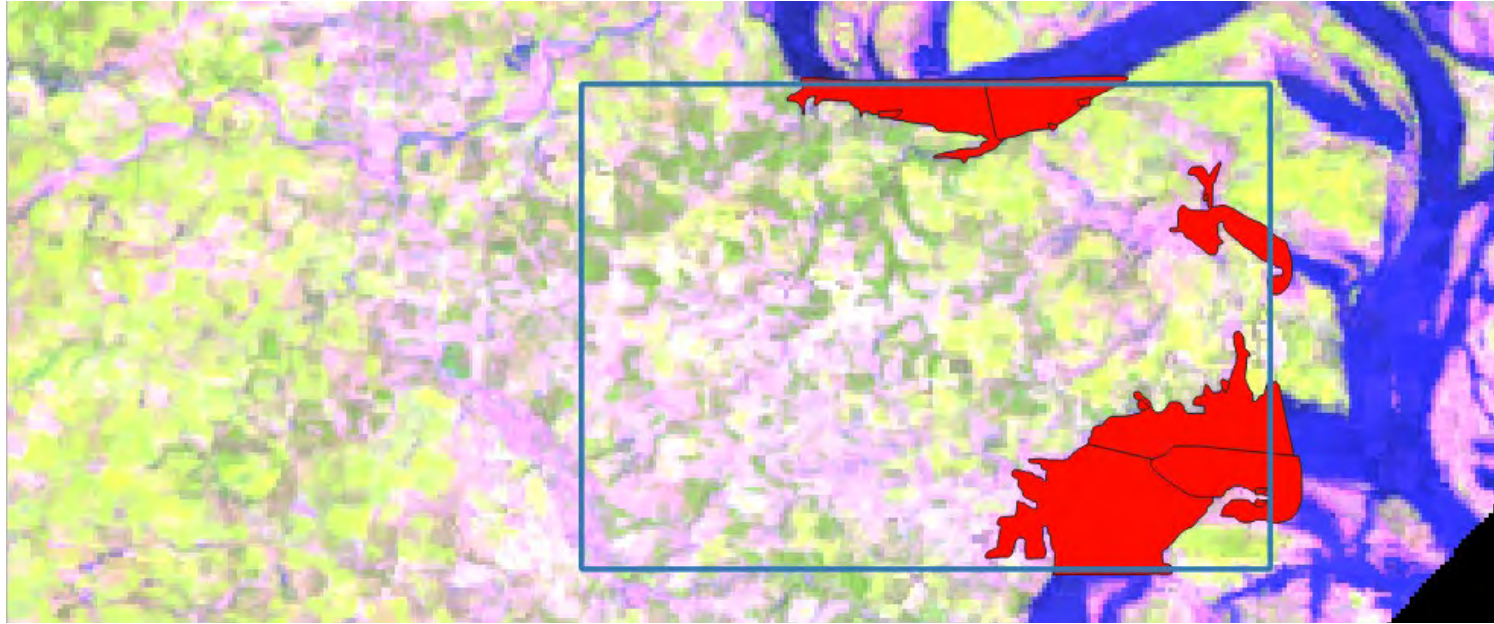


Training data collected as a set of polygonal shapefiles within the AOI.

Each classification allows to map only one target class. All other land cover are considered as the “background” class for the classification.

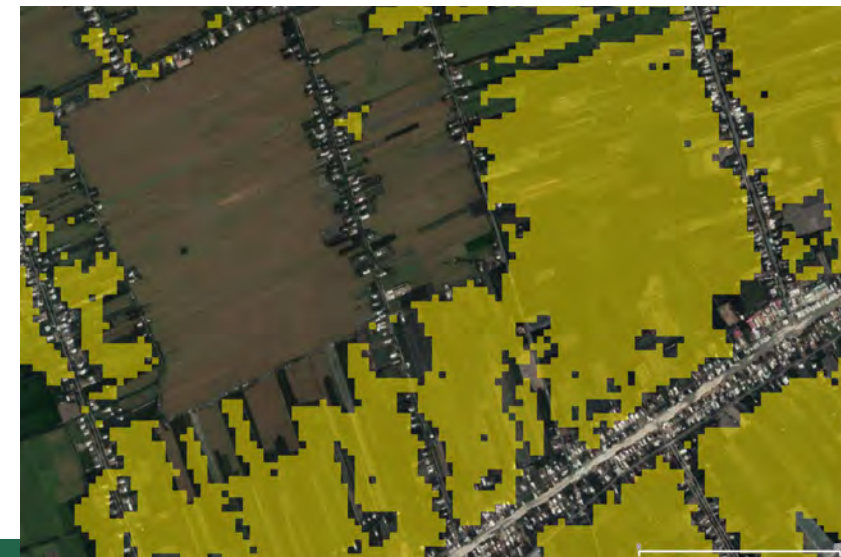
A set of empty training files provided in
C:\GLAD_1.1\Examples\classification

Land Cover Mapping



Example of water (red) and background (blue outline) classes training. The background class may overlap the target class polygons.

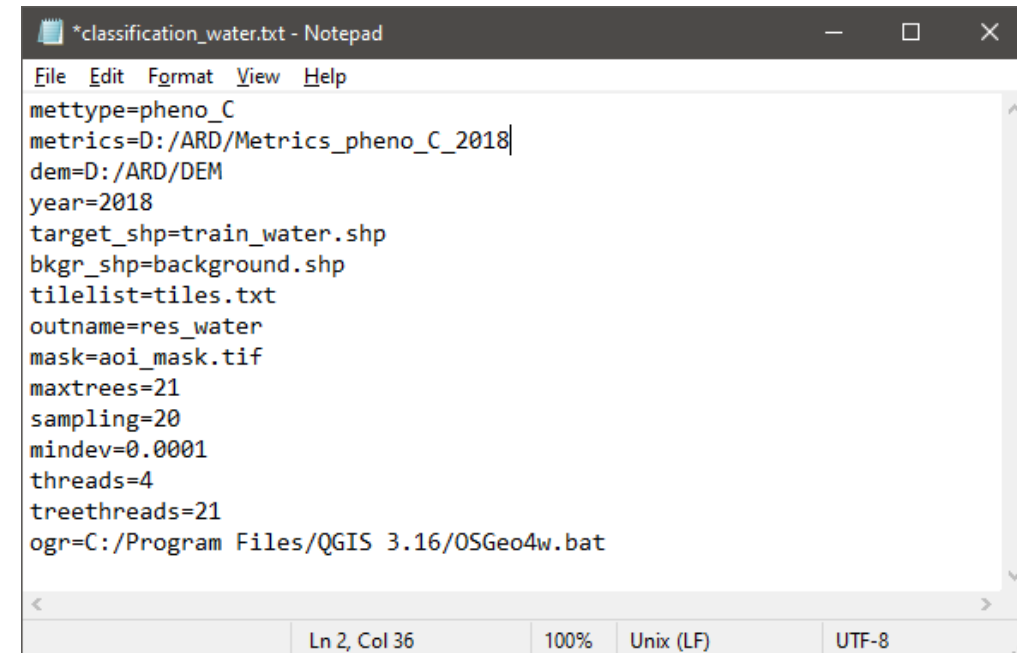
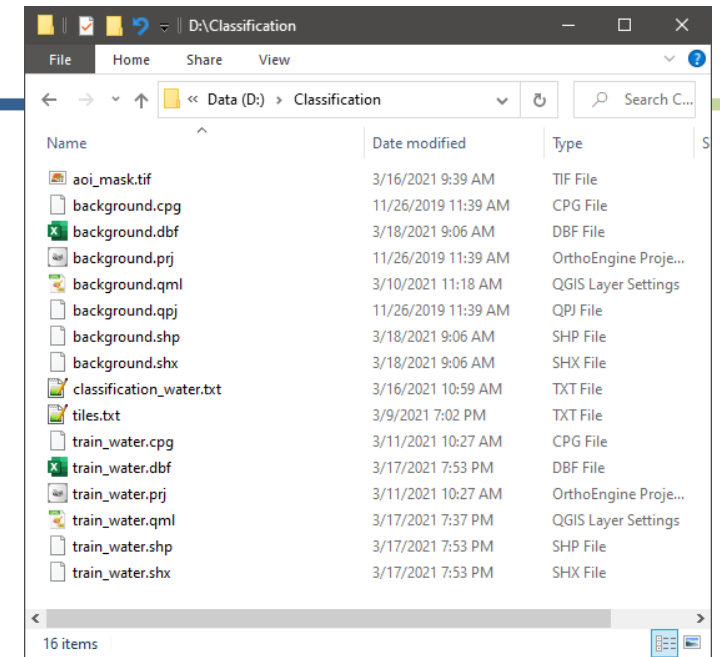
Drawing training polygons using Google Earth data in QGIS (using QMS plugin)



Land Cover Mapping

1. Make a separate folder with the following files:
 - tiles.txt (list of tiles)
 - classification_water.txt (classification parameter file, see below)
 - A shapefile for the target class (i.e. train_water.shp)
 - A shapefile for the background class (i.e. background.shp)
 - *aoi_mask.tif (AOI mask) (*optional)*
2. Edit training shapefiles
3. Prepare classification parameter file (see section 7.2. of the User Manual).
4. Before running classification, save both training shapefiles, project file, and close QGIS.
5. Open the CMD in the classification project folder and run the following command:

```
perl C:/GLAD_1.1/classification.pl classification_water.txt
```



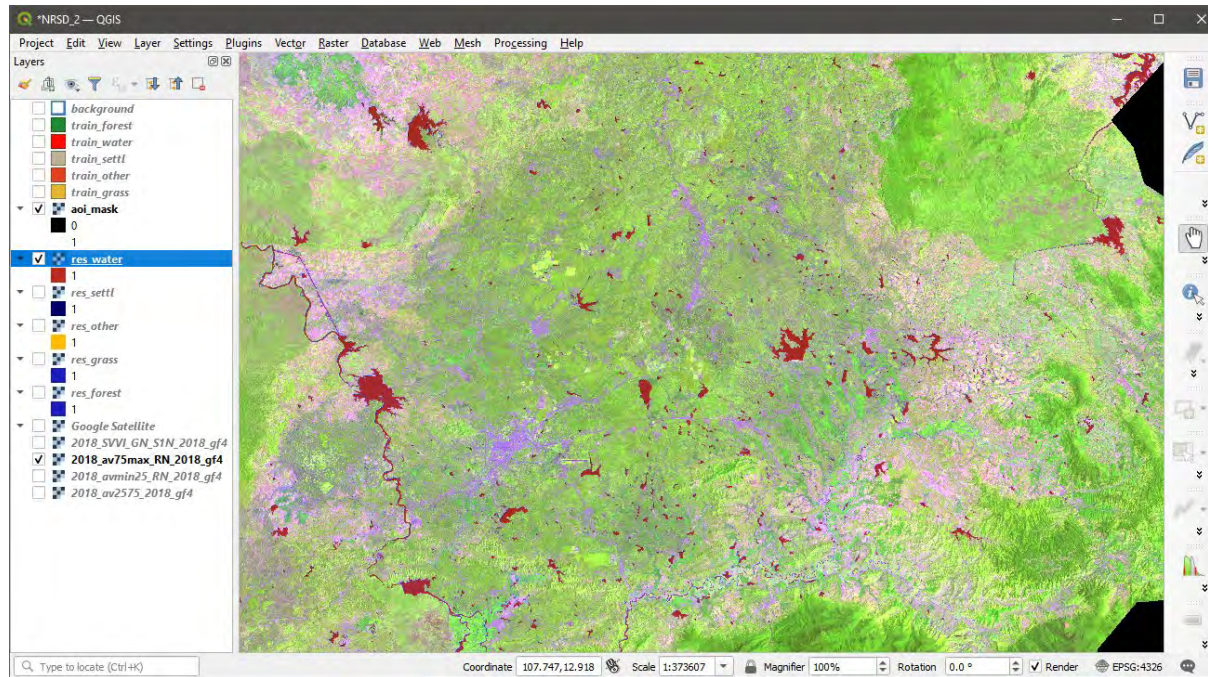
Land Cover Mapping

Open QGIS and load the classification result (res_water.tif).

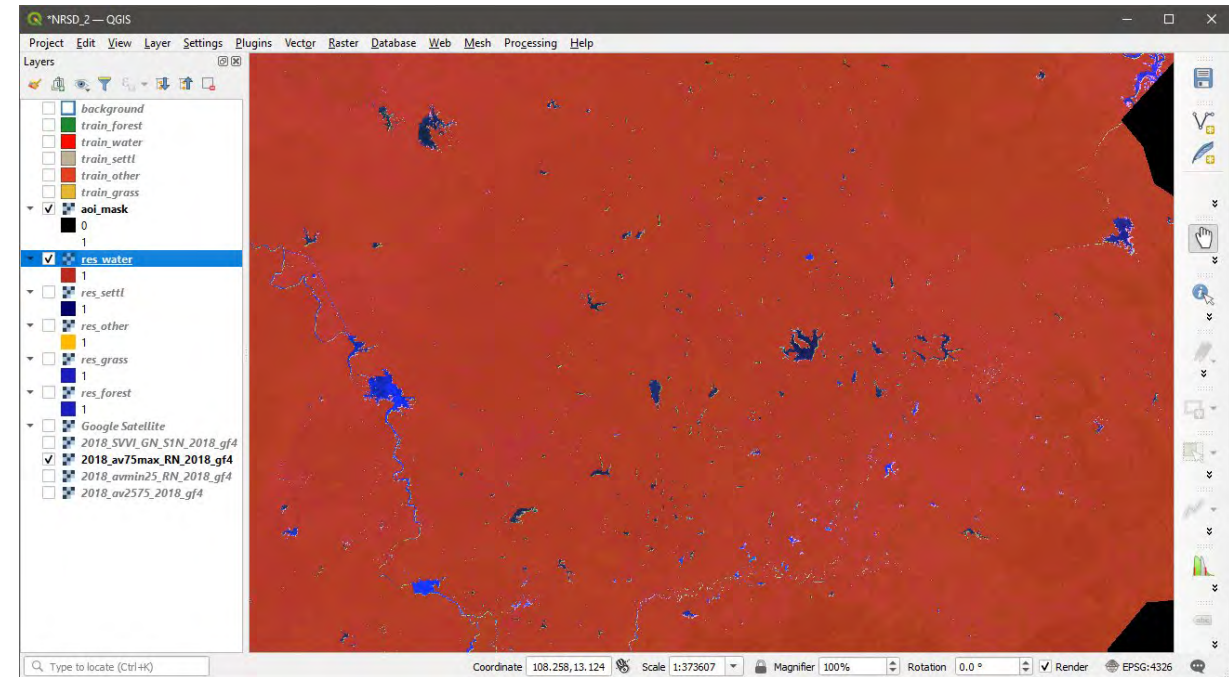
Use “single band pseudocolor” visualization type with a single value (1).

Set up layer transparency to mask out values below 50 (the likelihood threshold of the target class).

Mask of the target class (transparency 0-49)



Mask of the background class (transparency 50-100)



Land Cover Mapping

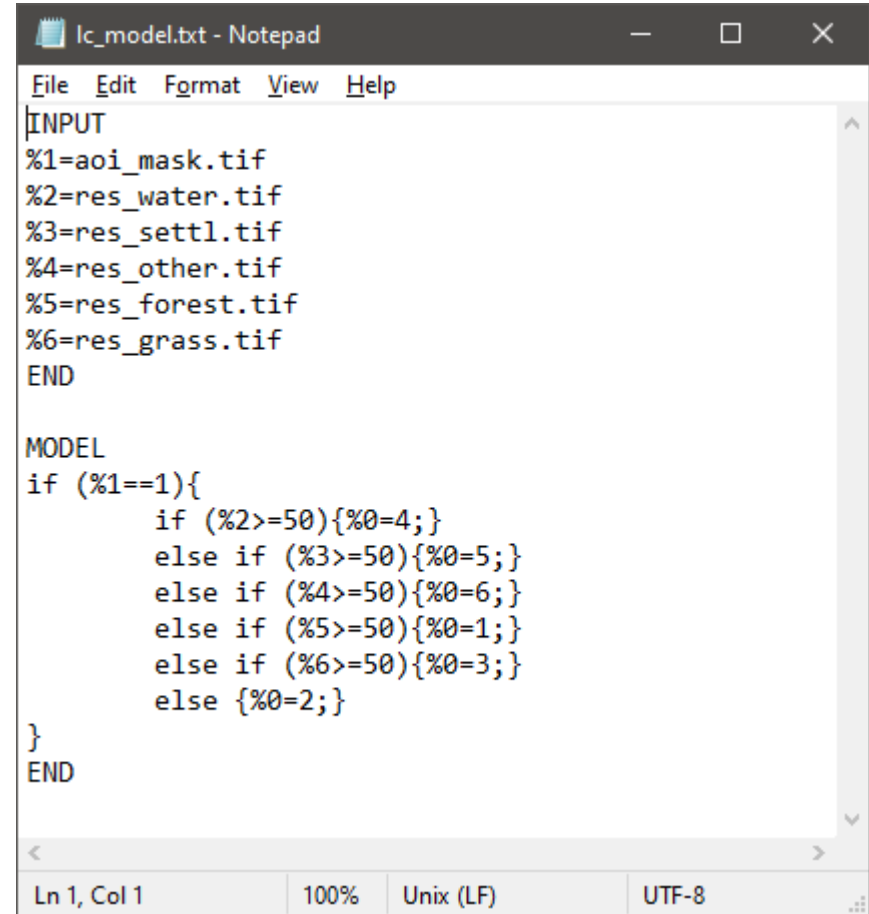
If separate classifications were used to create a set of land cover classes, the Image Modeler tool (User Manual, section 9.2) is employed to aggregate the output class likelihood maps into a LC/LU map. The model (lc_model.txt) assign the final class following the class priority

To run the model, use the following CMD command:

```
perl C:/GLAD_1.1/raster_model.pl lc_model.txt lc_2018.tif
```

The output map has the following classes (pixel values):

1. Forest
2. Cropland
3. Grassland/shrubland
4. Wetland
5. Settlements
6. Other land

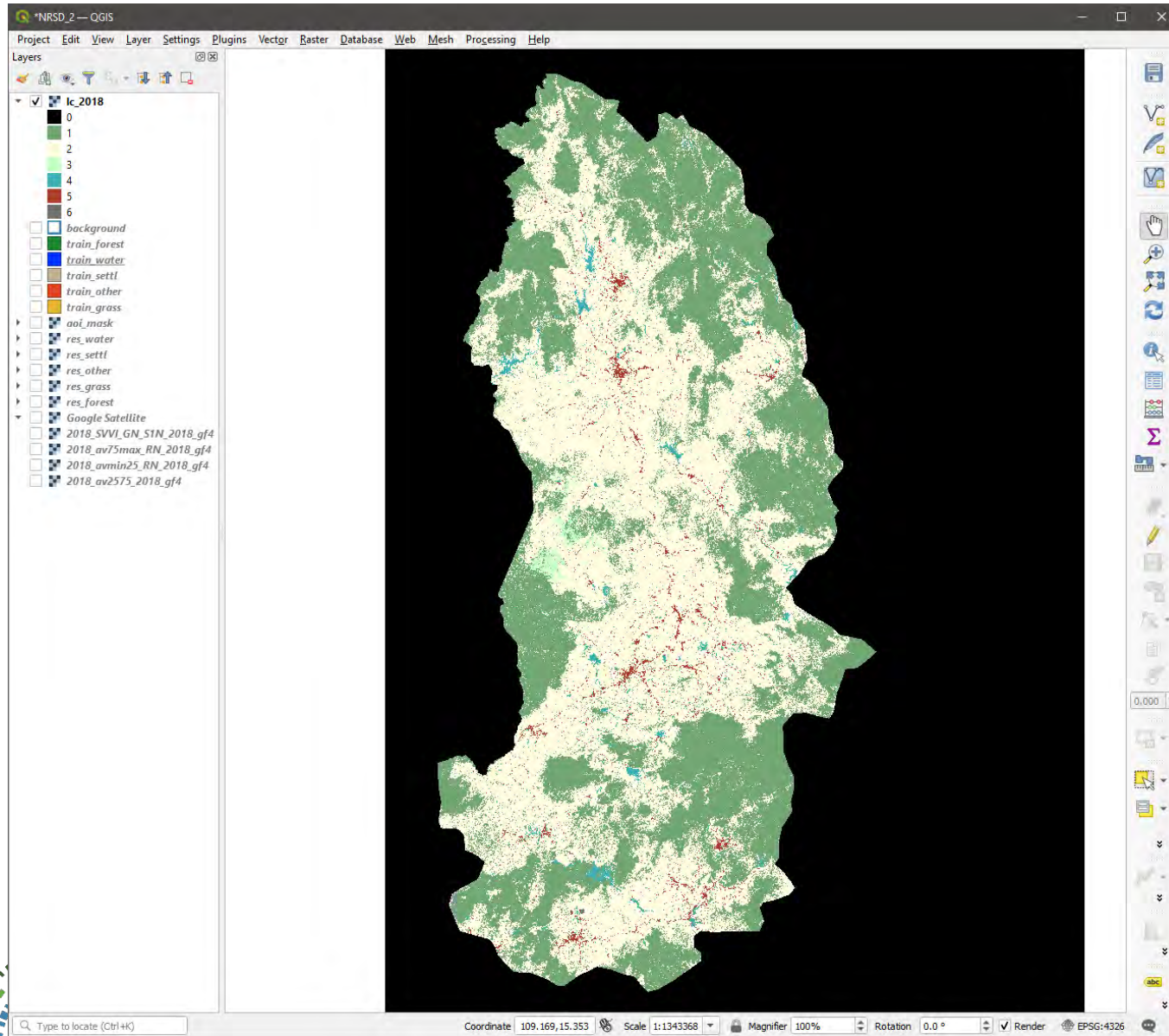


```
lc_model.txt - Notepad
File Edit Format View Help
INPUT
%1=aoi_mask.tif
%2=res_water.tif
%3=res_settl.tif
%4=res_other.tif
%5=res_forest.tif
%6=res_grass.tif
END

MODEL
if (%1==1){
    if (%2>=50){%0=4;}
    else if (%3>=50){%0=5;}
    else if (%4>=50){%0=6;}
    else if (%5>=50){%0=1;}
    else if (%6>=50){%0=3;}
    else {%0=2;}
}
END

Ln 1, Col 1    100%    Unix (LF)    UTF-8
```


Land Cover Mapping



The data is in geographic coordinates, and so the pixel area depends on the latitude. The area estimation tool is design to calculate area of a LC/LU map using spherical trapezoid method for pixel area calculation.

To calculate area of each class, use the following command:

```
C:\GLAD_1.1\get_area.exe lc_2018.tif
```

1. Forest
2. Cropland
3. Grassland/shrubland
4. Water/wetland
5. Settlements
6. Other land

Change Detection Metrics



Indonesia: Band 5 difference 2000 – maximum for 2000-2005

Change Detection Metrics

YYYY_B_T_S_C.tif

Where:

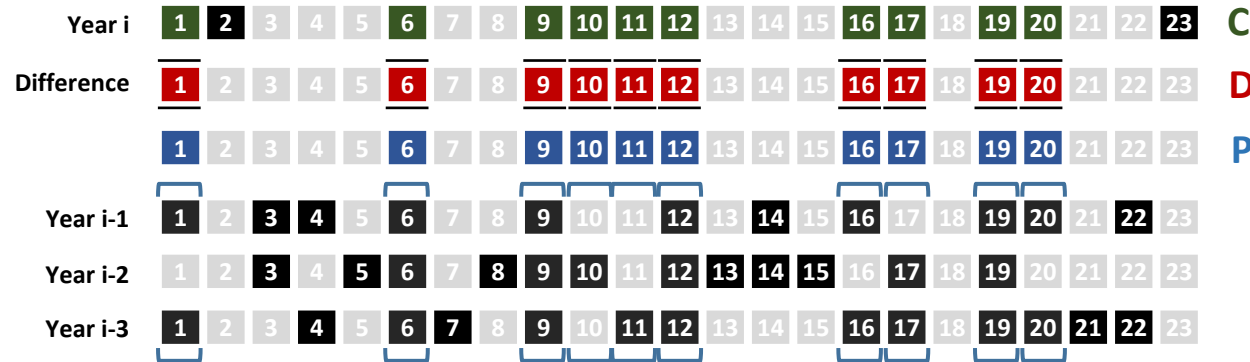
YYYY – corresponding year

B – spectral band or index

T – time-series from which the statistics were extracted. “c” represent the current year (time-series C), “p” stands for the preceding year (time-series P) and “dif” stands for a time-series of per-16-day interval differences between (time-series D). Regression and standard deviation metrics, which are calculated from the entire time-series, does not have this name section.

S – statistic

C – corresponding band or index used for ranking (only for metrics extracted from ranks defined by a corresponding value)



Source 16-day time-series C and time-series P data

Blue
Green
Red
NIR
SWIR1
SWIR2
Red/NIR* (NDVI)
SWIR1/NIR*
SWIR1/SWIR2*
Thermal
Quality flag

Metrics based on time-series P

Metrics based on time-series C

Corresponding NDVI ranks

Minimum (MIN)
Maximum (MAX)
Second lowest (SL)
Second highest (SH)
Q2

Corresponding Thermal band ranks

Minimum (MIN)
Maximum (MAX)
Second lowest (SL)
Second highest (SH)
Q2

Individual band ranks

Minimum (MIN)
Maximum (MAX)
Second lowest (SL)
Second highest (SH)
Q2
Average [MIN .. MAX]
Average [SL.. SH]

Source per-16-day interval differences (time-series D)

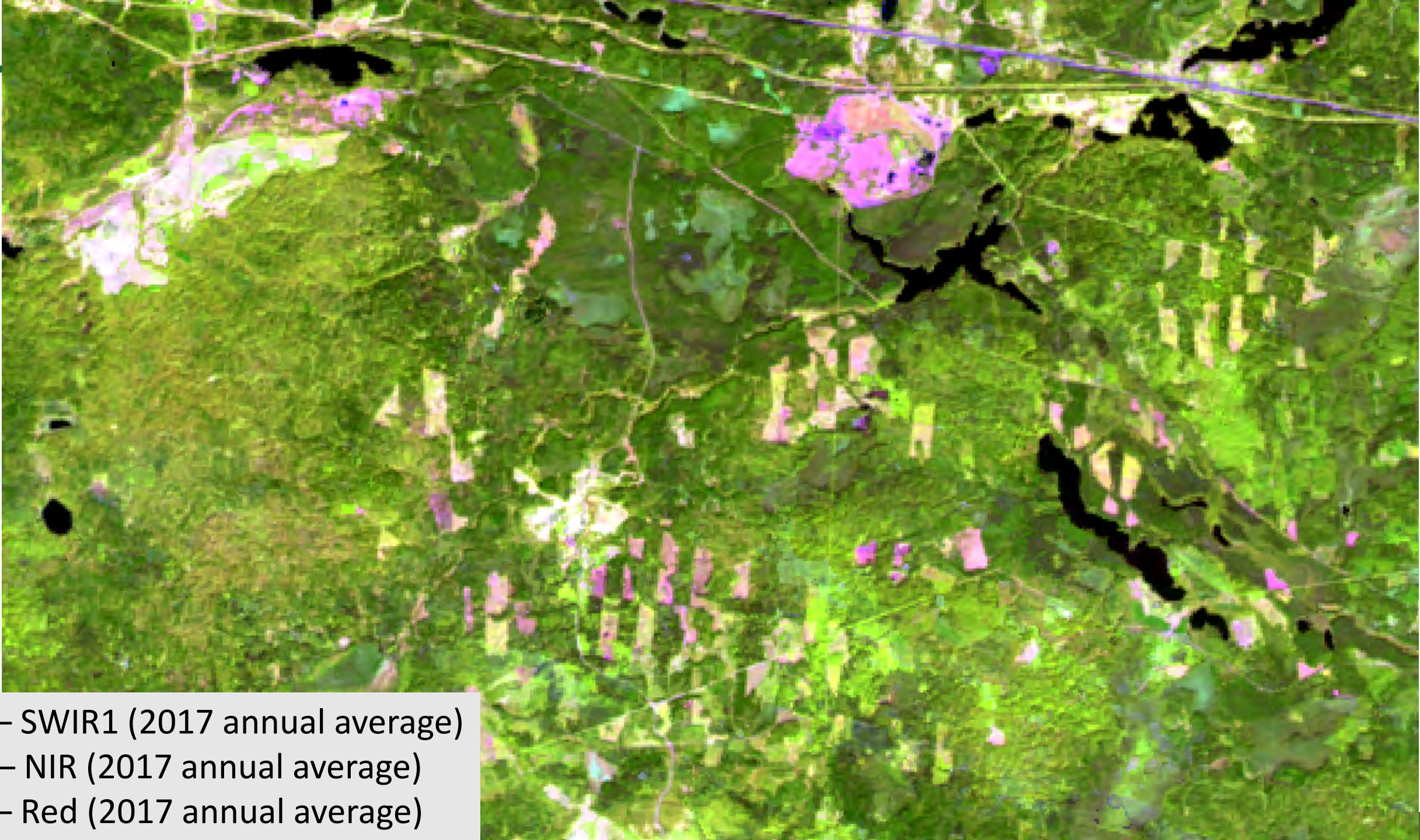
Blue
Green
Red
NIR
SWIR1
SWIR2
Red/NIR* (NDVI)
SWIR1/NIR*
SWIR1/SWIR2*

Metrics based on time series P and C

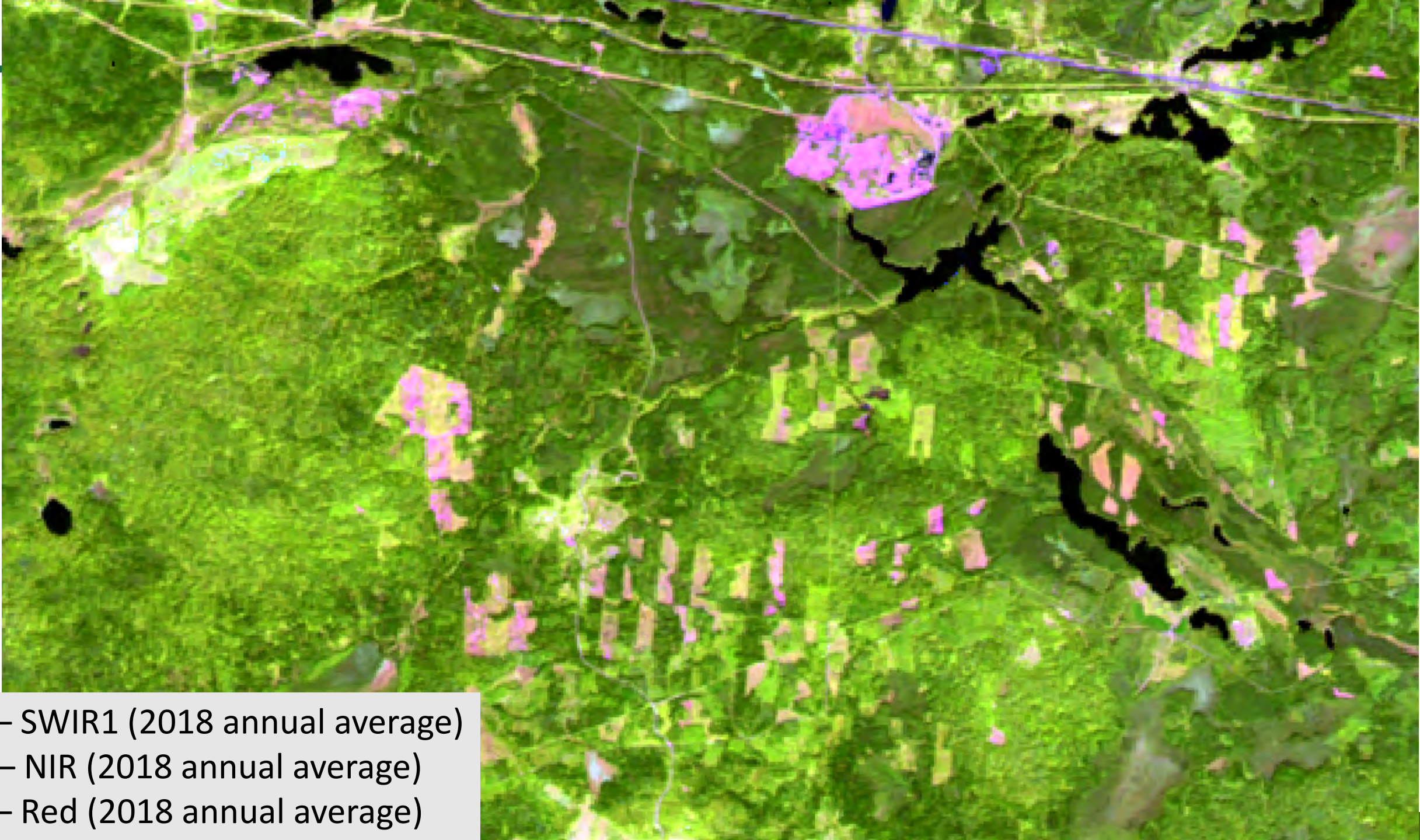
Standard deviation (SD)
Slope of linear regression (REG)

Metrics based on per-16-day interval differences

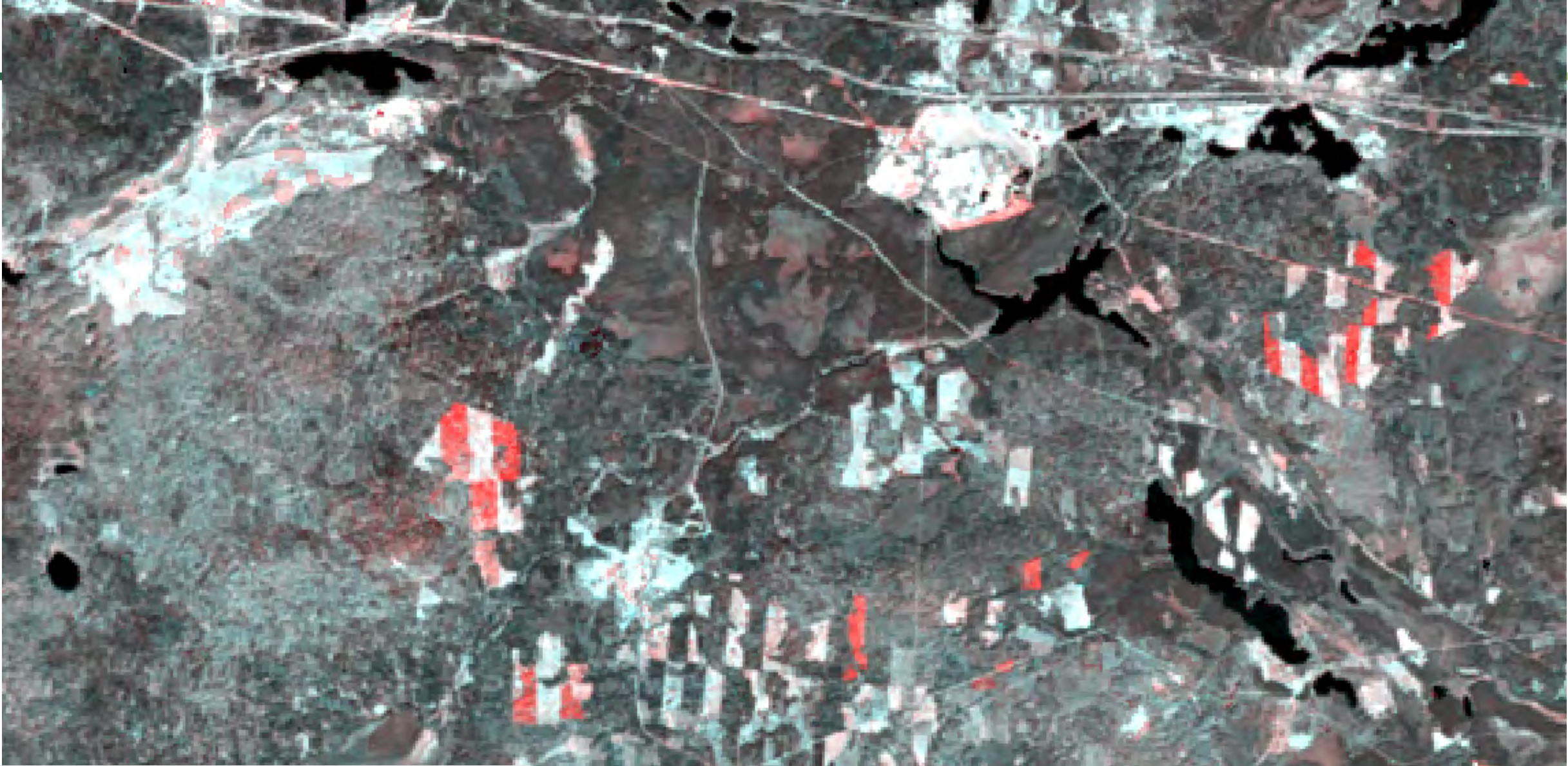
Minimum (MIN)
Maximum (MAX)
Second lowest (SL)
Second highest (SH)
Average [MIN .. MAX]
Average [SL.. SH]



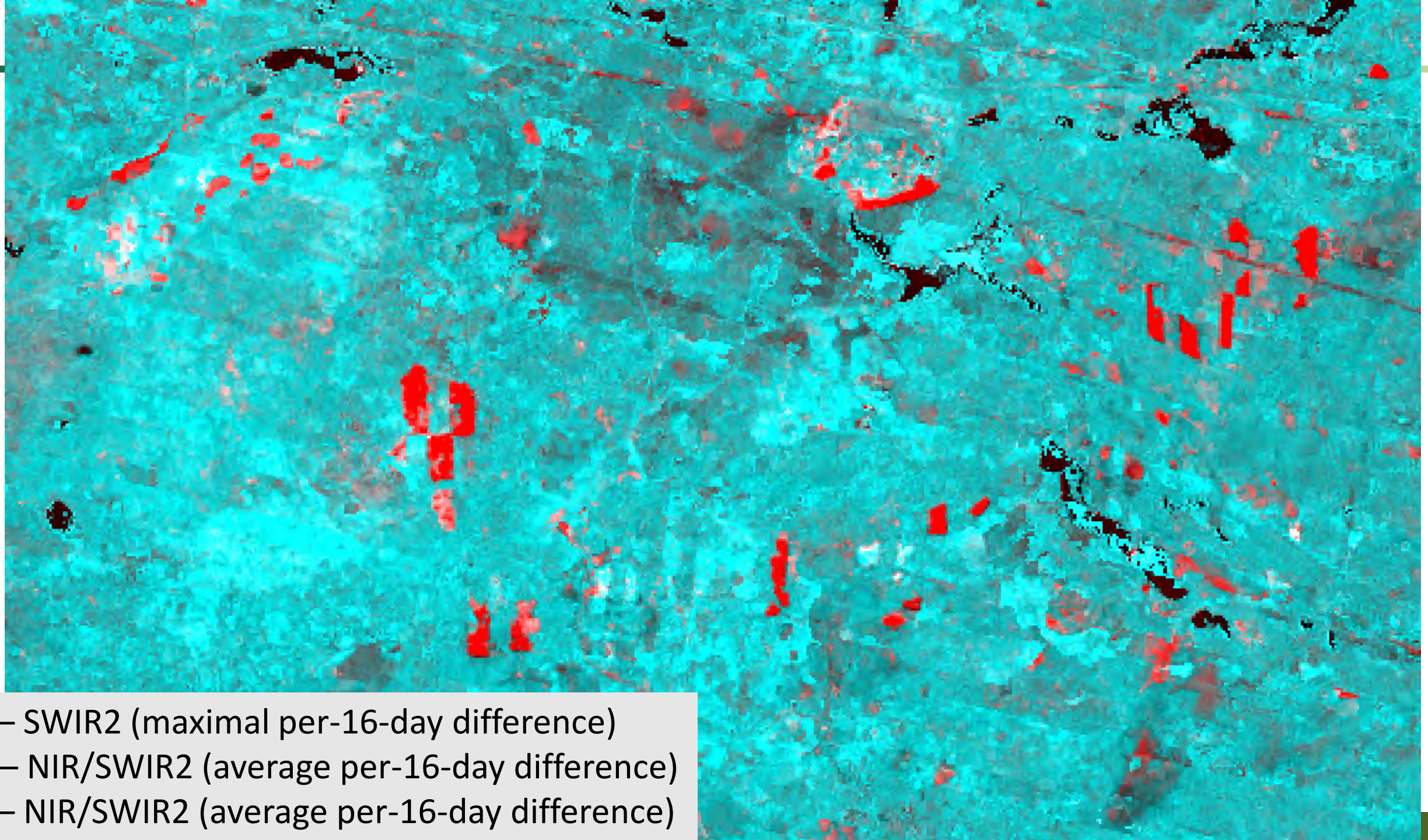
R – SWIR1 (2017 annual average)
G – NIR (2017 annual average)
B – Red (2017 annual average)



R – SWIR1 (2018 annual average)
G – NIR (2018 annual average)
B – Red (2018 annual average)

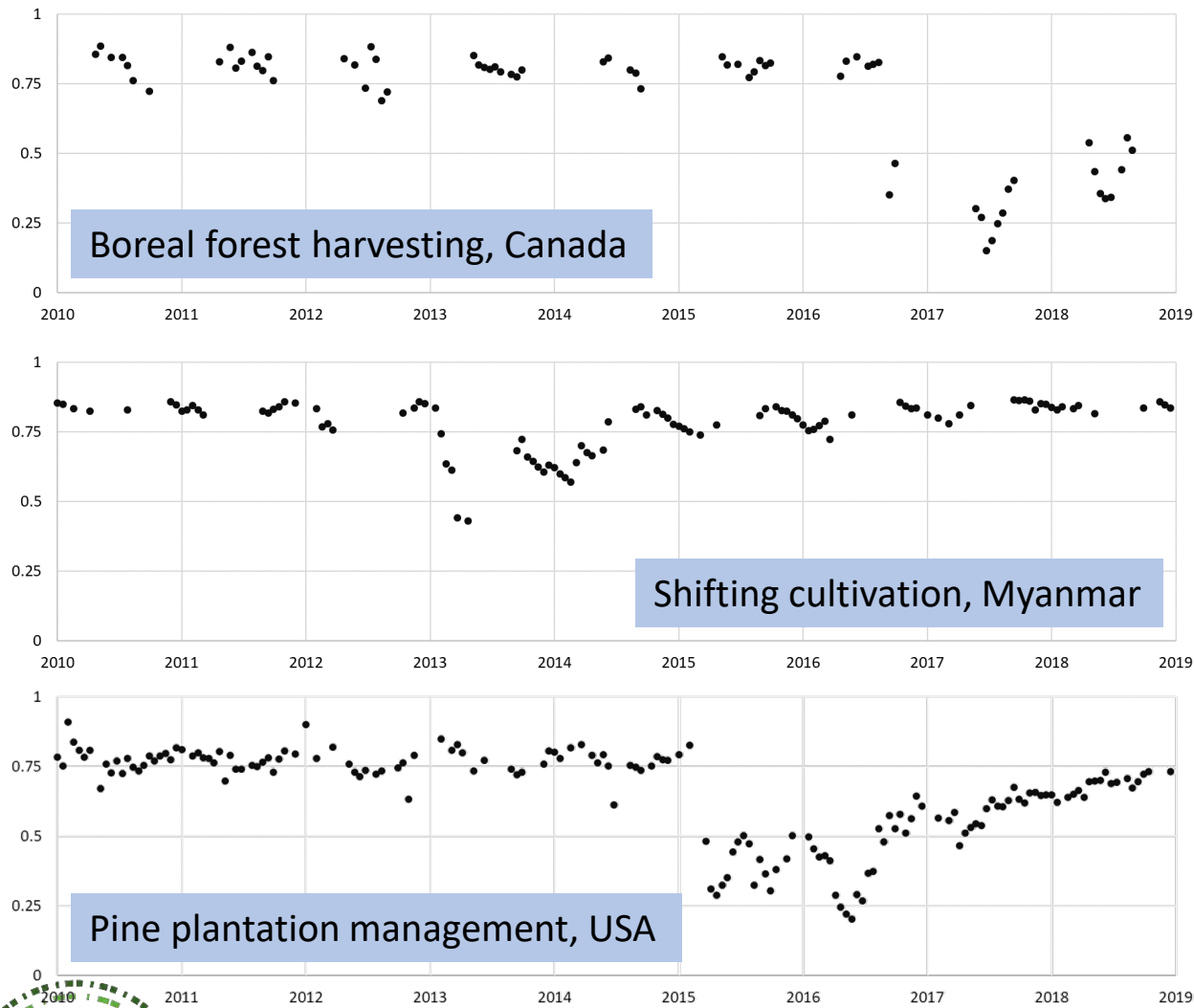


R – SWIR1 (2018 annual average)
G – SWIR1 (2017 annual average)
B – SWIR1 (2017 annual average)

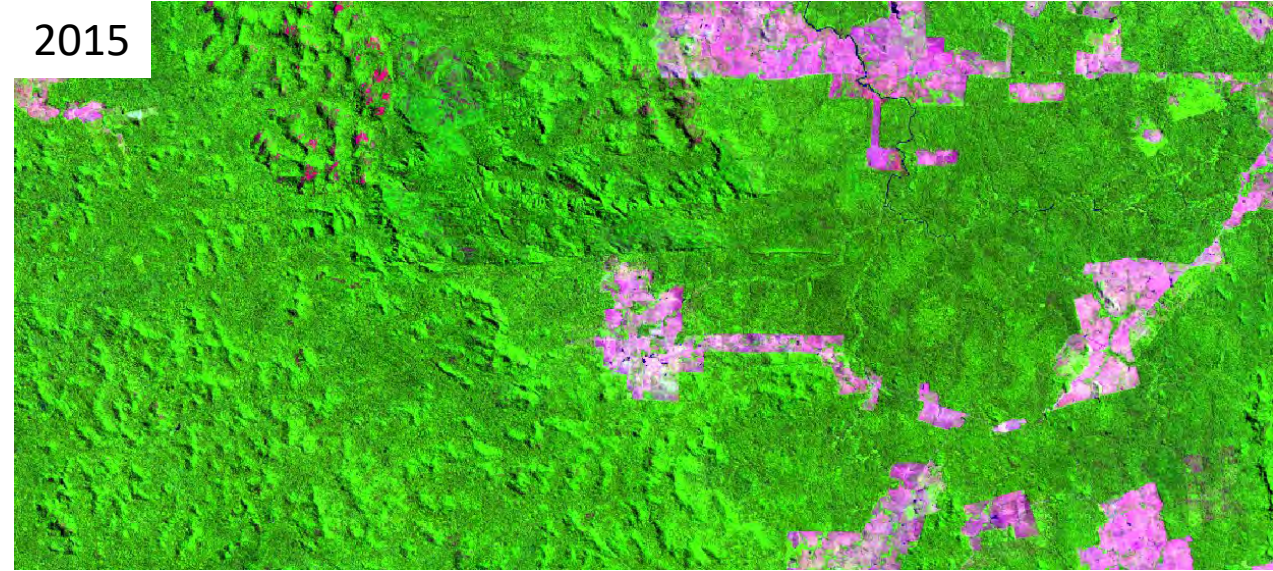


Change Detection Metrics

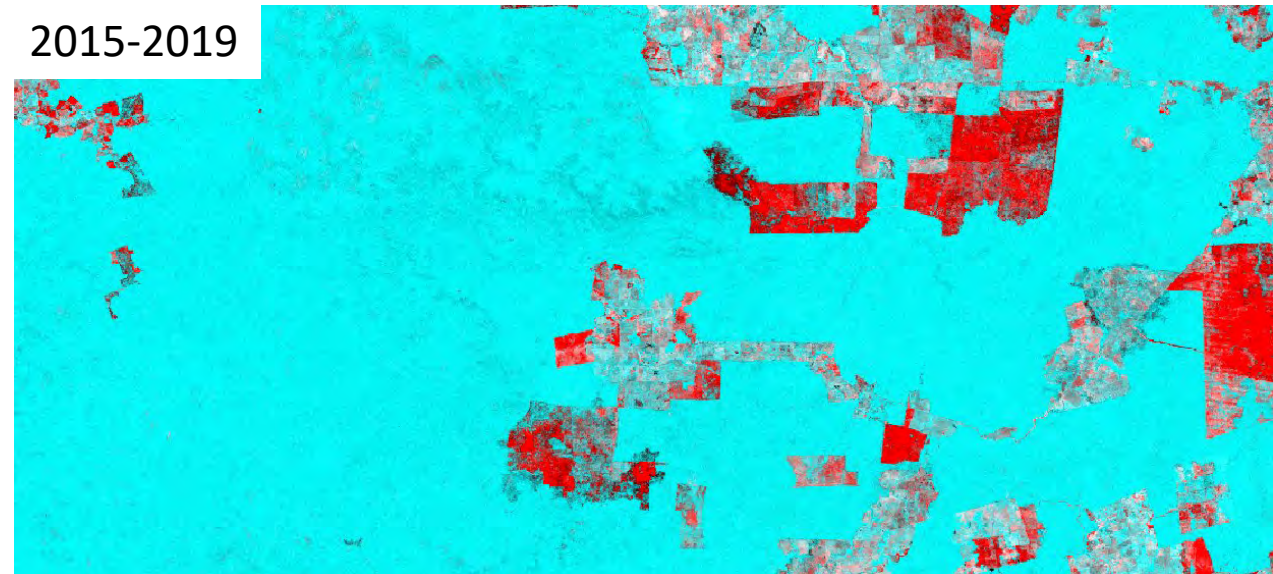
NDVI temporal profiles extracted from the 2010–2018 GLAD ARD



2015



2015-2019



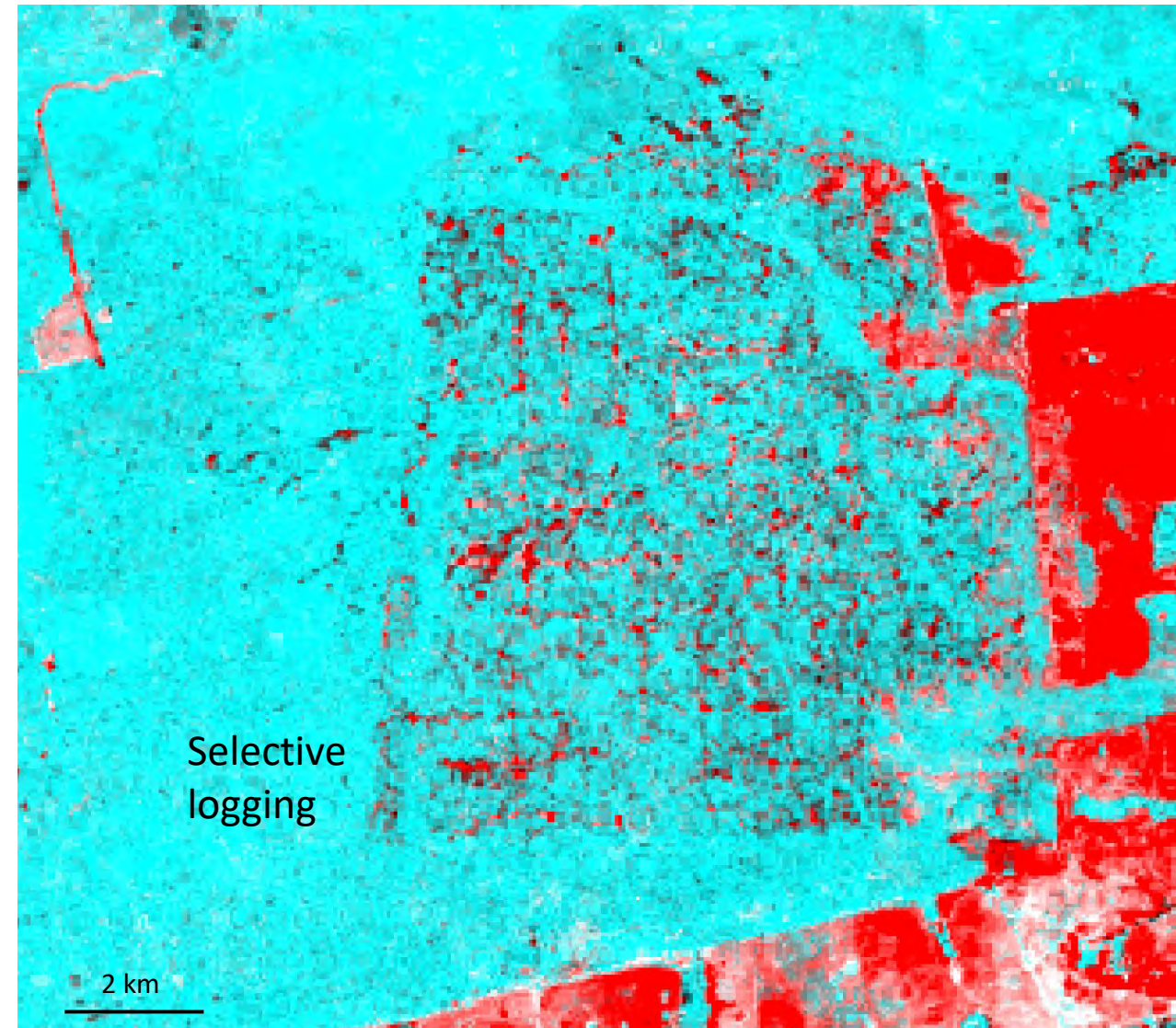
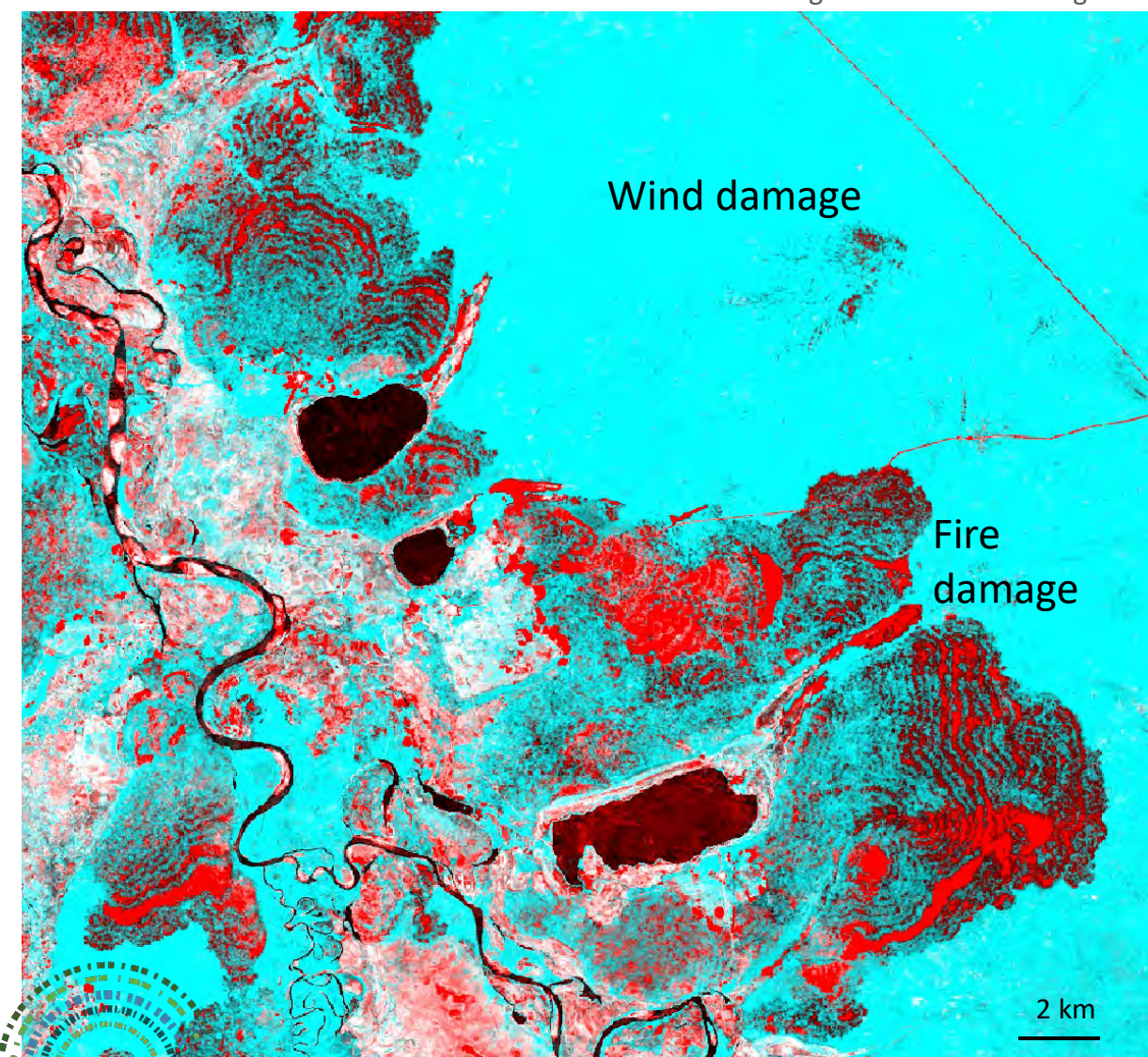
red: maximum per-16-day-interval SWIR2 band difference
green and blue: average per-16-day-interval NIR/SWIR2 normalized ratio
difference

Change Detection Metrics

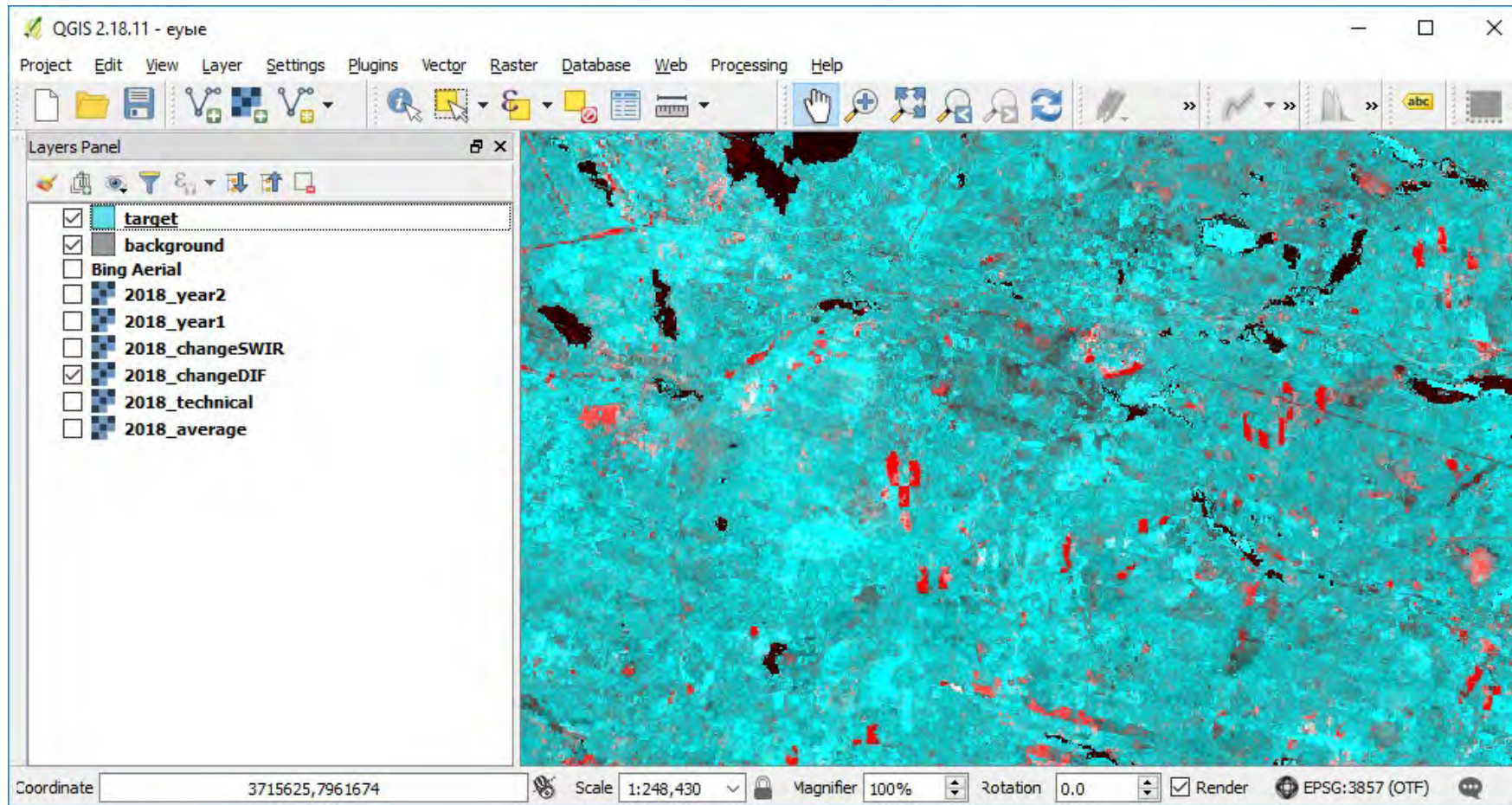
Xingu River, Brazil (MT)

red: maximum SWIR2 band difference
green and blue: average NIR/SWIR2 normalized ratio difference

Amazon Basin Forests, Brazil (MT)



Change Classification



Training data collected as a set of polygonal shapefiles within the AOI.

Change areas considered as a “target” class. All other land cover are considered as the “background” class for the classification.

Change Classification

Training data collected as a set of polygonal shapefiles within the AOI.
Change areas considered as a “target” class. All other land cover are considered as the “background” class for the classification.

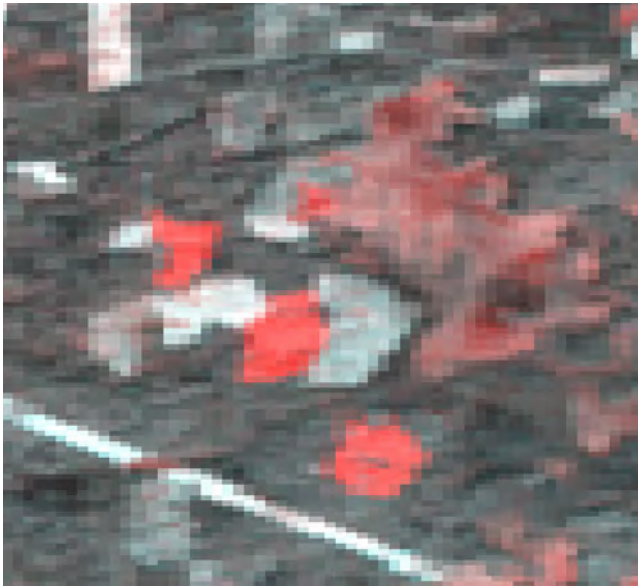
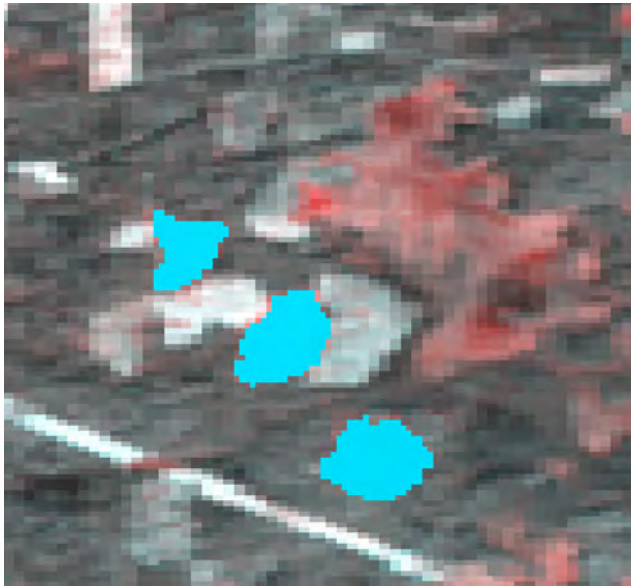
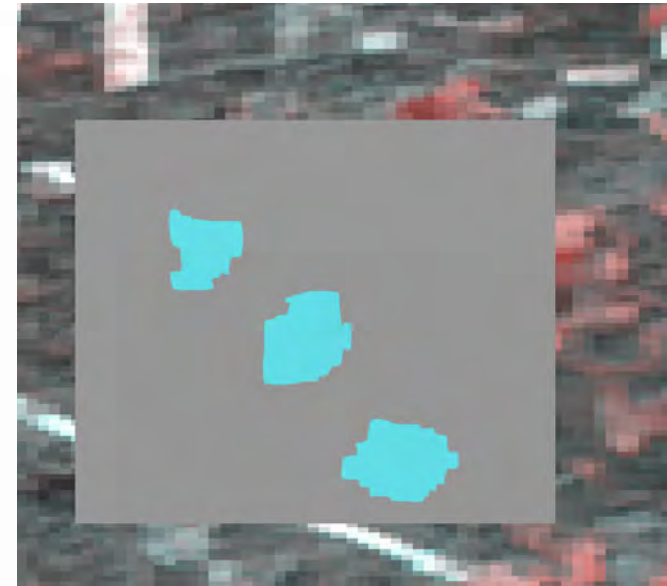


Image composite

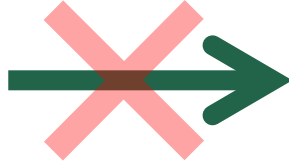
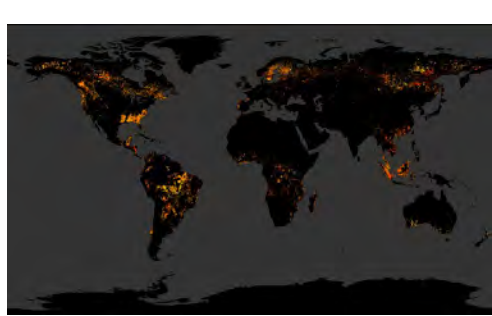


Target training



Background training (overlaid with target training)

Integrating Mapping and Statistical Sampling



Direct area
extraction from
the national or
global maps

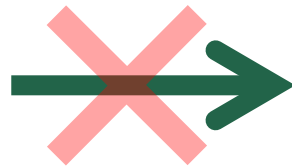
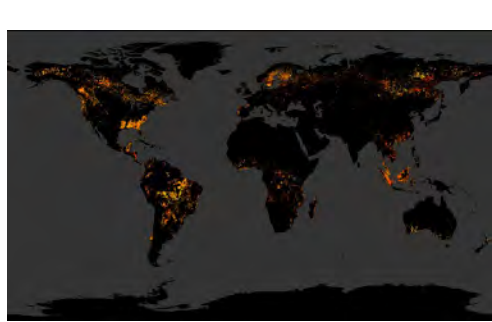


Satellite-based maps provides spatially consistent, wall-to-wall data...

However:

- All maps derived from remotely sensed data contain errors due to data limitation, classification/change detection algorithm limitation, analyst errors and bias, etc.
- Errors usually introduce bias in area estimations. The map errors may be spatially biased.
- The uncertainty of classification may not be estimated from the map alone.

Integrating Mapping and Statistical Sampling



Direct area extraction from the national or global maps



Recommend “good practice” for area reporting

National (wall-to-wall) land cover mapping and monitoring

- Usually implemented using free-of-charge remotely sensed data, or using regionally consistent analysis ready data, such as RLCMS.
- National mapping should be automated for sustainable annual application.

Stratified sampling design increases sample analysis efficiency (low uncertainty with fewer samples).

Sample reference data used for **map accuracy assessment**.

Sample analysis (national or sub-national)

- Reference data collected from free-of-charge or commercial remotely sensed imagery and using field measurements.
- Allows estimation of the unbiased area of land cover classes and changes with known uncertainties.
- Additional thematic attribution is possible (i.e., change drivers).

Sample analysis that employs probability sampling allows to estimate the **unbiased area** of land cover classes and change; estimate area **uncertainty**; and perform **value-added thematic analysis** based on sample reference data (e.g. differentiate land cover change by drivers).

Satellite-based maps provides spatially consistent, wall-to-wall data...

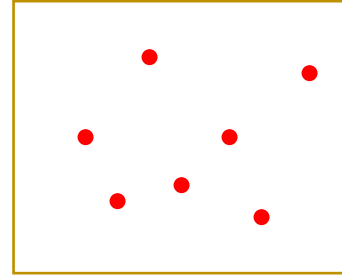
However:

- All maps derived from remotely sensed data contain errors due to data limitation, classification/change detection algorithm limitation, analyst errors and bias, etc.
- Errors usually introduce bias in area estimations. The map errors may be spatially biased.
- The uncertainty of classification may not be estimated from the map alone.

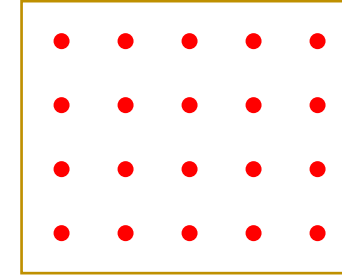
Integrating Mapping and Statistical Sampling

Common probability sampling designs

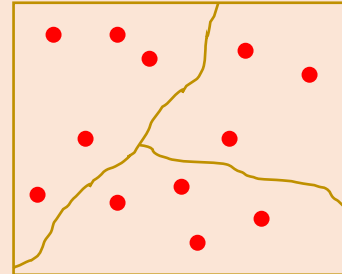
1. Simple random



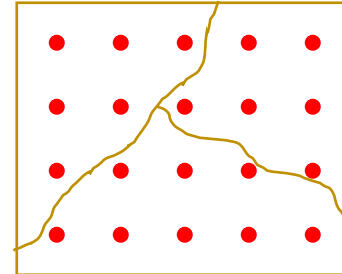
2. Systematic



3. Stratified random

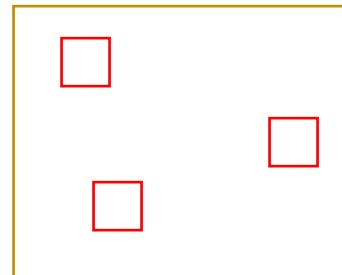


3. Stratified systematic



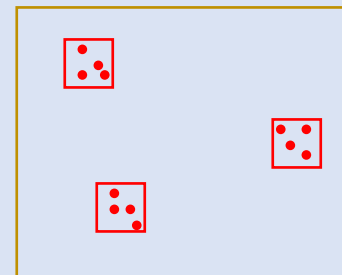
4. Cluster random one-stage

Reference data obtained for all pixels in the block (cluster)



4. Cluster random two-stage

Reference data obtained for a sample of pixels in the block (cluster)



Integrating Mapping and Statistical Sampling

Estimating
deforestation in Legal
Brazilian Amazon
using different
sampling design



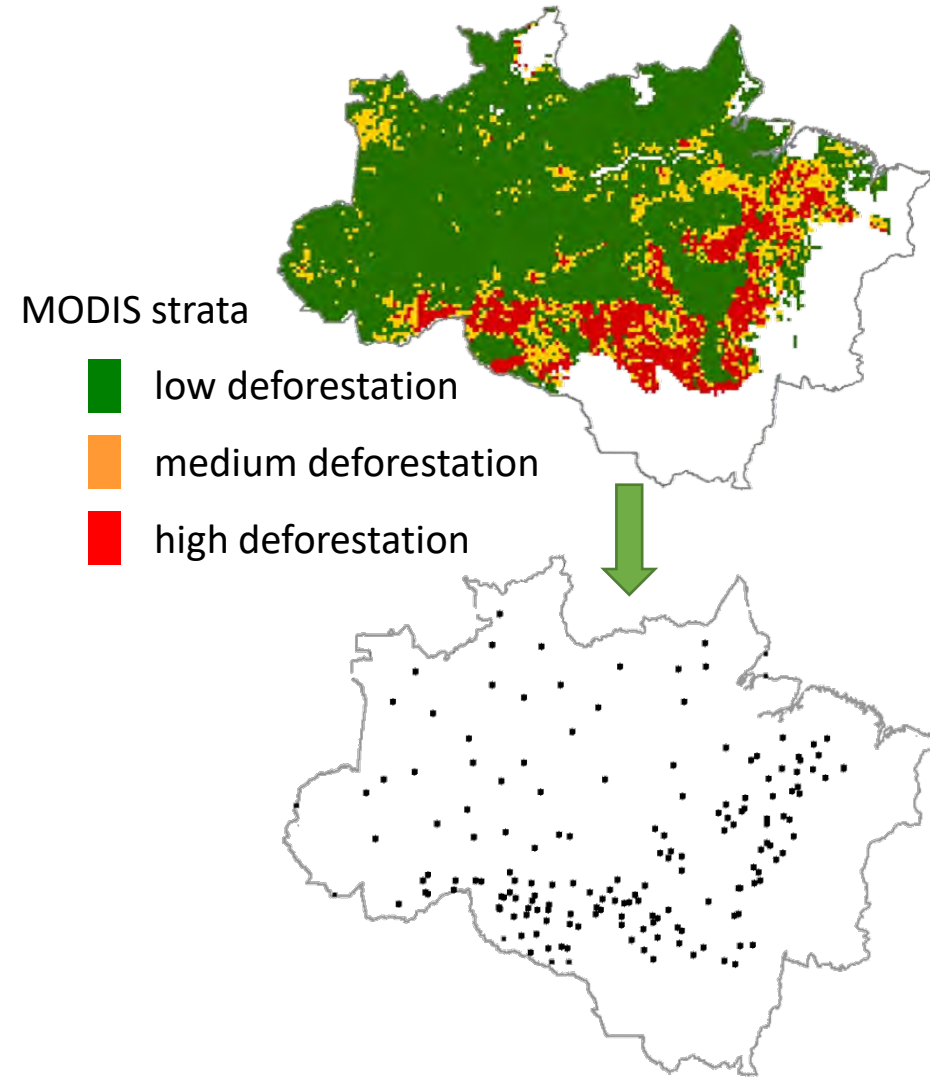
Random sampling



Systematic sampling



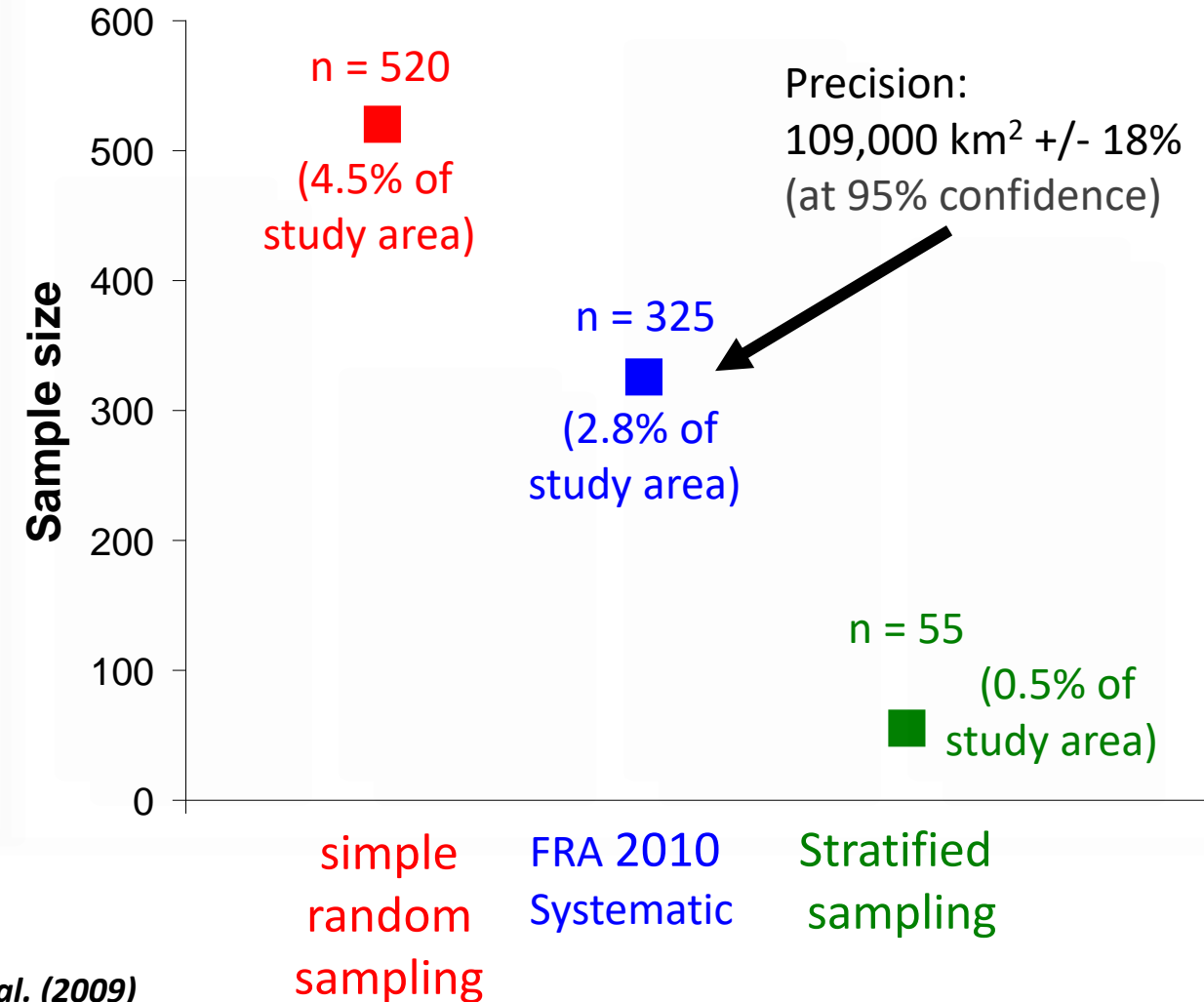
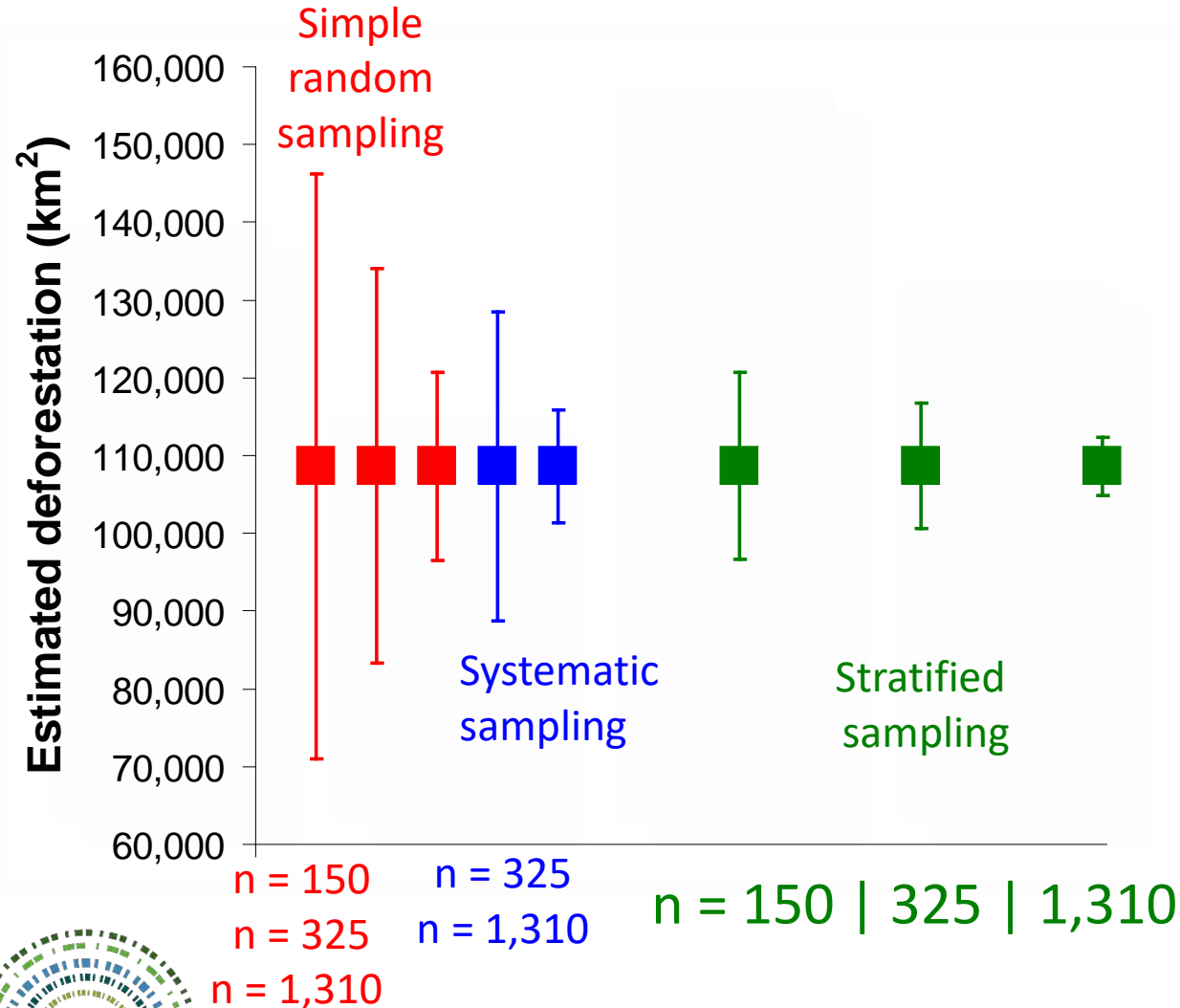
Stratified sampling



Integrating Mapping and Statistical Sampling

Random Systematic Stratified sampling

Sample size needed to achieve precision of FRA 2010
(systematic one-degree grid design)



Broich et al. (2009)

Integrating Mapping and Statistical Sampling

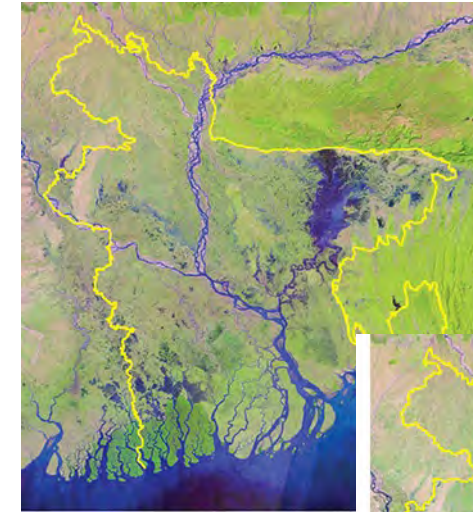
Stehman (2009)

Table 4. Relative strengths and weaknesses of basic sampling designs according to desirable design criteria. The criteria are: *C1*) probability sample, *C2*) practical, *C3*) cost, *C4*) spatial balance, *C5*) precise estimates of class-specific accuracy, *C6*) ability to estimate standard errors, and *C7*) flexible to change in sample size. The rating symbols are ●=strength and ○=weakness; absence of a symbol indicates the design is 'neutral' with regard to that criterion. See also section 5.4 in text.

Design	<i>C1</i>	<i>C2</i>	<i>C3</i>	<i>C4</i>	<i>C5</i>	<i>C6</i>	<i>C7</i>
<i>D1</i> : Simple random	●	●	○	○	○	●	●
<i>D2</i> : Systematic	●	●	○	●	○	○	○
<i>D3</i> : Stratified (land cover) random	●	●	○	○	●	●	●
<i>D4</i> : Stratified (land cover) systematic	●		○		●	○	○
<i>D5a</i> : Stratified (spatial) random ($n_h=1$)	●	●	○	●	○	○	
<i>D5b</i> : Stratified (spatial) random ($n_h>1$)	●	●	○		○	●	●
<i>D6</i> : Stratified (spatial) systematic	●	●	○	●	○	○	○
<i>D7</i> : Cluster random	●		●	○	○	●	
<i>D8</i> : Cluster systematic	●		●		○	○	○
<i>D9</i> : Stratified random cluster	●		●	○			
<i>D10</i> : Stratified systematic cluster	●		●			○	

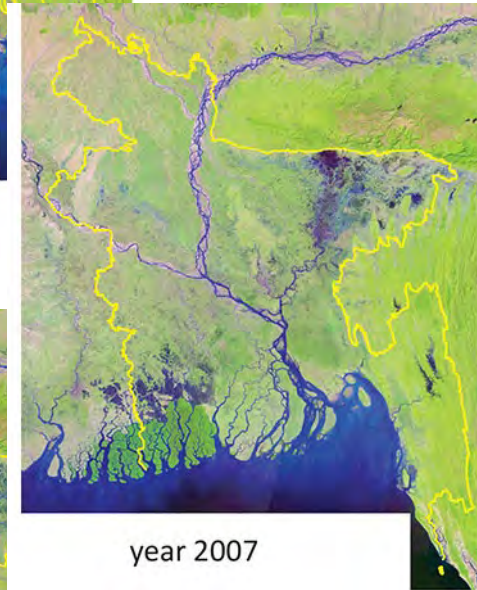
National Forest and TOF Monitoring in Bangladesh

- 156 million people
- 1.5 million ha forests
- Forested land per capita 0.009 ha/person



year 2000

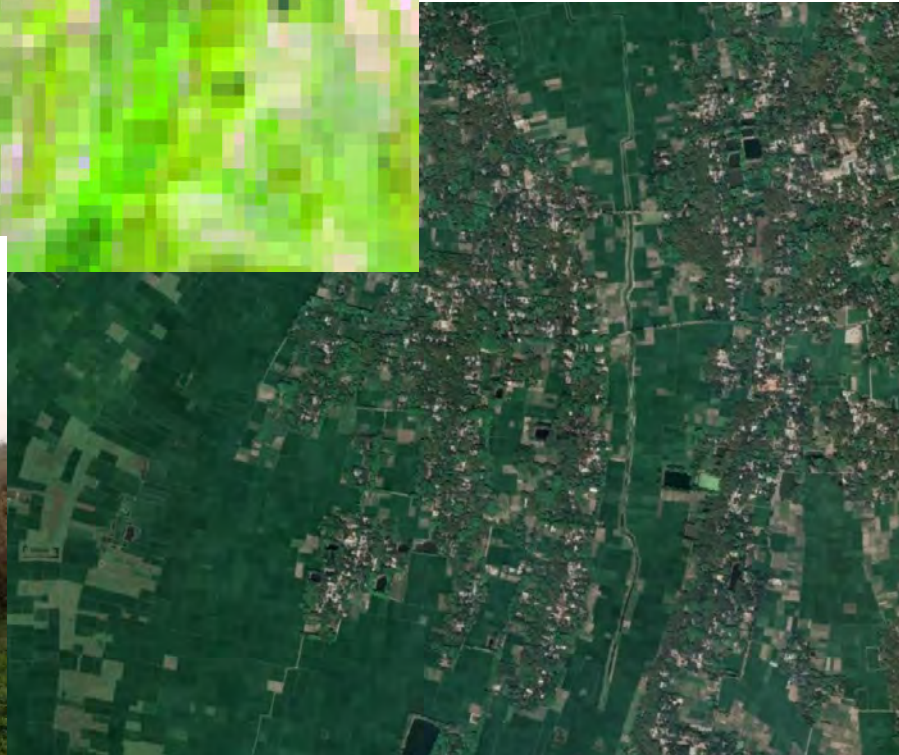
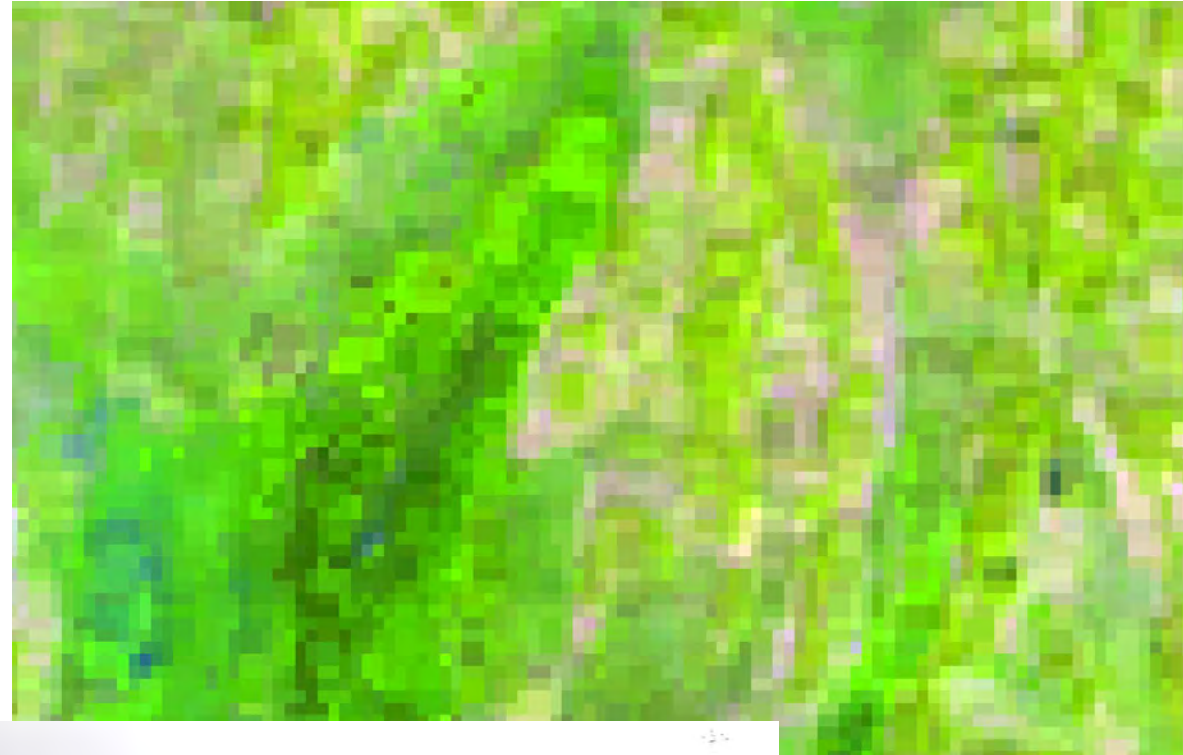
Spatially, and temporally consistent Landsat ARD data



year 2007



year 2014



National Forest and TOF Monitoring in Bangladesh



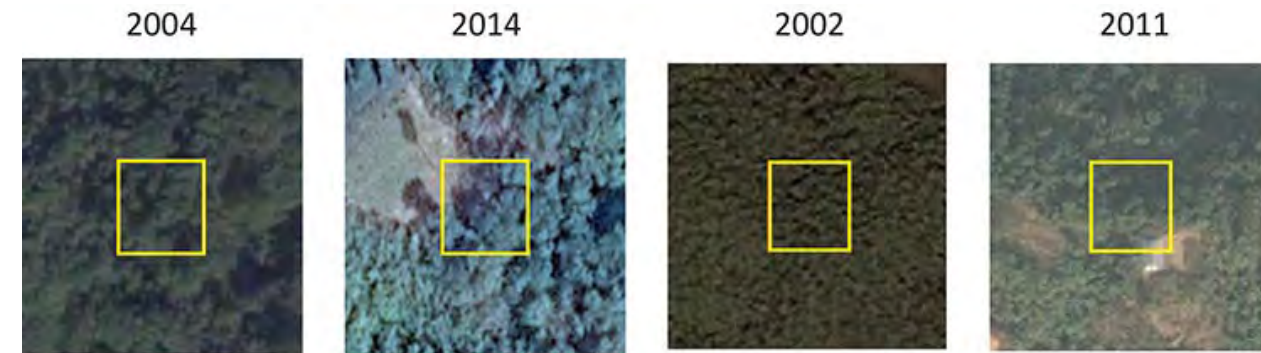
Stratified sampling design

- Stable tree cover/no trees (1,000 samples)
- Gross tree cover loss (1,500 samples)
- Gross tree cover gain (1,500 samples)

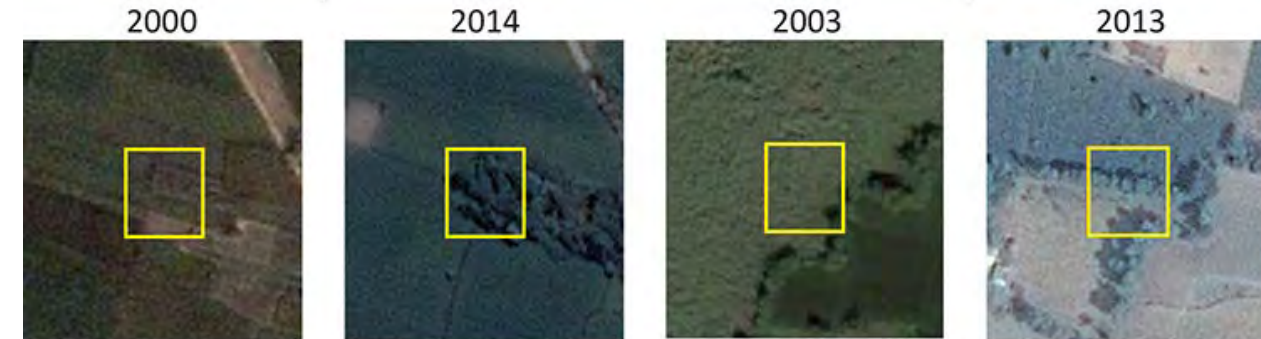


3 sub-plots intersect canopy

Tree cover loss



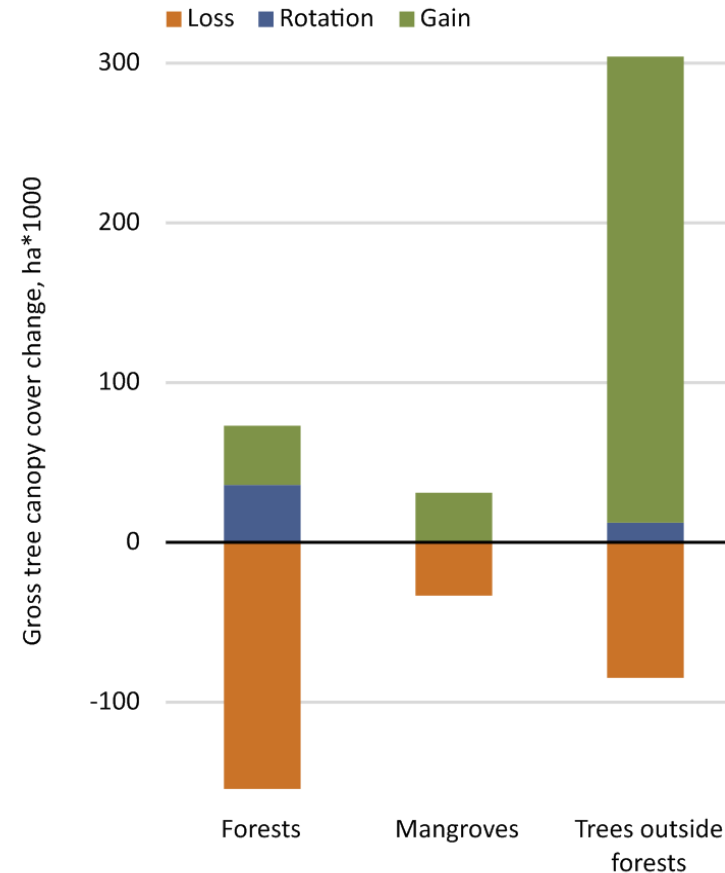
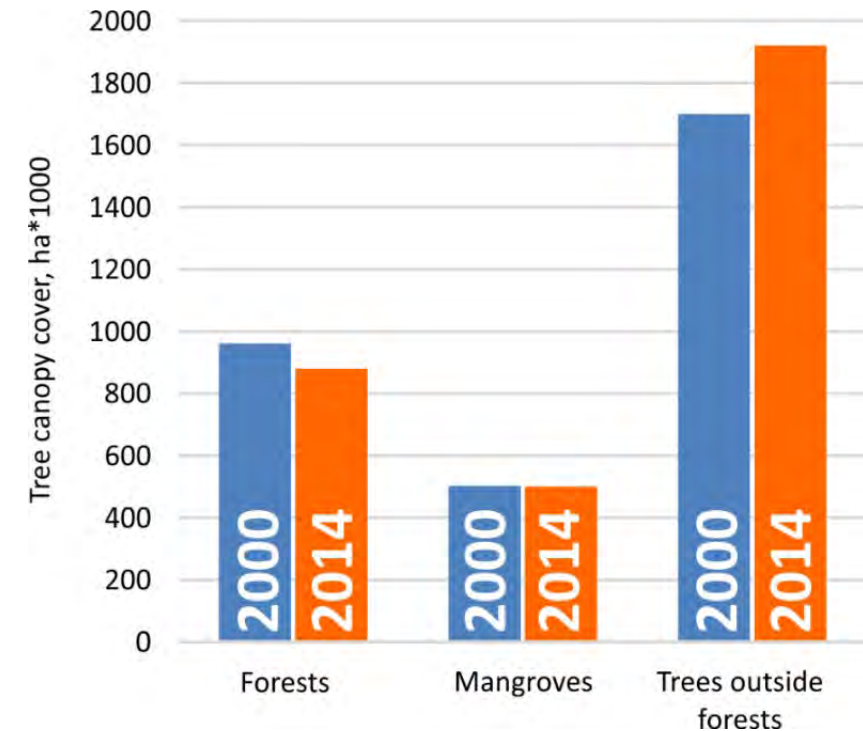
Tree cover gain



National Forest and TOF Monitoring in Bangladesh

National sample-based tree canopy cover and change estimates for Bangladesh

National tree cover dynamics, 2000-2014

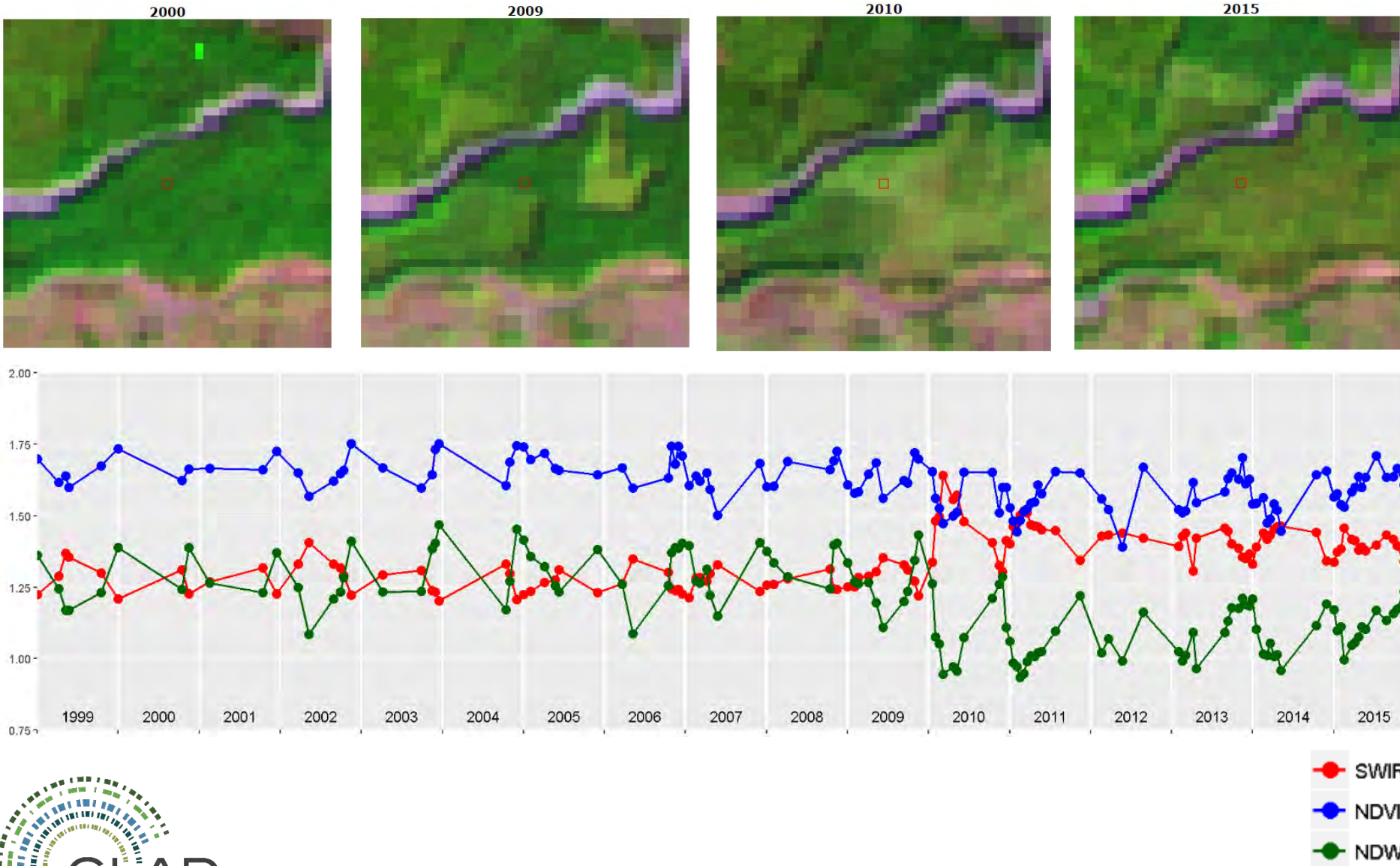


Comparison with FAO FRA report



Using GLAD ARD for Sample Analysis

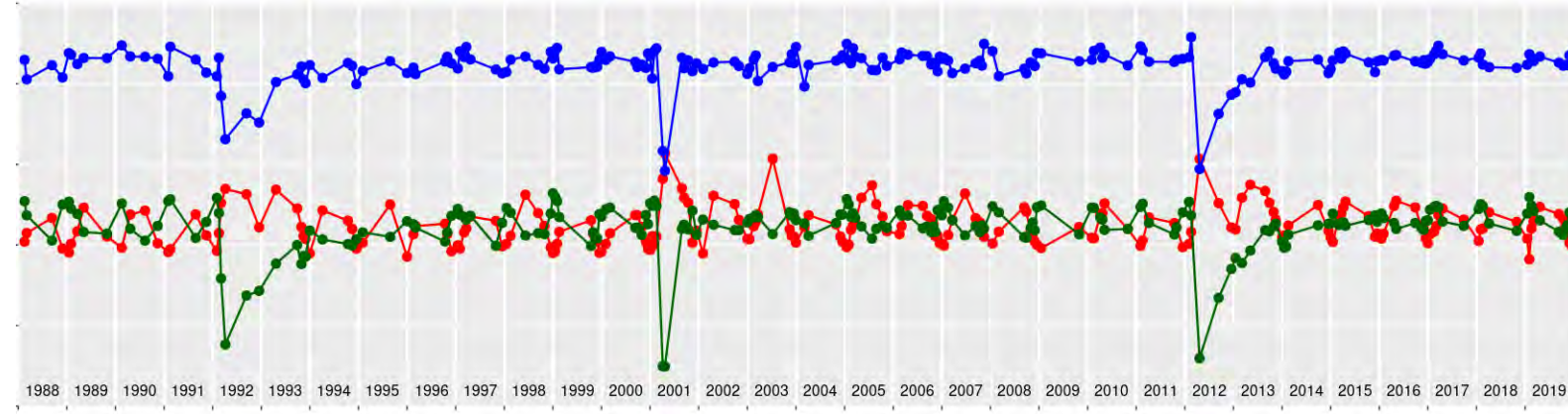
Sampling block example



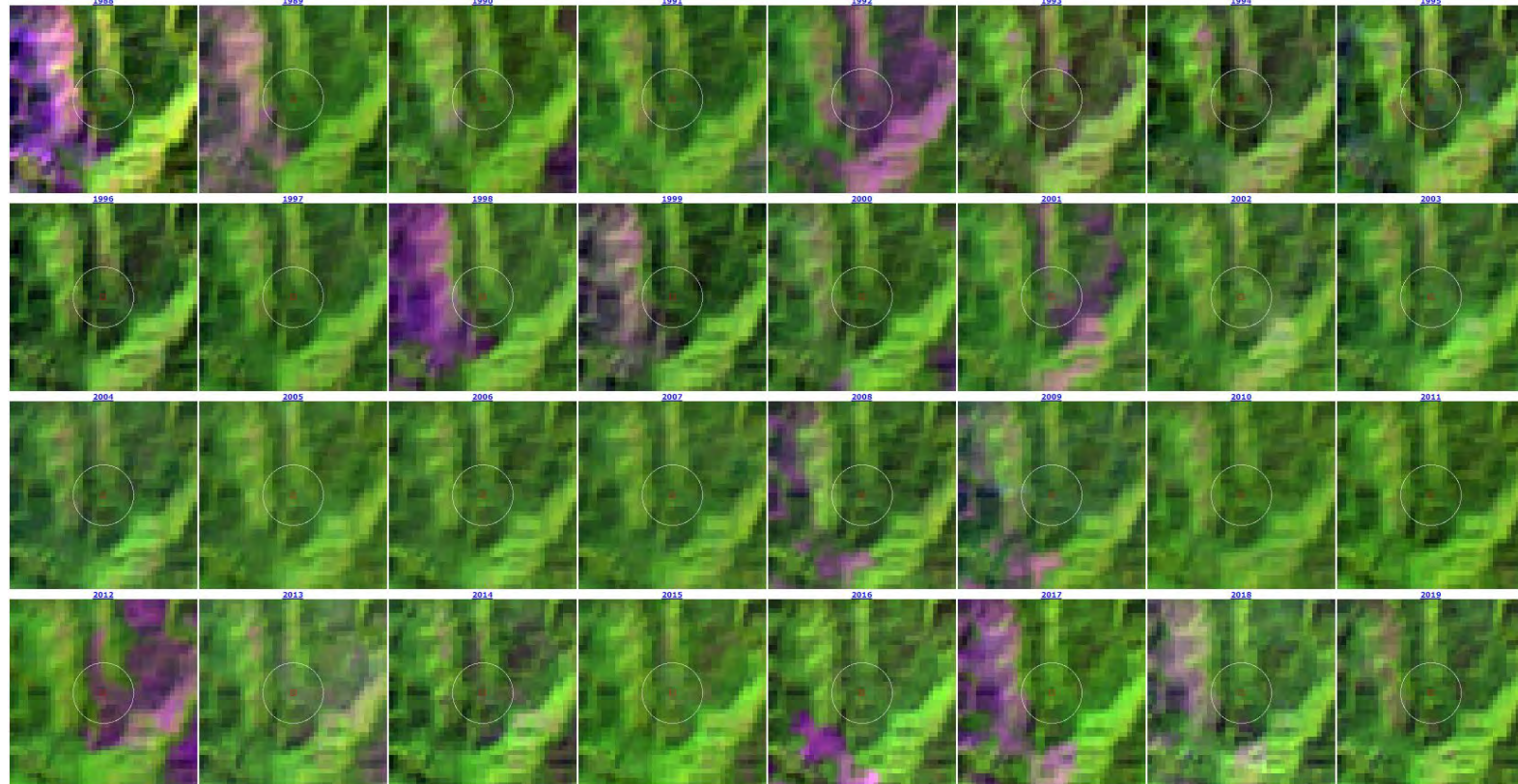
Using GLAD ARD for Sample Analysis

Sample ARD
time-series

● SWIR
● NDVI
● NDWI

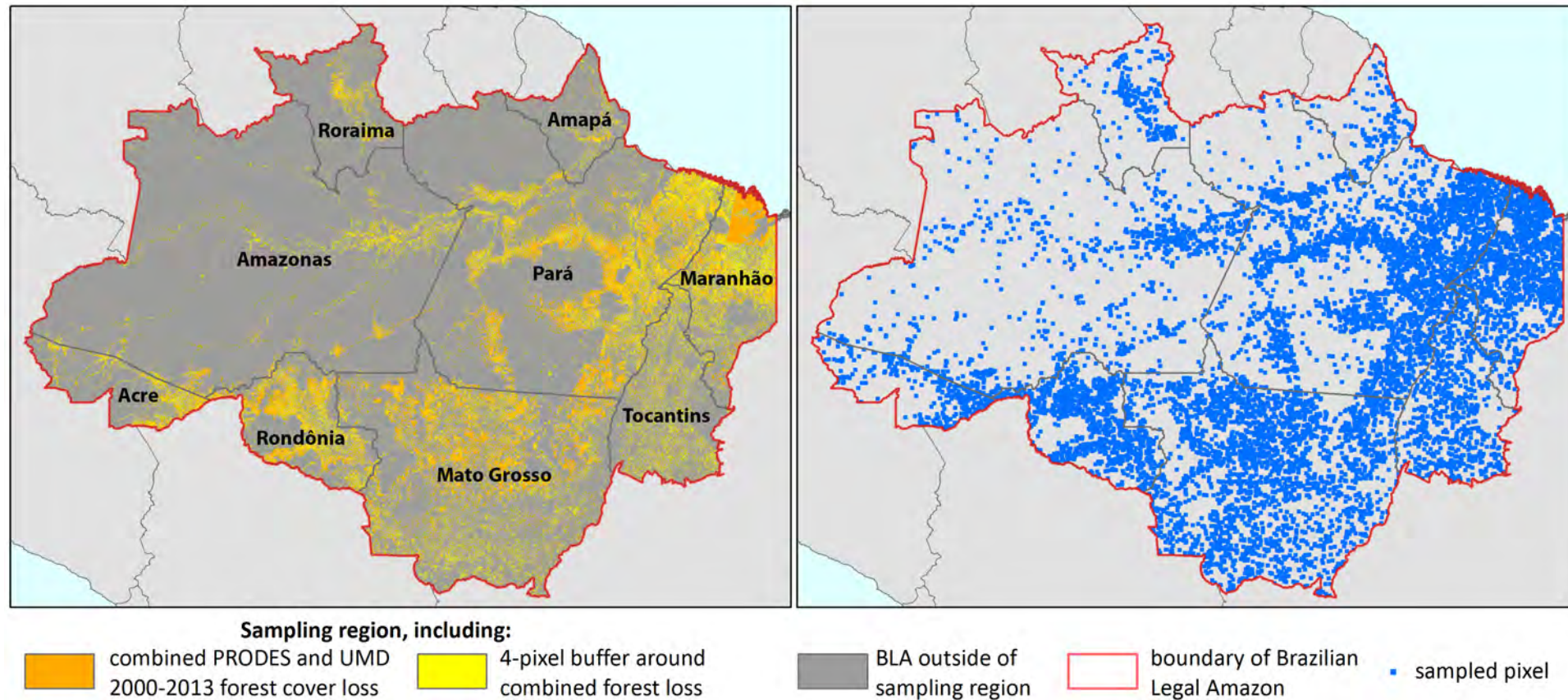


2013
high-resolution data



Value-added Sample Analysis: Deforestation of the Brazilian Amazon

Sampling design: 10,000 random samples



SCIENCE ADVANCES | RESEARCH ARTICLE

ENVIRONMENTAL SCIENCES

Types and rates of forest disturbance in Brazilian Legal Amazon, 2000–2013

Alexandra Tyukavina,^{1*} Matthew C. Hansen,¹ Peter V. Potapov,¹ Stephen V. Stehman,² Kevin Smith-Rodriguez,¹ Chima Okpa,¹ Ricardo Aguilar¹

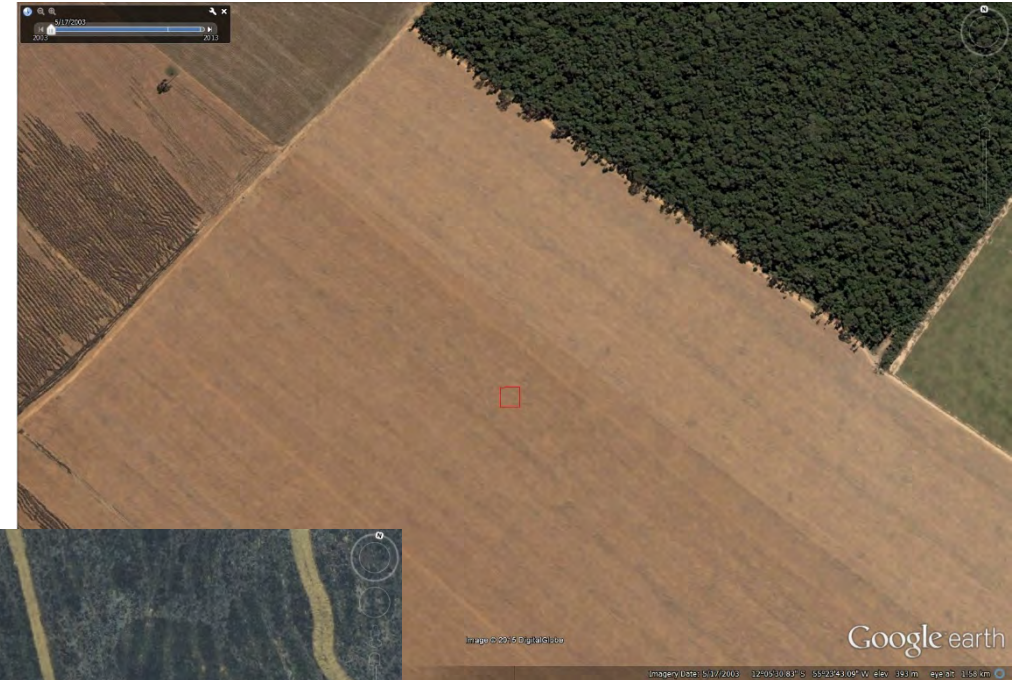
Value-added Sample Analysis: Deforestation of the Brazilian Amazon

Proximate causes of forest loss in Brazil



Selective logging

Cropland conversion

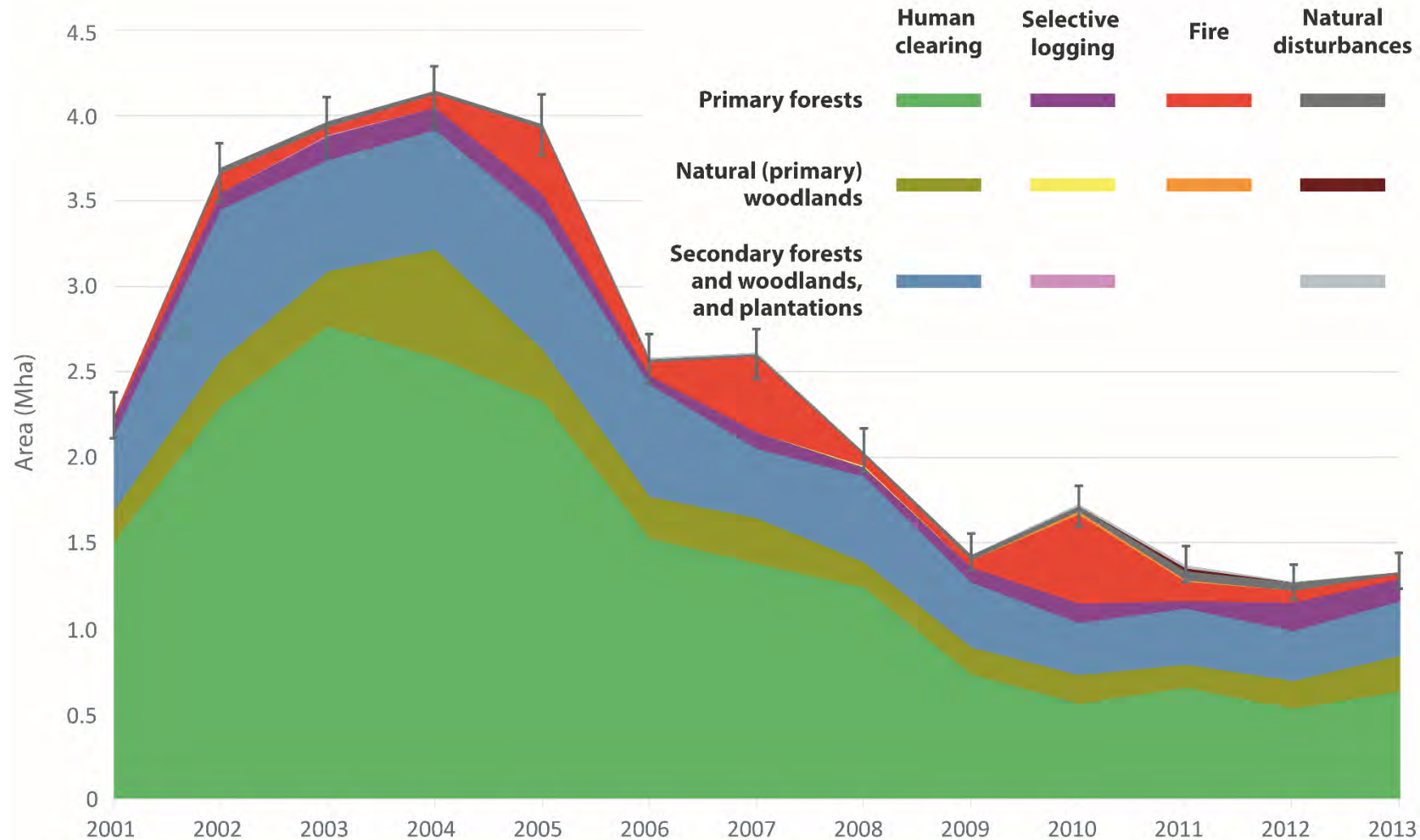


Construction



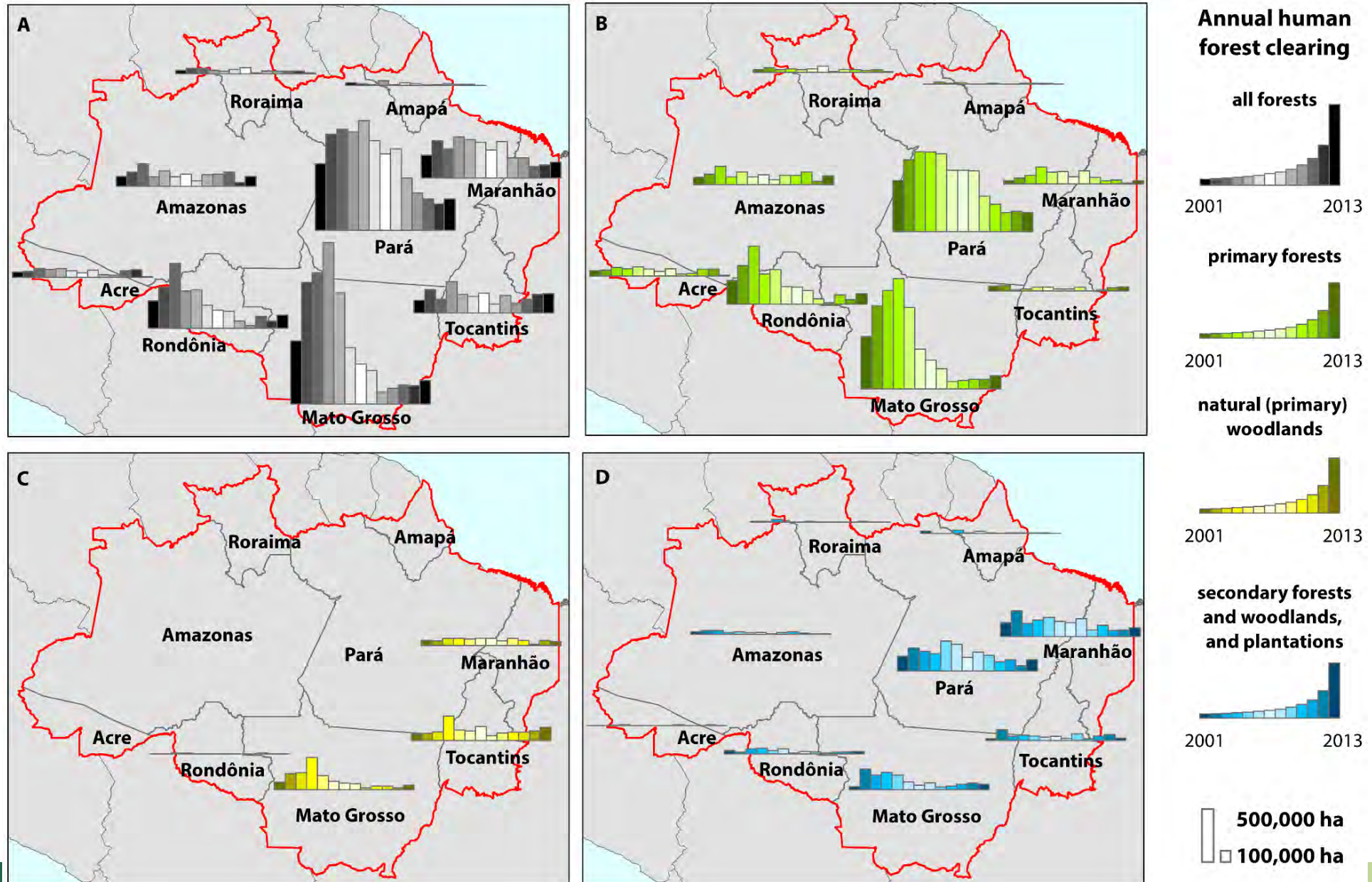
Value-added Sample Analysis: Deforestation of the Brazilian Amazon

Annual tree cover loss in BLA by pre-disturbance forest type and disturbance cause group



Value-added Sample Analysis: Deforestation of the Brazilian Amazon

Annual tree cover loss in BLA by pre-disturbance forest type and disturbance cause group



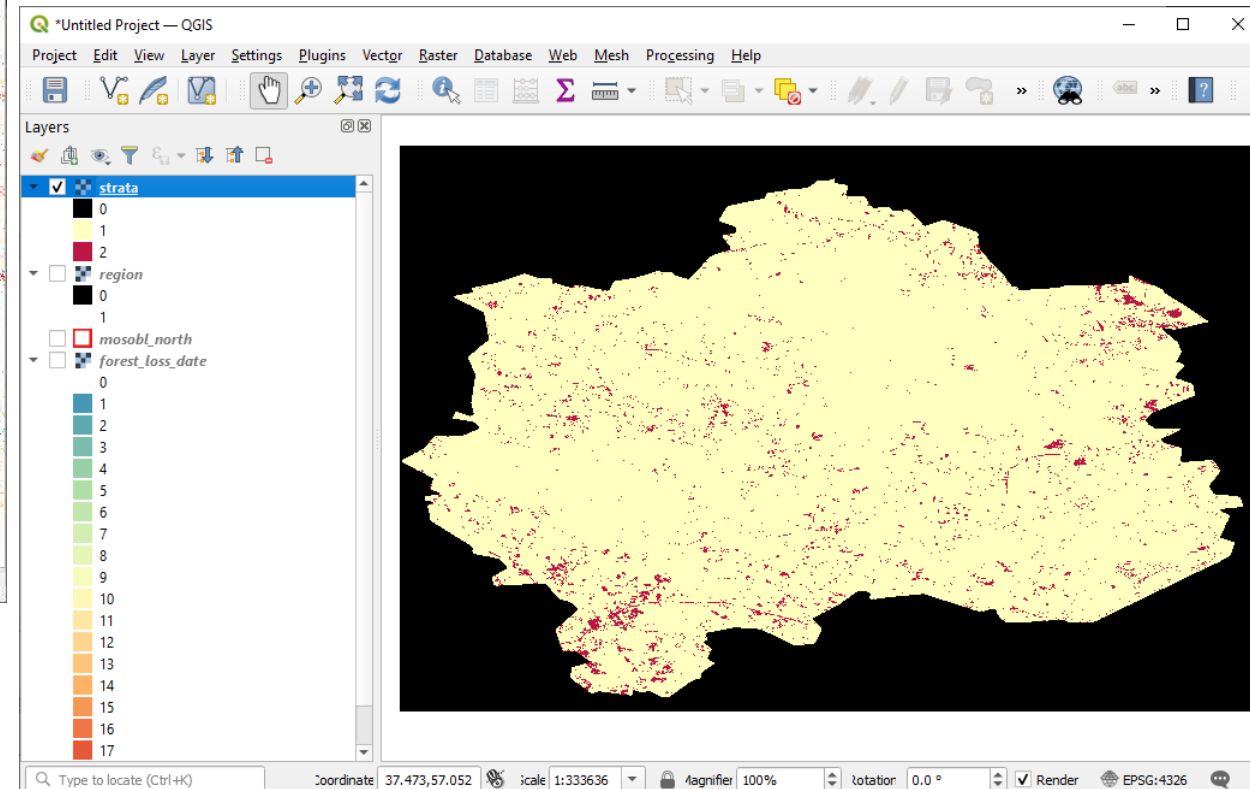
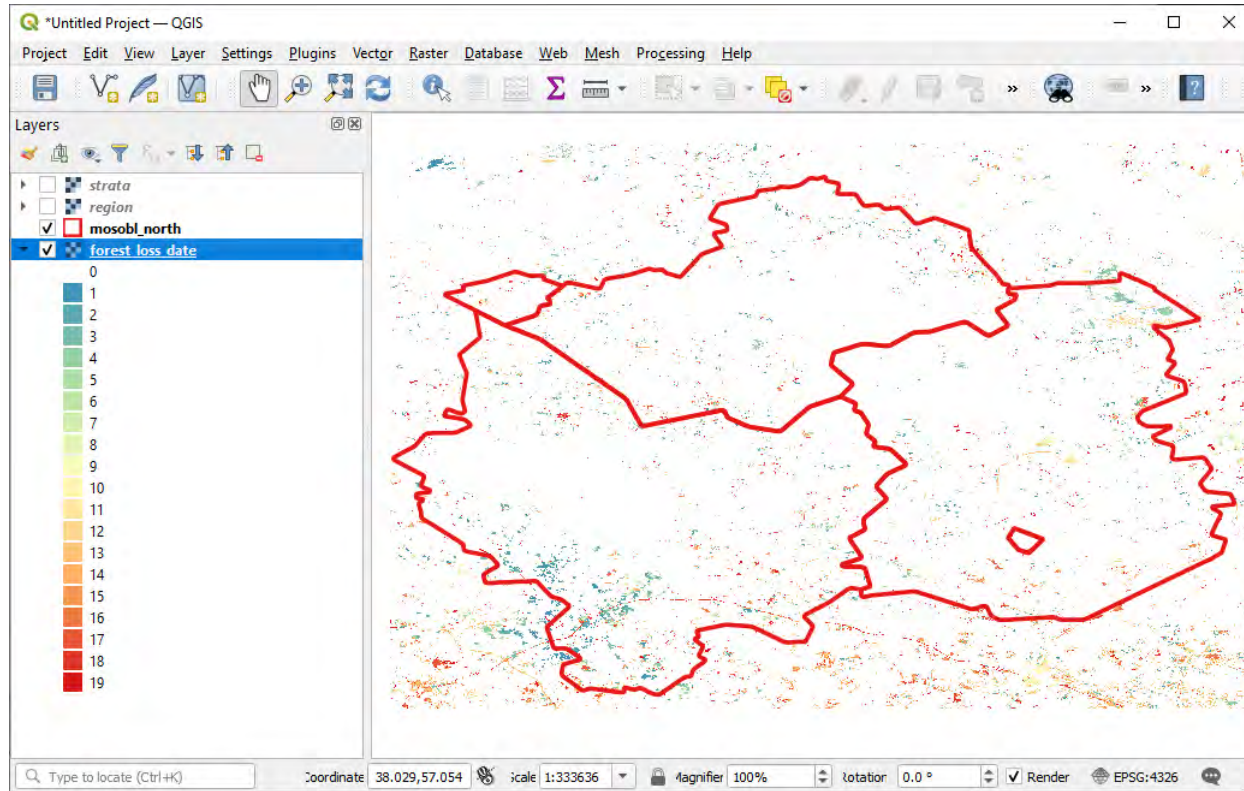
Sample Analysis Using GLAD Tools

Source wall-to-wall map (i.e., global forest change data)
and vector API

- Make the list of tiles and specify the data analysis extent.
- Rasterize vector data in OSGeo4W

```
gdal_rasterize -te 37 56 39 57 -tr 0.00025 0.00025 -ot Byte -of GTiff -co  
COMPRESS=LZW -co BIGTIFF=IF_SAFER -burn 1 mosobl_north.shp region.tif
```

- Use Image Modeler tool to create strata (1 – no forest loss, 2 – forest loss).



Sample Analysis Using GLAD Tools

1. Calculate strata area

```
C:\GLAD_1.1\get_area.exe strata.tif
```

i	area,m2	count,pixels
0	7893168978.0	18424055
1	5594431209.8	13046740
2	227272774.0	529205

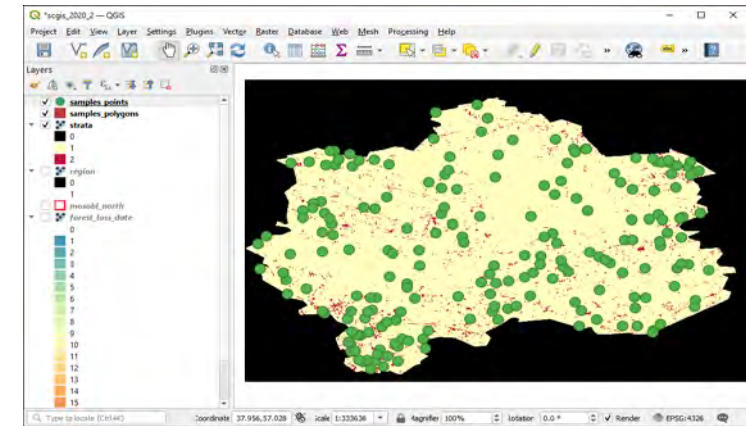
2. Generate samples using GLAD Tools

```
perl C:/GLAD_1.1/samples_generate.pl generate_samples.txt
```

```
*generate_samples.txt - Notepad
File Edit Format View Help
strata=strata.tif
R=C:/R-4.0.3/bin/Rscript.exe
first=1
SAMPLING
1      13046740      100
2      529205       100
END
```

3. Generate KML outlines for samples

```
perl C:/GLAD_1.1/samples_kml.pl sample_coordinates.txt
```



4. Extract sample data

```
perl C:/GLAD_1.1/samples_data.pl extract_sample_data.txt
```

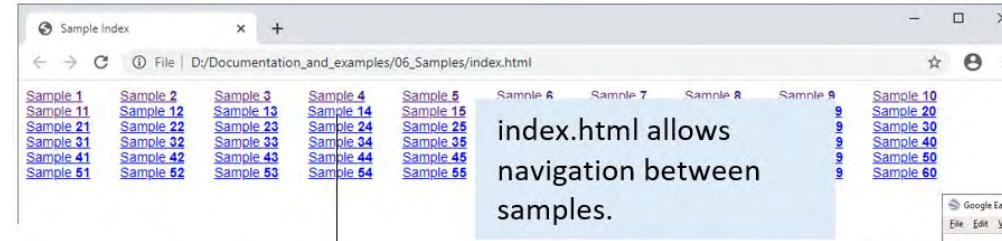
```
extract_sample_data.txt - Notepad
File Edit Format View Help
tile_list=tiles.txt
sample_list=sample_coordinates.txt
start_year=2000
end_year=2019
ARD=D:/ARD
threads=20
ogr=C:/Program Files/QGIS 3.14/OSGeo4w.bat
R=C:/R-4.0.3/bin/Rscript.exe
```


Sample Analysis Using GLAD Tools

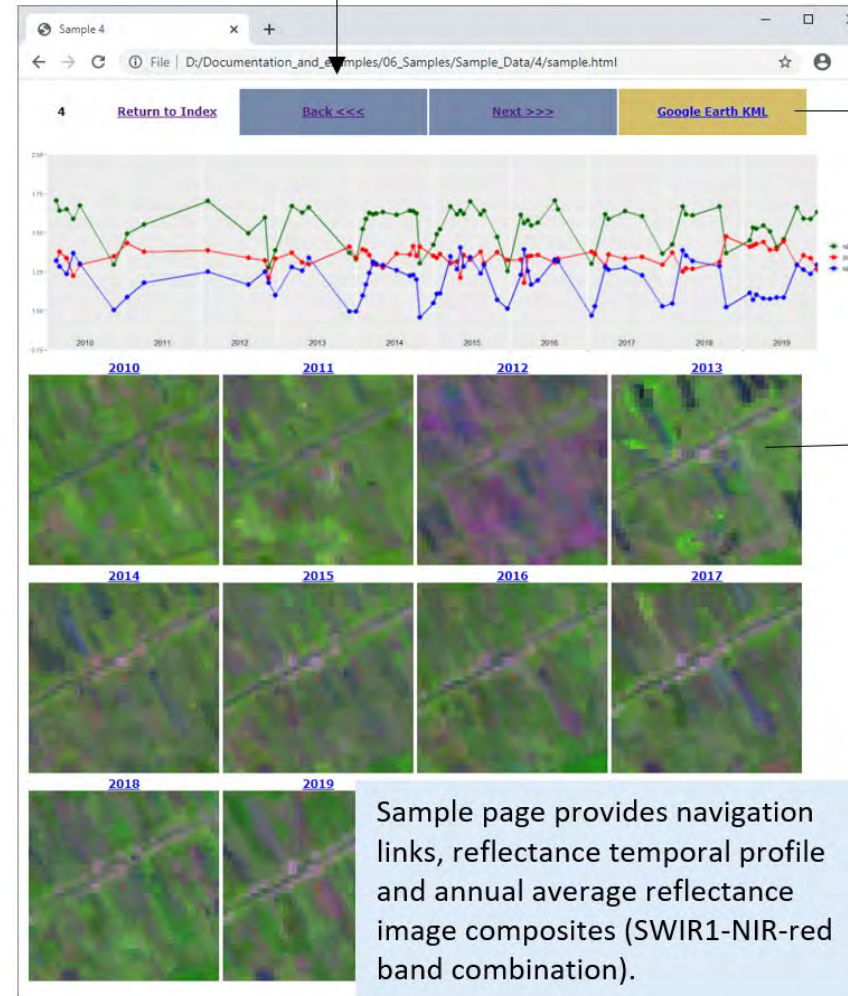
Sample interpretation

- Forest loss presence.
- Year of forest loss.
- Proximate cause of forest loss.

	A	C	D	E	F	G
1	ID	X	Y	Type	Year	Cause
2	1	37.39513	56.07088	NL		
3	2	38.07588	56.41488	L	2012	gas infrastructure
4	3	37.54688	56.11163	L	2009	logging
5	4	37.31788	56.75288	L	2010	logging
6	5	37.75188	56.23363	NL		
7	6	37.43438	56.43538	NL		
8	7	38.21763	56.27963	NL		
9	8	37.86763	56.28588	NL		
10	9	38.34713	56.71038	L	2010	fire
11	10	38.34863	56.38888	NL		
12	11	38.35413	56.68263	L	2011	fire
13	12	38.31363	56.37638	NL		
14	13	37.32113	56.10063	L	2002	logging
15	14	37.31163	56.20963	NL		
16	15	37.75763	56.25213	NL		
17	16	37.52738	56.43713	NL		
18	17	37.60713	56.68613	NL		
19	18	37.61838	56.70013	L	2005	logging
20	19	37.99788	56.77013	L	2008	logging



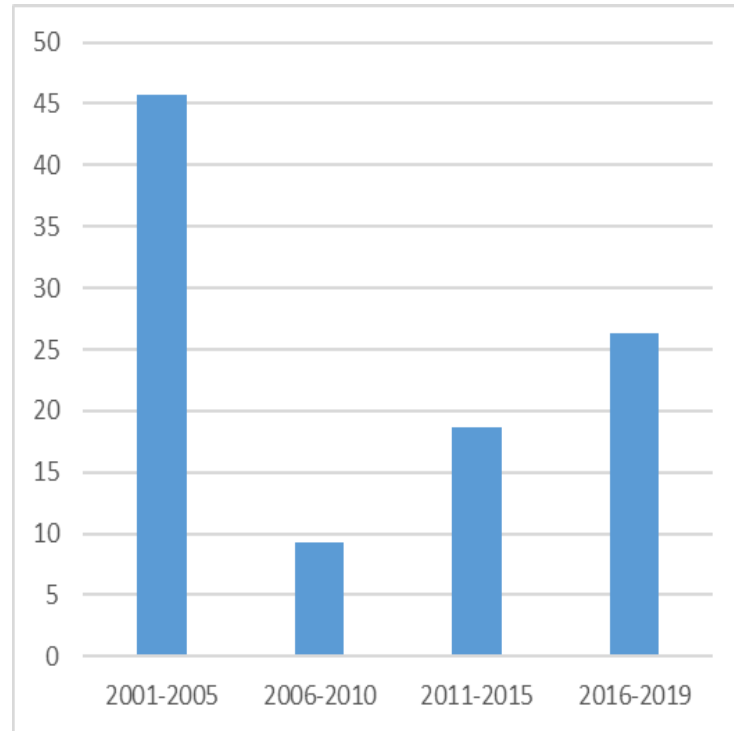
The link to Google Earth simplifies VHR data analysis



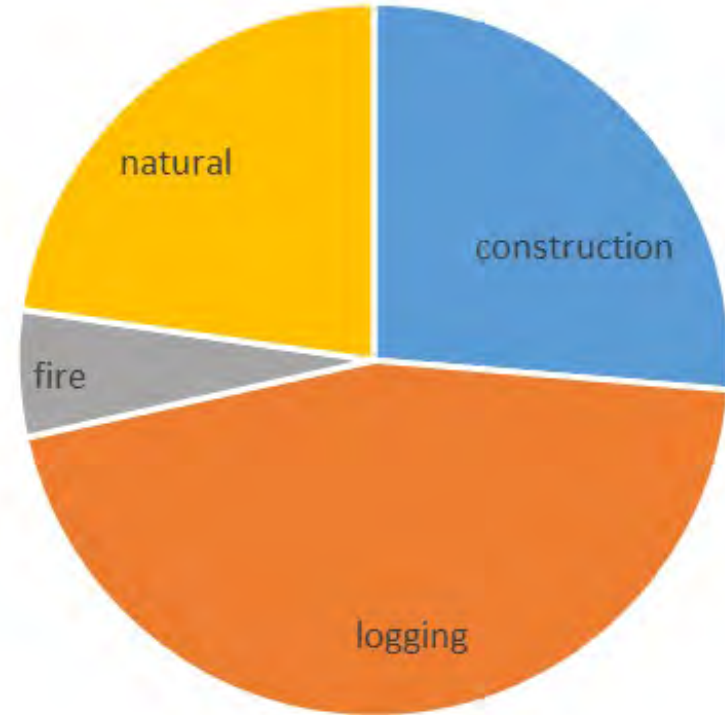
Sample Analysis Using GLAD Tools

Sample estimation output examples

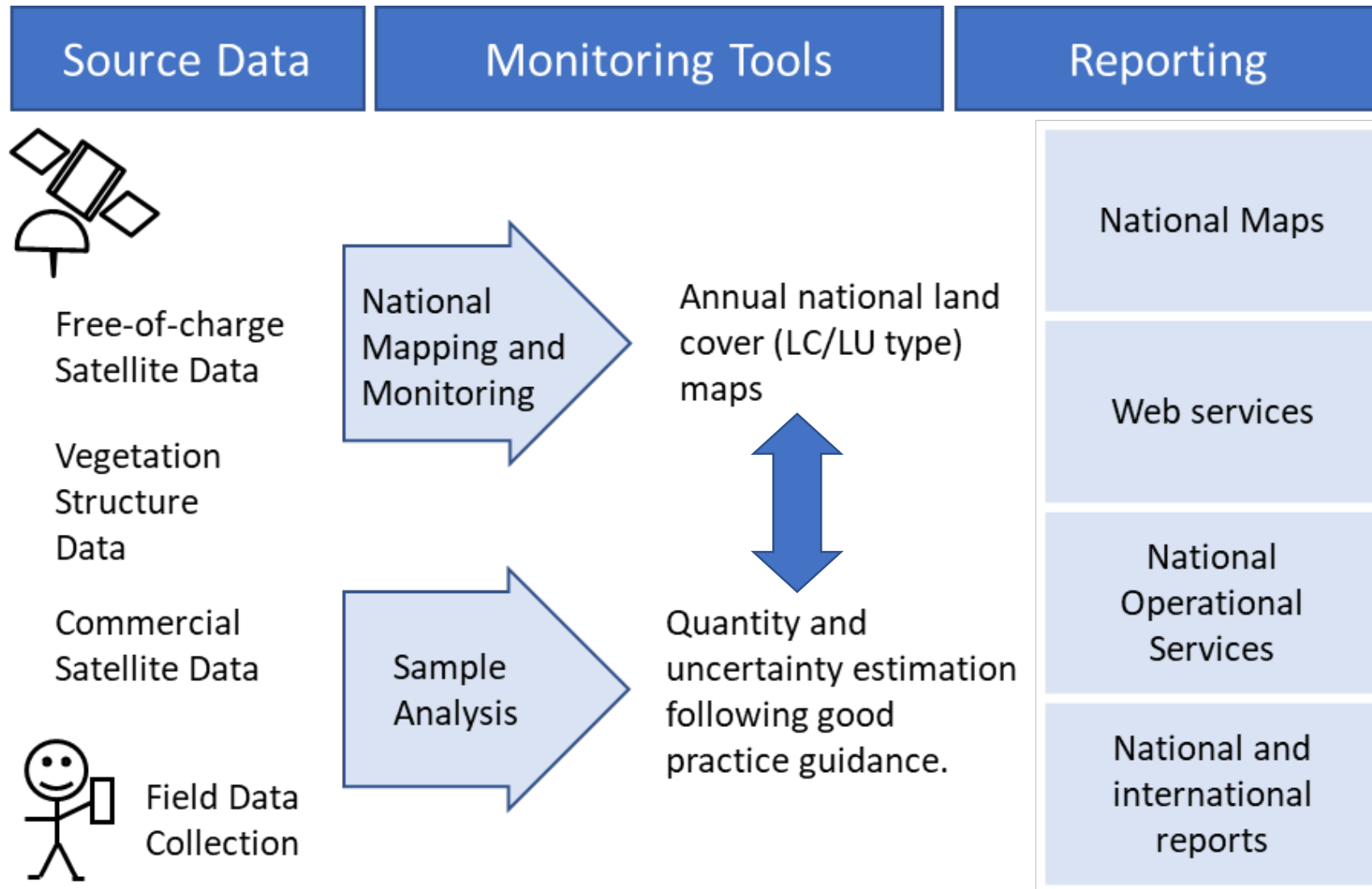
Total forest loss area by interval



Proximate causes of forest loss

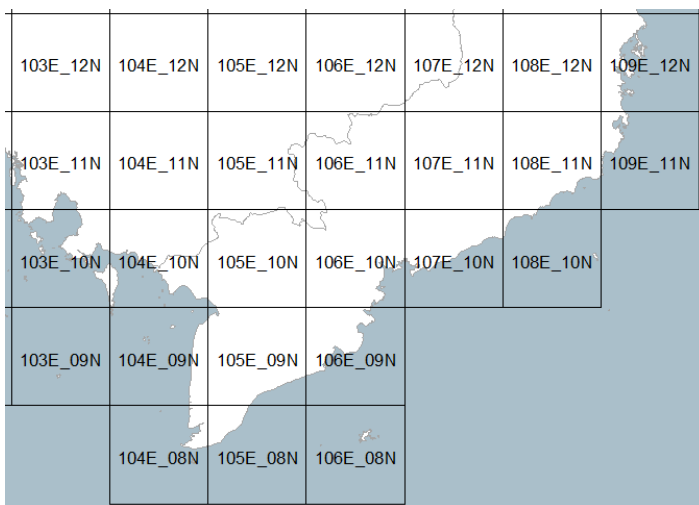


Integrating Mapping and Statistical Sampling



Application of phenological metrics time-series (Mekong Delta, Vietnam)

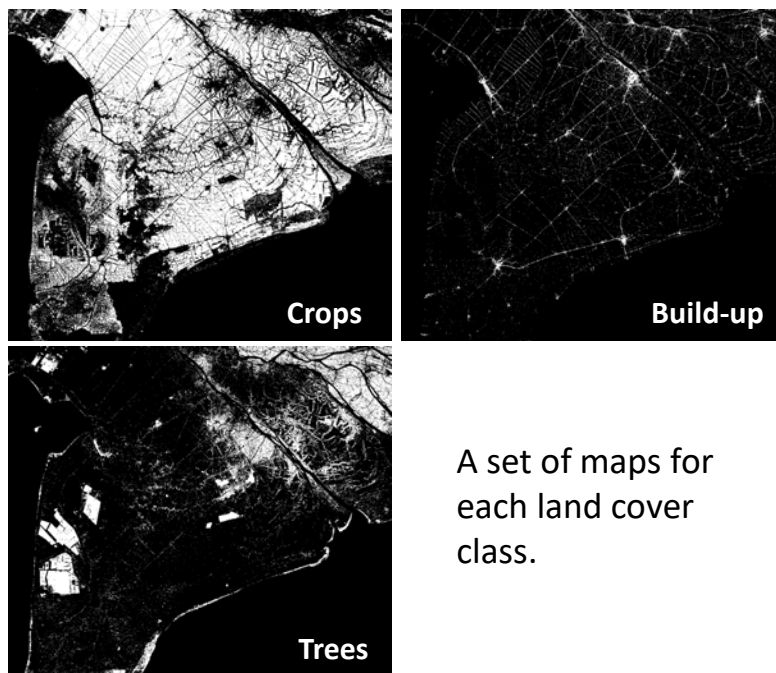
1 ARD Data download.



2 Creating multi-temporal metrics for selected years.



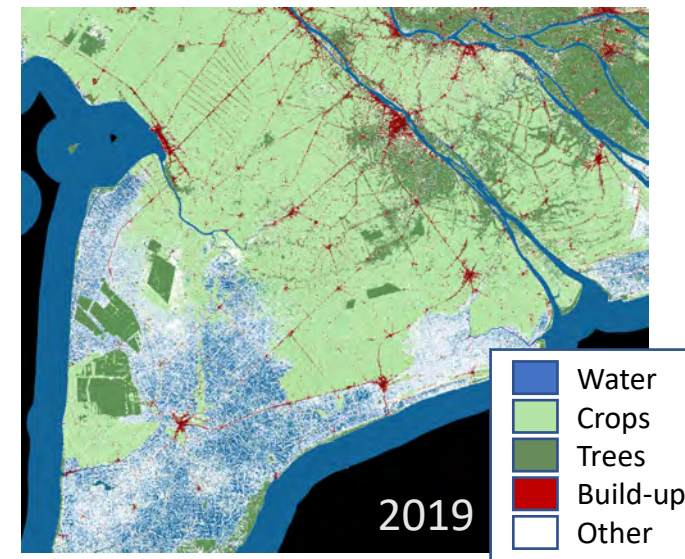
3 Expert-driven supervised image classification.



A set of maps for each land cover class.

4

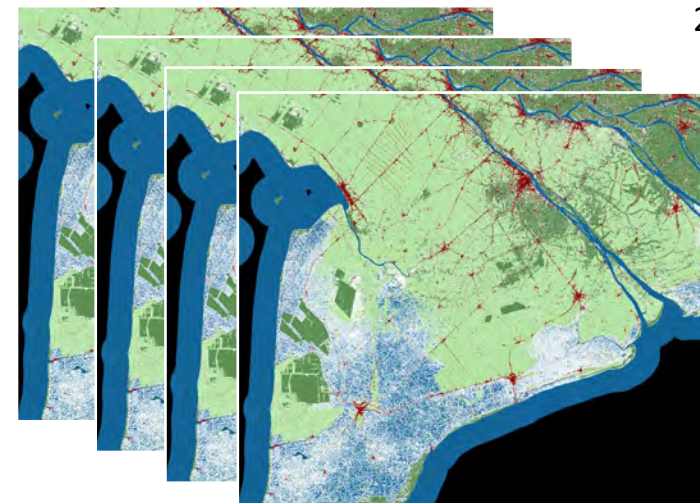
Land cover map.

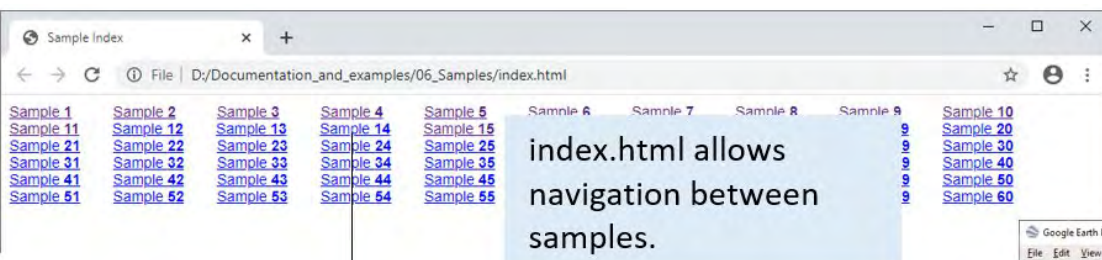


5

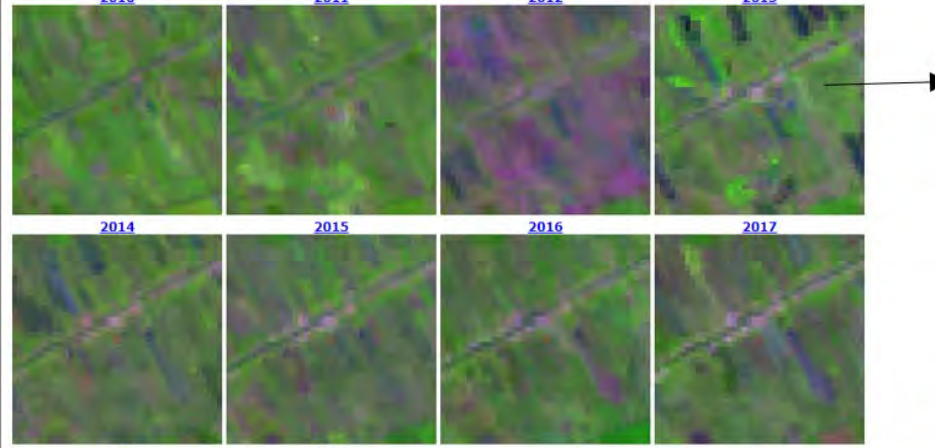
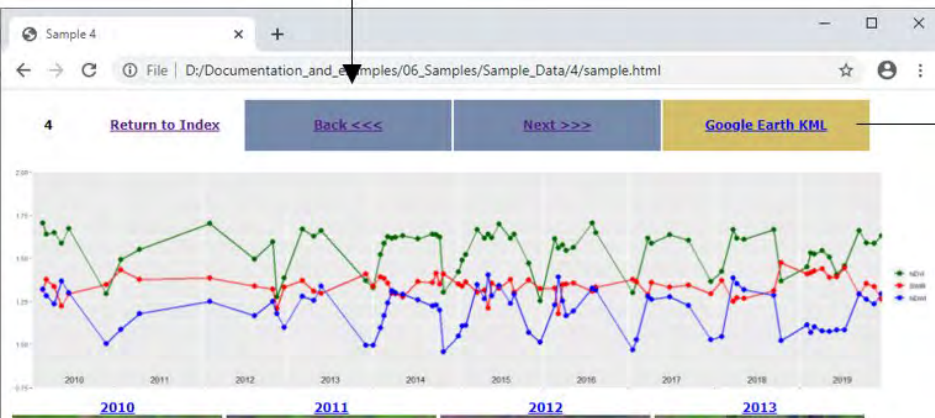
Application of the same classification model in time to produce a time-series of land cover maps.

2000
2005
2010
2019

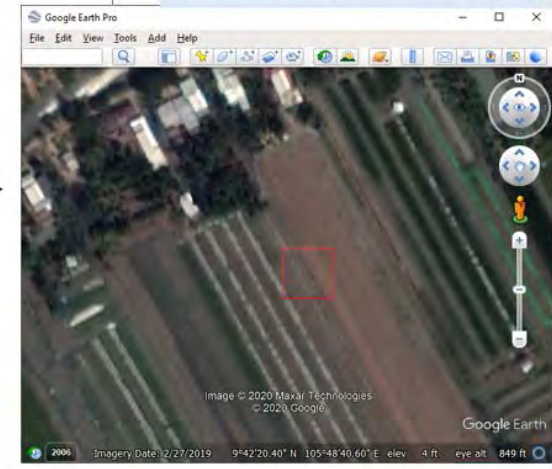




The link to Google Earth simplifies VHR data analysis

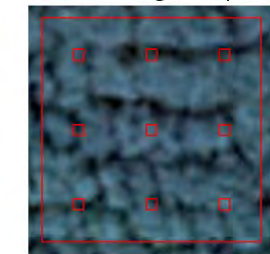


Sample page provides navigation links, reflectance temporal profile and annual average reflectance image composites (SWIR1-NIR-red band combination).



Bi-monthly data provides average reflectance for every two month.

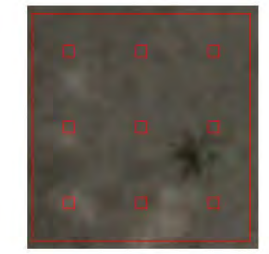
Sample Analysis Tools



9 sub-plots intersect canopy



3 sub-plots intersect canopy



0 sub-plots intersect canopy. Even there is trees within this sample none of the sub-plots intersect it.

Unbiased area with known uncertainty

ha $\times 10^6$	1988	2009
Forest area (map)	20.6	18.0
Forest area (samples)	20.2	17.5
95% confidence interval	1.5	1.6

Map accuracy

	Overall Accuracy	User's Accuracy	Producer's Accuracy
Forest 1988	90.4	94.5	94.6
Forest 2019	91.6	94.3	94.7

