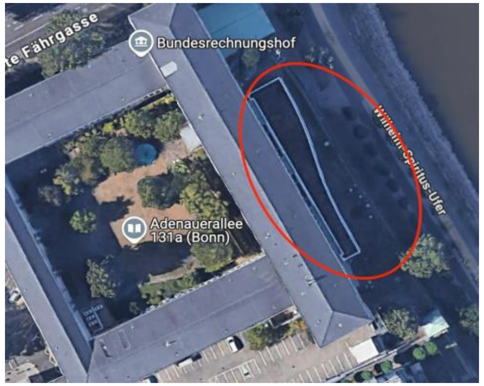
SATELLITE DATA IN AGRICULTURAL AND ENVIRONMENTAL ECONOMICS

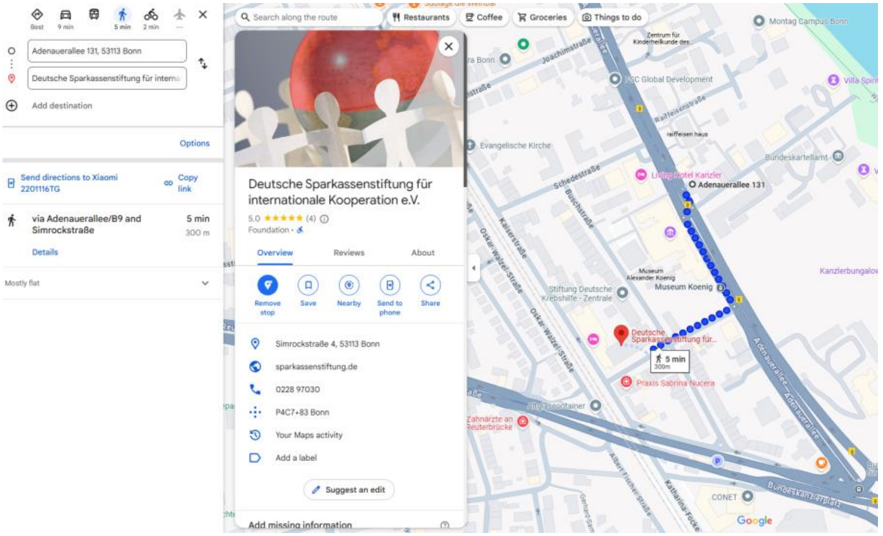
DAVID WUEPPER, HADI, WYCLIFE AGUMBA OLUOCH

02.06.2025 – 06.06.2025
Bonn

LOGISTICS

- If eduroam issues: https://cat.eduroam.org/
- Lunch: Bundesrechnungshof
- When in the building





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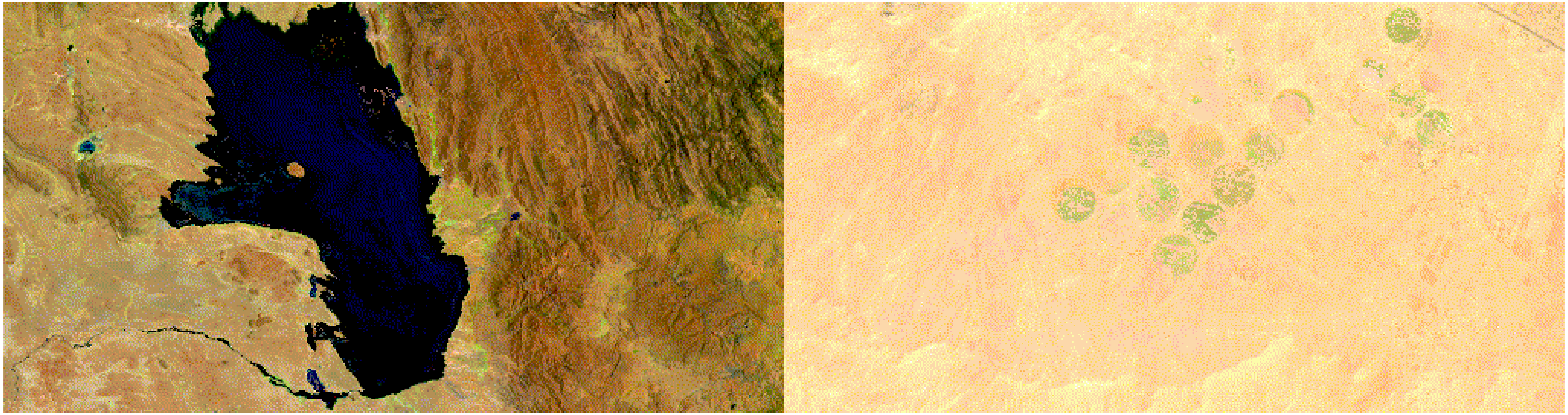

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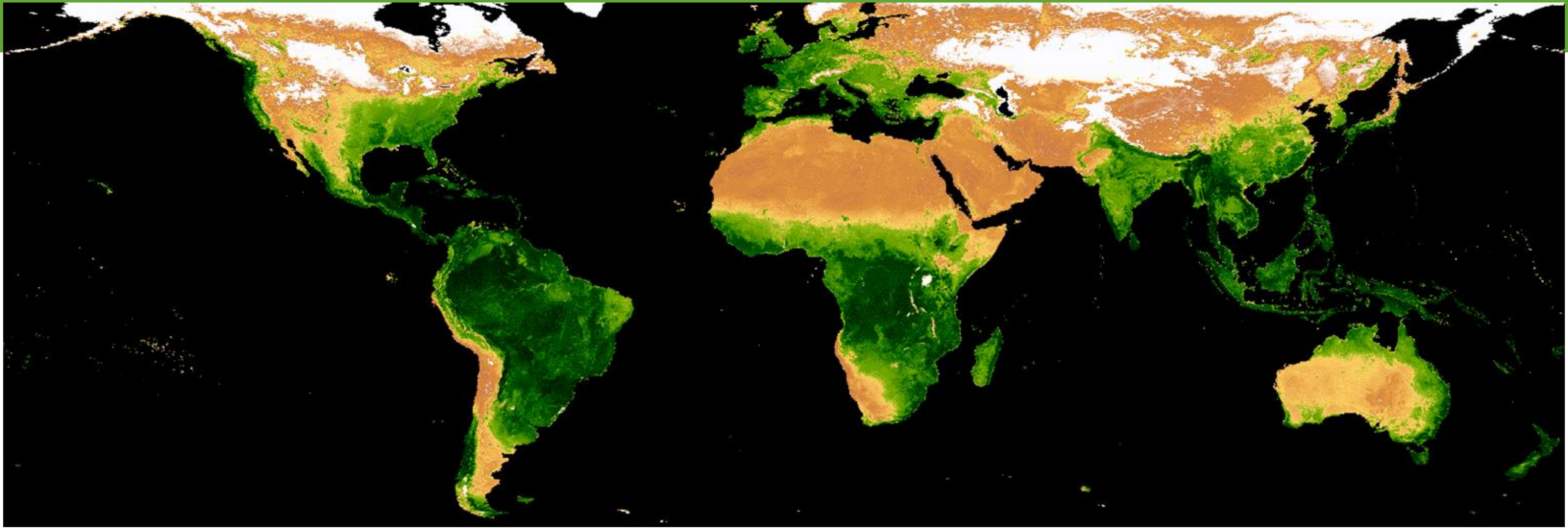

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Global Landsat Timelapse Animations

https://earthengine.google.com/timelapse/

Columbia Glacier Retreat, 1984-2011

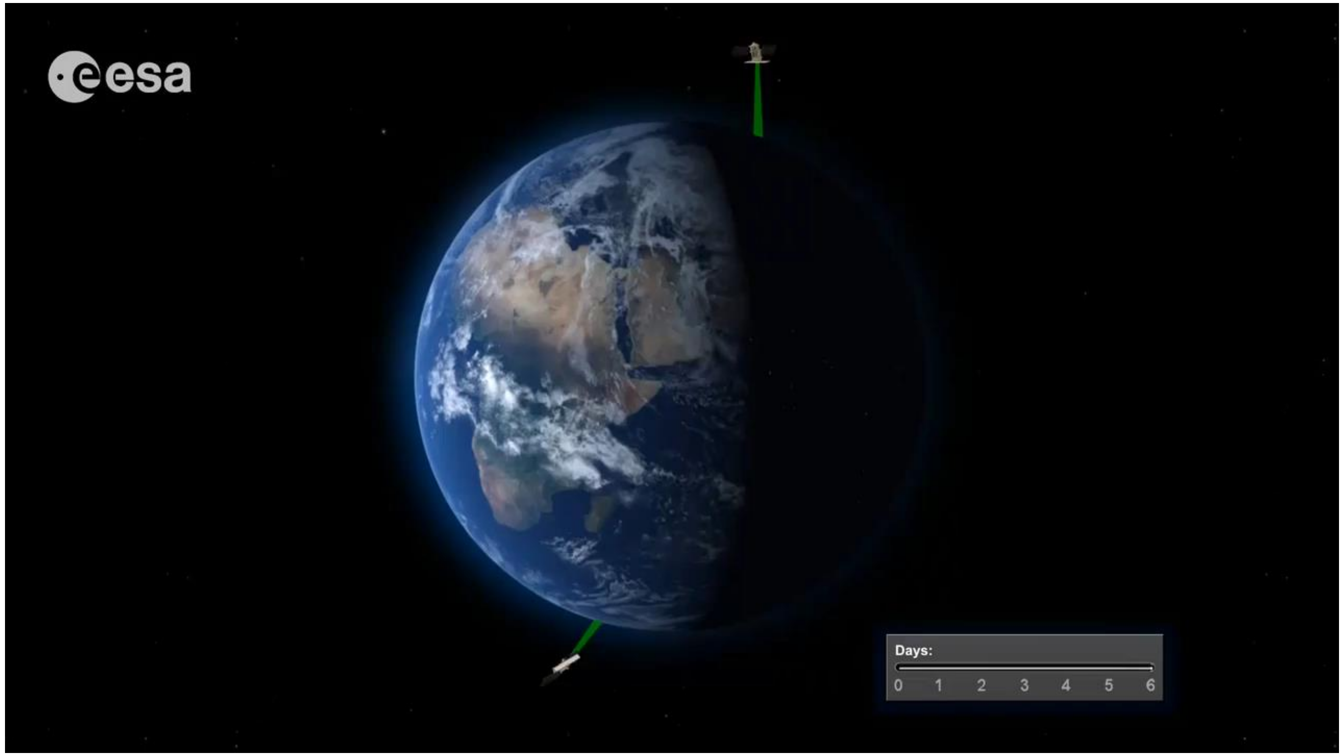
Saudi Arabia Irrigation, 1984-2012

Las Vegas Urban Growth, 1986-2012

Brazilian Amazon Deforestation, 1984-2012

SATELLITE REMOTE SENSING (EARTH OBSERVATION)

©NASA



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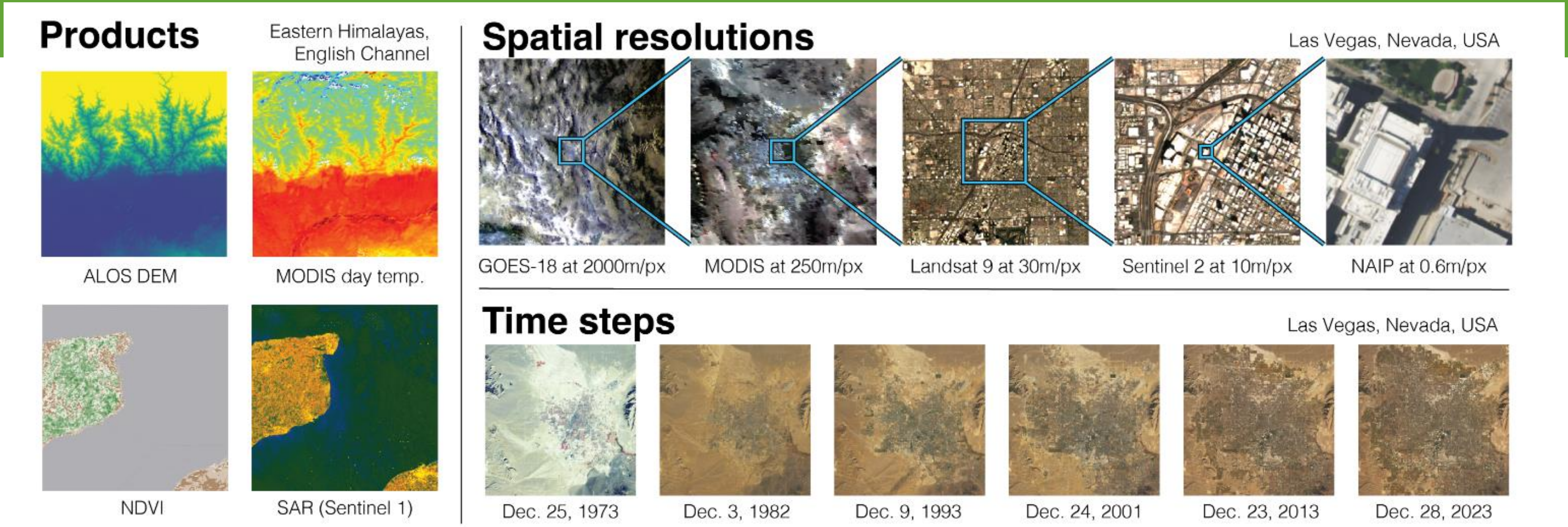

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Rolf, E., Klemmer, K., Robinson, C., & Kerner, H. (2024). Mission Critical--Satellite Data is a Distinct Modality in Machine Learning. *arXiv preprint arXiv:2402.01444*.

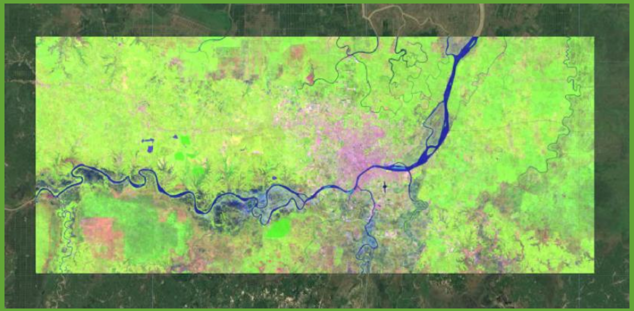
Sentinel satellite launched to picture Planet Earth

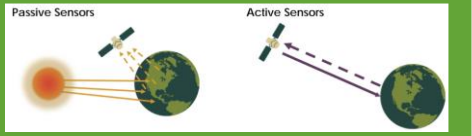
By Jonathan Amos
BBC Science Correspondent

7 March 2017 | Science & Environment

Share

Sentinel-2B was successfully launched into orbit from French Guiana





©NASA

05 September 2024

Space

Airbus built Sentinel-2C satellite successfully launched

Third Sentinel-2 satellite for EU Copernicus Earth monitoring programme

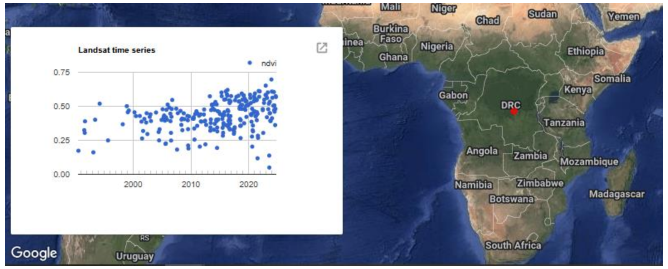
Sentinel Launches

esa

S1A/B: Radar Mission (up to 5 meter)	3 Apr 2014 / 25 Apr 2016
S2A/B: High Resolution Optical Mission (10-60 m)	23 June 2015 / 6 March 2017
S3A/B: Medium Resolution Imaging and Altimetry Mission (300-500 m)	16 Feb 2016 / Q1 2018
S4A/B: Geostationary Atmospheric Chemistry Mission (8 km)	2021/2027
S5P: Low Earth Orbit Atmospheric Chemistry Mission (7 km)	Oct 2017
S5A/B/C: Low Earth Orbit Atmospheric Chemistry Mission	2021/2027
S6A/B: Altimetry Mission	2020/2025

European Space Agency

© USGS



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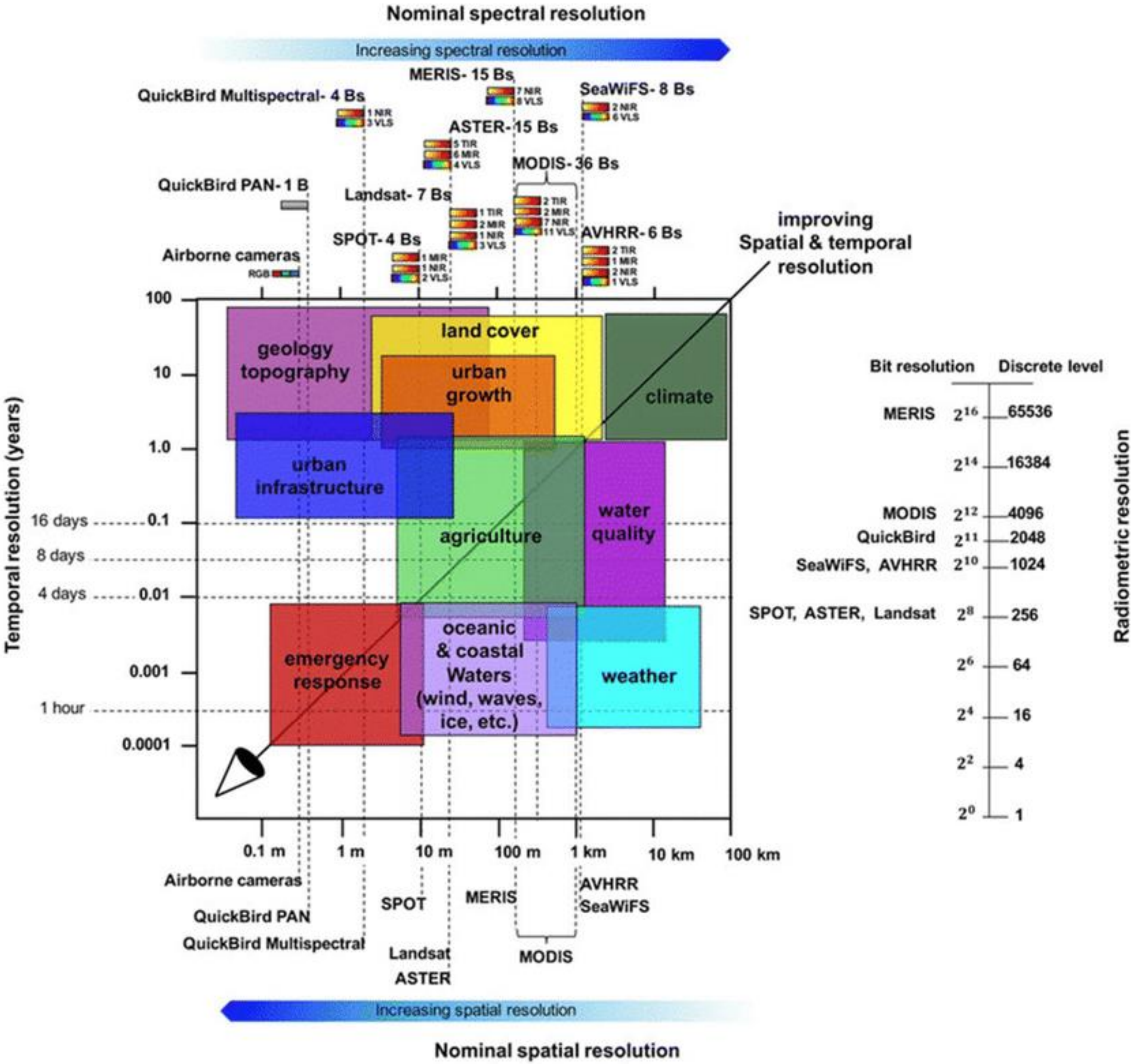
bit.ly/landsat-time-series

https://code.earthengine.google.com/8f4a31f9d61d6e80707487a64c22cf45



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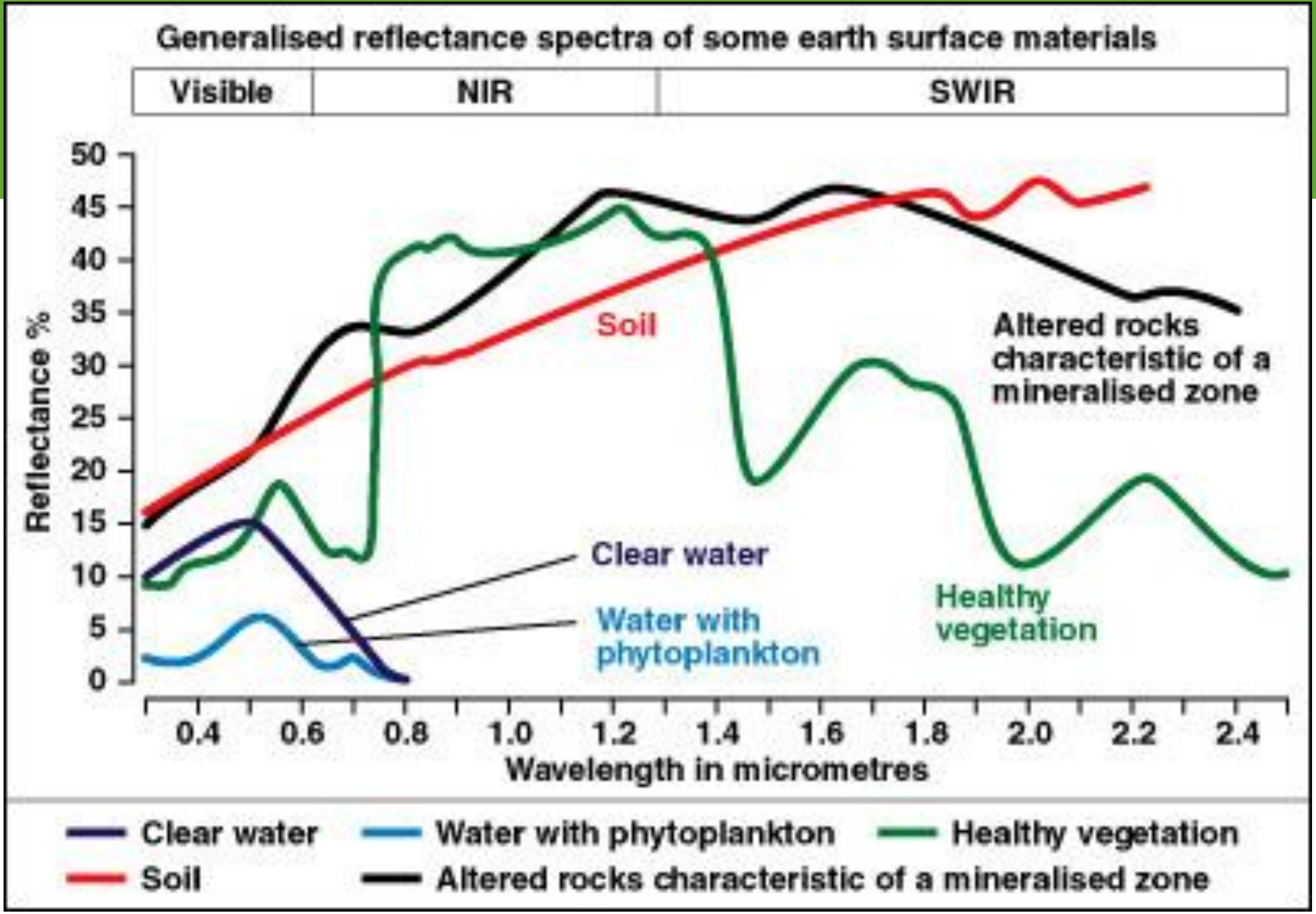
©Kasampalis et al. 2018



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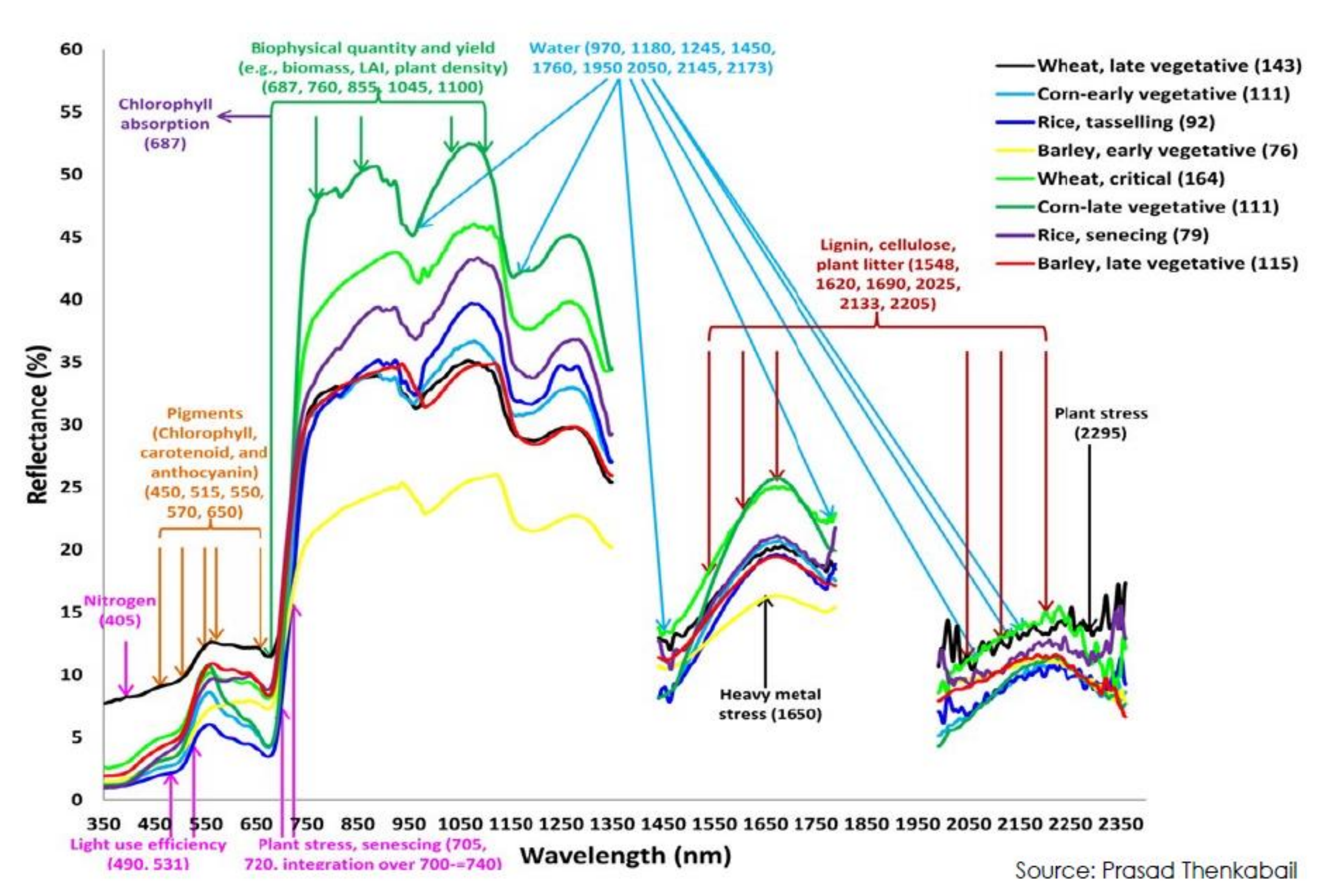
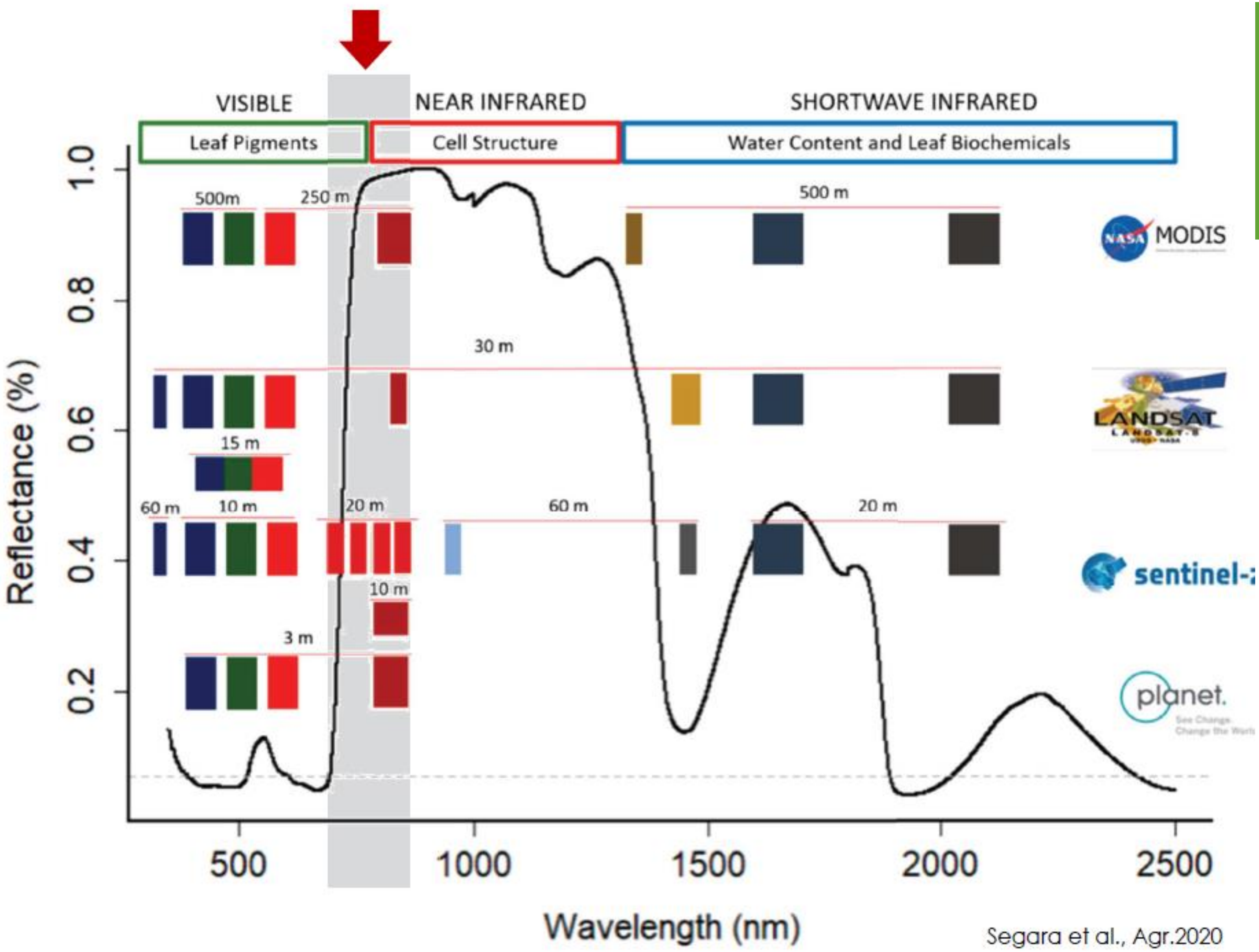
VI GALORE



https://awesome-ee-spectral-indices.readthedocs.io/en/latest/list.html#

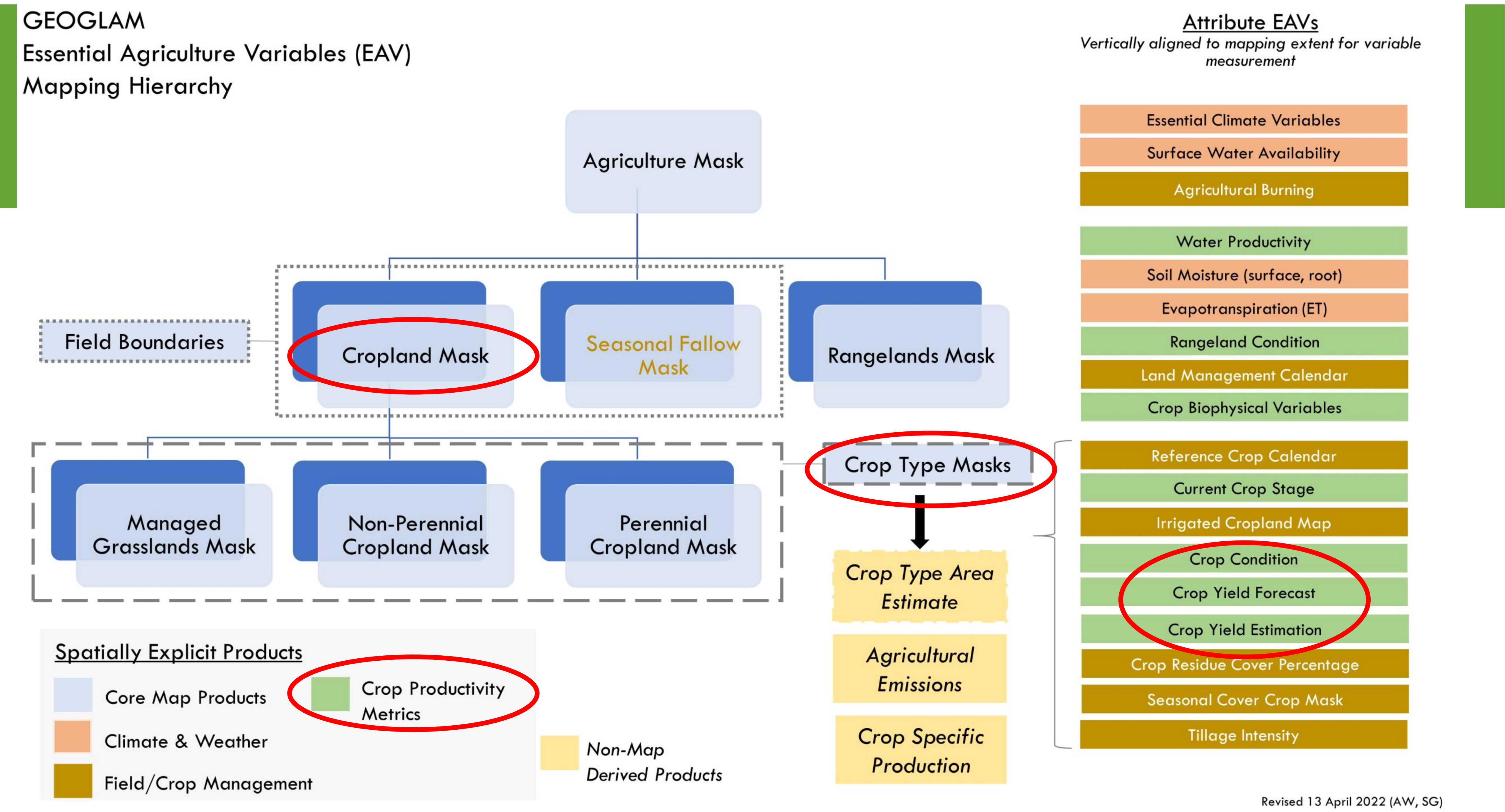
https://www.indexdatabase.de/db/i.php

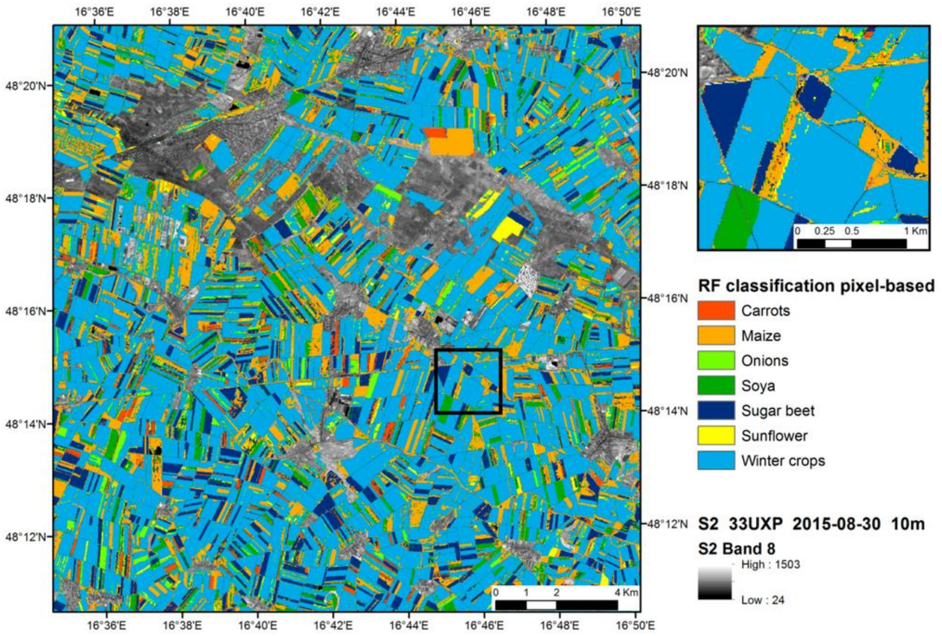


Segara et al., Agr.2020

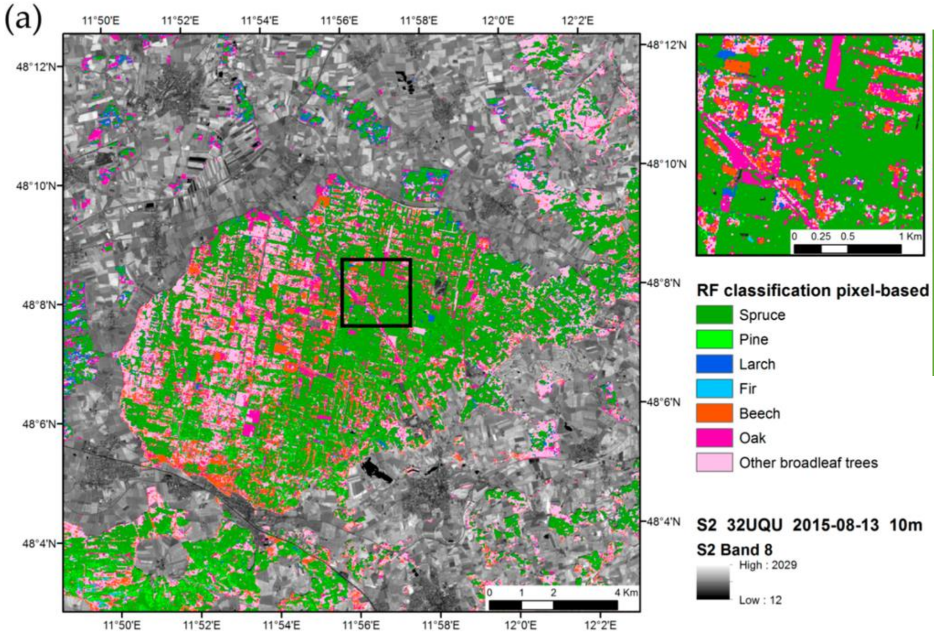
MODIS DATA PRODUCTS

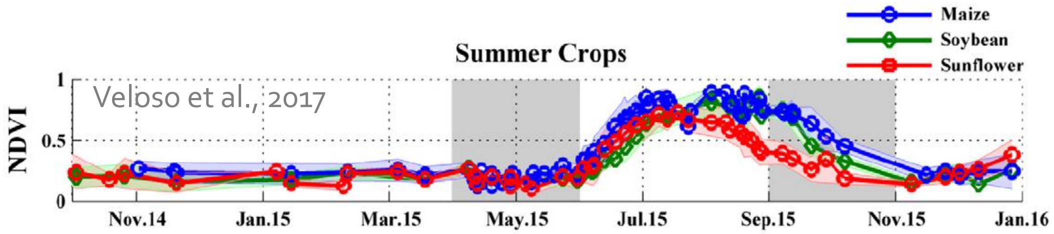
MODIS Name	Product Name Short name	Spatial Resolution (m)	Temporal
MOD 09	Surface Reflectance	500	8-day
MOD 11	Land Surface Temperature	1000	Daily, 8-day
MOD 12	Land Cover/Change	500	8-day, Yearly
MOD 13	Vegetation Indices	250-1000	16 day, monthly
MOD 14	Thermal Anomalies/Fire	1000	Daily, 8-day
MOD 15	Leaf Area Index/Fraction of Absorbed Photosynthetically Active Radiation (FPAR)	1000	4-day, 8-day
MOD 16	Evapotranspiration		
MOD 17	Primary Production	1000	8-day, yearly
MOD 43	Bidirectional reflectance distribution function (BRDF)/Albedo	500-1000	16-day
MOD 44	Vegetation Continuous Fields	250	yearly
MOD 45	Burned Area	500	monthly


GEOGLAM
Essential Agriculture Variables (EAV)
Mapping Hierarchy
Attribute EAVs
Vertically aligned to mapping extent for variable measurement
Agriculture Mask
Field Boundaries
Cropland Mask
Seasonal Fallow Mask
Rangelands Mask
Managed Grasslands Mask
Non-Perennial Cropland Mask
Perennial Cropland Mask
Crop Type Masks
Crop Type Area Estimate
Agricultural Emissions
Crop Specific Production
Essential Climate Variables
Surface Water Availability
Agricultural Burning
Water Productivity
Soil Moisture (surface, root)
Evapotranspiration (ET)
Rangeland Condition
Land Management Calendar
Crop Biophysical Variables
Reference Crop Calendar
Current Crop Stage
Irrigated Cropland Map
Crop Condition
Crop Yield Forecast
Crop Yield Estimation
Crop Residue Cover Percentage
Seasonal Cover Crop Mask
Tillage Intensity
Spatially Explicit Products
Core Map Products
Crop Productivity Metrics
Climate & Weather
Field/Crop Management
Non-Map Derived Products
Revised 13 April 2022 (AW, SG)

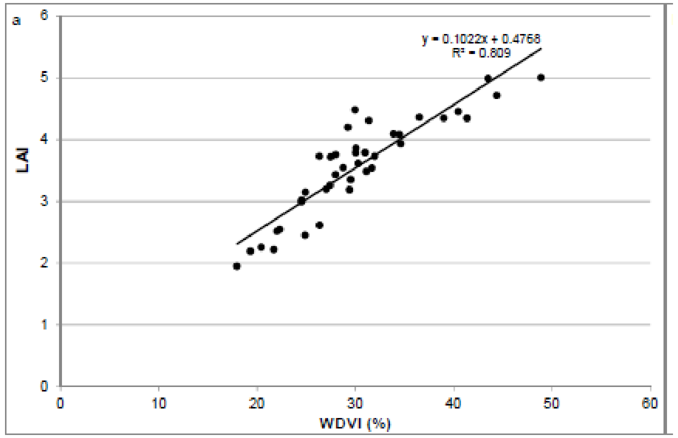


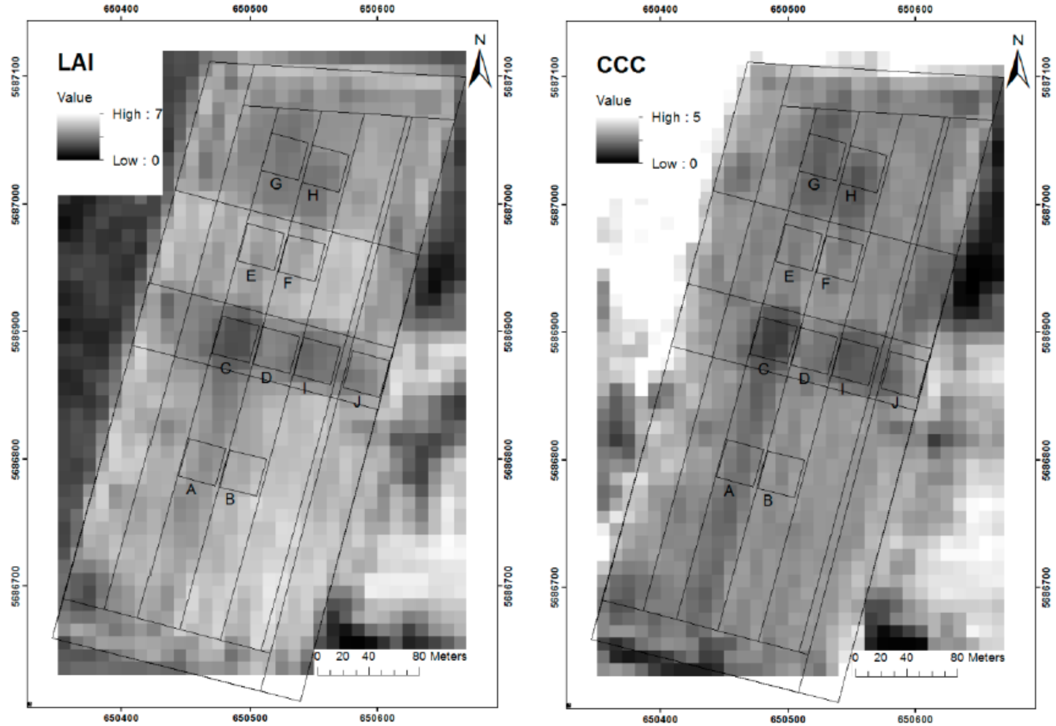
Immitzer et al., 2016





Veloso et al., 2017





Clevers et al., 2017

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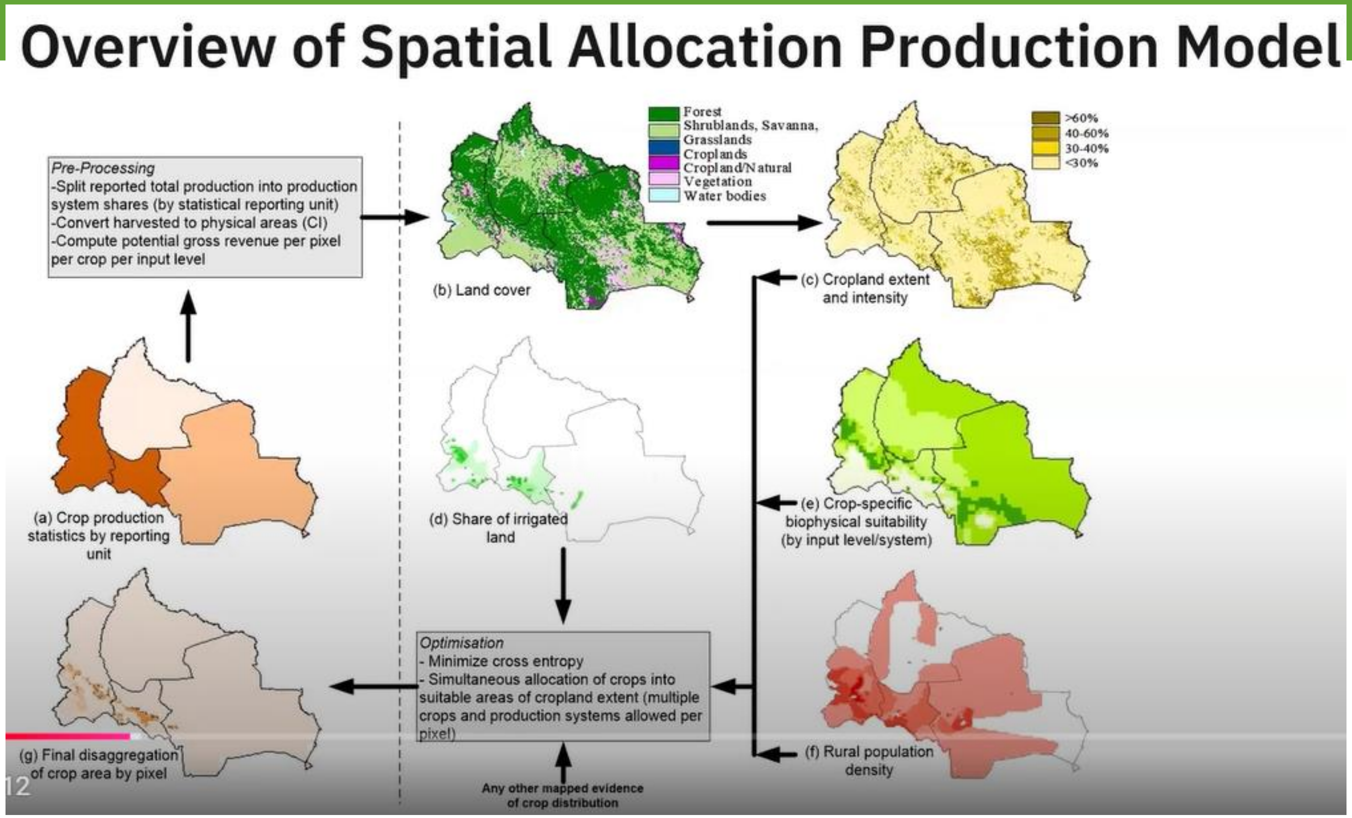
HYBRID PRODUCT

- Spatial Production Allocation Model (SPAM)
- Physical area (ha), harvested area (ha), production (kg), yield (kg/ha)
- 2000, 2005, 2010, 2017, 2020
- 5 arc-minute (~10 km)
- 46 crops
- Rainfed, irrigated, total



Yu, Q., You, L., Wood-Sichra, U., Ru, Y., Joglekar, A. K., Fritz, S., ... & Yang, P. (2020). A cultivated planet in 2010–Part 2: The global gridded agricultural-production maps. *Earth System Science Data*, *12*(4), 3545-3572.

https://mapspam.info/

https://cgiardata.projects.earthengine.app/view/spam

Sources of underlying data for SPAM 2020

Zhe Guo

- Subnational agricultural statistics
  - Average of 2019-2021
  - Georeferenced to subnational boundary
- National statistics
  - FAOStat
    National statistics of 2019, 2020, and 2021
- Cropland
  - Harmonized from Multiple sources
    Globalland30, 30m, 2020
    GLC-FC30, 30m, 2020
    Esri land cover, 10m, 2020
    ESA WorldCover, 10m, 2020
    UMD Global Cropland, 30m, 2019
- Irrigated area
  - Harmonized of irrigated area from different sources
    Global map of irrigated area (v5)
    Global Irrigated area
- Suitability surfaces
  - Global AEZ V4.0 (IIASA and FAO)
    Suitability area index
    Potential yield
- Population
  - CIESIN GPW 2020
  - EU's Joint Research Centre Global human settlement
- Market access
  - Travel time to cities in recent year

CHALLENGES WITH SATELLITE BASED MEASURES

- Sample size vs **measurement error**
  - Errors in RS **data**, or in RS **models**
  - E.g., saturation effects, cloud cover, atmospheric effects, non random misclassification
  - In regression, errors on dependent variable or on independent variables or both
- **Spatial units**
  - Unit of measurement vs unit of treatment
- Remote sensing model **accuracy** is inconsistent across the **range of measurement**
- ML-based remote sensing model **transferability** across space and time
  - Labels distribution shift in the primary/"ground truth"/reference data
  - Covariates (features) distribution shift
  - Use QA, calibrate and validate over study area
- **Temporal inconsistency**
- Circularity

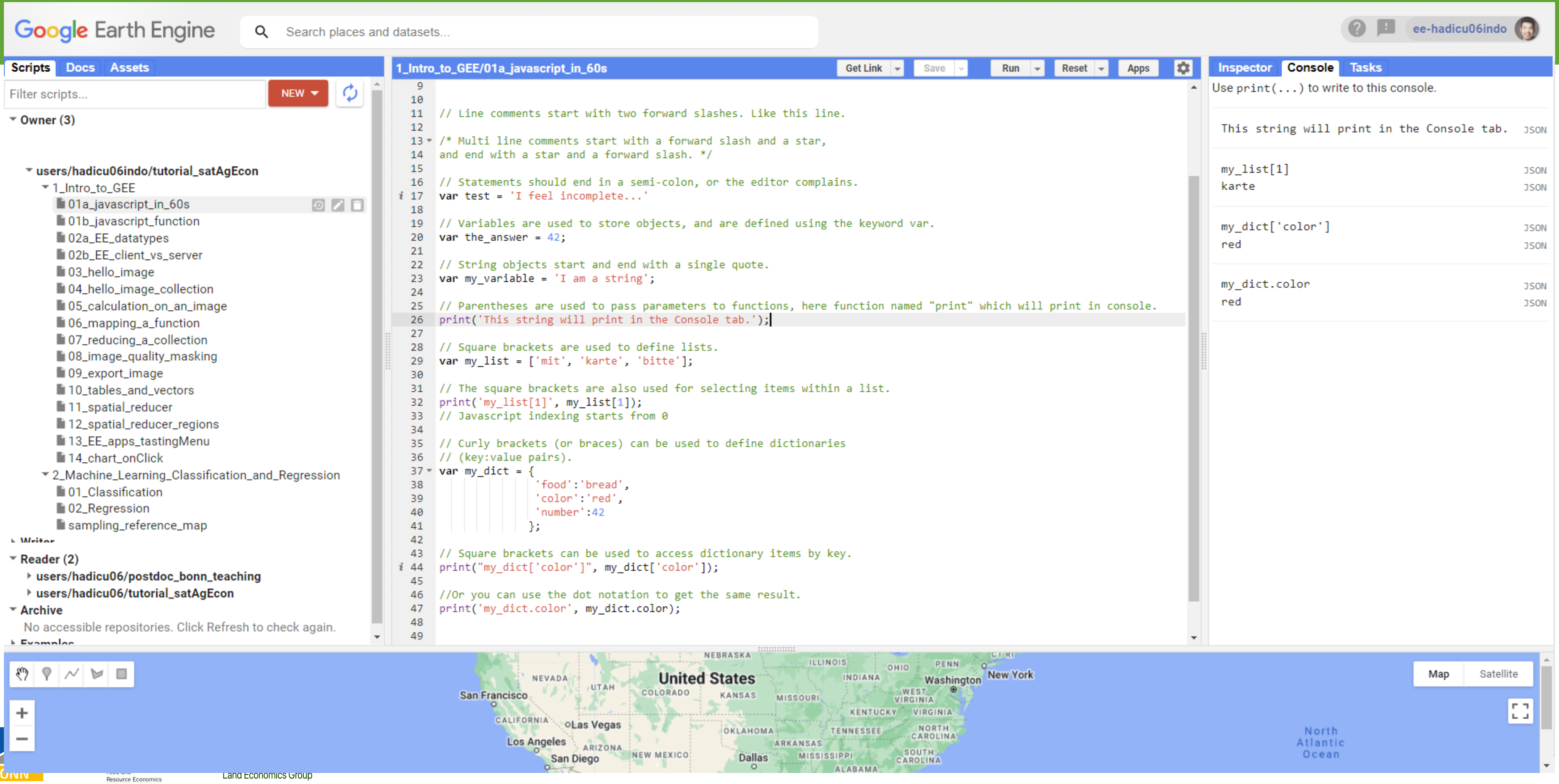
Blackman, A., Leguízamo, E., & Villalobos, L. (2024). Points, cells, or polygons? On the choice of spatial units in forest conservation policy impact evaluation. *Environmental Research Letters*, *19*(5), 054046.

Kluger, D. M., Wang, S., & Lobell, D. B. (2021). Two shifts for crop mapping: Leveraging aggregate crop statistics to improve satellite-based maps in new regions. *Remote Sensing of Environment*, *262*, 112488.

https://www.povertyactionlab.org/blog/2-21-24/new-resource-incorporating-remote-sensing-data-randomized-evaluations

PRACTICAL

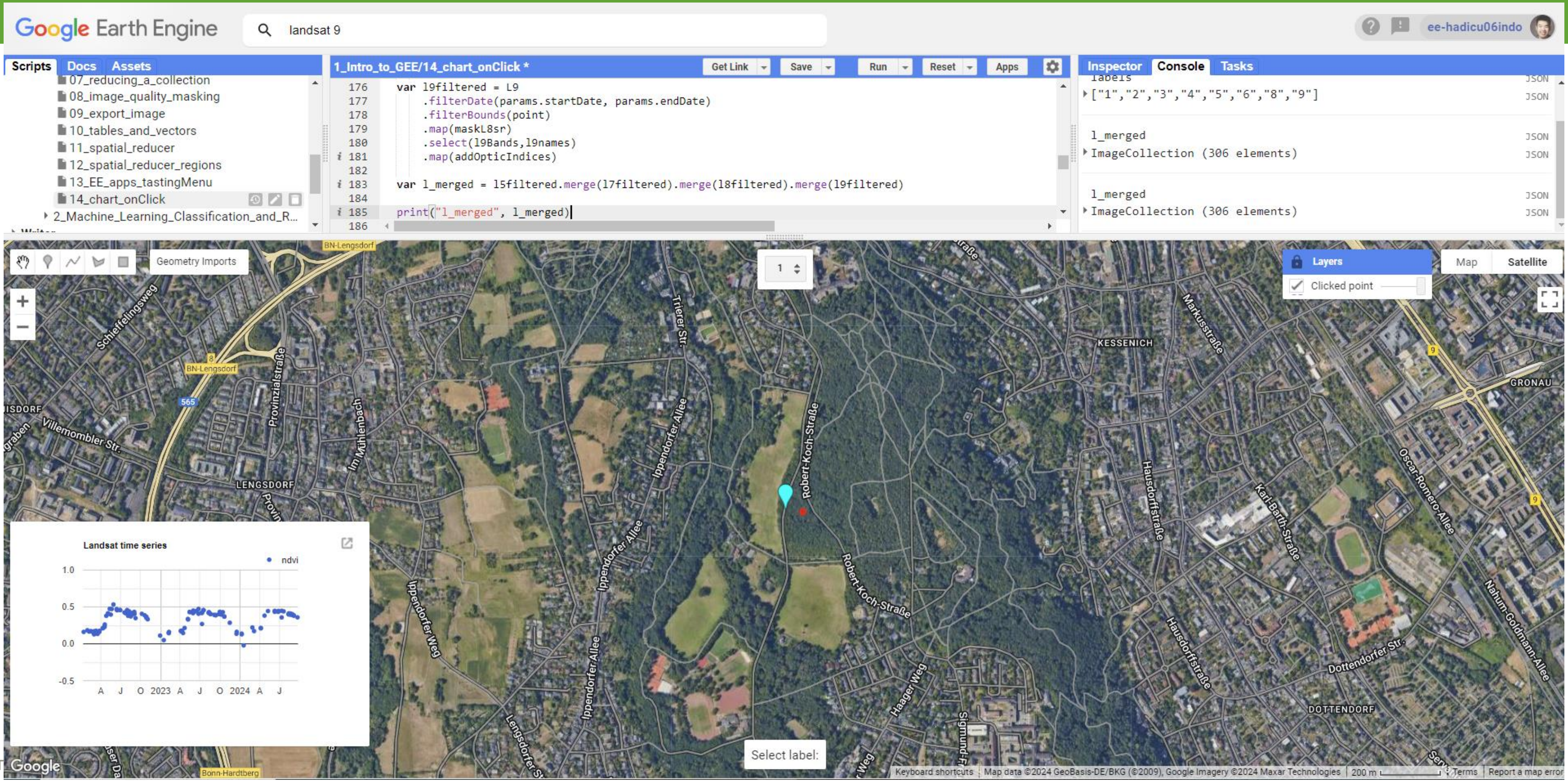
WE WILL START FROM THE VERY BASICS..

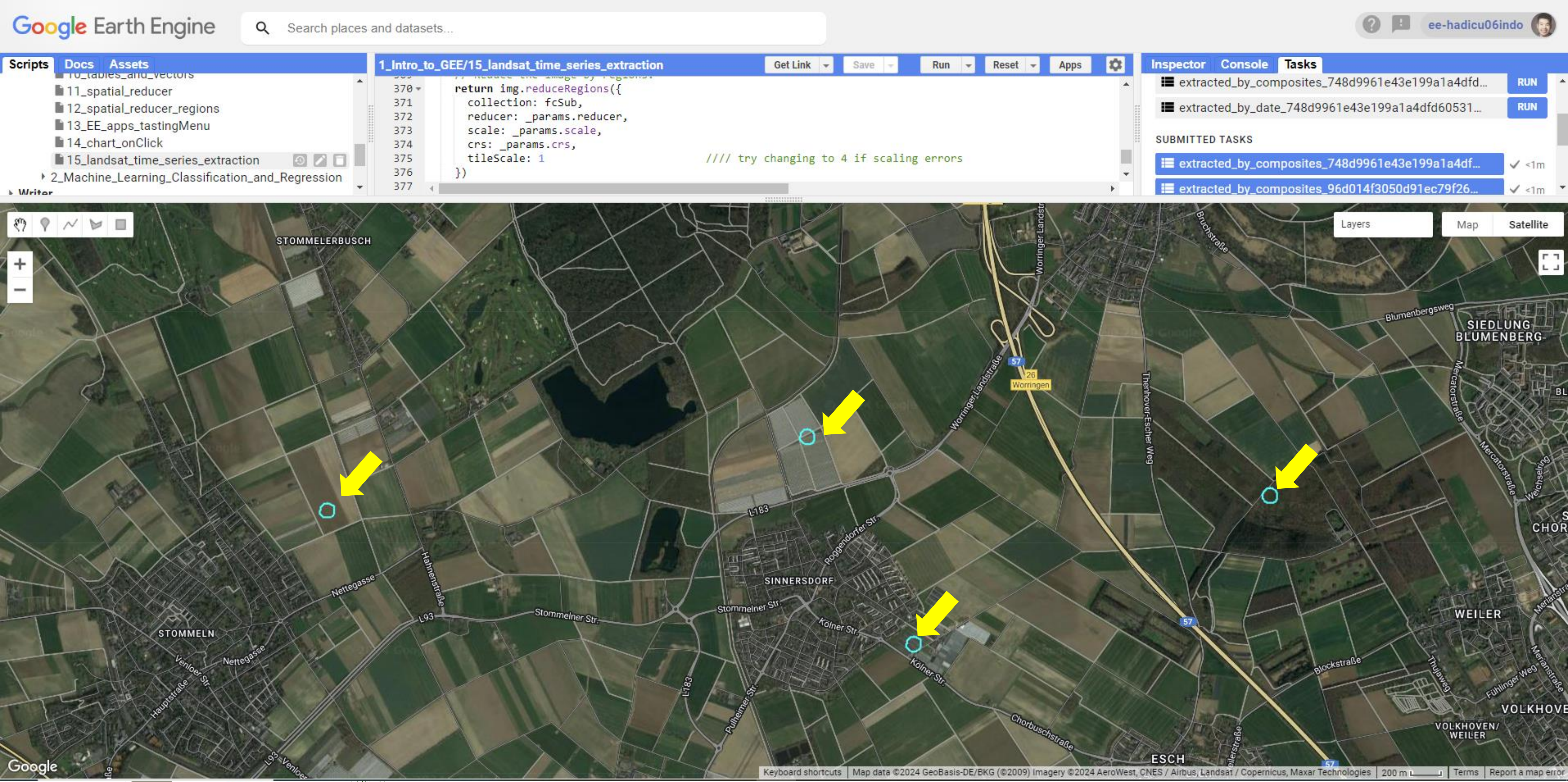


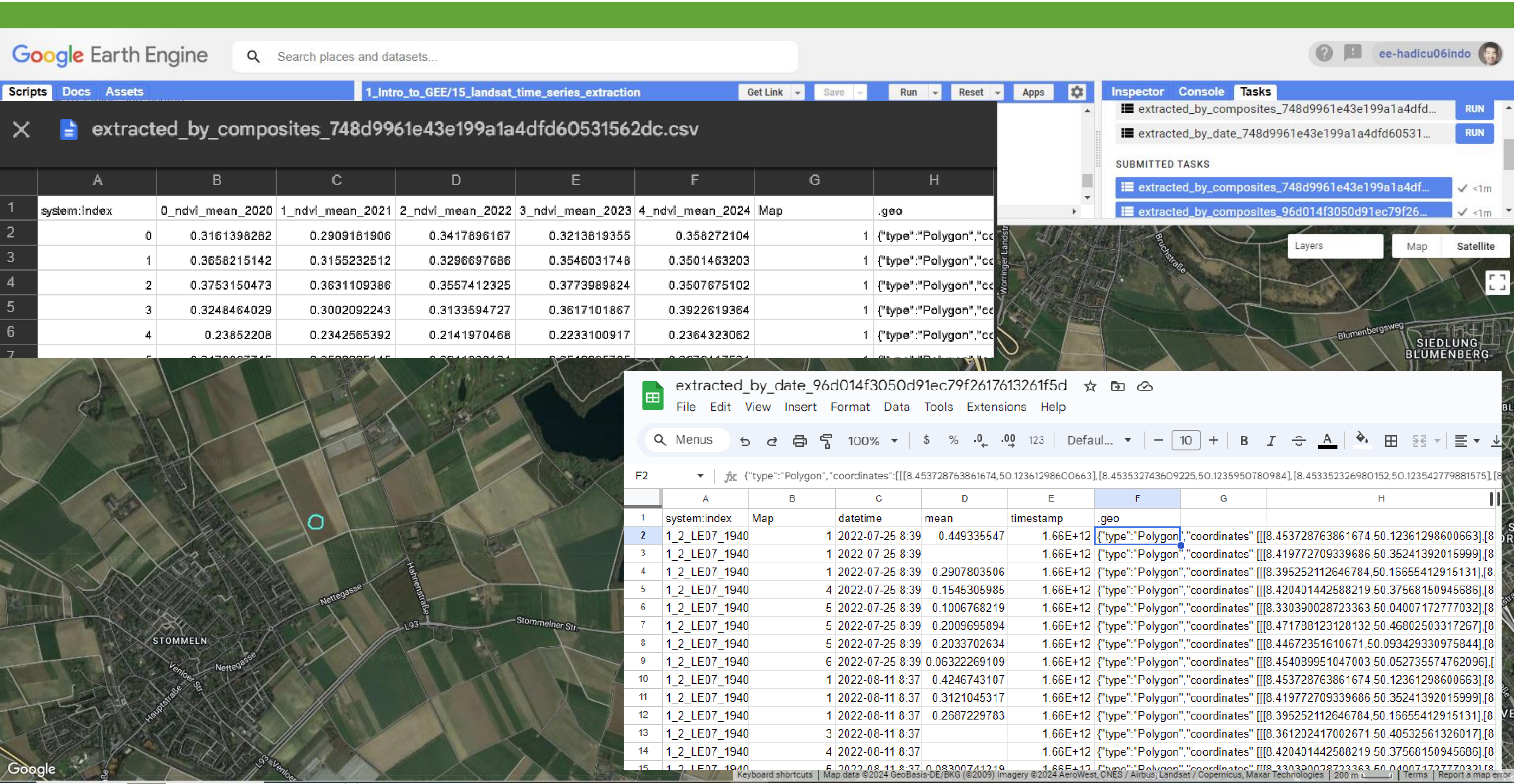
WHAT CAN YOU DO WITH EARTH ENGINE?

- Visualize data (maps, charts)
- Computations on images (per pixel)
- Machine learning (classification, regression, clustering)
- Reductions (in space and/or time)
- Data import and export
- Segmentation
- Neighborhood operations (convolutions)
- Time series analysis
- Interactive apps

DATA EXTRACTION AT LARGE SPATIAL AND TEMPORAL SCALES




Google Earth Engine
Search places and datasets...
ee-hadicu06indo
Scripts Docs Assets
11_spatial_reducer
12_spatial_reducer_regions
13_EE_apps_tastingMenu
14_chart_onClick
15_landsat_time_series_extraction
2_Machine_Learning_Classification_and_Regression
1_Intro_to_GEE/15_landsat_time_series_extraction
Get Link Save Run Reset Apps
370 return img.reduceRegions({
371 collection: fcSub,
372 reducer: _params.reducer,
373 scale: _params.scale,
374 crs: _params.crs,
375 tileScale: 1 //// try changing to 4 if scaling errors
376 })
Inspector Console Tasks
extracted_by_composites_748d9961e43e199a1a4dfd... RUN
extracted_by_date_748d9961e43e199a1a4dfd60531... RUN
SUBMITTED TASKS
extracted_by_composites_748d9961e43e199a1a4df... <1m
extracted_by_composites_96d014f3050d91ec79f26... <1m
Layers Map Satellite
STOMMELERBUSCH
STOMMELN
SINNERSDORF
SIEDLUNG BLUMENBERG
WEILER
VOLKHOVEN/WEILER
ESCH
Worringen
Stommelner Str.
Kölner Str.
Roggendorfer Str.
Nettegasse
Hahnenstraße
Woringer Landstraße
Thenhover-Escher Weg
Chorbuschstraße
Blockstraße
Blumenbergsweg
L183
L93
Keyboard shortcuts Map data ©2024 GeoBasis-DE/BKG (©2009) Imagery ©2024 AeroWest, CNES / Airbus, Landsat / Copernicus, Maxar Technologies 200 m Terms Report a map error



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0	0.3161398282	0.2909181906	0.3417896167	0.3213819355	0.358272104	1	{"type":"Polygon","cc
1	0.3658215142	0.3155232512	0.3296697686	0.3546031748	0.3501463203	1	{"type":"Polygon","cc
2	0.3753150473	0.3631109386	0.3557412325	0.3773989824	0.3507675102	1	{"type":"Polygon","cc
3	0.3248464029	0.3002092243	0.3133594727	0.3617101867	0.3922619364	1	{"type":"Polygon","cc
4	0.23852208	0.2342565392	0.2141970468	0.2233100917	0.2364323062	1	{"type":"Polygon","cc

system:index	Map	datetime	mean	timestamp	.geo
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1_2_LE07_1940	1	2022-07-25 8:39		1.66E+12	{"type":"Polygon","coordinates":[[[8.419772709339686,50.35241392015999],[8
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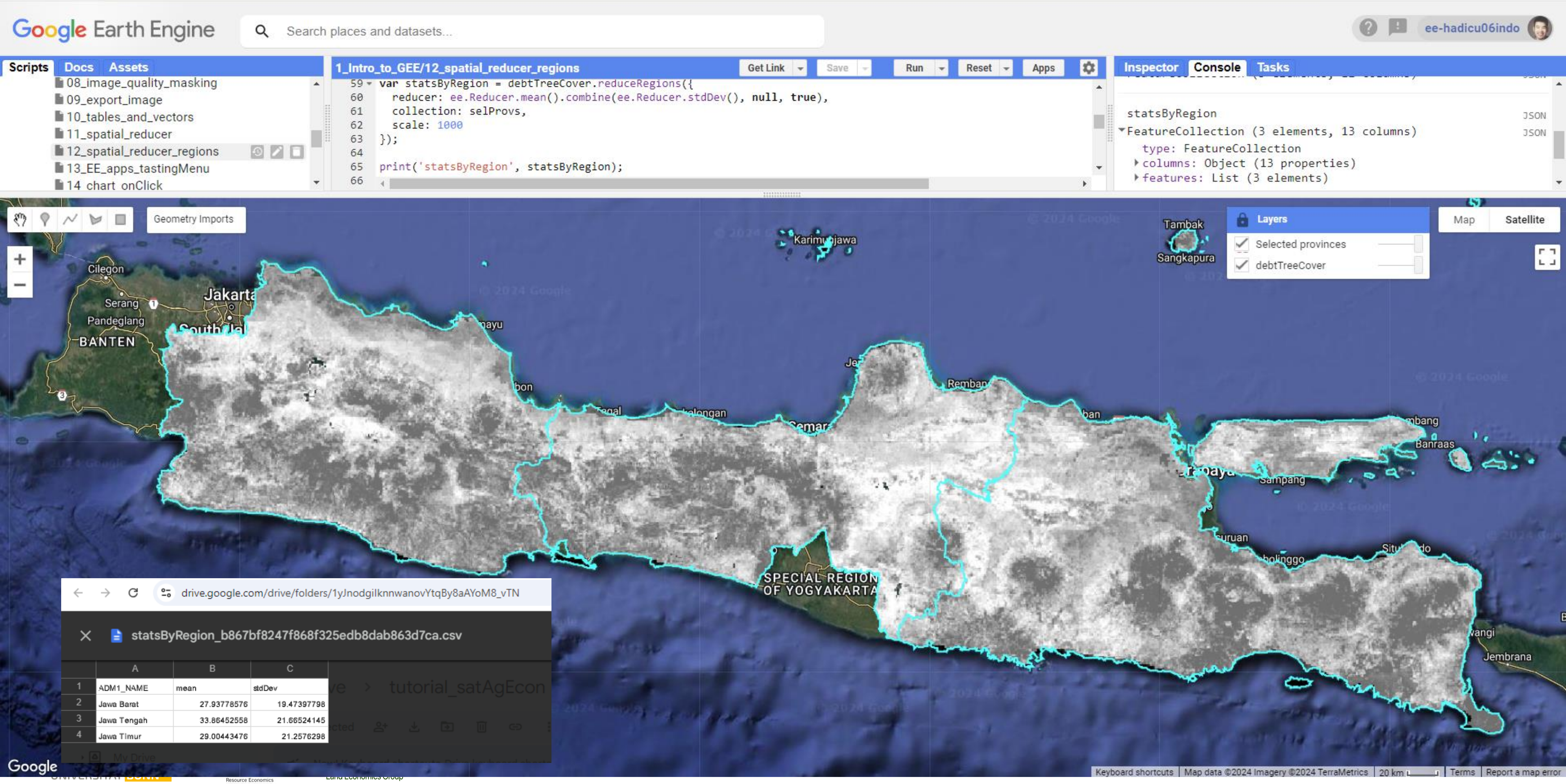
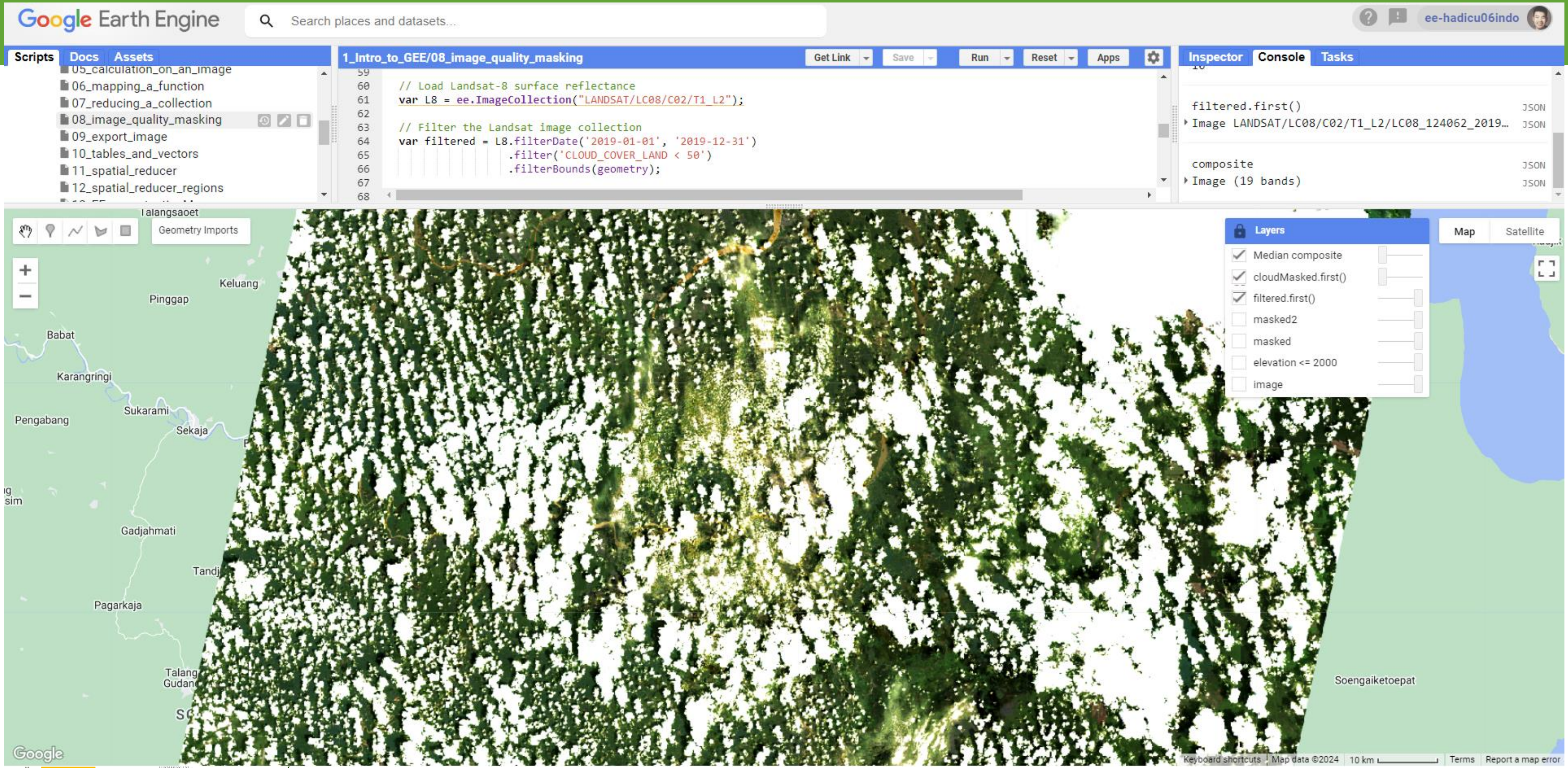
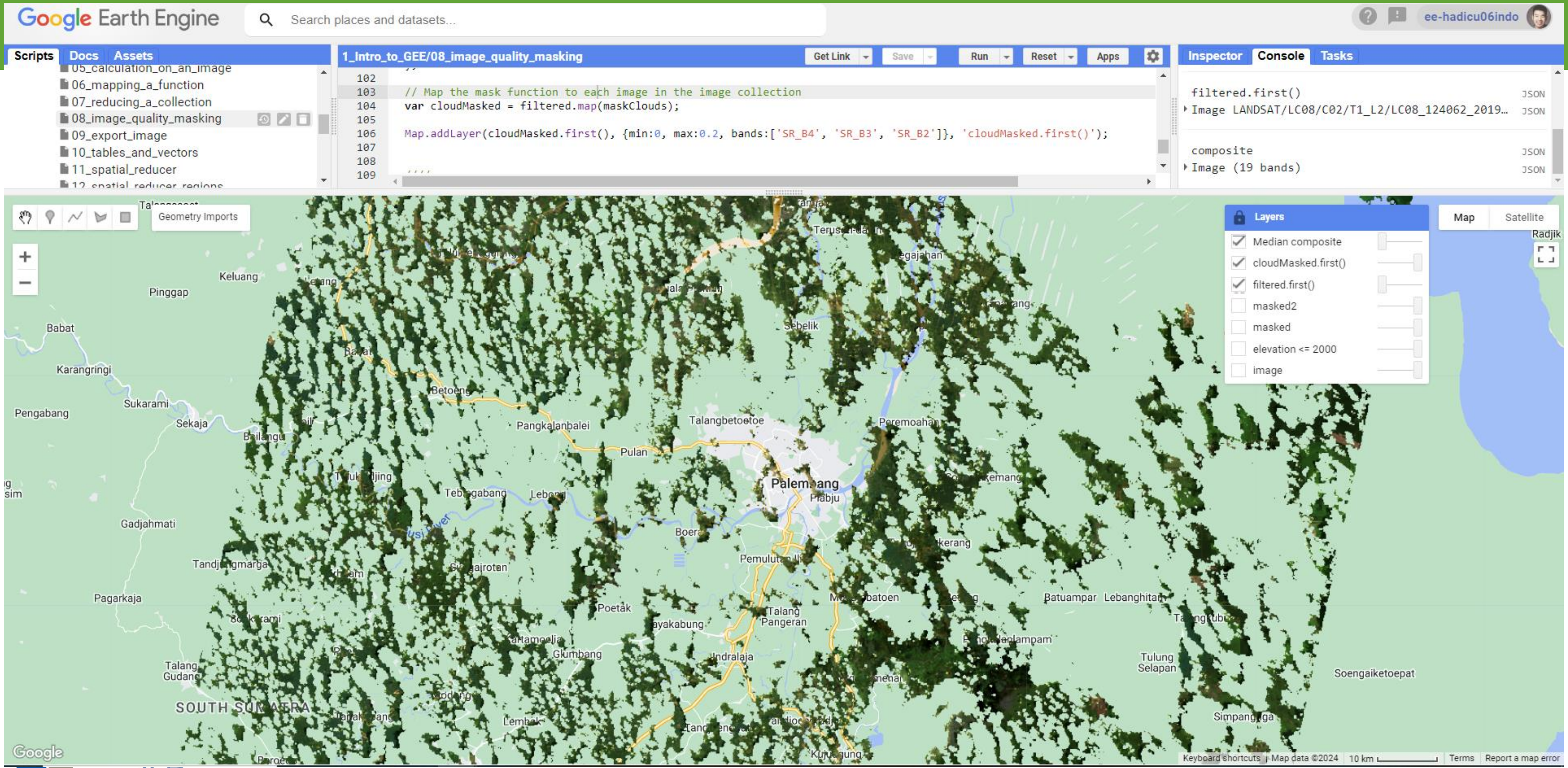
1_2_LE07_1940	4	2022-08-11 8:37		1.66E+12	{"type":"Polygon","coordinates":[[[8.420401442588219,50.37568150945686],[8



	A	B	C
1	ADM1_NAME	mean	stdDev
2	Jawa Barat	27.93778576	19.47397798
3	Jawa Tengah	33.86452558	21.66524145
4	Jawa Timur	29.00443476	21.2576298

DATA QUALITY ASSURANCE/CONTROL





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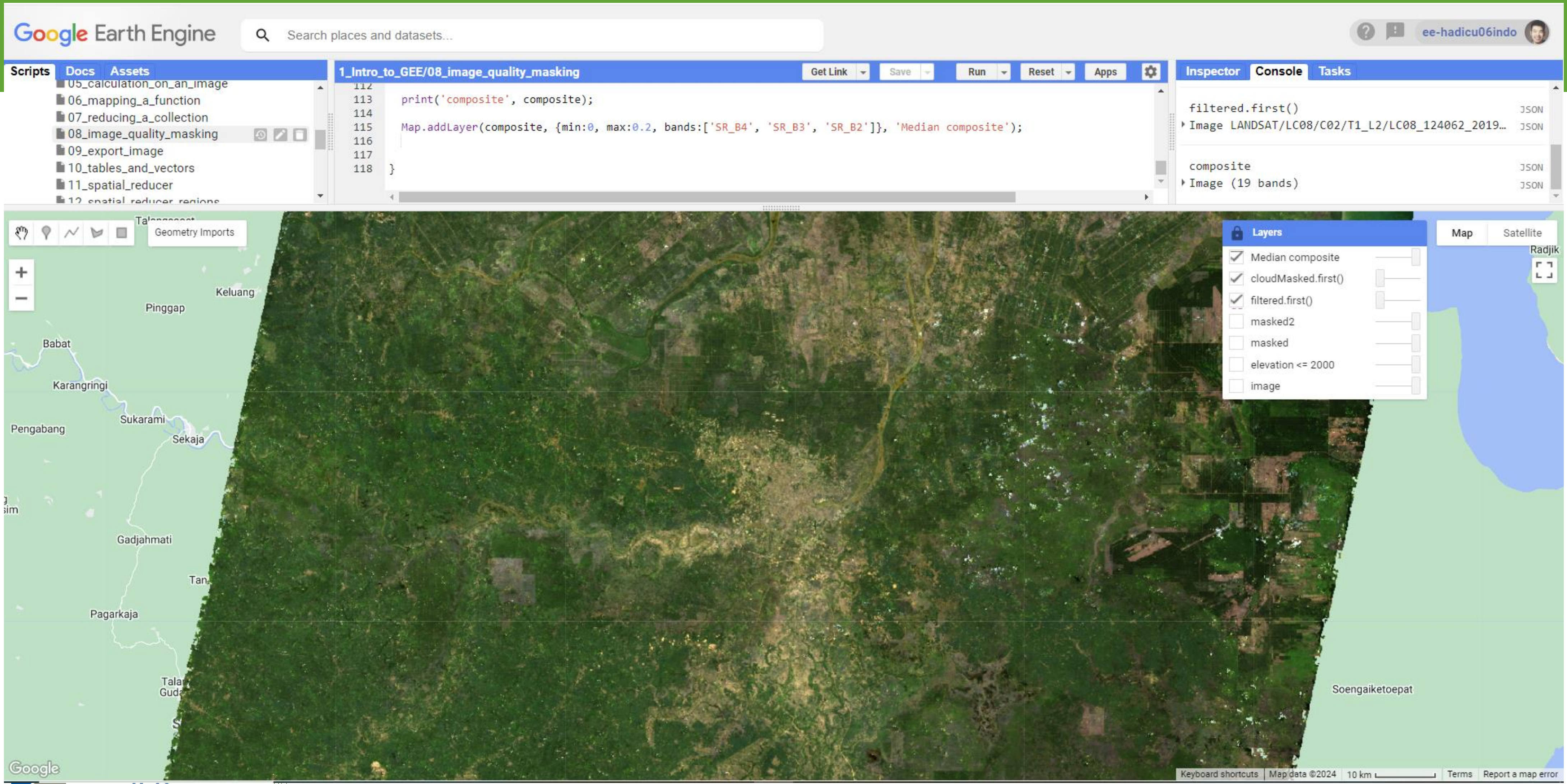
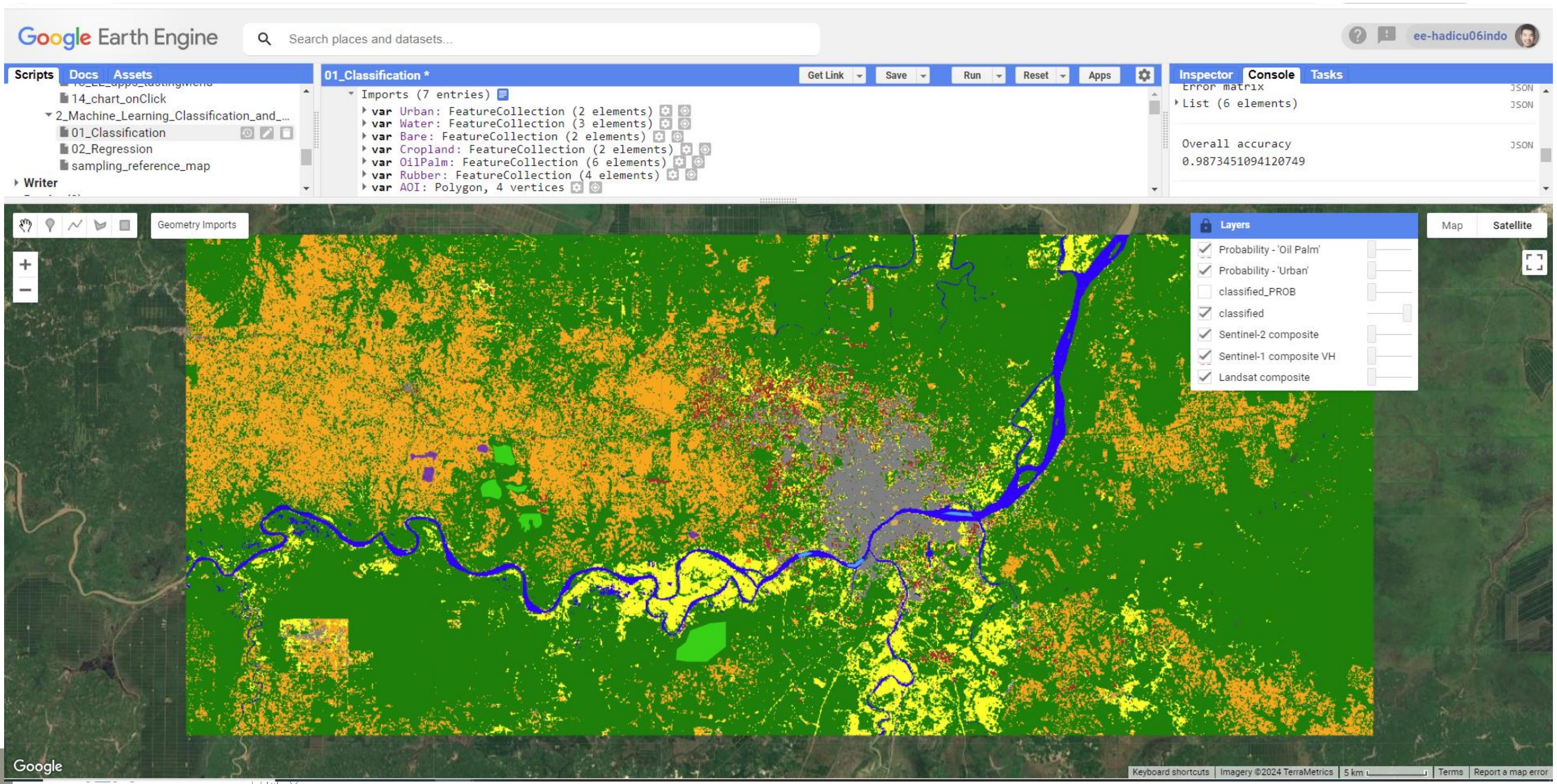
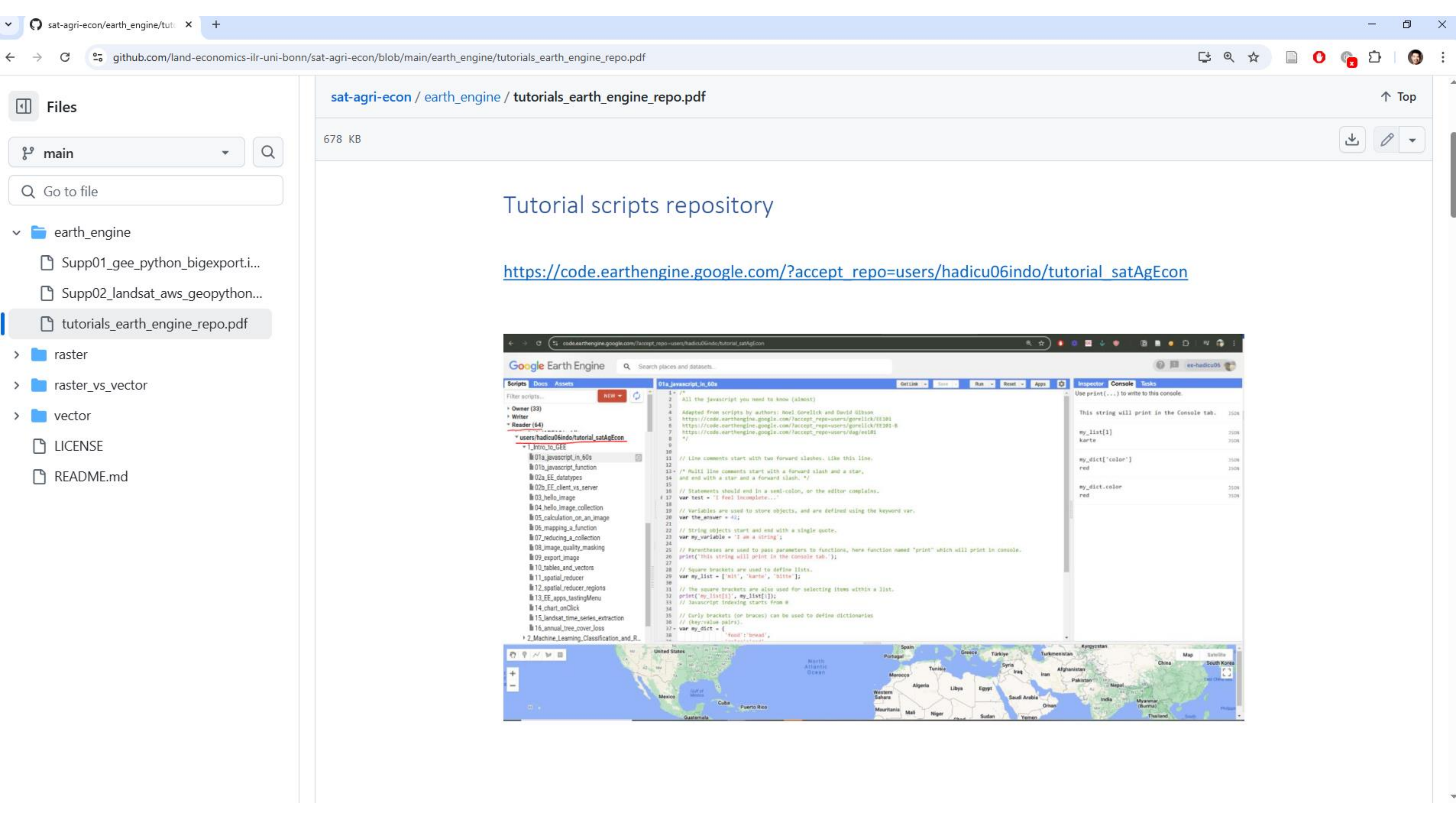

Google Earth Engine
Search places and datasets...
ee-hadicu06indo
Scripts
Docs
Assets
05_calculation_on_an_image
06_mapping_a_function
07_reducing_a_collection
08_image_quality_masking
09_export_image
10_tables_and_vectors
11_spatial_reducer
1_Intro_to_GEE/08_image_quality_masking
Get Link
Save
Run
Reset
Apps
print('composite', composite);
Map.addLayer(composite, {min:0, max:0.2, bands:['SR_B4', 'SR_B3', 'SR_B2']}, 'Median composite');
}
Inspector
Console
Tasks
filtered.first()
Image LANDSAT/LC08/C02/T1_L2/LC08_124062_2019...
composite
Image (19 bands)
JSON
Geometry Imports
Layers
Median composite
cloudMasked.first()
filtered.first()
masked2
masked
elevation <= 2000
image
Map
Satellite
Keluang
Pinggap
Babat
Karangringi
Pengabang
Sukarami
Sekaja
Gadjahmati
Pagarkaja
Radjik
Soengaiketoepat
Keyboard shortcuts
Map data ©2024
10 km
Terms
Report a map error

MACHINE LEARNING TO CREATE A THEMATIC DATA PRODUCT




sat-agri-econ/earth_engine/tut
github.com/land-economics-ilr-uni-bonn/sat-agri-econ/blob/main/earth_engine/tutorials_earth_engine_repo.pdf
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main
Go to file
earth_engine
Supp01_gee_python_bigexport.i...
Supp02_landsat_aws_geopython...
tutorials_earth_engine_repo.pdf
raster
raster_vs_vector
vector
LICENSE
README.md
sat-agri-econ / earth_engine / tutorials_earth_engine_repo.pdf
Top
678 KB
Tutorial scripts repository
https://code.earthengine.google.com/?accept_repo=users/hadicu06indo/tutorial_satAgEcon
Google Earth Engine
Scripts
Docs
Assets
Owner (33)
Writer
Reader (64)
users/hadicu06indo/tutorial_satAgEcon
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01b_javascript_function
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02b_EE_client_vs_server
03_hello_image
04_hello_image_collection
05_calculation_on_an_image
06_mapping_a_function
07_reducing_a_collection
08_image_quality_masking
09_export_image
10_tables_and_vectors
11_spatial_reducer
12_spatial_reducer_regions
13_EE_apps_tastingMenu
14_chart_onClick
15_landsat_time_series_extraction
16_annual_tree_cover_loss
2_Machine_Learning_Classification_and_R...
Inspector
Console
Tasks
This string will print in the Console tab.
my_list[1]
karte
my_dict['color']
red
my_dict.color
red

```
cloud_project = 'ee-hadicu06indo' # replace with your project id

ee.Authenticate()
ee.Initialize(project=cloud_project)
```

```
task = ee.batch.Export.table.toDrive(
    collection=outputFc,
    description=outputAssetName,
    folder=driveFolder,
    fileFormat='CSV',
    selectors=propNamesToKeep
)

# ----- Start the export job! --------

task.start()
```

evi_annualMean_spatialMean_Canada.csv

	A	B	C	D	E
1	evi	year	shapeGroup	shapeType	shapeName
2	2538.755798	2001	CAN	ADM0	Canada
3	2675.000757	2002	CAN	ADM0	Canada
4	2729.612223	2003	CAN	ADM0	Canada
5	2763.500421	2004	CAN	ADM0	Canada
6	2845.413806	2005	CAN	ADM0	Canada
7	2779.820037	2006	CAN	ADM0	Canada
8	2731.473878	2007	CAN	ADM0	Canada
9	2853.420921	2008	CAN	ADM0	Canada
10	2629.416634	2009	CAN	ADM0	Canada
11	2789.347995	2010	CAN	ADM0	Canada
12	3009.08914	2011	CAN	ADM0	Canada
13	2949.204257	2012	CAN	ADM0	Canada
14	3235.610816	2013	CAN	ADM0	Canada
15	3072.613728	2014	CAN	ADM0	Canada
16	2822.147027	2015	CAN	ADM0	Canada
17	3043.295452	2016	CAN	ADM0	Canada
18	2944.244359	2017	CAN	ADM0	Canada
19	3029.155882	2018	CAN	ADM0	Canada
20	3084.231846	2019	CAN	ADM0	Canada
21	3162.431889	2020	CAN	ADM0	Canada
22	2609.603138	2021	CAN	ADM0	Canada

- **And more!**

```python
catalog = pystac_client.Client.open(
    'https://earth-search.aws.element84.com/v1')

search = catalog.search(
    collections=['sentinel-2-c1-l2a'],
    bbox=bbox,
    datetime='2024-06-01/2024-08-31',
    query={'eo:cloud_cover': {'lt': 30}},
)
```

```python
ds = stac_load(
    items,
    bands=['red', 'green', 'blue', 'nir', 'scl'],
    resolution=10,
    bbox=bbox,
    chunks={},  # <-- use Dask
    groupby='solar_day',
)
ds
```

xarray.Dataset

▶ Dimensions: (**y**: 205, **x**: 133, **time**: 12)

▼ Coordinates:

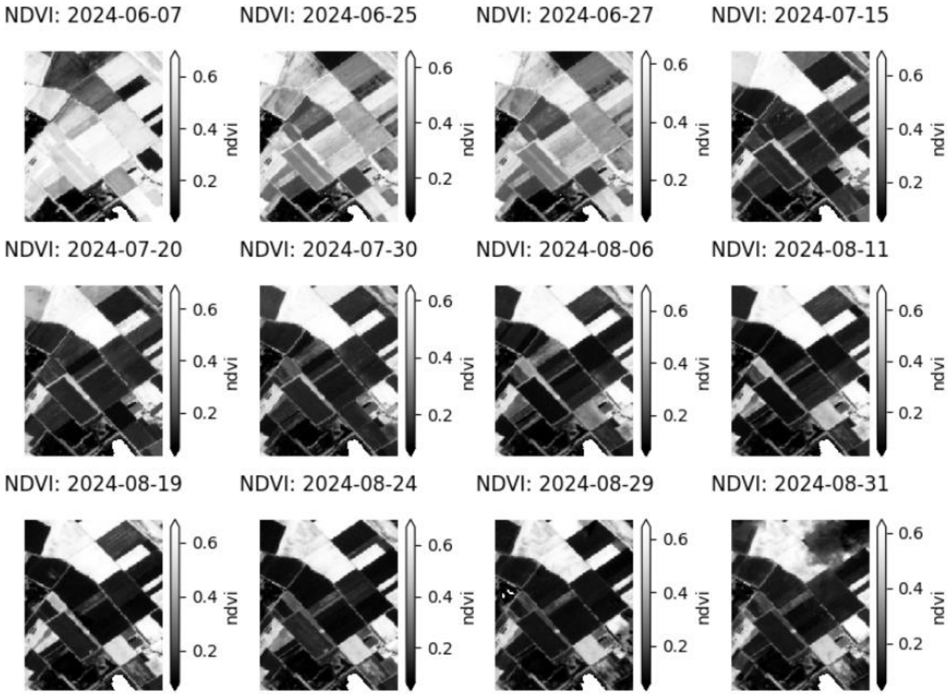
y	(y)	float64	5.622e+06 5.622e+06 ... 5.62e+06
x	(x)	float64	3.482e+05 3.482e+05 ... 3.495e+05
spatial_ref	()	int32	32632
time	(time)	datetime64[ns]	2024-06-07T10:36:55.279000 ... 2...

▼ Data variables:

red	(time, y, x)	uint16	dask.array<chunksize=(1, 205, 133), meta=np.nd...
green	(time, y, x)	uint16	dask.array<chunksize=(1, 205, 133), meta=np.nd...
blue	(time, y, x)	uint16	dask.array<chunksize=(1, 205, 133), meta=np.nd...
nir	(time, y, x)	uint16	dask.array<chunksize=(1, 205, 133), meta=np.nd...
scl	(time, y, x)	uint8	dask.array<chunksize=(1, 205, 133), meta=np.nd...

▶ Indexes: (3)

▶ Attributes: (0)



SCALING ISSUES

Scaling issues
”Error: Computation timed out”
”Error: User memory limit exceeded”
“Error: Too many aggregations”
“Error: Internal server error”

- Export the result to Asset / Drive / Cloud Storage

Bad — don't do this!

```
var ridiculousComputation = ee.Image(1).reduceRegion({
  reducer: 'count',
  geometry: ee.Geometry.Rectangle([-180, -90, 180, 90],
  scale: 100,
  maxPixels: 1e11
});

// Error: Computation timed out.
print(ridiculousComputation);
```

Good — use `Export`!

```
Export.table.toDrive({
  collection: ee.FeatureCollection([
    ee.Feature(null, ridiculousComputation)
  ]),
  description: 'ridiculousComputation',
  fileFormat: 'CSV'
});
```

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For more best practices see https://developers.google.com/earth-engine/best_practices ebugging

How I Debug Your Code - my checklist

Low Hanging Fruit

- getInfo()
- for loops
- iterate()
- toList()
- Complex geometries
- Don't clip
- image.reduceToVectors()
- image.reproject()
- image.resample()
- image.reduceResolution()
- Joins

Collections

- filterDate / filterBounds
- calendarRange() without filterDate()
- collection.geometry()
- toBands() / toArray()

Aggregations

- Tilescale in reduce*
- Combine reducers
- image.reduceNeighborhood()
  - Neighborhood size
  - Use optimizations

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- https://radiantearth.github.io/stac-browser/#/?.language=en

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THANK YOU

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EXTRA: VARIABLES

NEW GENERATION 10-M LAND COVER MAPS

Table 1
Overview of GLC products used in this study.

Dataset name	Data source	Classification model	Period of data	Number of classes	Spatial resolution (m)	Temporal frequency	Reported overall accuracy	Reference	GEE asset ID
WorldCover	Sentinel-1, Sentinel-2	Gradient boosting decision tree (CatBoost)	2020, 2021	11	10	Yearly	76.7%	Zanaga et al., 2022	"ESA/WorldCover/v200"
Dynamic World	Sentinel-2	Fully Convolutional Neural Network (FCNN)	2015–2023	9	10	2–5 days	73.8%	Brown et al., 2022	"GOOGLE/DYNAMICWORLD/V1"
ESRI LULC	Sentinel-2	Convolutional Neural Network - UNet	2017–2022	9	10	Yearly	85.0%	Karra et al., 2021	The most recent version (July 2023) is not available on GEE but can be accessed through AWS[1], Esri Living Atlas[2], and Microsoft Azure[3].

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Xu, P., Tsendbazar, N. E., Herold, M., de Bruin, S., Koopmans, M., Birch, T., ... & Zanaga, D. (2024). Comparative validation of recent 10 m-resolution global land cover maps. *Remote Sensing of Environment*, *311*, 114316.

NEW GENERATION 10-M LAND COVER MAPS

Table 2

Overview of harmonized and original land cover classes of the GLC products. Numbers in the brackets indicate class code. The original class definitions can be found in Table S1 of the supplementary material.

New label	Reference data	WorldCover	Dynamic World	ESRI LULC
Water (0)	Open water (80)	Permanent water bodies (80)	Water (0)	Water (1)
Trees (1)	Closed forest (11); Open forest (12)	Tree cover (10)	Trees (1)	Trees (2)
Mixed vegetation (2)	Shrubs (20); Herbaceous vegetation (30); Wetland herbaceous vegetation (90)	Shrubland (20); Grassland (30); Moss and lichen (100); Herbaceous wetland (90); Mangroves (95)	Grass (2); Shrub & Scrub (5); Flooded vegetation (3)	Rangeland (11); Flooded vegetation (4)
Crops (4)	Cropland (40)	Cropland (40)	Crops (4)	Crops (5)
Built area (6)	Urban/built up (50)	Built-up (50)	Built area (6)	Built Area (7)
Bare ground (7)	Bare/sparse vegetation (60)	Bare / sparse vegetation (60)	Bare ground (7)	Bare ground (8)
Snow & Ice (8)	Snow and ice (70)	Snow and ice (70)	Snow & Ice (8)	Snow/ice (9)

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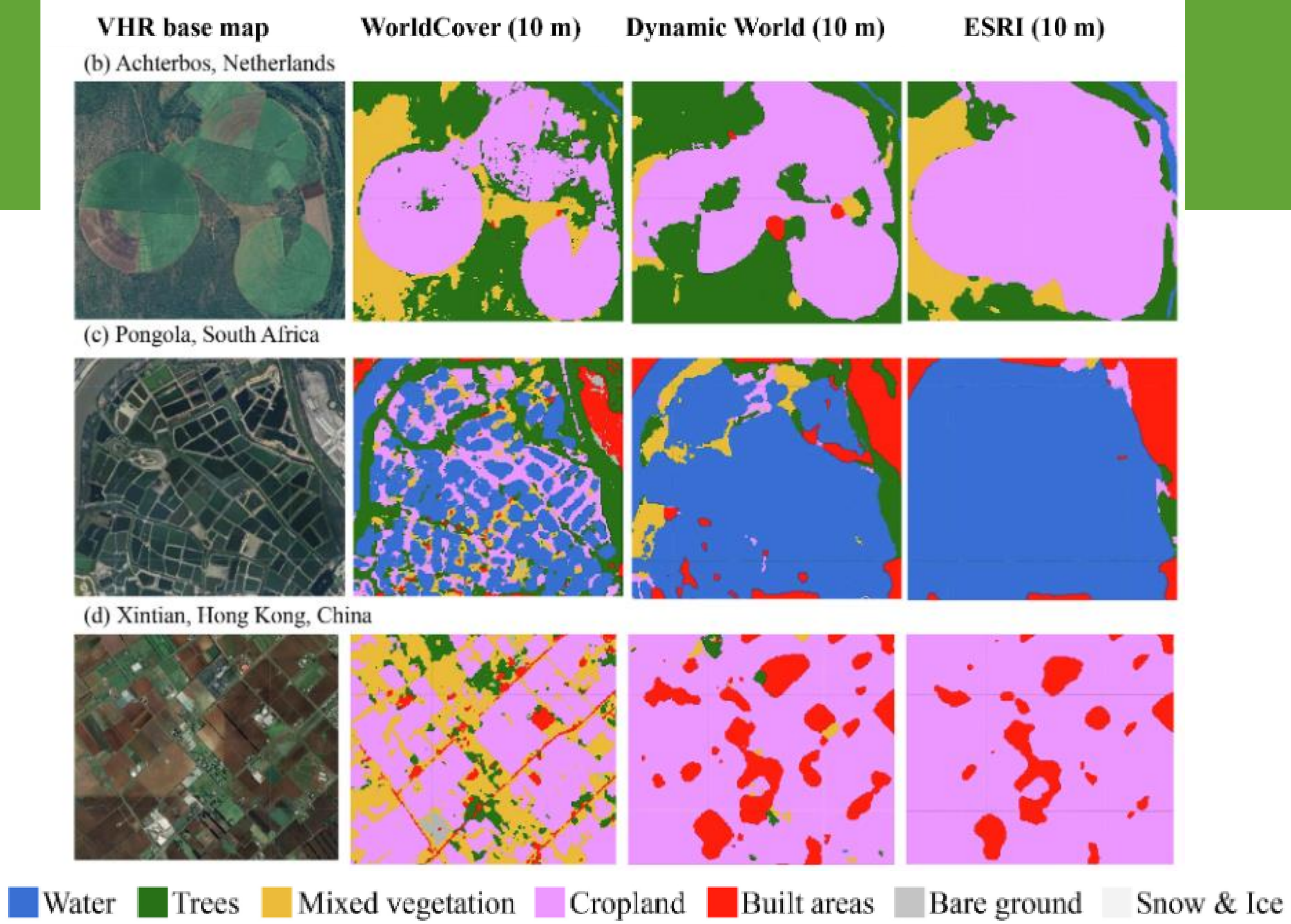
Xu, P., Tsendbazar, N. E., Herold, M., de Bruin, S., Koopmans, M., Birch, T., ... & Zanaga, D. (2024). Comparative validation of recent 10 m-resolution global land cover maps. *Remote Sensing of Environment*, *311*, 114316.



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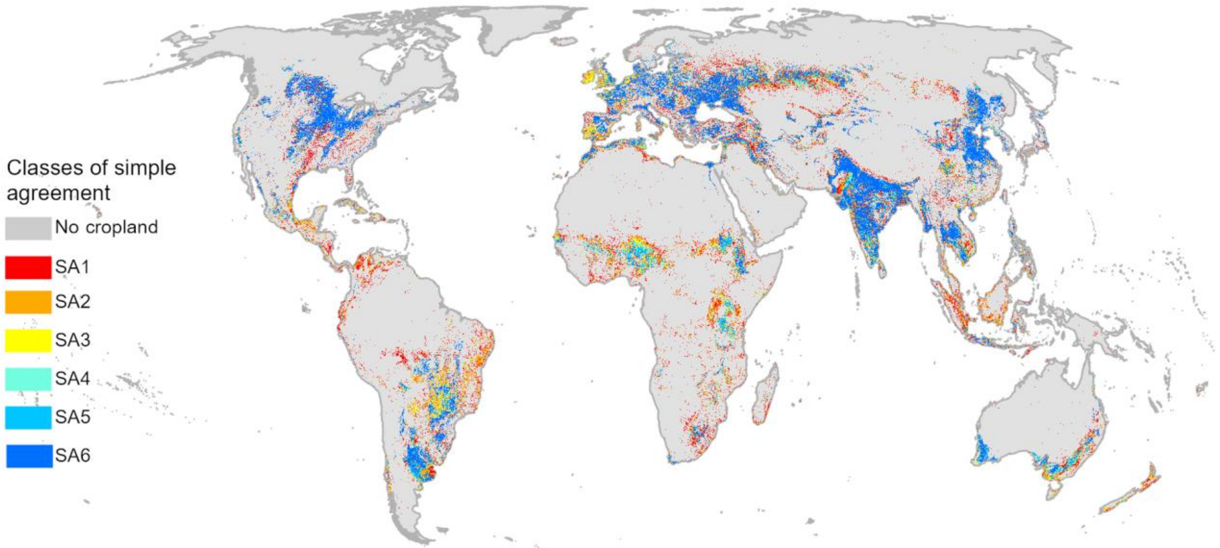
FAO GAEZ V5

Dataset	Label	Definition	Cropland class no.	Accuracy[a]
ESRI (ESR)	Crops	Human planted/plotted cereals, grasses and crops not at tree height; examples include corn, wheat, soy and fallow plots of structured land.	5	PA 89.9 %; UA 91 %
FROM-GLC Plus[b] (FRG)	Croplands	Land that has clear traits of intensive human activity. It varies a lot: bare field, seeding, crop growing, and harvesting. It includes arable and tillage land with herbaceous/shrub crops and land with plastic foam or grass roof protection with distinguishing spectral properties. Fruit trees are classified as forests.	10 – Level 1	OA 71.9 %
GLAD (GLD)	Cropland	Land used for annual and perennial herbaceous crops for human consumption, forage (including hay) and biofuel. Perennial woody crops, permanent pastures and shifting cultivation are excluded from the definition. The fallow length is limited to 4 years for the cropland class.	1	PA 86.4 %; UA: 88.5 %
GLC-FCS30-2020[c] (FCS30)	Cropland	Rainfed cropland, irrigated cropland, herbaceous cover, and tree or shrub cover (orchard)	10 – Level 1 20 – Level 1 11 – Level 2 12 – Level 2[d]	PA 88.0 %; UA 83.9 %
Globeland30 (GL30)	Cultivated land	Category includes paddy fields, irrigated dry land, rain-fed dry land, vegetable land, pasture planting land, greenhouse land, land and mainly for planting crops with fruit trees and other economic trees, as well as tea gardens, coffee gardens and other shrubs.	10	OA 85.7 %
WorldCover (WCO)	Cropland	Land covered with annual cropland that is sowed/planted and harvestable at least once within the 12 months after the sowing/planting date. The annual cropland produces a herbaceous cover and is sometimes combined with some tree or woody vegetation. Note that perennial woody crops will be classified as the appropriate tree cover or shrub land cover type. Greenhouses are considered as built-up.	40	PA 76.7 %; UA 81.1 %



Tubiello, F. N., Conchedda, G., Casse, L., Hao, P., De Santis, G., and Chen, Z.: A new cropland area database by country circa 2020, Earth Syst. Sci. Data, 15, 4997–5015, https://doi.org/10.5194/essd-15-4997-2023, 2023.

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GLOBAL FOREST CHANGE (HANSEN)

Earth Engine Data Catalog

Search /

Description | Bands | Terms of Use | Citations | DOIs

Resolution

30.92 meters

Bands

Name	Units	Min	Max	Wavelength	Description
`treecover2000`	%	0	100		Tree canopy cover for year 2000, defined as canopy closure for all vegetation taller than 5m in height.
`loss`					Forest loss during the study period, defined as a stand-replacement disturbance (a change from a forest to non-forest state).
Bitmask for loss					
`gain`					Forest gain during the period 2000-2012, defined as the inverse of loss (a non-forest to forest change entirely within the study period). Note that this has not been updated in subsequent versions.
Bitmask for datamask					
`lossyear`		0	23		Year of gross forest cover loss event. Forest loss during the study period, defined as a stand-replacement disturbance, or a change from a forest to non-forest state. Encoded as either 0 (no loss) or else a value in the range 1-23, representing loss detected primarily in the year 2001-2023, respectively.

https://storage.googleapis.com/earthenginepartners-hansen/GFC-2023-v1.11/download.htm l

GLCLUC2020

Data Download (GeoTIFF, Lat/long, WGS84)

All layers provided as a global set of 10×10° tiles. Tile database available here (ESRI shapefile).

Forest height, 2000 (pixel value: forest height in meters)
Forest height gain, 2000-2020 (pixel value: forest height gain in meters)
Forest extent, 2000 (pixel value: 0/1, 1 indicate forest presence)

Forest height, 2020 (pixel value: forest height in meters)
Forest height loss, 2000-2020 (pixel value: forest height loss in meters)
Forest extent, 2020 (pixel value: 0/1, 1 indicate forest presence)

Dataset Access in Google Earth Engine

Forest height, 2000: projects/glad/GLCLU2020/Forest_height_2000
Forest height gain, 2000-2020: projects/glad/GLCLU2020/Forest_height_netgain
Stable forest extent, 2000-2020: projects/glad/GLCLU2020/Forest_stable
Forest extent gain, 2000-2020: projects/glad/GLCLU2020/Forest_gain

Forest height, 2020: projects/glad/GLCLU2020/Forest_height_2020
Forest height loss, 2000-2020: projects/glad/GLCLU2020/Forest_height_netloss
Forest extent loss, 2000-2020: projects/glad/GLCLU2020/Forest_loss
Forest dynamic type, 2000-2020: projects/glad/GLCLU2020/Forest_type

Classes:

1 - Stable forest extent, 2000-2020
2 - Forest extent loss, 2001-2020
3 - Forest extent gain, 2001-2020
4 - Forests affected by stand-replacement disturbances or degradation, 2001-2020

Potapov P., Hansen M.C., Pickens A., Hernandez-Serna A., Tyukavina A., Turubanova S., Zalles V., Li X., Khan A., Stolle F., Harris N., Song X.-P., Baggett A., Kommareddy I., Kommareddy A. (2022) The global 2000-2020 land cover and land use change dataset derived from the Landsat archive: first results. Frontiers in Remote Sensing [https://doi.org/10.3389/frsen.2022.856903]

https://glad.umd.edu/dataset/GLCLUC2020

Dataset	Year(s)	Res. (m/px)	Model Scale	Coverage	Definition of Cropland
DEA Cropland Extent	2019	10	AEZ	Continent	"A piece of land of minimum 0.01 ha that is sowed/planted and harvestable at least once within the 12 months after the sowing/planting date."[27,49]
Dynamic World	2015–2024	10	Global	Global	"Human planted/plotted cereals, grasses, and crops"[21]
Esri LULC	2017–2022	10	Global	Global	"Human planted/plotted cereals, grasses, and crops not at tree height; examples: corn, wheat, soy, fallow plots of structured land."[23,50]
ESA WorldCover	2020–2021	10	Global	Global	"Land covered with annual cropland that is sowed/planted and harvestable at least once within the 12 months after the sowing/planting date. The annual cropland produces an herbaceous cover and is sometimes combined with some tree or woody vegetation. Note that perennial woody crops will be classified as the appropriate tree cover or shrub land cover type. Greenhouses are considered as built-up."[22,43,51]
ESA CCI Africa	2016	20	Continent	Continent	No explicit definition provided[28,52]
GFSAD	2015	30	AEZ	Global	"Cropland that is cultivated and harvested for food, feed, and (or) fiber, one or more times during a 12-month period; Cropland that is left fallow, even when equipped for agriculture; and Cropland that is permanently cropped with plantations (for example, orchards, vineyards, coffee, tea, and rubber)."[29,53]
Nabil *et al.*	2016	30	Mixed	Continent	"all agricultural annual standing croplands, cropland fallows, and permanent plantation crops"[24,54]
GLAD	2003, 2007,2011, 2015, 2019	30	1° × 1°	Global	"[…] land used for annual and perennial herbaceous crops for human consumption, forage (including hay) and biofuel. Perennial woody crops, permanent pastures and shifting cultivation are excluded from the definition."[30,55]
Copernicus Land Cover	2015–2019	100	Biome	Global	"Cultivated and managed vegetation/agriculture. Lands covered with temporary crops followed by harvest and a bare soil period (e.g., single and multiple cropping systems). Note that perennial woody crops will be classified as the appropriate forest or shrub land cover type."[31,56]
ESA GlobCover	2005, 2009	300	Strata	Global	"Post-flooding or irrigated croplands," "rainfed croplands," "Mosaic Cropland (50–70%)/Vegetation (grassland, shrubland, forest) (20–50%)," and "Mosaic Vegetation (grassland, shrubland, forest) (50–70%)/Cropland (20–50%)"[32,57]
ASAP Crop Mask	2017	1000	Mixed	Global	"arable land and permanent crops…independently of their life forms (e.g., tree forms), production systems (i.e., both rainfed and irrigated), and density of cover"[11,13,58]

Table 3. Description of map data products evaluated in this study.

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Kerner, H., Nakalembe, C., Yang, A., Zvonkov, I., McWeeny, R., Tseng, G., & Becker-Reshef, I. (2024). How accurate are existing land cover maps for agriculture in Sub-Saharan Africa?. *Scientific Data*, *11*(1), 486.

Table 1 | Cropland area estimates

Product	Land Use definitions	~2020	2000	Note[a]
		Area (Mha)	**Area (Mha)**	
GLAD	Cropland. Land used for annual and perennial herbaceous crops for human consumption, forage (including hay) and biofuel. Perennial woody crops, permanent pastures and shifting cultivation are excluded.	1,215	1,019[a]	M_AL
ESRI	Crops. Human planted and/or plotted cereals, grasses and crops not at tree height, such as corn, wheat, soy and fallow plots of structured land.	1,350	NA	AL
FROM-GLC	Croplands. ... includes arable and tillage land with herbaceous and/or shrub crops ... Fruit trees are classified into forests.	1,467	NA	AL
GLC-FCS30	Cropland. Rainfed and irrigated cropland. Detailed ... data include herbaceous, tree or shrub cover.	1,945	NA	CL
GLOBELAND30	Cropland. Category includes paddy fields, irrigated dry land, rain-fed dry land, vegetable land, pasture planting land ..., fruit trees ... as well as tea gardens, coffee gardens and other shrubs.	2,002	NA	CL
WORLDCOVER	Cropland. Land covered with annual cropland ... produces an herbaceous cover ... perennial woody crops classified as the appropriate tree cover or shrub land cover type ...	1,260	NA	AL
Aggregate		1,540±370		
		2020	**2000**	
FAO	Cropland. Land used for cultivation of crops. The total of areas under 'Arable land' and 'Permanent crops'.	1,562	1,499	
	Permanent crops. Land cultivated with long-term crops which do not have to be replanted for several years...	175	139	
	Arable land. Land used for cultivation of crops in rotation with fallow, meadows and pastures within cycles of up to five years. The total of areas under "Temporary crops," "Temporary meadows and pastures," and "Temporary fallow."...	1,387	1,360	
	Temporary crops. Land used for crops with a less-than-one-year growing cycle, which must be newly sown or planted for further production after the harvest.... Multiple-cropped areas are counted only once.	1,061	963[b]	
	Temporary fallow. Land that is not seeded for one or more growing seasons. The maximum idle period is usually less than five years. This land may be in the form sown for the exclusive production of green manure....	176	203[b]	
	Temporary meadows and pasture. Land temporarily cultivated with herbaceous forage crops for mowing or pasture, as part of crop rotation periods of less than five years.	145	189[b]	
	Modified arable land. Arable land minus temporary meadows and pastures (Note: this is not per se a FAO land use category)	1,237	1,181[b]	

Land use definitions (abridged for relevance to this analysis) of cropland across six high-resolution cropland maps (Supplementary Information), alongside those of the relevant FAO categories. For the latter, complete land use definitions can be found in the Land Use, Irrigation and Agricultural Practice Questionnaire (https://www.fao.org/statistics/data-collection/en/). The world total area is provided for each product, and the FAO land use categories for 2020 and 2000, where available. The mean and 95% confidence intervals of the six cropland maps is also provided. [a]The last column maps each of the six products 'cropland' definitions into the most relevant FAO land use category: CL=Cropland; AL=Arable land; M_AL=Modified arable land. [b]Year 2001 data.

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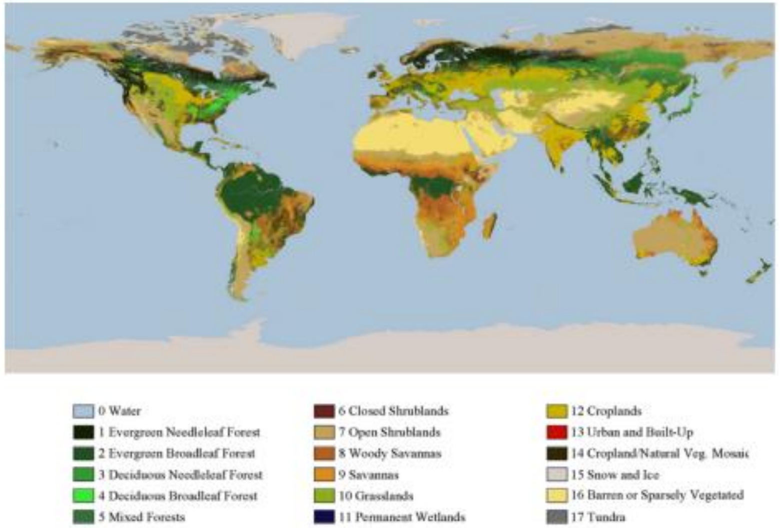
Tubiello, F.N., Conchedda, G., Casse, L. *et al.* Measuring the world's cropland area. *Nat Food* **4**, 30–32 (2023).

ANNUAL LAND COVER MAPS, 2001 -

MODIS Land Products: Land Cover (MCD12Q1)

- Yearly 500 meter product
- Primary Land Cover Type Scheme: International Geosphere Biosphere Program (IGBP) global vegetation classification scheme
  - 11 vegetation classes
  - 3 developed classes
  - 3 non-vegetated classes



http://reverb.echo.nasa.gov/

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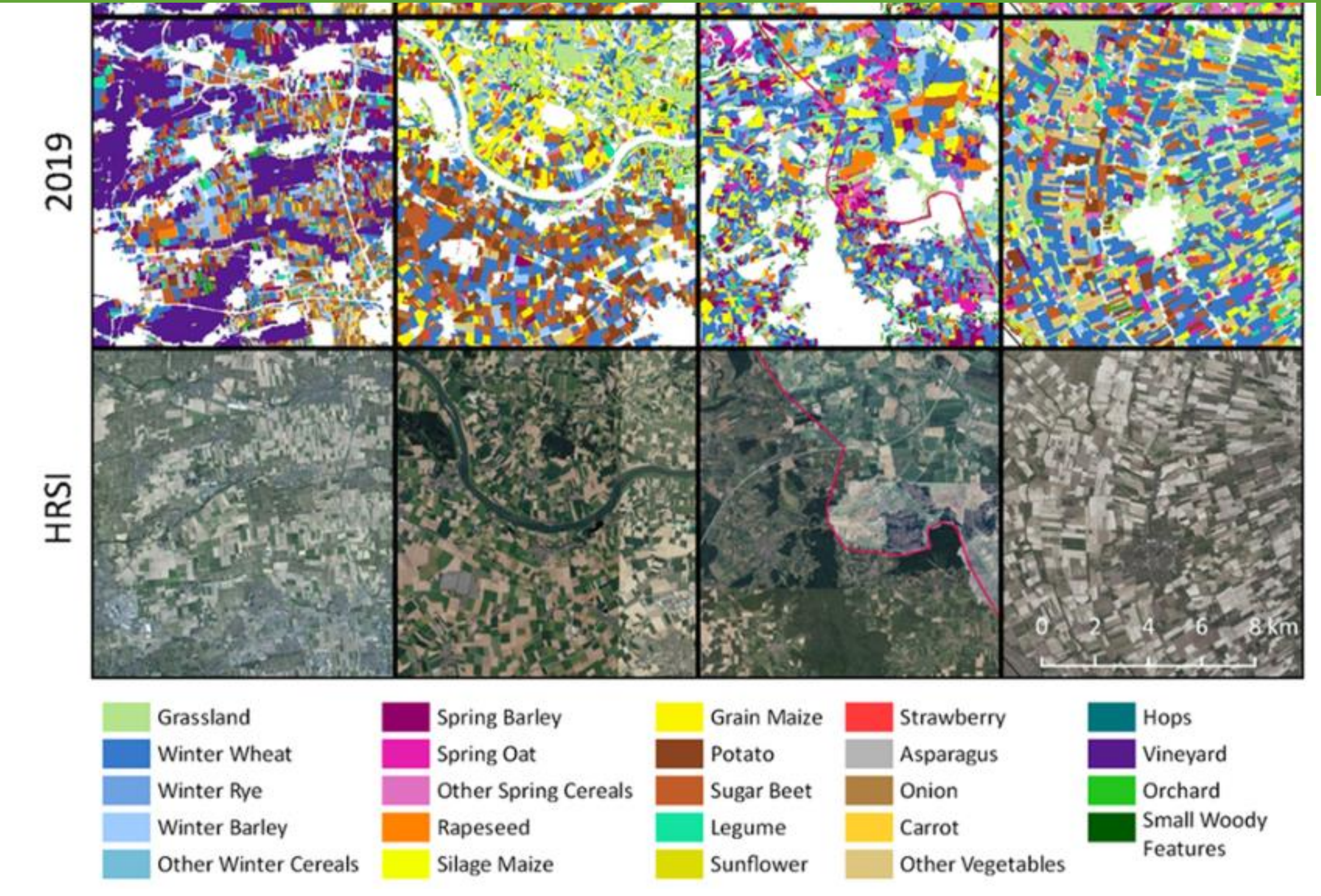

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Blickensdörfer, L., Schwieder, M., Pflugmacher, D., Nendel, C., Erasmi, S., & Hostert, P. (2022). Mapping of crop types and crop sequences with combined time series of Sentinel-1, Sentinel-2 and Landsat 8 data for Germany. *Remote sensing of environment*, *269*, 112831.

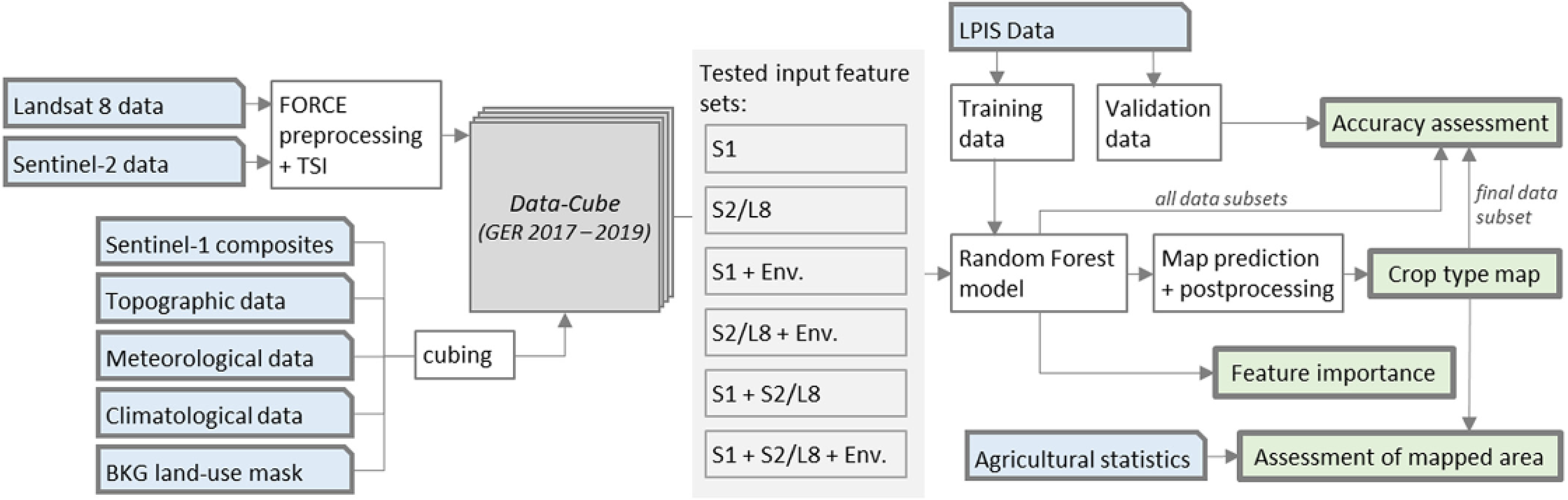


Fig. 1. Mapping workflow overview. Blue boxes: input data sets; green boxes: analysis results. S1: Sentinel-1; S2/L8: Sentinel-2/Landsat 8; Env.: Environmental data. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Blickensdörfer, L., Schwieder, M., Pflugmacher, D., Nendel, C., Erasmi, S., & Hostert, P. (2022). Mapping of crop types and crop sequences with combined time series of Sentinel-1, Sentinel-2 and Landsat 8 data for Germany. *Remote sensing of environment*, *269*, 112831.

CROP TYPE

- Best Available Crop Specific masks (BACS)
- Wheat, maize, rice, soybeans
- 0.05 degrees (~ 5 km)

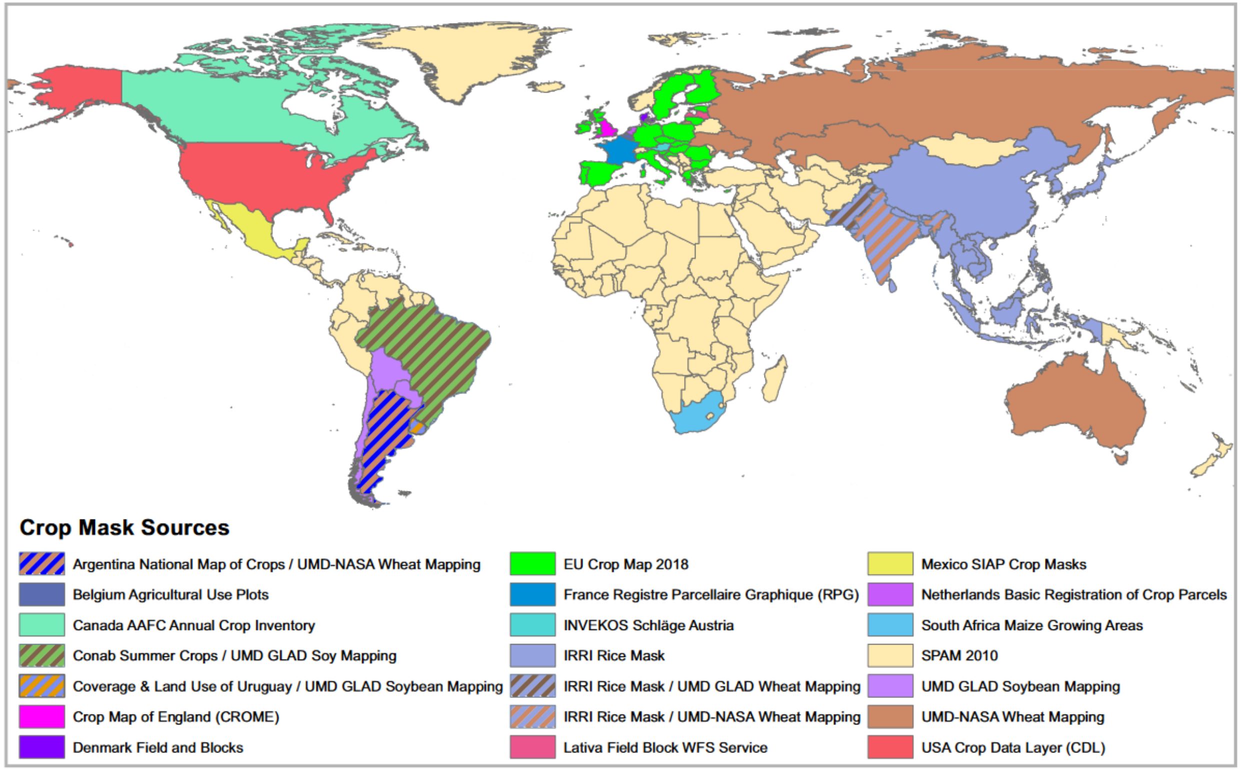
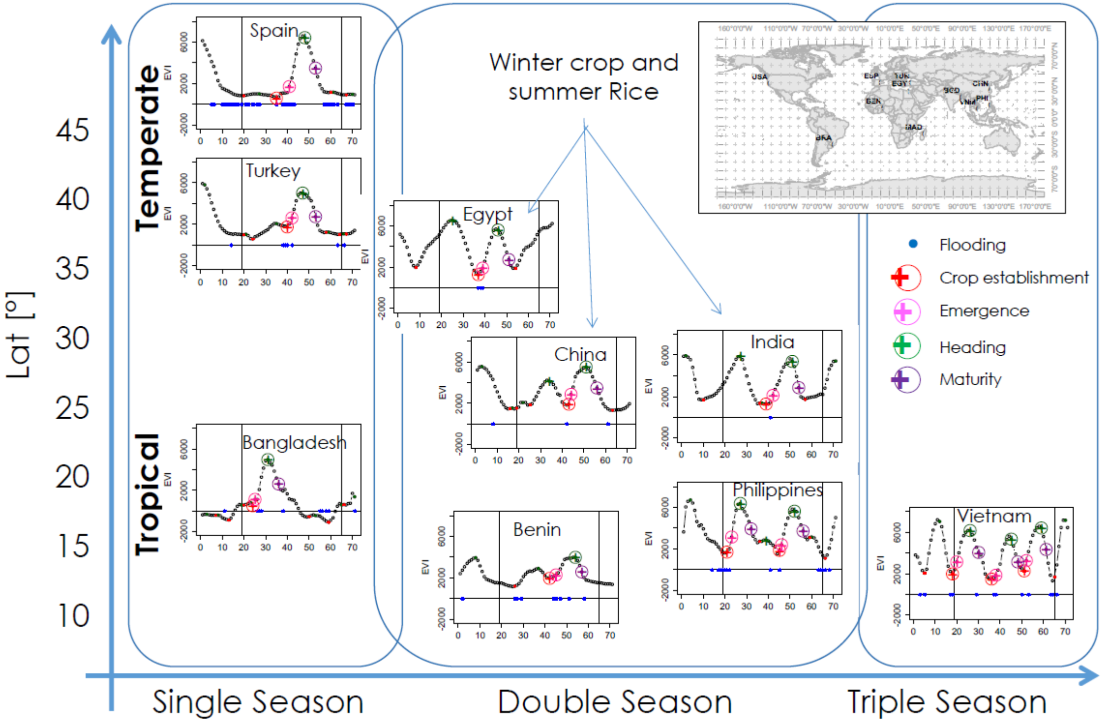


Fig. 1 Individual products used per country to assemble the final GEOGLAM Best Available Crop Masks.

Becker-Reshef, I., Barker, B., Whitcraft, A., Oliva, P., Mobley, K., Justice, C., & Sahajpal, R. (2023). Crop type maps for operational global agricultural monitoring. *Scientific Data*, *10*(1), 172.

Country/Region of Coverage	Product	Crop(s) covered	Native Resolution	Season Coverage	References
Argentina	National Map of Crops 2018/2019 campaign	Maize, Soybean	30 meter	2018–2019	41
Argentina	UMD/NASA Wheat Mapping	Winter Wheat	500 meter	2015	42
Asia	IRRI Rice Mask	Rice	500 meter	2000–2003	43–46
Australia	UMD/NASA Wheat Mapping	Winter Wheat	500 meter	2014–2018 avg	42
Austria	INVEKOS Schläge Austria 2019	Maize, Soybean, Winter Wheat, Spring Wheat	Field Scale	2019	47
Belgium	Agricultural use plots ALV 2016, Anonymous agricultural plot (2018) (PAA)	Maize, Soybean, Winter Wheat, Spring Wheat	Field Scale	2018, 2016	48
Brazil	Conab summer crop areas	Maize, Rice, Winter Wheat	Field Scale to 250 m	2014–2021	49
Argentina, Brazil, Bolivia, Chile, Paraguay, Uruguay	UMD GLAD Annual Soybeans	Soybean	30 meter	2020	50,51
Canada	AAFC Canada Annual Crop Inventory	Maize, Soybean, Winter Wheat, Spring Wheat	30 meter	2019	52
Denmark	Fields and Blocks	Maize, Winter Wheat, Spring Wheat	Field Scale	2019	N/A (not publicly accessible)
England	Crop Map of England (CROME) 2019	Maize, Soybean, Winter Wheat, Spring Wheat	64 meter	2019	53
European Union	EU Crop Map 2018	Winter wheat, Maize	10 meter	2018	54
France	France Registre Parcellaire Graphique (RPG)	Maize, Soybean, Rice, Winter Wheat, Spring Wheat	Field Scale	2018	55
Global	SPAM 2010 v2.0	Maize, Soybean, Rice, Wheat	0.083 degrees	2010	56
India	UMD/NASA Wheat Mapping	Winter Wheat	500 meter	2014	42
Kazakhstan	UMD/NASA Wheat Mapping	Spring Wheat	500 meter	2015	42
Latvia	Field Block WFS service	Maize, Soybean, Winter Wheat, Spring Wheat	Field Scale	2019	N/A (not publicly accessible)
Mexico	Mexico SIAP crop mask	Maize, Winter Wheat, Spring Wheat	Field Scale	2019	N/A (not publicly accessible)
Netherlands	Basic Registration of Crop Parcels (BRP) 2019	Maize, Soybean, Winter Wheat, Spring Wheat	Field Scale	2019	57
Pakistan	UMD GLAD Pakistan Winter Wheat	Winter Wheat	250 meter	2014	58
Russian Federation	UMD/NASA Wheat Mapping	Winter Wheat	500 meter	2019	42
South Africa	Maize growing areas	Maize	Field Scale	2014	N/A (not publicly accessible)
Ukraine	UMD/NASA Wheat Mapping	Winter Wheat	500 meter	2019	42
Uruguay	Integrated Map of Coverage/Land Use of Uruguay	Rice	10 meter	2018	59
USA	USDA NASS CDL	Maize, Soybean, Rice, Winter Wheat, Spring Wheat	30 meter	2019	60,61

Becker-Reshef, I., Barker, B., Whitcraft, A., Oliva, P., Mobley, K., Justice, C., & Sahajpal, R. (2023). Crop type maps for operational global agricultural monitoring. *Scientific Data*, *10*(1), 172.



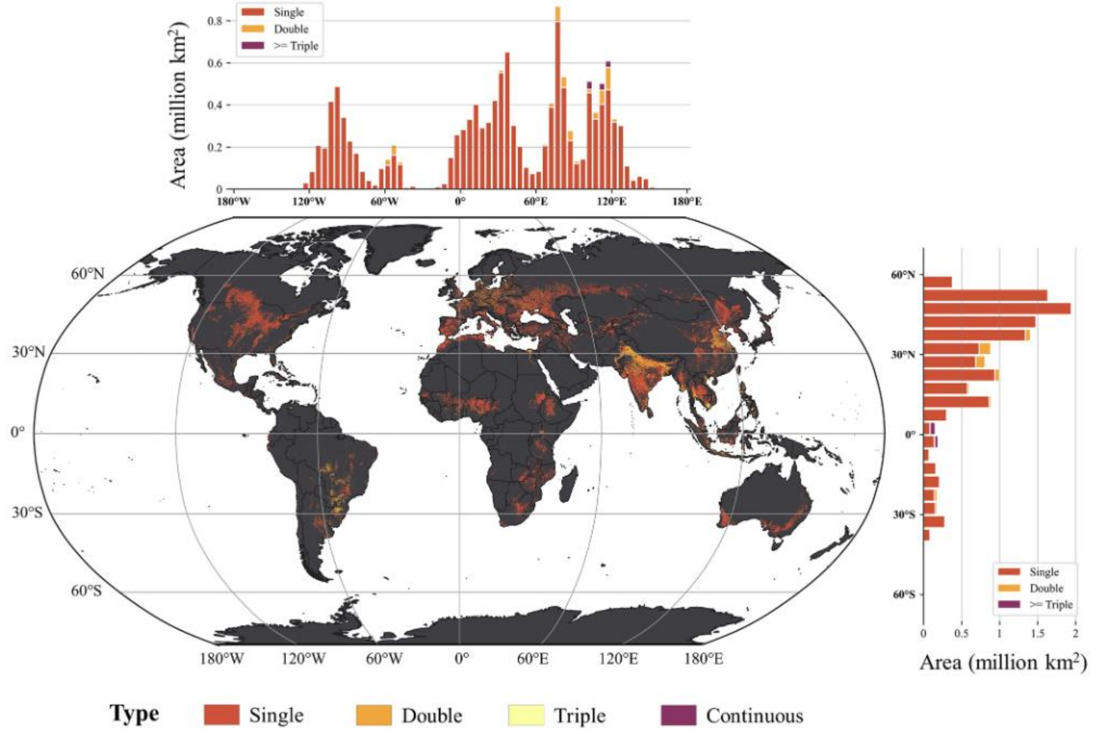


Figure 6. Geographical distribution of global CI types during 2016 to 2018 identified by GCI30. The area statistics along latitude and longitude are derived with an interval of 5°. The area unit is 1×10^6 km^2.

Zhang, M., Wu, B., Zeng, H., He, G., Liu, C., Tao, S., ... & Wang, Z. (2021). GCI30: A global dataset of 30-m cropping intensity using multisource remote sensing imagery. *Earth System Science Data Discussions*, *2021*, 1-22.

CROP YIELD

Table 2. Spectral Vegetation Indices (VIs) Employed in This Study

Name	Equation	Equation using Sentinel-2 bands	Reference
NDVI (Normalized Difference Vegetation Index)	$(R_{NIR} - R_{RED}) / (R_{NIR} + R_{RED})$	(B8 – B4) / (B8 + B4)	(Rouse et al. 1973)
GCVI (Green Chlorophyll Vegetation Index)	$(R_{NIR} / R_{GREEN}) - 1$	(B8/B3) - 1	(Gitelson et al. 2003)
MTCI (MERIS Terrestrial Chlorophyll Index)	$(R_{NIR} - R_{705}) / (R_{705} - R_{RED})$	(B8-B5) / (B5 – B4)	(Dash and Curran 2004)
NDVI705 (Red-Edge $NDVI_{705}$)	$(R_{NIR} - R_{705}) / (R_{NIR} + R_{705})$	(B8 – B5) / (B8 + B5)	(Gitelson et al. 2003)
NDVI740 (Red-Edge $NDVI_{740}$)	$(R_{NIR} - R_{740}) / (R_{NIR} + R_{740})$	(B8 – B6) / (B8 + B6)	(Gitelson et al. 2003)

Note: R refers to reflectance, and B refers to the corresponding sentinel-2 band number used to compute the VI.

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Lobell, D. B., Azzari, G., Burke, M., Gourlay, S., Jin, Z., Kilic, T., & Murray, S. (2020). Eyes in the sky, boots on the ground: Assessing satellite-and ground-based approaches to crop yield measurement and analysis. *American Journal of Agricultural Economics*, *102*(1), 202-219.

Table 1. Examples of gridded cropping system data products for the area, yield and crop calendar.

Data product name (source)	Variable(s) and related notes		Crop coverage	Temporal coverage and resolution	Spatial coverage and resolution	Reference
M3Crops (census)	Area harvested and yield	No distinction among seasons/systems	175 crops	Circa 2000 (1997–2003 or 1990–1996)	Global; 0.083° (10 km; national or subnational)	Monfreda *et al* (2008)
MIRCA (census)	Area harvested and planting and harvesting months	Rainfed and irrigated seasons/systems are distinguishable	26 crops	Monthly, circa 2000 (1998–2002)	Global; 0.083° (10 km; national or subnational)	Portmann *et al* (2010)
SPAM (hybrid: census, satellite and model)	Area harvested and yield	Irrigated, rainfed high-input, rainfed low-input and rainfed-subsistence systems are distinguishable but no distinction among seasons	42 crops	Circa 2010 (2009–2011). No time continuity is guaranteed with its pre-decessors SPAM 2000 (You *et al* 2014) and 2005 (Wood-Sichra *et al* 2016)	Global; 0.083° (10 km)	Yu *et al* (2020)
GAEZ (hybrid: census and model)	Area harvested, yield and produc-tion; crop suitability and agro-ecological attainable yield	Rainfed and irrigated seasons/systems are distinguishable; crop suitability includes distinctions between single and multiple cropping	23 crops	Circa 2010 (2009–2011)	Global; 0.083° (10 km)	Fischer *et al* (2021)
Ray2012 (census)	Area harvested and yield	No distinction among seasons/systems	4 crops (maize, rice, wheat and soybean)	1961–2008 and annual. Three 5 yr averages, 1995 (1993–1997), 2000 (1998–2002), and 2005 (2003–2007), are publicly available.	Global; 0.083° (10 km; national or subnational)	Ray *et al* (2012)

FERTILIZER

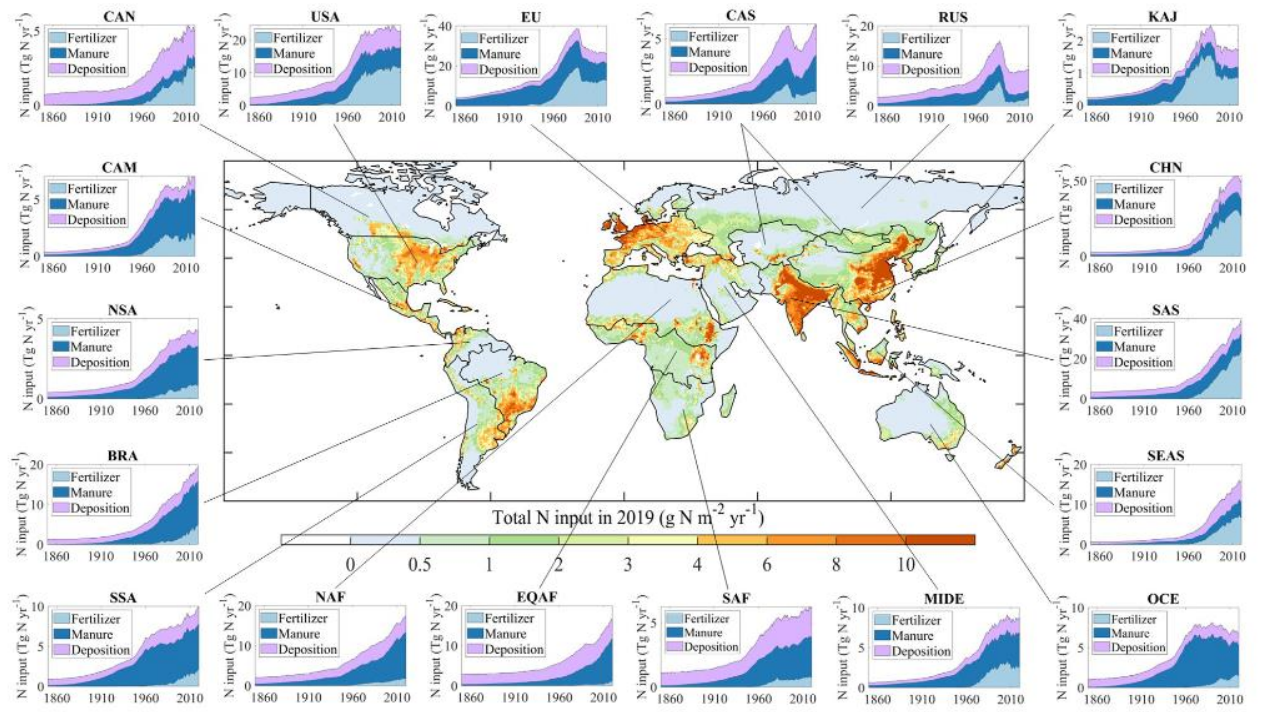
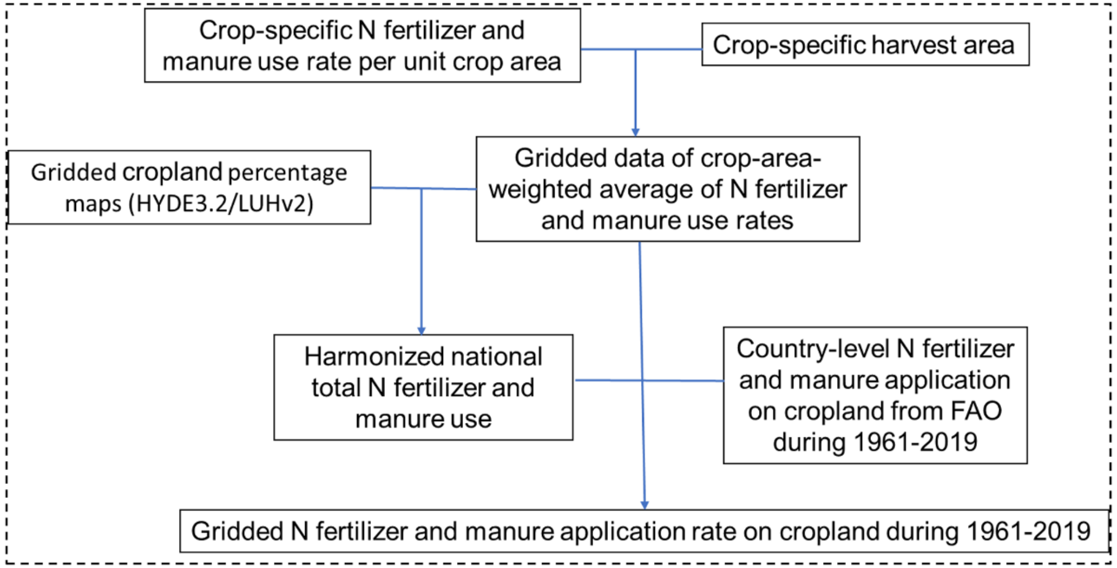


Figure 6. Long-term trends and variations in regional N inputs (synthetic fertilizer, livestock manure, and atmospheric deposition) to terrestrial ecosystems during the period from 1860 to 2019. The 18 regions are the USA (USA), Canada (CAN), Central America (CAM), northern South America (NSA), Brazil (BRA), southwestern South America (SSA), Europe (EU), Northern Africa (NAF), Equatorial Africa (EQAF), Southern Africa (SAF), Russia (RUS), Central Asia (CAS), the Middle East (MIDE), China (CHN), Korea and Japan (KAJ), South Asia (SAS), Southeast Asia (SEAS), and Oceania (OCE).



Tian, H., Bian, Z., Shi, H., Qin, X., Pan, N., Lu, C., ... & Zhang, B. (2022). History of anthropogenic Nitrogen inputs (HaNi) to the terrestrial biosphere: A 5-arcmin resolution annual dataset from 1860 t 2019. *Earth System Science Data Discussions*, *2022*, 1-32.

IRRIGATION & PESTICIDE

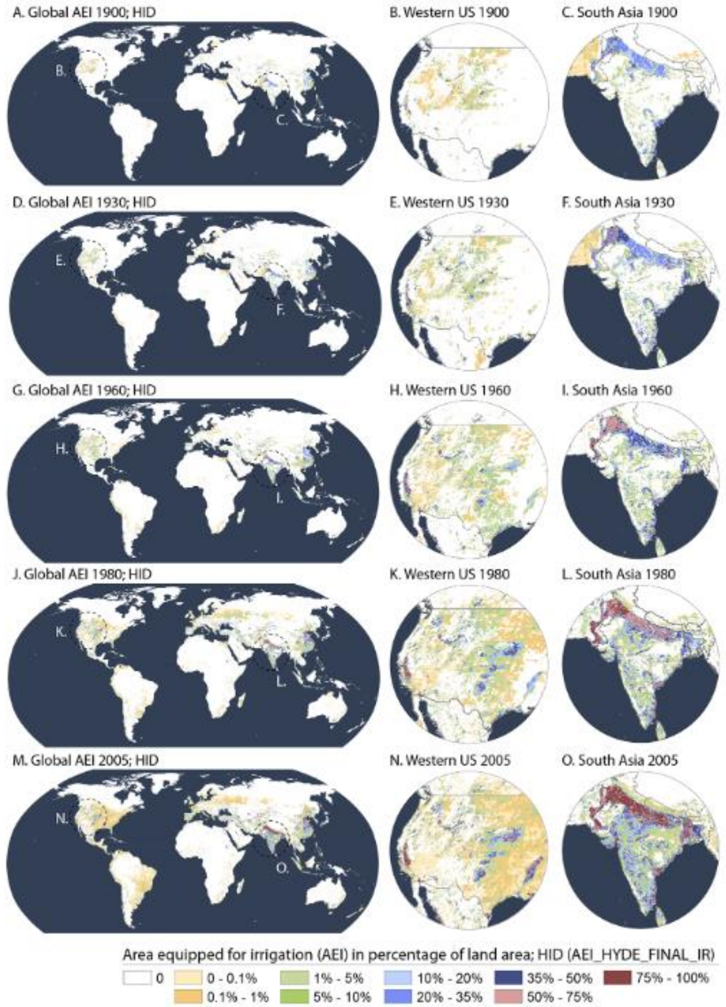


Figure 5. Spatial and temporal evolution of global area equipped for irrigation (AEI) for five time steps (1900, 1930, 1960, 1980, and 2005) based on the product AEI_HYDE_FINAL_IR of the historical irrigation data set (HID). The maps are presented at global scale and for two selected close-up areas, namely western USA and South Asia, for each time step.

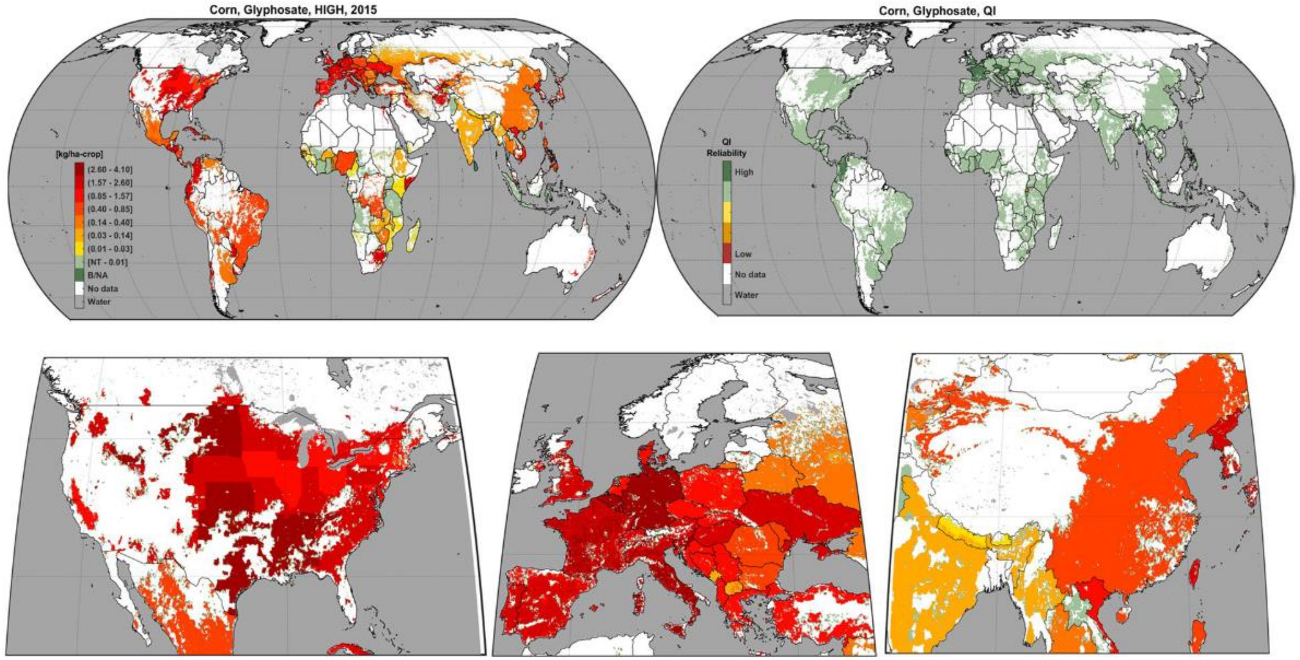


Fig. 4 Examples of global gridded application rate and quality index maps. The top two panels show the high (HIGH) estimate in 2015 for the annual application rate of glyphosate on corn globally gridded and the corresponding quality index QI map. Panes in the second row show regional application rates.

Maggi, F., Tang, F. H., la Cecilia, D., & McBratney, A. (2019). PEST-CHEMGRIDS, global gridded maps of the top 20 crop-specific pesticide application rates from 2015 to 2025. *Scientific data*, *6*(1), 170.

Siebert, S., Kummu, M., Porkka, M., Döll, P., Ramankutty, N., & Scanlon, B. R. (2015). A global data set of the extent of irrigated land from 1900 to 2005. *Hydrology and Earth System Sciences*, *19*(3), 1521-1545.

TERRAIN

Data Descriptor | Open access | Published: 28 May 2020

Geomorpho90m, empirical evaluation and accuracy assessment of global high-resolution geomorphometric layers

Giuseppe Amatulli, Daniel McInerney, Tushar Sethi, Peter Strobl & Sami Domisch

Scientific Data **7**, Article number: 162 (2020) | Cite this article

Geomorphometric variable group	Geomorphometric variable name	Geomorphometric variable abbreviation	Software used
First order derivative	Slope	*slope*	GDAL: gdaldem[66]
	Aspect	*aspect*	GDAL: gdaldem[66]
	Aspect cosine	*aspect-cosine*	GDAL: gdaldem gdal_calc.py[66]
	Aspect sine	*aspect-sine*	GDAL: gdaldem gdal_calc.py[66]
	Eastness	*eastness*	GDAL: gdaldem gdal_calc.py[66]
	Northness	*northness*	GDAL: gdaldem gdal_calc.py[66]
	Convergence	*convergence*	GRASS GIS: r.convergence[67]
	Compound topographic index	*cti*	GRASS GIS: r.watershed[67]
	Stream power index	*spi*	GRASS GIS: r.watershed[67]
	East-West first order partial derivative	*dx*	GRASS GIS: r.slope.aspect[67]
	North-South first order partial derivative	*dy*	GRASS GIS: r.slope.aspect[67]
Second order derivative	Profile curvature	*pcurv*	GRASS GIS: r.slope.aspect[67]
	Tangential curvature	*tcurv*	GRASS GIS: r.slope.aspect
	East-West second order partial derivative	*dxx*	GRASS GIS: r.slope.aspect[67]
	North-South second order partial derivative	*dyy*	GRASS GIS: r.slope.aspect[67]
	Second order partial derivative	*dxy*	GRASS GIS: r.slope.aspect[67]
Ruggedeness	Elevation standard deviation	*elev-stdev*	PKTOOLS: pkfilter[69]
	Terrain ruggedness index	*tri*	GDAL: gdaldem[66]
	Roughness	*roughness*	GDAL: gdaldem[66]
	Vector ruggedness measure	*vrm*	GRASS GIS: r.vector.ruggedness.py[67]
	Topographic position index	*tpi*	GDAL: gdaldem[66]
	Maximum multiscale deviation	*dev-magnitude*	Whitebox: MaxElevationDeviation[68]
	Scale of the maximum multiscale deviation	*dev-scale*	Whitebox: MaxElevationDeviation[68]
	Maximum multiscale roughness	rough-magnitude	Whitebox: MultiscaleRoughness[68]
	Scale of the maximum multiscale roughness	*rough-scale*	Whitebox: MultiscaleRoughness[68]
geomorphological forms	Geomorphon	*geom*	GRASS: r.geomorphon[67]

Amatulli, G., McInerney, D., Sethi, T., Strobl, P., & Domisch, S. (2020). Geomorpho90m, empirical evaluation and accuracy assessment of global high-resolution geomorphometric layers. *Scientific Data*, *7*(1), 162.

WEATHER/CLIMATE

Historical climate data

This is WorldClim version 2.1 climate data for 1970-2000. This version was released in January 2020.

There are monthly climate data for minimum, mean, and maximum temperature, precipitation, solar radiation, wind speed, water vapor pressure, and for total precipitation. There are also 19 "bioclimatic" variables.

The data is available at the four spatial resolutions, between 30 seconds (~1 km2) to 10 minutes (~340 km2). Each download is a "zip" file containing 12 GeoTiff (.tif) files, one for each month of the year (January is 1; December is 12).

variable	10 minutes	5 minutes	2.5 minutes	30 seconds
minimum temperature (°C)	tmin 10m	tmin 5m	tmin 2.5m	tmin 30s
maximum temperature (°C)	tmax 10m	tmax 5m	tmax 2.5m	tmax 30s
average temperature (°C)	tavg 10m	tavg 5m	tavg 2.5m	tavg 30s
precipitation (mm)	prec 10m	prec 5m	prec 2.5m	prec 30s
solar radiation (kJ m^{-2} day^{-1})	srad 10m	srad 5m	srad 2.5m	srad 30s
wind speed (m s^{-1})	wind 10m	wind 5m	wind 2.5m	wind 30s
water vapor pressure (kPa)	vapr 10m	vapr 5m	vapr 2.5m	vapr 30s

Below you can download the standard (19) WorldClim Bioclimatic variables for WorldClim version 2. They are the average for the years 1970-2000. Each download is a "zip" file containing 19 GeoTiff (.tif) files, one for each month of the variables.

variable	10 minutes	5 minutes	2.5 minutes	30 seconds
Bioclimatic variables	bio 10m	bio 5m	bio 2.5m	bio 30s

For reference, here is the elevation data that was used to produce WorldClim 2.1. These were derived from the SRTM elevation data.

variable	10 minutes	5 minutes	2.5 minutes	30 seconds
Elevation	elev 10m	elev 5m	elev 2.5m	elev 30s

Citation:

Fick, S.E. and R.J. Hijmans, 2017. WorldClim 2: new 1km spatial resolution climate surfaces for global land areas. International Journal of Climatology 37 (12): 4302-4315.

BIO1 = Annual Mean Temperature

BIO2 = Mean Diurnal Range (Mean of monthly (max temp - min temp))

BIO3 = Isothermality (BIO2/BIO7) (×100)

BIO4 = Temperature Seasonality (standard deviation ×100)

BIO5 = Max Temperature of Warmest Month

BIO6 = Min Temperature of Coldest Month

BIO7 = Temperature Annual Range (BIO5-BIO6)

BIO8 = Mean Temperature of Wettest Quarter

BIO9 = Mean Temperature of Driest Quarter

BIO10 = Mean Temperature of Warmest Quarter

BIO11 = Mean Temperature of Coldest Quarter

BIO12 = Annual Precipitation

BIO13 = Precipitation of Wettest Month

BIO14 = Precipitation of Driest Month

BIO15 = Precipitation Seasonality (Coefficient of Variation)

BIO16 = Precipitation of Wettest Quarter

BIO17 = Precipitation of Driest Quarter

BIO18 = Precipitation of Warmest Quarter

BIO19 = Precipitation of Coldest Quarter

https://www.worldclim.org/data/index.html

Abatzoglou, J. T., Dobrowski, S. Z., Parks, S. A., & Hegewisch, K. C. (2018). TerraClimate, a high-resolution global dataset of monthly climate and climatic water balance from 1958–2015. *Scientific data*, *5*(1), 1-12.

SOIL

Articles / Volume 7, issue 1 / SOIL, 7, 217–240, 2021

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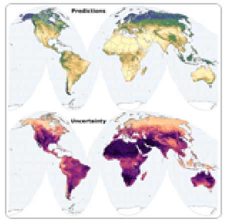
Original research article | **Highlight paper** |

14 Jun 2021

SoilGrids 2.0: producing soil information for the globe with quantified spatial uncertainty

Laura Poggio, Luis M. de Sousa, Niels H. Batjes, Gerard B. M. Heuvelink, Bas Kempen, Eloi Ribeiro, and David Rossiter



~250 meter

Poggio, L., De Sousa, L. M., Batjes, N. H., Heuvelink, G. B., Kempen, B., Ribeiro, E., & Rossiter, D. (2021). SoilGrids 2.0: producing soil information for the globe with quantified spatial uncertainty. *Soil*, *7*(1), 217-240.

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Name	Description	Mapped units	Conversion factor	Conventional units
bdod	Bulk density of the fine earth fraction	cg/cm^3	100	kg/dm^3
cec	Cation Exchange Capacity of the soil	mmol(c)/kg	10	cmol(c)/kg
cfvo	Volumetric fraction of coarse fragments (> 2 mm)	cm3/dm3 (vol‰)	10	cm3/100cm3 (vol%)
clay	Proportion of clay particles (< 0.002 mm) in the fine earth fraction	g/kg	10	g/100g (%)
nitrogen	Total nitrogen (N)	cg/kg	100	g/kg
phh2o	Soil pH	pHx10	10	pH
sand	Proportion of sand particles (> 0.05 mm) in the fine earth fraction	g/kg	10	g/100g (%)
silt	Proportion of silt particles (≥ 0.002 mm and ≤ 0.05 mm) in the fine earth fraction	g/kg	10	g/100g (%)
soc	Soil organic carbon content in the fine earth fraction	dg/kg	10	g/kg
ocd	Organic carbon density	hg/dm^3	10	kg/dm^3
ocs	Organic carbon stocks	t/ha	10	kg/m^2

SOCIOECONOMIC

Data Descriptor | Open access | Published: 06 February 2018

Gridded global datasets for Gross Domestic Product and Human Development Index over 1990–2015

Matti Kummu, Maija Taka & Joseph H. A. Guillaume

Scientific Data 5, Article number: 180004 (2018) | Cite this article

~10 km

Table 1 List of introduced development indicator datasets with their spatial extent, resolution and temporal extent.

From: Gridded global datasets for Gross Domestic Product and Human Development Index over 1990–2015

Dataset	Description	Spatial extent and resolution	Temporal extent
GDP per capita (PPP)	Gross Domestic Production per capita (purchasing power parity), in constant 2011 international USD	Global; 5 arc-min; WGS84 projection	Annual; for each year over 1990–2015
GDP (PPP) *	Gross Domestic Production (purchasing power parity), in constant 2011 international USD	Global; 5 arc-min, 30 arc-sec; WGS84 projection	*5 arc-min*: Annual; for each year over 1990–2015. *30 arc-sec*: Annual; for years 1990, 2000, 2015
HDI	Human Development Index, based on method introduced 2010 and updated 2011. Dimensionless indicator between 0 and 1.	Global; 5 arc-min; WGS84 projection	Annual; for each year over 1990–2015

* Derived from GDP per capita (PPP) by multiplying it with i) 5 arc-min annual population dataset HYDE 3.2[7] and ii) 30 arc-sec population data Global Human Settlement (GHS)[1].

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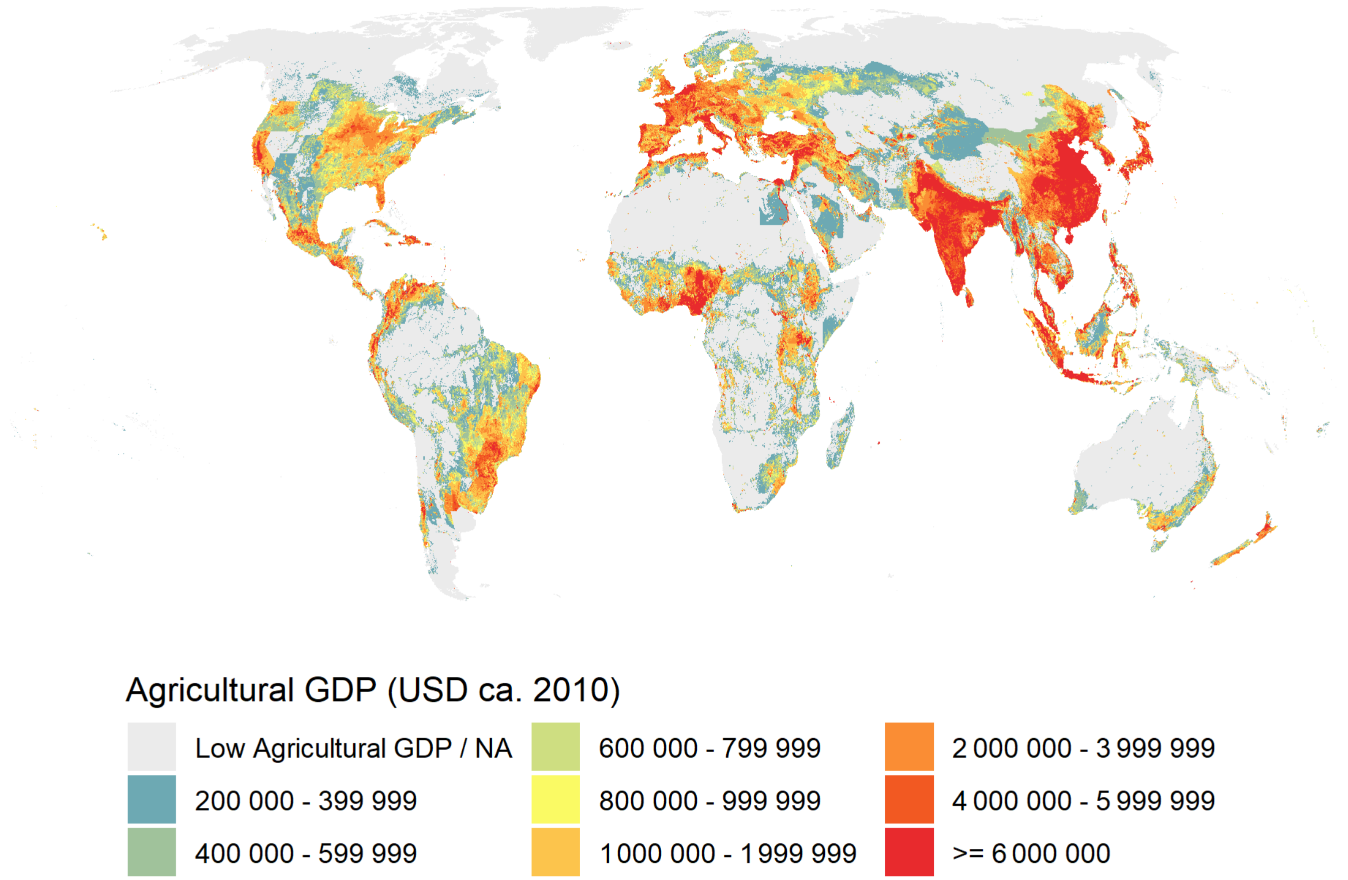
SOCIOECONOMIC

- Crop, livestock, forestry (timber and non-timber), fishing.

~10 km



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Ru, Y., Blankespoor, B., Wood-Sichra, U., Thomas, T. S., You, L., & Kalvelagen, E. (2022). Estimating Local Agricultural GDP across the World. *Earth System Science Data Discussions*, *2022*, 1-36.

SOCIOECONOMIC

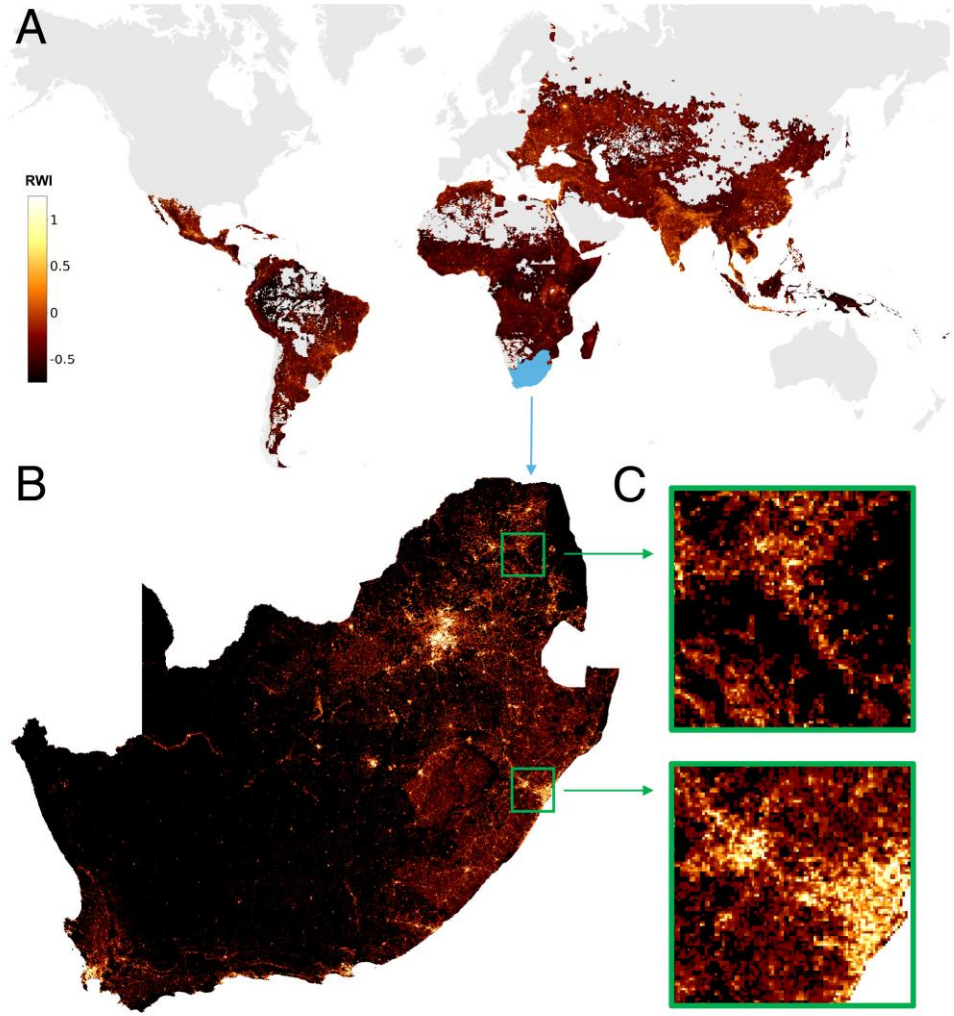
RESEARCH ARTICLE | ECONOMIC SCIENCES

Microestimates of wealth for all low- and middle-income countries

Guanghua Chi, Han Fang, Sourav Chatterjee, and Joshua E. Blumenstock Authors Info & Affiliations

Edited by Jose Scheinkman, Department of Economics, Columbia University, New York, NY; received July 24, 2021; accepted November 14, 2021

January 11, 2022 | 119 (3) e2113658119 | https://doi.org/10.1073/pnas.2113658119



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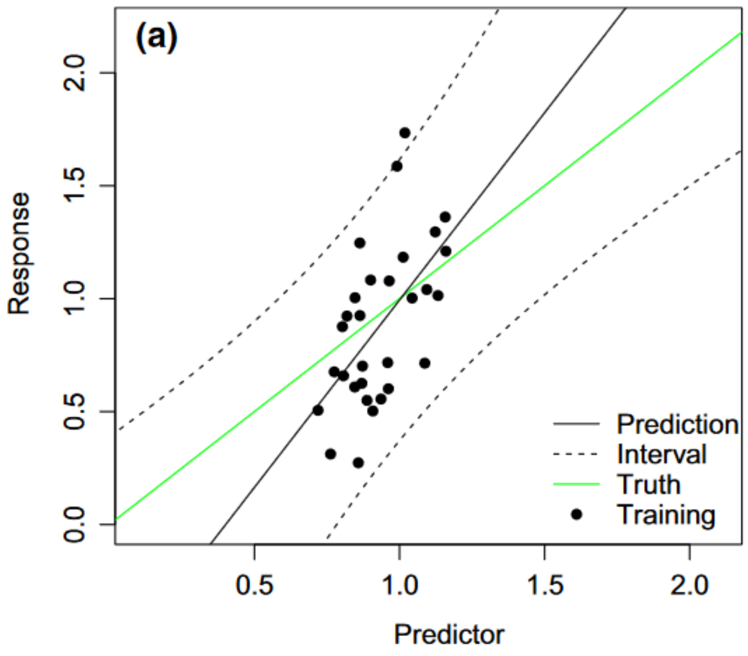
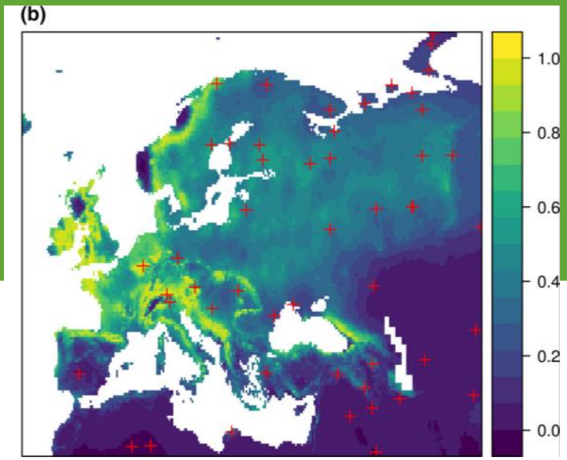
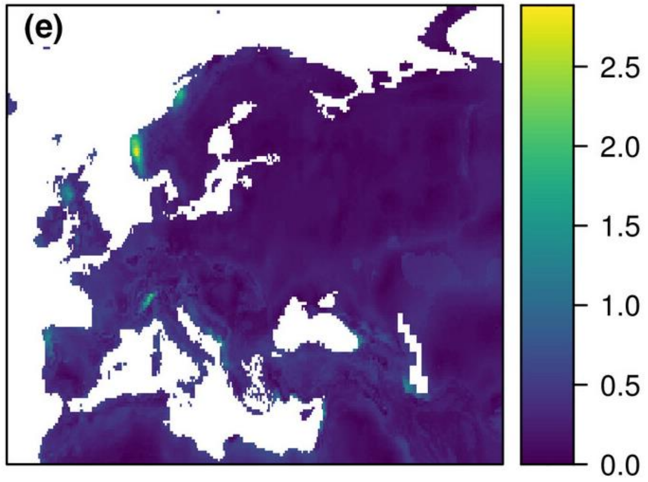
EXTRA: ERROR & UNCERTAINTY

TRANSFERABILITY





Reference; training points



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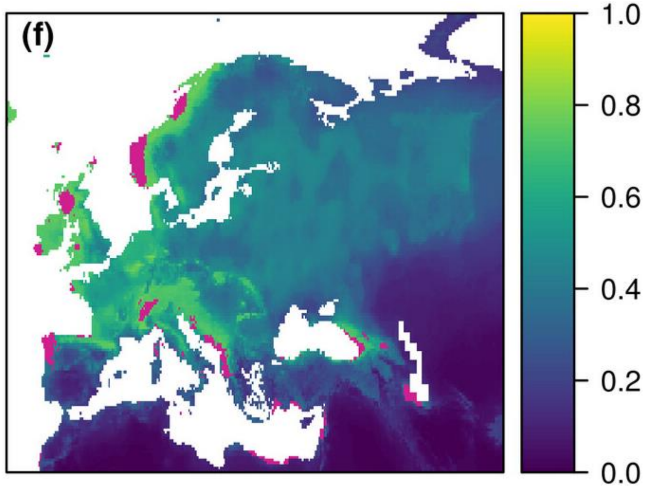


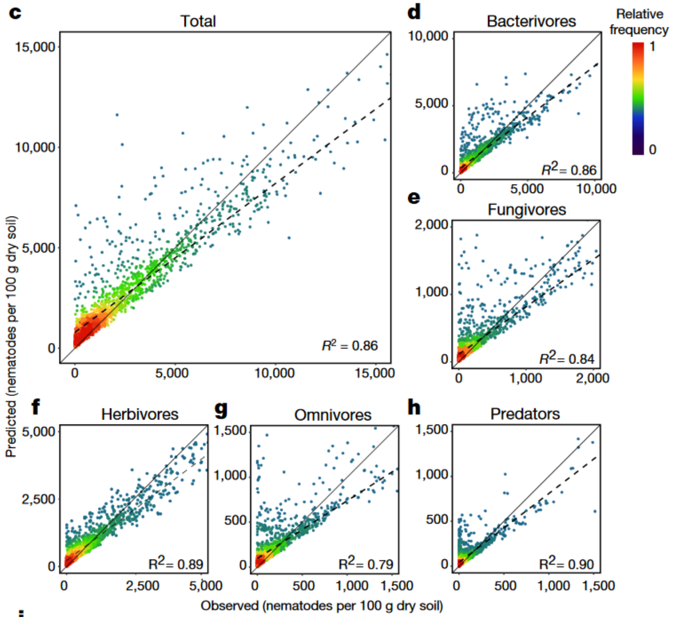
Prediction masked by AOA

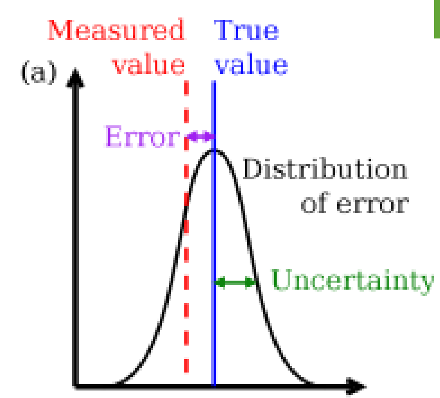
Meyer, H., & Pebesma, E. (2022). Machine learning-based global maps of ecological variables and the challenge of assessing them. *Nature Communications*, *13*(1), 2208.

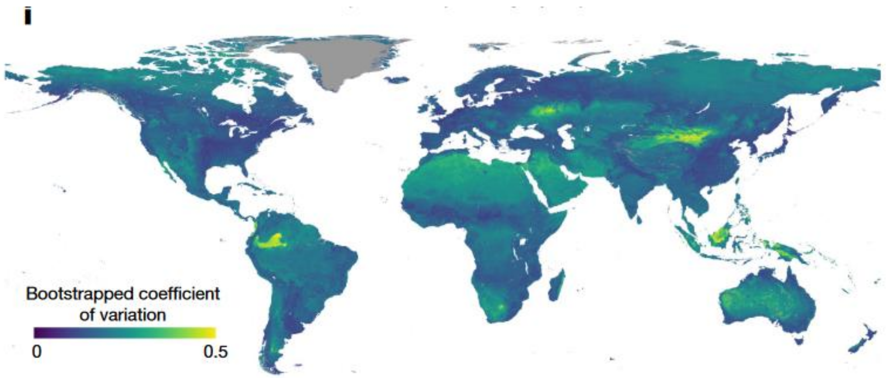
Meyer, H., & Pebesma, E. (2021). Predicting into unknown space? Estimating the area of applicability of spatial prediction models. *Methods in Ecology and Evolution*, *12*(9), 1620-1633.

ERROR AND UNCERTAINTY

		Reference			
		No change	Forest loss	Total	User's accuracy (SE)
Map	No change	97.990*	0.465	98.455	99.5% (0.2%)
	Forest loss	0.120	1.426	1.546	92.2% (1.9%)
	Total	98.110	1.891	100.00	—
Producer's accuracy (SE)		99.8% (0.1%)	75.4% (2.5%)	Overall accuracy (SE) = 99.4% (0.2%)	







Povey, A. C., & Grainger, R. G. (2015). Known and unknown unknowns: uncertainty estimation in satellite remote sensing. *Atmospheric Measurement Techniques*, *8*(11), 4699-4718

Van Den Hoogen, J., Geisen, S., Routh, D., Ferris, H., Traunspurger, W., Wardle, D. A., ... & Crowther, T. W. (2019). Soil nematode abundance and functional group composition at a global scale. *Nature*, *572*(7768), 194-198.

https://glad.umd.edu/Potapov/Madagascar_2017/Documents/03_GLAD_Sampling.pdf

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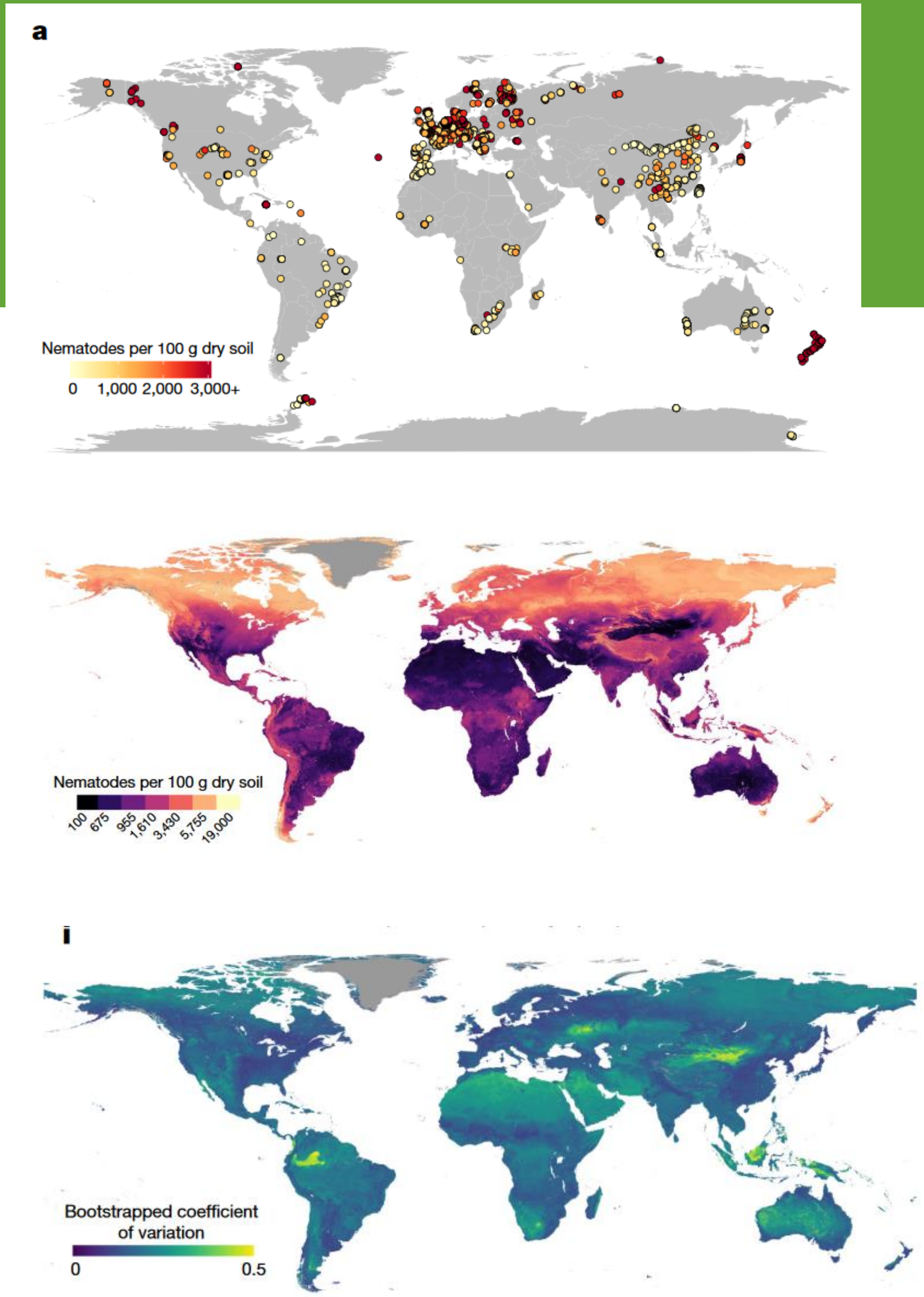

Van Den Hoogen, J., Geisen, S., Routh, D., Ferris, H., Traunspurger, W., Wardle, D. A., ... & Crowther, T. W. (2019). Soil nematode abundance and functional group composition at a global scale. *Nature*, *572*(7768), 194-198.

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Dataset	Uncertainty Quantification method	Spatio-temporal coverage	Reference
Soil carbon storage in terrestrial ecosystems of Canada	Quantile regression	National-Canada (N/A)	1
Irrecoverable carbon in Earth's ecosystems	Standard error of the uncertainty layers of the used datasets.	Global (2010, and 2018)	2
Soil Grids 250m v2.0	Quantile regression	Global (N/A)	3
Global Mangrove Project	Bootstrapping for confidence intervals around accuracy statistics	Global (1996, 2007-2010, 2015- 2020)	4
Land Change Monitoring, Assessment, and Projection (LCMAP) v1.3	Model Quality Flags includes persistent snow, insufficient data and clear conditions and Sample based area estimates.	National-CONUS (1985-2021)	5
ETH Global Sentinel-2 10m Canopy Height (2020)	Negative log likelihood loss function for aleatoric uncertainty and ensemble predictions for epistemic uncertainty.	Global (2020)	6
High Resolution Tree Species Information for Canada	Distance to second class (DS2C) based on 100*(1-nVotesC2/nVotesC1)	National-Canada (2019)	7
Canada Landsat Derived Forest harvest disturbance 1985-2020	DS2C based on 100*(1-nVotesC2/nVotesC1)	National-Canada (1985-2020)	8

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Singh, G., Moncrieff, G., Venter, Z., Cawse-Nicholson, K., Slingsby, J., & Robinson, T. B. (2024). Uncertainty quantification for probabilistic machine learning in earth observation using conformal prediction. *Scientific Reports*, *14*(1), 16166.

Rangeland Analysis Platform layers (rangeland fractional cover)	Ensemble based prediction variance	National-CONUS (2019)	[9–11]
Ensemble Source Africa Cropland Mask 2016	Sample based area estimates	Continental-Africa (2016)	[12]
Highly Scalable Temporal Adaptive Reflectance Fusion Model (HISTARFM) database	Kalman filter	National-CONUS (2009-2021)	[13]
Global Photovoltaics Inventory (2016-2018)	Custom mechanistic approach which makes distribution assumptions and bootstrapping.	Global (2016-2018)	[14]
Canada Landsat Derived Wildfire disturbance & Magnitude 1985-2020	(DS2C) based on 100*(1-nVotesC2/nVotesC1)	National-Canada (1985-2020)	[8]
RADD Forest Disturbance Alert	Probabilistic mapping using Gaussian mixture models and Bayesian methods	Global (2019-2020)	[15]
iSDASoil	Quantile regression and bootstrapping.	Continental – Africa (2021)	[16]

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Singh, G., Moncrieff, G., Venter, Z., Cawse-Nicholson, K., Slingsby, J., & Robinson, T. B. (2024). Uncertainty quantification for probabilistic machine learning in earth observation using conformal prediction. *Scientific Reports*, *14*(1), 16166.

SoilGrids v2.0.	Quantile regression	Global (N/A)	[3]
Global urban projections under SSPs (2020-2100)	Ensemble based prediction variance	Global (2020-2100)	[17,18]
Murray Global Intertidal Change	Quality flags that contain the number of input pixels for modelling.	Global (1984-2016 in 3-year intervals)	[19]
USDA NASS cropland data layers	A hybrid ensemble expert voting system.	National-CONUS (1997-2023)	[20]
MCD12Q1.061 MODIS Land Cover Type Yearly Global 500m	A hybrid ensemble expert voting system.	Global (2001-2022)	[21]

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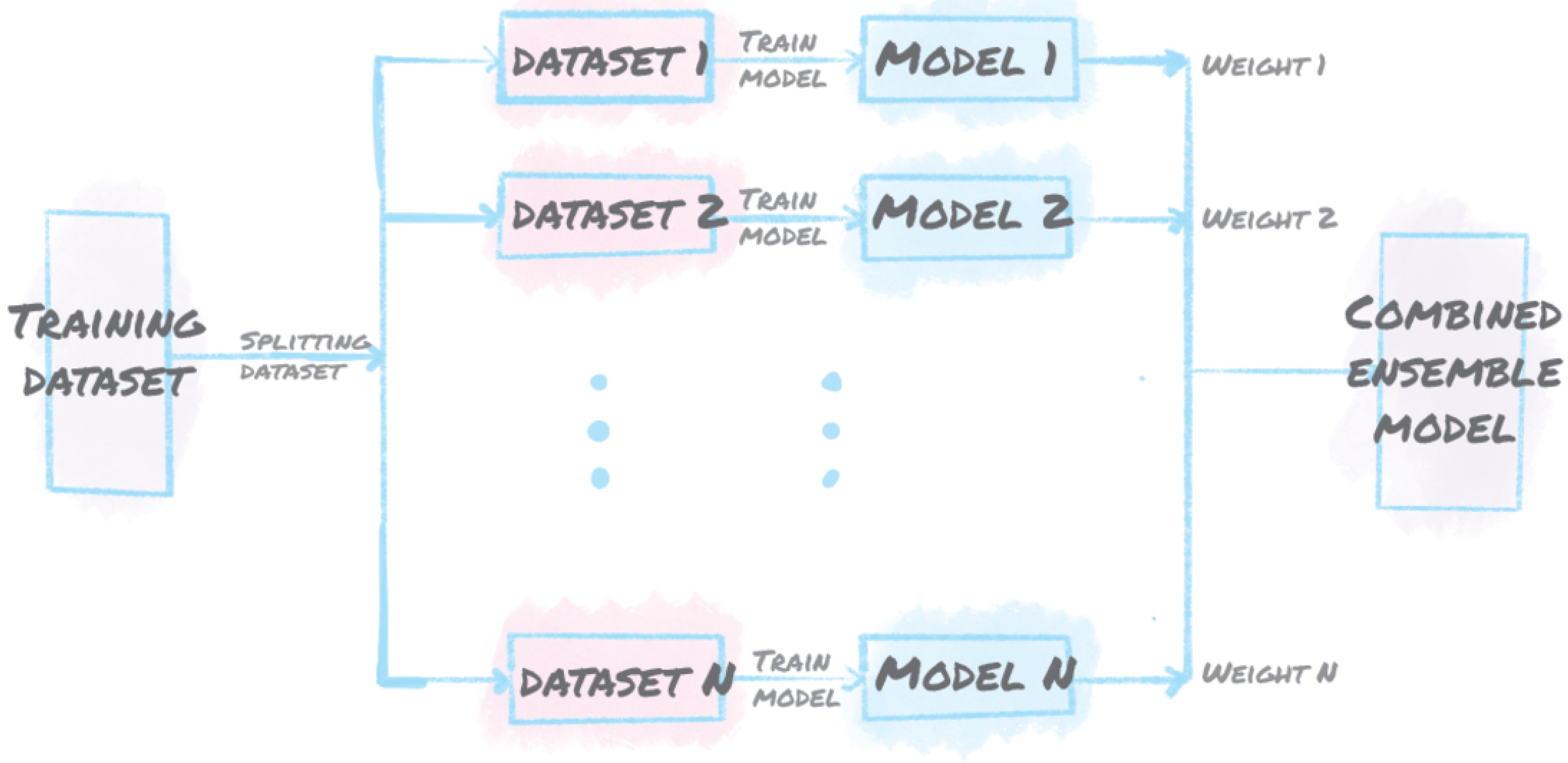
Singh, G., Moncrieff, G., Venter, Z., Cawse-Nicholson, K., Slingsby, J., & Robinson, T. B. (2024). Uncertainty quantification for probabilistic machine learning in earth observation using conformal prediction. *Scientific Reports*, *14*(1), 16166.



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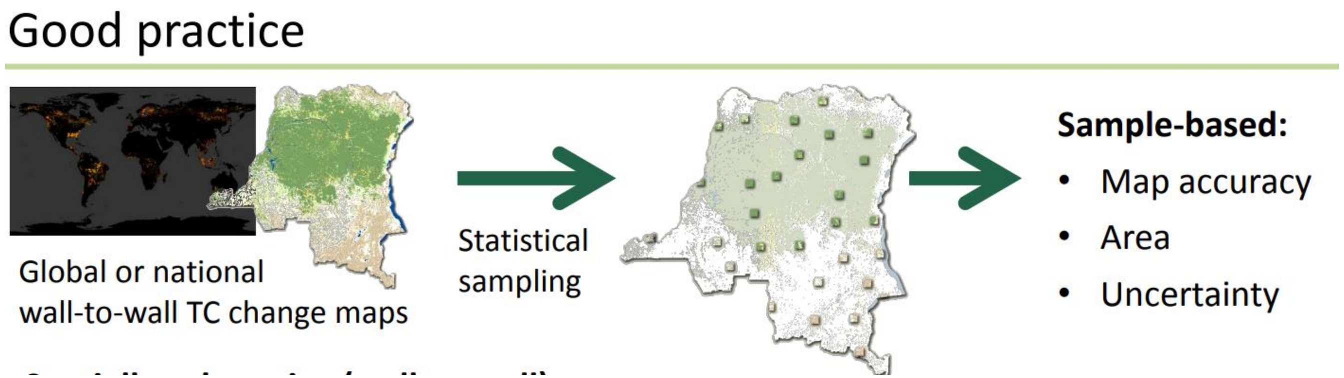
https://www.rossidata.com/UncertaintyQuantificationandEnsembleLearning

EXTRA: IDEAL ACCURACY ASSESSMENT

ACCURACY ASSESSMENT

- Reference sample data can be used to produce an unbiased estimate of area of map classes with known uncertainty
- Probability sampling allows to: - Quantify map accuracy (Overall, User's, Producer's).
  - Estimate "true" (unbiased) areas of mapped classes.
  - Estimate uncertainty of the mapped classes area.



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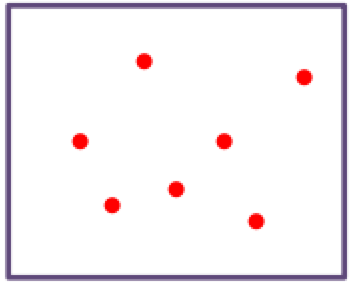
Olofsson, P., Foody, G. M., Herold, M., Stehman, S. V., Woodcock, C. E., & Wulder, M. A. (2014). Good practices for estimating area and assessing accuracy of land change. *Remote sensing of Environment*, *148*, 42-57.

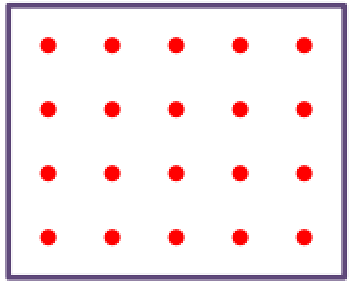
https://glad.umd.edu/Potapov/Madagascar_2017/Documents/03_GLAD_Sampling.pdf

Common probability sampling designs

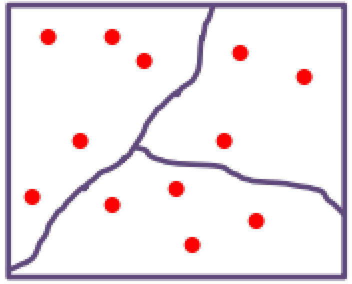
1. Simple random



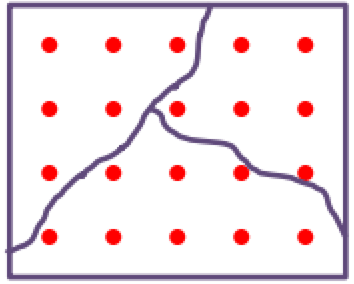
2. Systematic



3. Stratified random

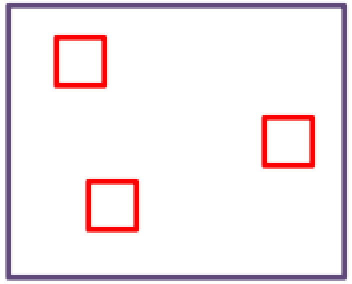


3. Stratified systematic



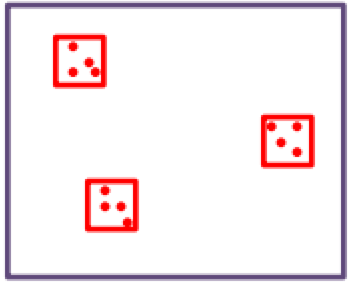
4. Cluster random one-stage

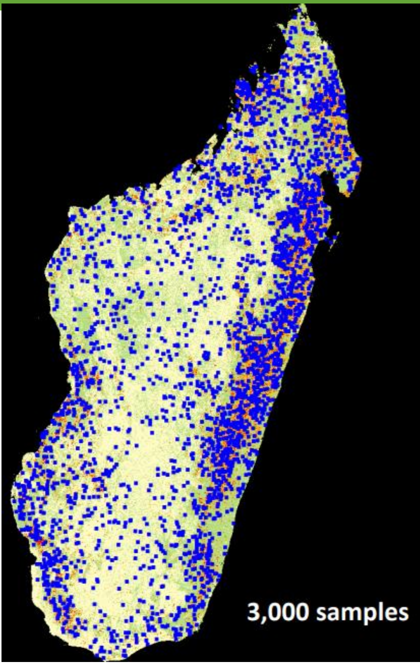
Reference data obtained for all pixels in the block (cluster)



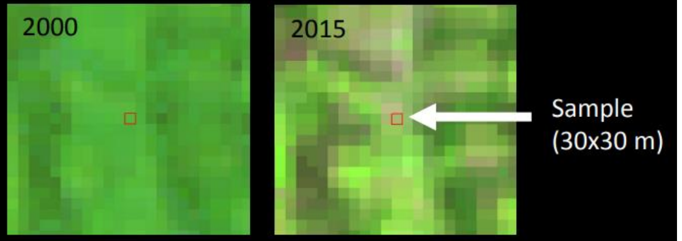
4. Cluster random two-stage

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

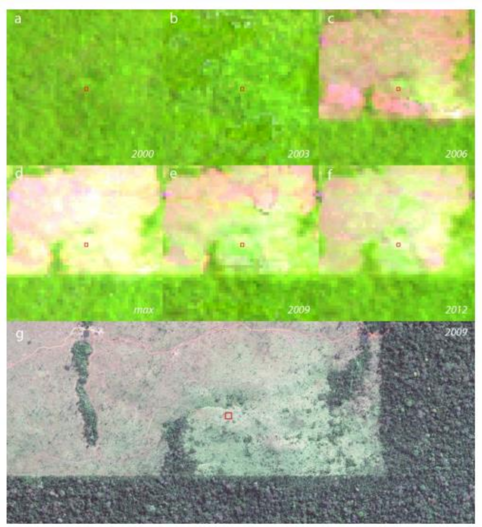


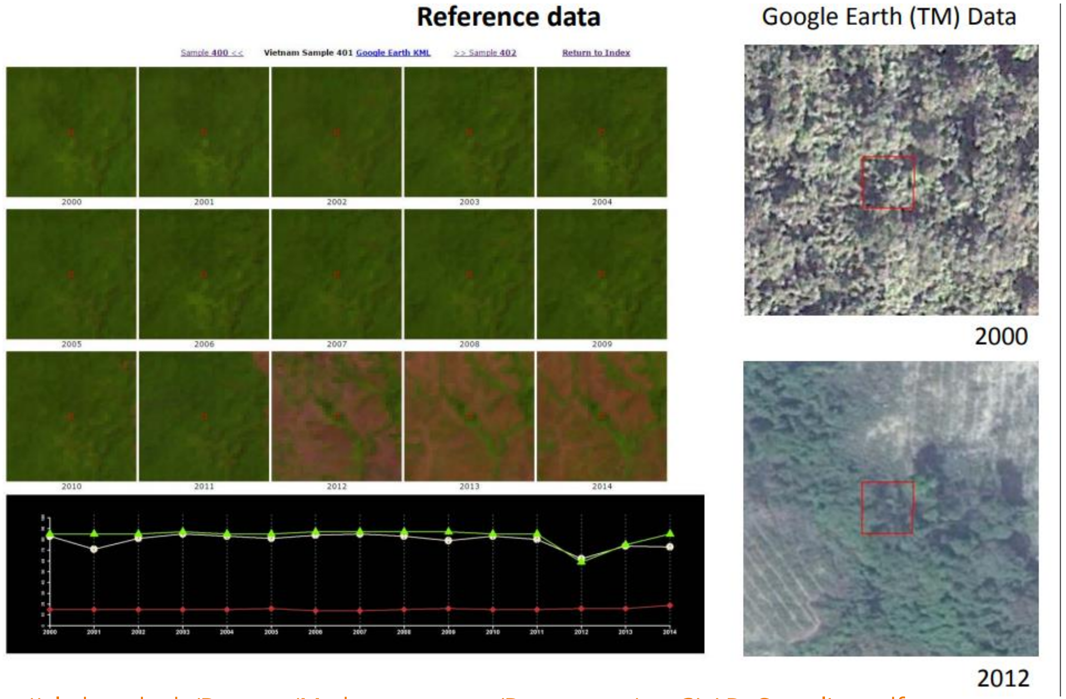


Stratum	area, ha	count, 30x30m pixels	% total	Total samples	Training goal
No loss / no trees	25,141,547	348008206	43	200	50
No loss / tree cover	23,815,964	327272139	40	800	150
Loss 2001-2015	2,658,505	36480651	4	1000	150
Buffer around loss	7,528,648	103251036	13	1000	150
Total	*59,144,663*	*815012032*		*3000*	*500*



- No tree cover
- Tree cover 2016
- Gross tree cover loss, 2000-2016
- 60-m proximity of GTCL





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https://glad.umd.edu/Potapov/Madagascar_2017/Documents/03_GLAD_Sampling.pdf