

Way of Water



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Cloud Geographer

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Cloud Geographer

Presentation Link:
goo.gl/g4g23-water-slides

October 2023 | #GeoForGood23



In this module, you learn to ...

- | | | |
|----|--|--|
| 01 | Examples |  15 min |
| 02 | Water dynamics mapping (JRC) |  10 min |
| 03 | Water detection with optical satellite imagery |  30 min |
| 04 | Questions and Discussion |  5 min |



01

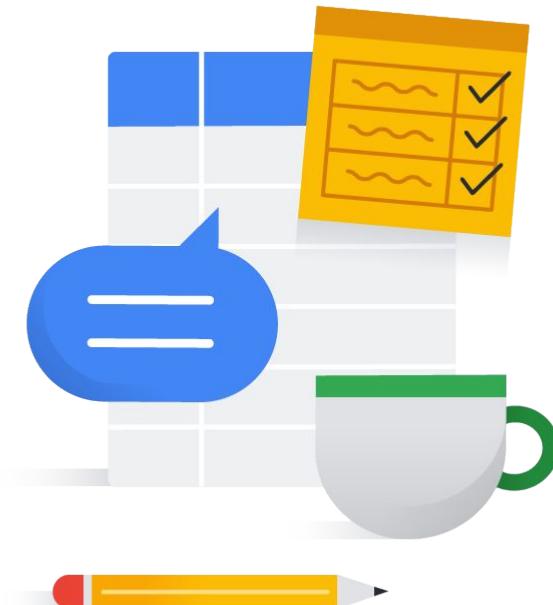
Examples

15 min

Group

Water Examples

water cycle
precipitation
moisture
water mapping
water change mapping
floods
droughts
bathymetry
...



How to map waterbodies?

Where have **floods** happened?

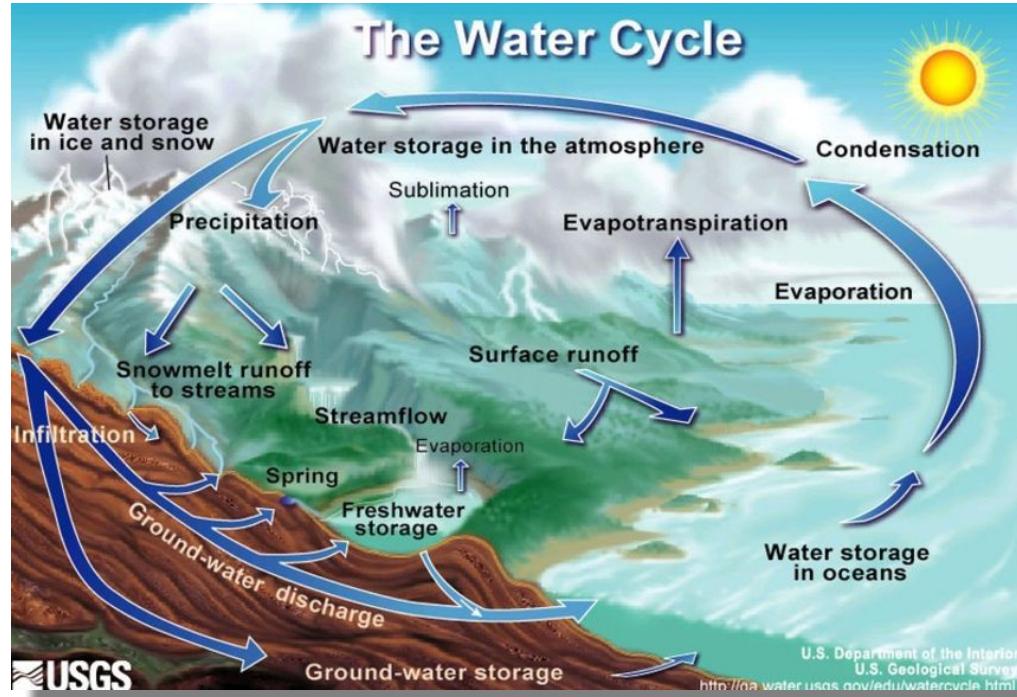
Is my **coastline eroding**?

How much water do we have in **rootzone**?

How large are **intertidal changes**?

Can we detect **water pollution** (oil, algae, plastic)?

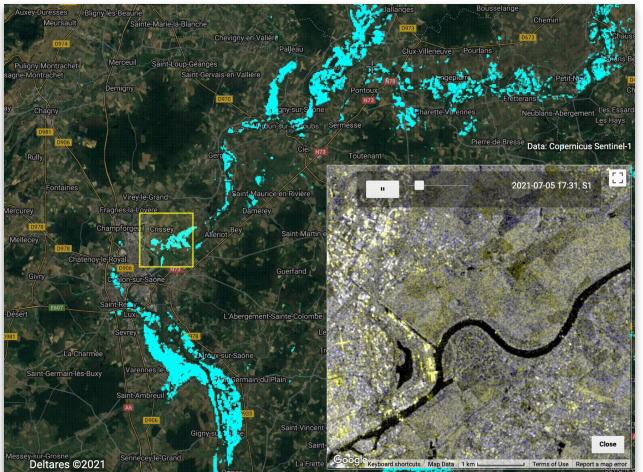
How quickly do **glaciers melt**?



Do we have **enough water** to drink and irrigate crops?

Is there a **droughts** occurring and where?

Flood Mapping



EU 2021 flood app

<https://gena.users.earthengine.app/view/flood-eu>

The New York Times

<https://www.nytimes.com/interactive/2021/07/17/world/europe/europe-flood-map.html>

SECTION A1: HUMAN APPLICATIONS

SECTION A2: AQUATIC AND HYDROLOGICAL APPLICATIONS

A2.1 Groundwater monitoring with GRACE
AJ Purdy, J.S. Famiglietti

A2.2 Benthic Habitats
Dimitris Poursanidis, Aurélie C. Shapiro, Spyros Christoforakis

A2.3 Surface Water Mapping
Kai Markert, Gennadii Donchyts, Arjen Haag

A2.4 River morphology
Xiao Yang, Theodore Langhorst, Tamlin Pavelsky

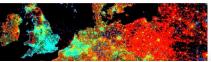
A2.5 Water Balance and Drought
Ate Poortinga, Quyen Nguyen, Nyein Soe Thwai, Andréa Puzzi Nicolau

A2.6 Defining Seasonality: First Date of No Snow
Amanda Armstrong, Morgan Tassone, Justin Braaten

[GO TO SECTION A2](#)

[Go to section A2](#)

Cloud-Based Remote Sensing with Google Earth Engine



Welcome to Cloud-Based Remote Sensing with Google Earth Engine: Fundamentals

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



Launch The Hydrologic Remote Sensing Analysis for Floods (HYDRAFloods)



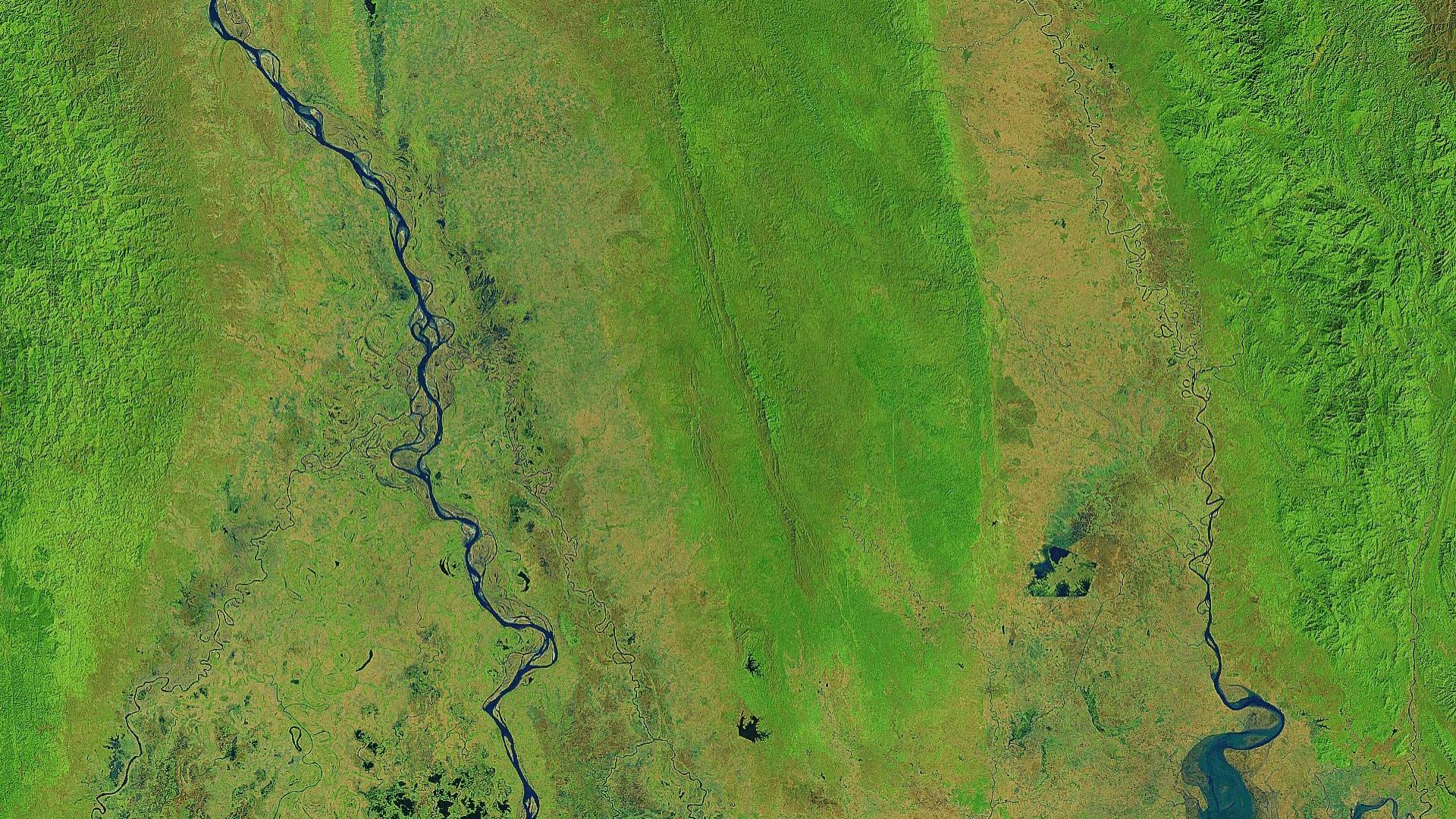
LAUNCH TOOL



<https://servir.adpc.net/tools/hydrologic-remote-sensing-analysis-floods-hydrafloods>

1984





1985

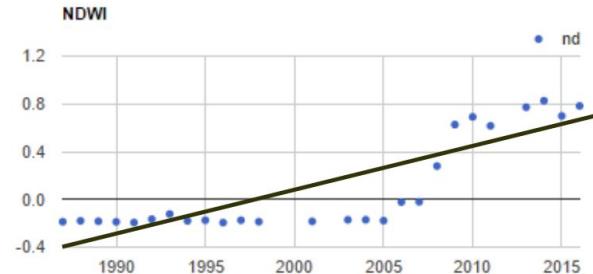
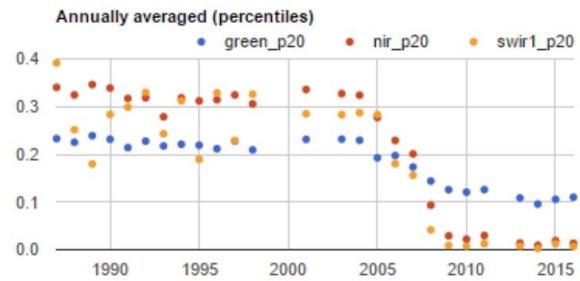
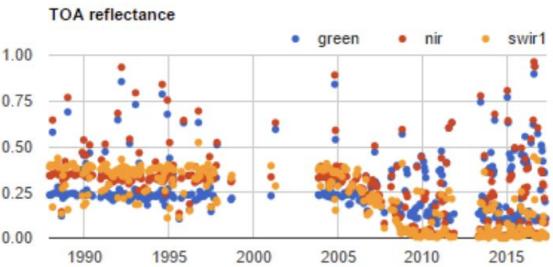
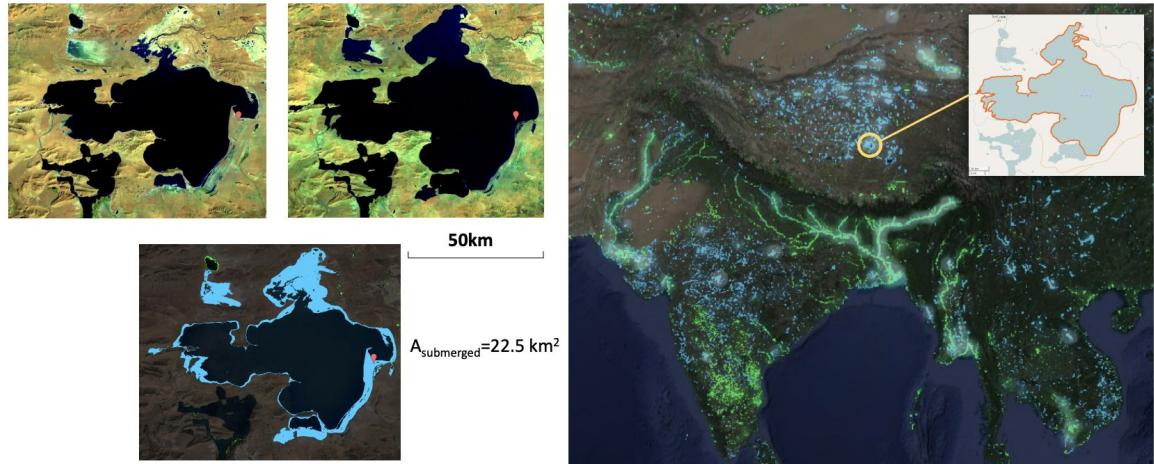
New Land

New Water



Deltas

Surface water change detection using annual percentile composite images and linear regression of spectral water indices



Check Chapter 5-6 in [Donchyts G, 2018](#)

Surface water changes (1985-2017)

Green and blue colors represent areas where surface water changes occurred during the last 30 years. Green pixels show where surface water has been turned into land (accretion, land reclamation, droughts). Blue pixels show where land has been changed into surface water (erosion, reservoir construction).

The results of the analysis are published in:

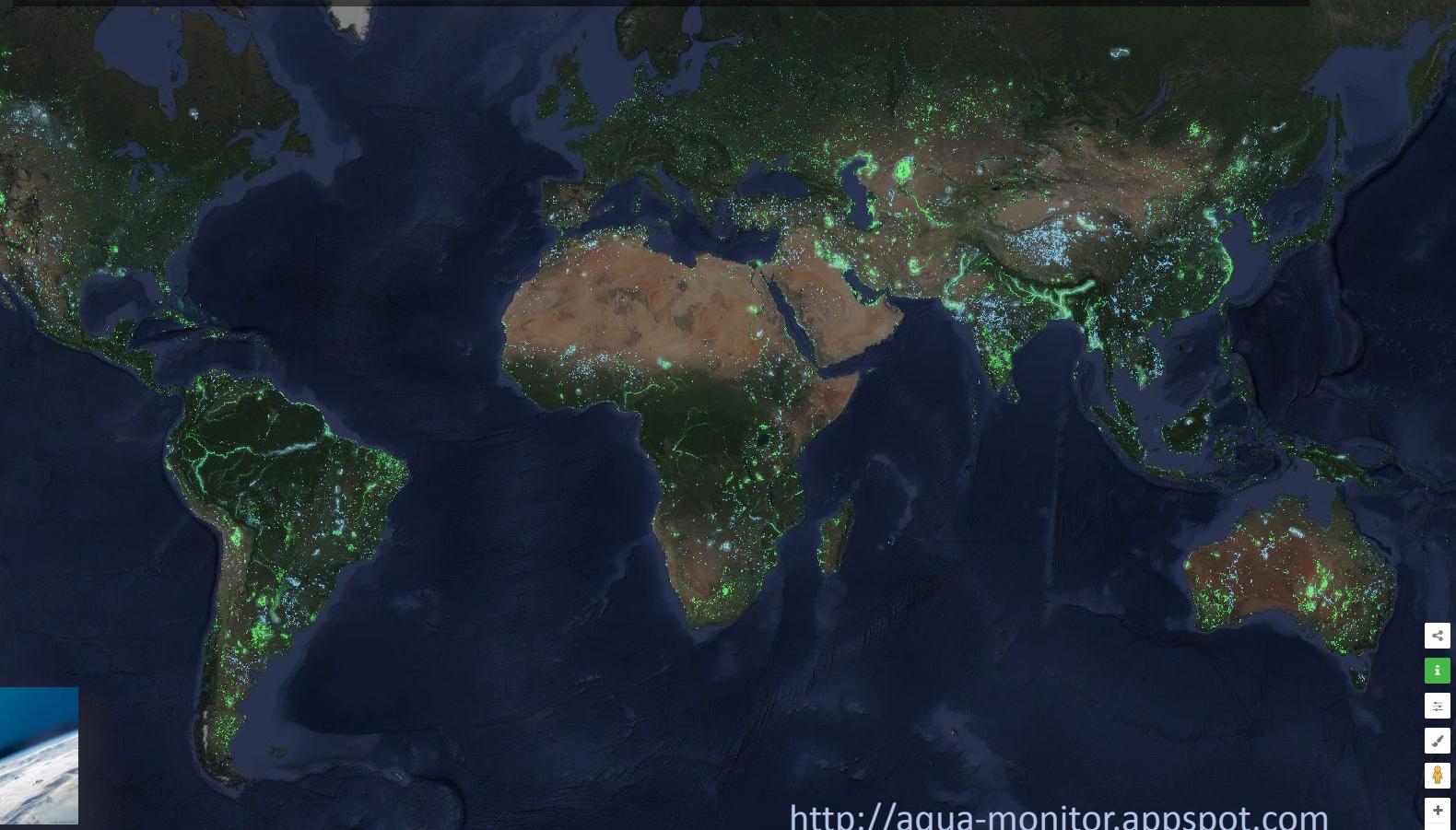
Donchyts et.al. 2016, Nature Climate Change

Powered by
Google Earth Engine



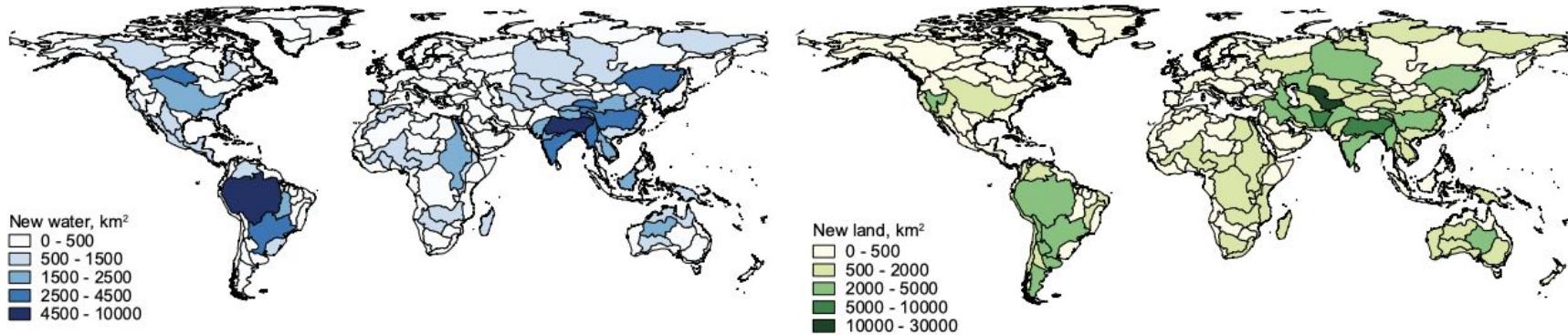
Earth's surface water change over the past 30 years

Gennadii Donchyts, Fedor Baart, Hessel Winsemius, Noel Gorelick, Jaap Kwadijk & Nick van de Giesen



<http://aqua-monitor.appspot.com>

nature
climate change



Name	Area, km ²
Tibetan Plateau	7661
Amazon River	7058
Ganges-Brahmaputra Rivers	5495
Rio de la Plata	4410
River Nelson	4101
India	3677
River Amur	3494
Yangtze River	3238
Tigris & Euphrates Rivers	2636
Thanlyin; Sittang; Ayeyarwady	2592
Indus River	2312
Mississippi River	2231
Mekong River	2074

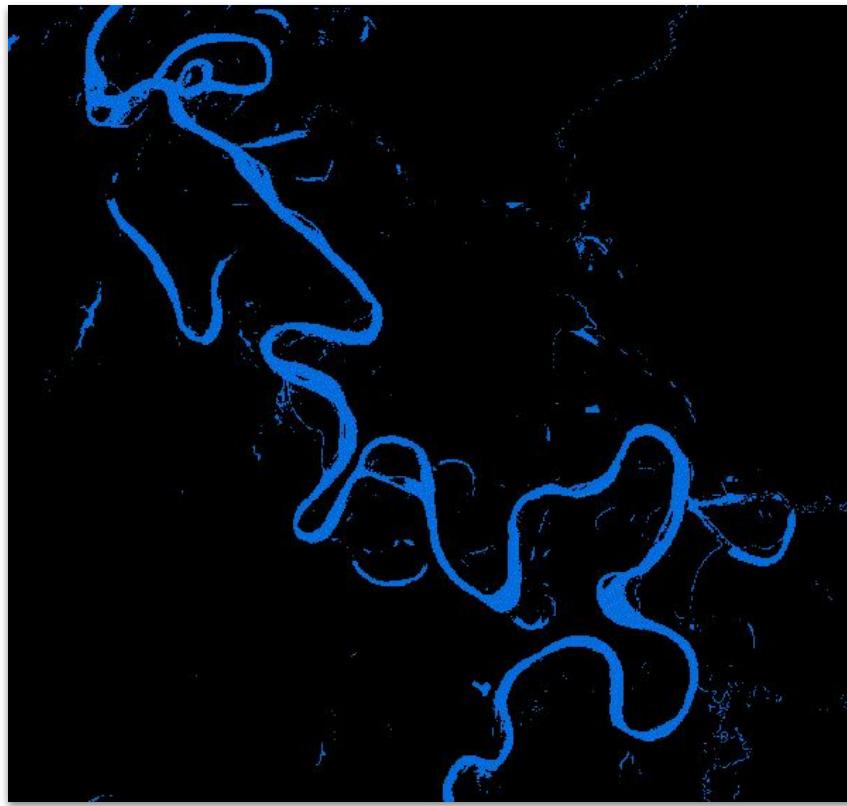
Name	Area, km ²
Aral Sea	27841
Ganges-Brahmaputra Rivers	9580
Hamun Lake	6044
Tigris & Euphrates Rivers	4897
Amazon River	4888
Lake Eyre	4672
Rio de la Plata	4020
India	3851
Lake Urmia, Caspian Sea	3759
Great Salt Lake; Malheur Lake	3752
Ural River	3455
Amur River	3344
Ob River	3068

Figure 6.2: Largest surface water and land changes from 1985 until 2015 grouped by drainage basins. Left: changes from land to water in blue. Right: changes from water to land in green.



Updated data for 2021

A virtual time machine that maps the location and temporal distribution of water surfaces at the global scale over the past 3.8 decades, and provides statistics on their extent and change to support better informed water-management decision-making.

[START EXPLORING!](#)

▼ Global Surface Water

[Introduction](#)[Water Occurrence \(1984-2015\)](#)[Water Occurrence Change Intensity](#)[Water Class Transition](#)

Search Box

Shoreline

Map Satellite

The State of the World's Beaches

Arjen Luijendijk, Gerben Hagenaars, Roshanka Ranasinghe, Fedor Baart, Gennadii Donchyts & Stefan Aarninkhof

Long-term Shoreline Changes (1984-2016)

The bars represent the erosion/accretion along coasts, every 500m, over the period 1984-2016. Green bars indicate where shoreline accretion has occurred (natural accretion, land reclamation, nourishments). Red bars indicate erosive shorelines, based on a linear fit through shoreline positions. If you're zoomed in you can click on a profile to see a time series chart.

-3m/yr  3m/yr

The results of the global analysis and methods can be found in: [Luijendijk et al., 2018, Scientific Reports](#)

For inquiries please fill in this form.

This dataset is created in collaboration with the Delft University of Technology.



nature

SCIENTIFIC
REPORTS

Google



Deltas

<http://shorelinemonitor.deltares.nl/>

Imagery ©2019 NASA, TerraMetrics

500 km

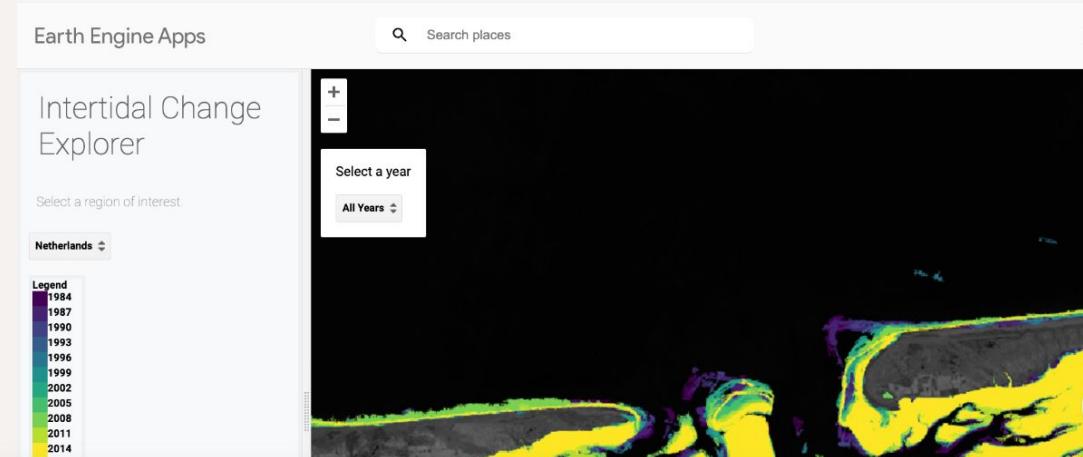
Terms of Use

Intertidal change

Mapping the Global Distribution and Trajectory of Tidal Flat Ecosystems

The intertidal environment is one of the last remaining unmapped coastal ecosystems on Earth. We developed a new machine-learning analysis of over 700,000 satellite images to map the global distribution and change of intertidal areas over a 30-year period.

Published as: Murray N. J., Phinn S. R., DeWitt M., Ferrari R., Johnston R., Lyons M. B., Clinton N., Thau D. & Fuller R. A. (2019)
The global distribution and trajectory of tidal flats. *Nature*. 565:222-225. <http://dx.doi.org/10.1038/s41586-018-0805-8>



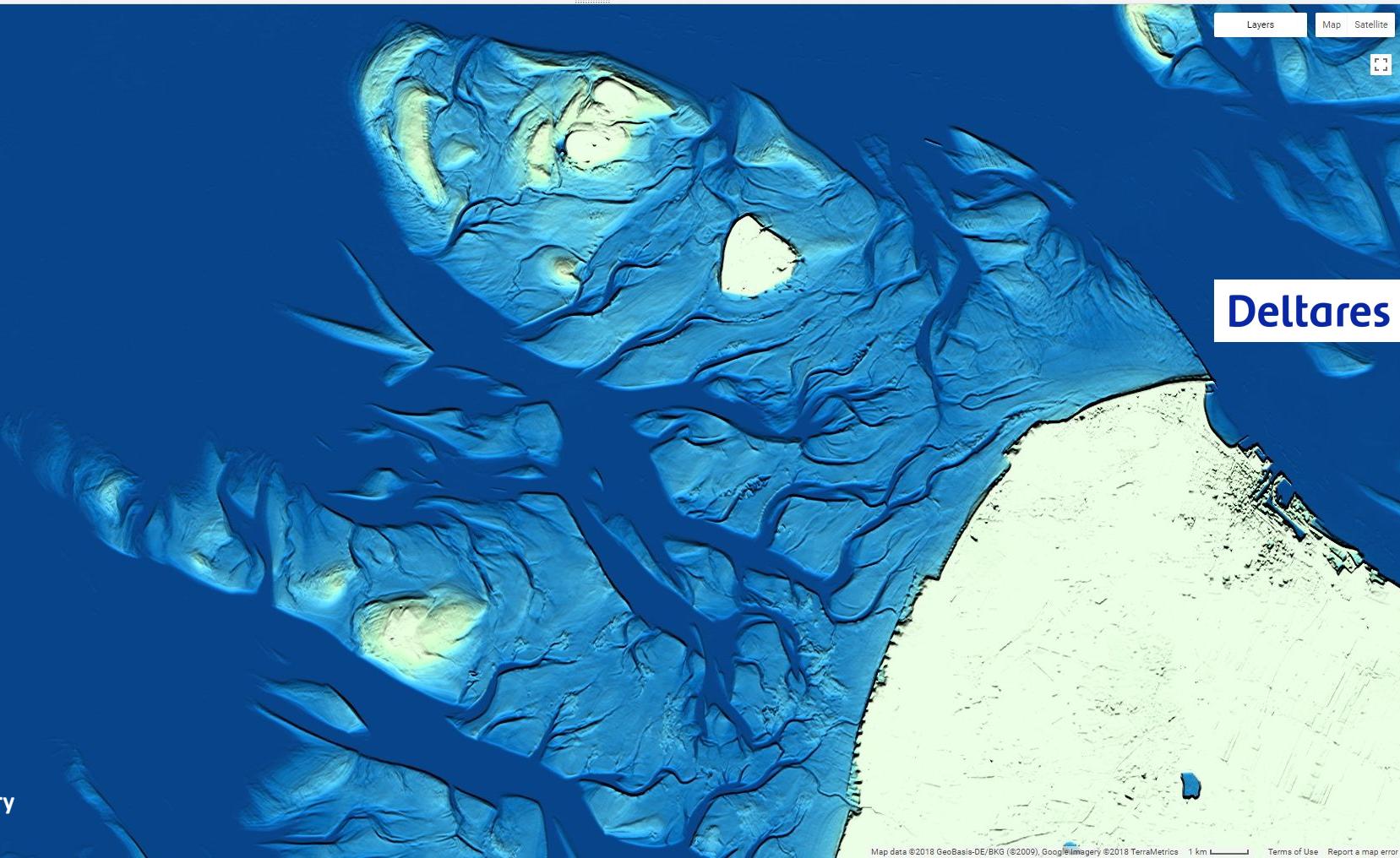
2017-01-08



Geometry Imports

Layers

Map Satellite



Intertidal Bathymetry



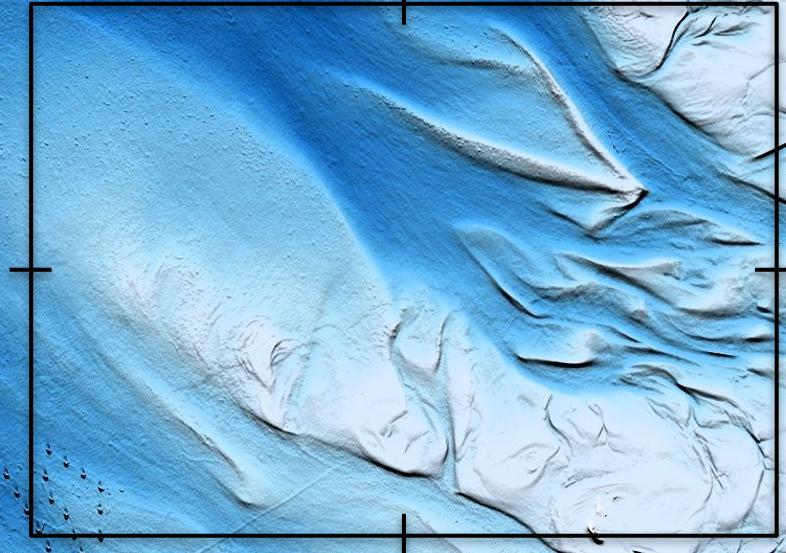
Layers

Map Satellite

Geometry Imports

+

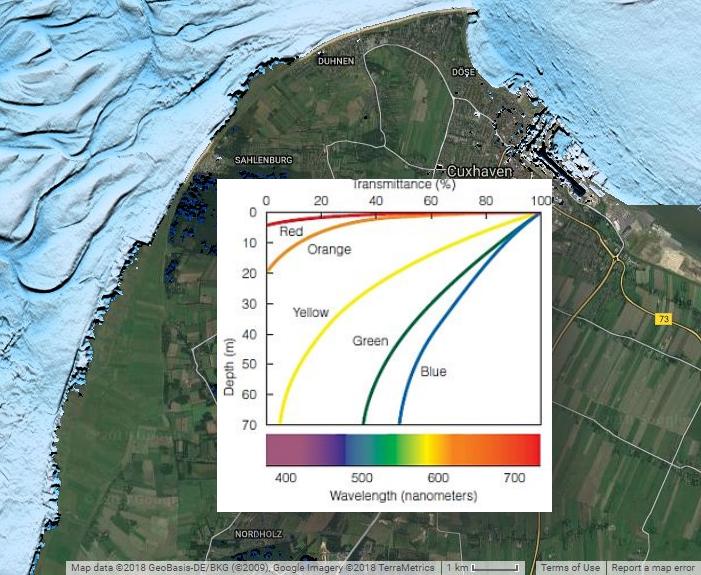
-

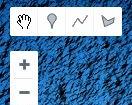


$$D = E[d] = \sum d \cdot w(f_{clouds}, x, y, t)$$

$$d = \log(\rho - \rho_{deep})$$

Deltas

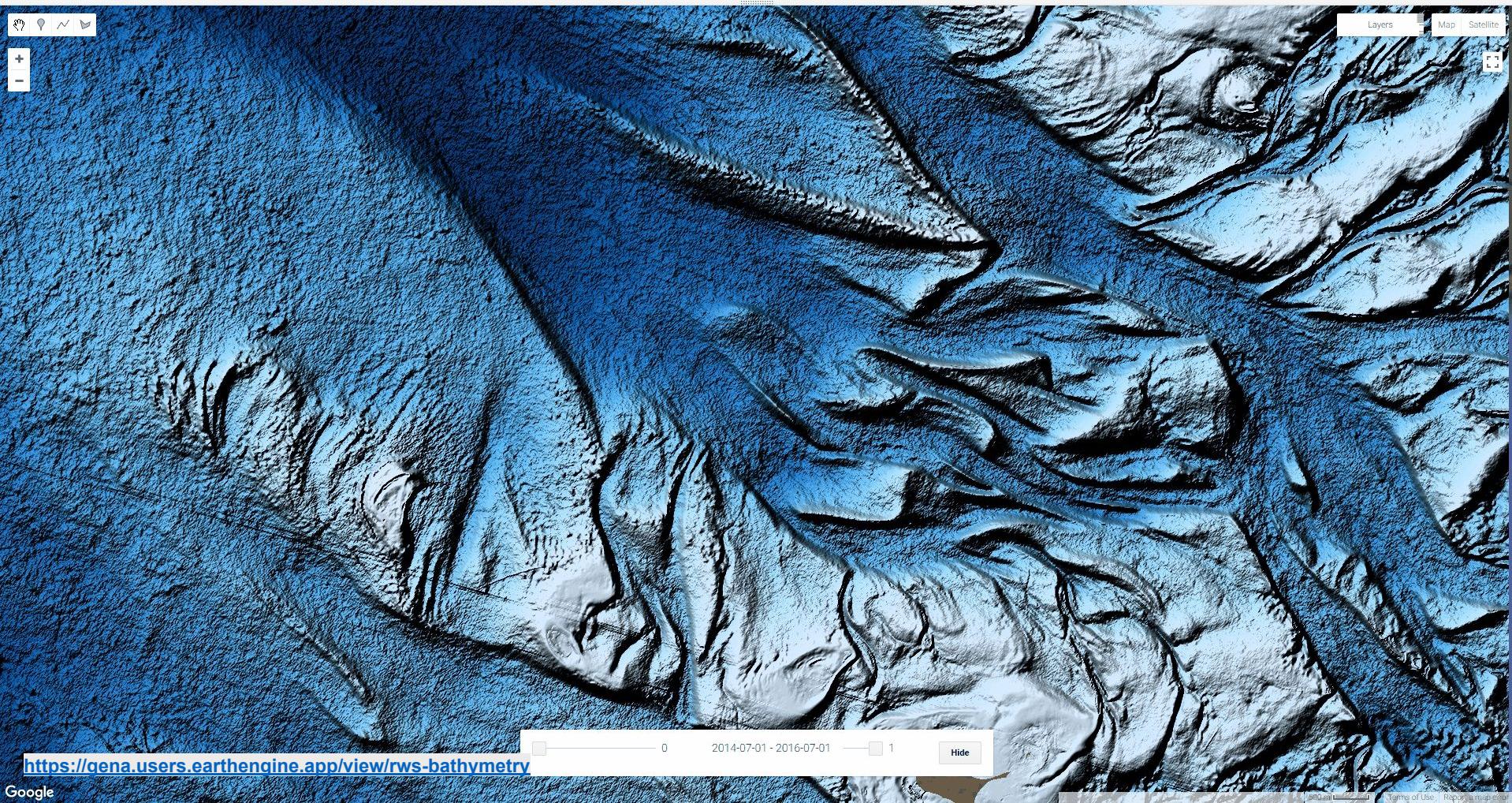




Layers

Map

Satellite



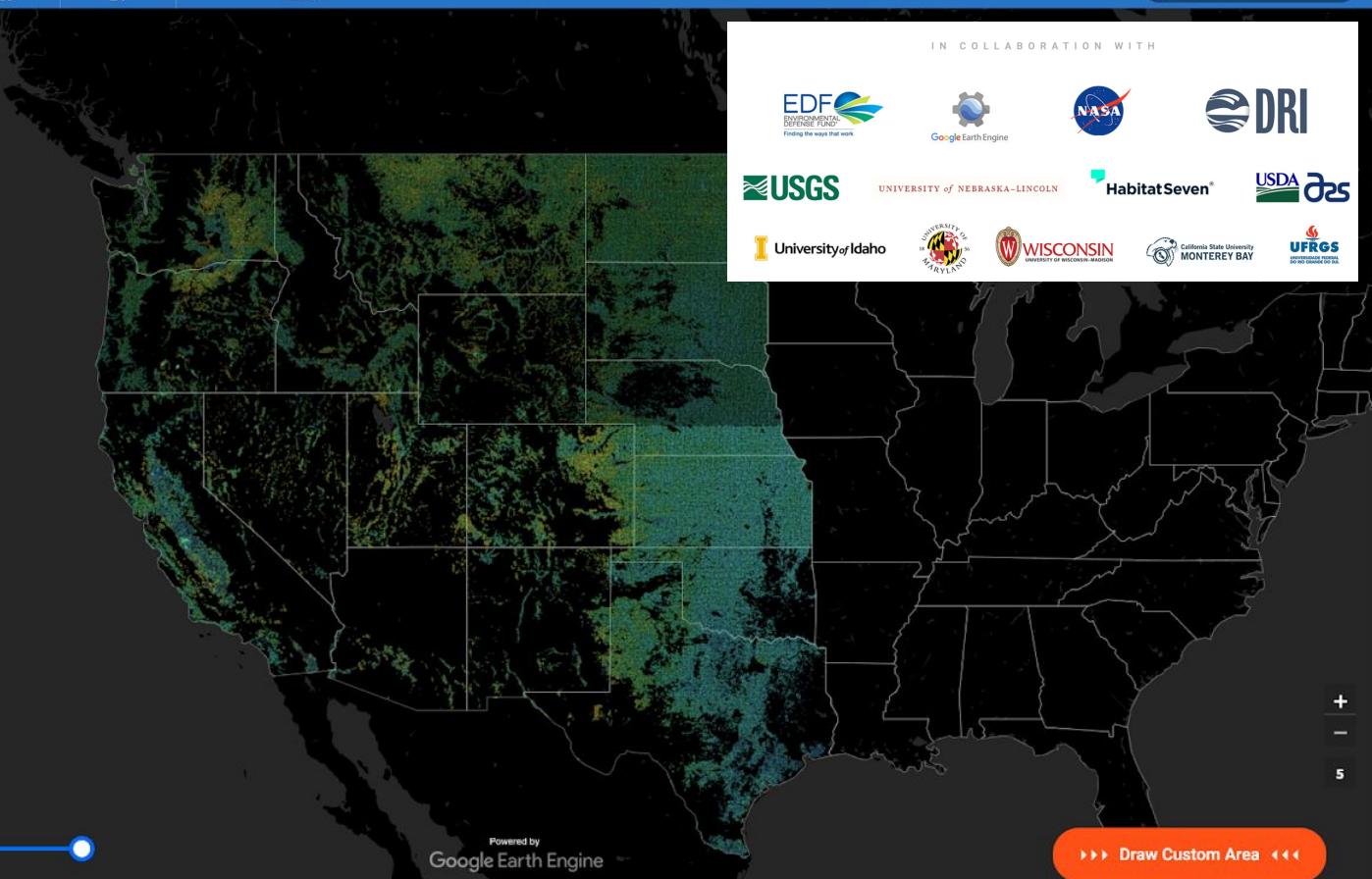
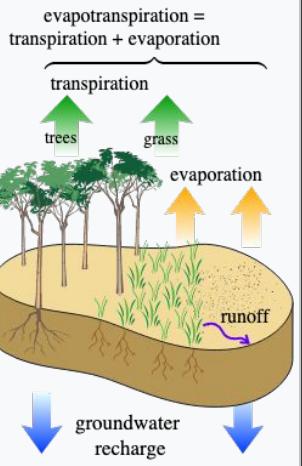
Search

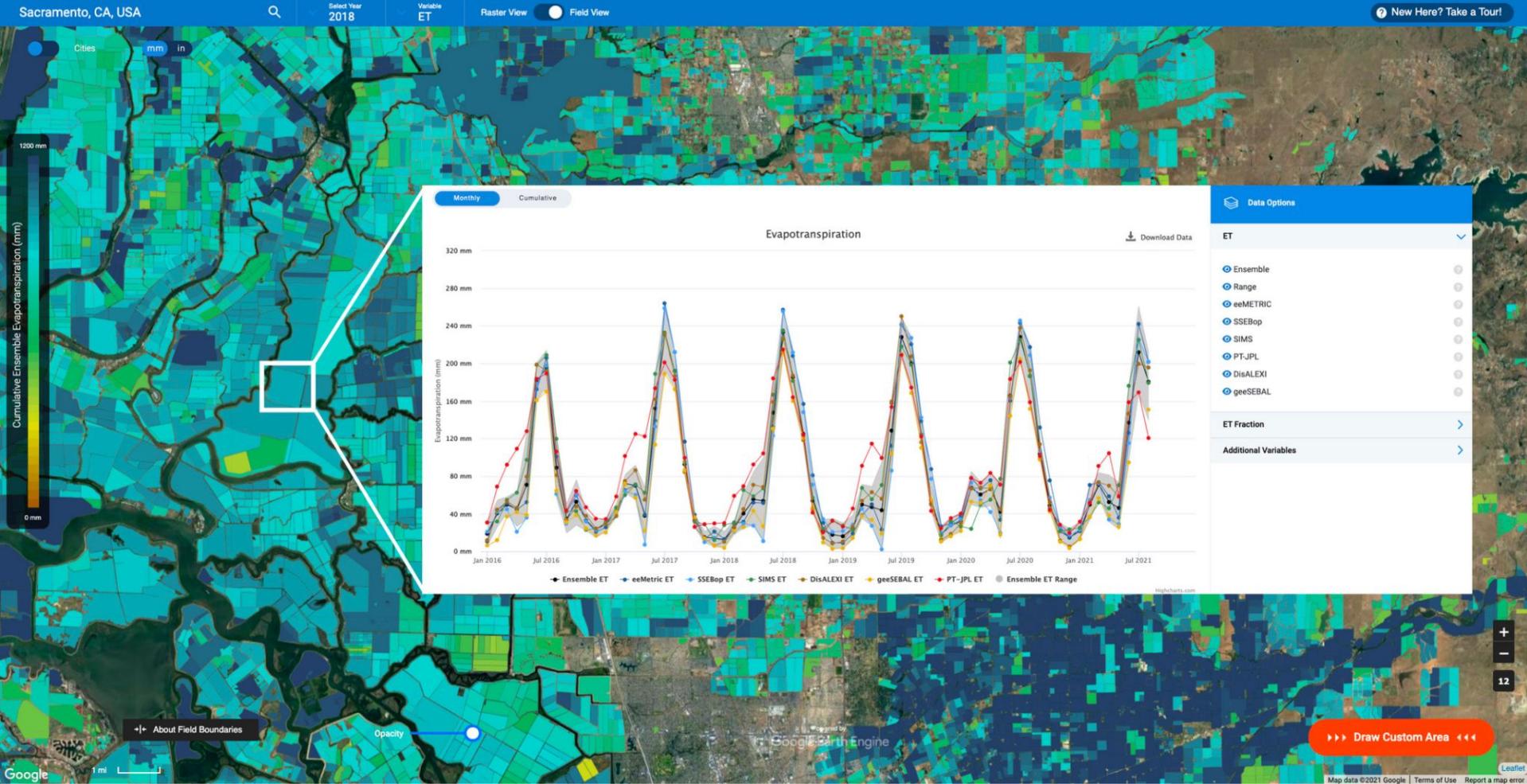
Select Year
2020Variable
ET

Raster View

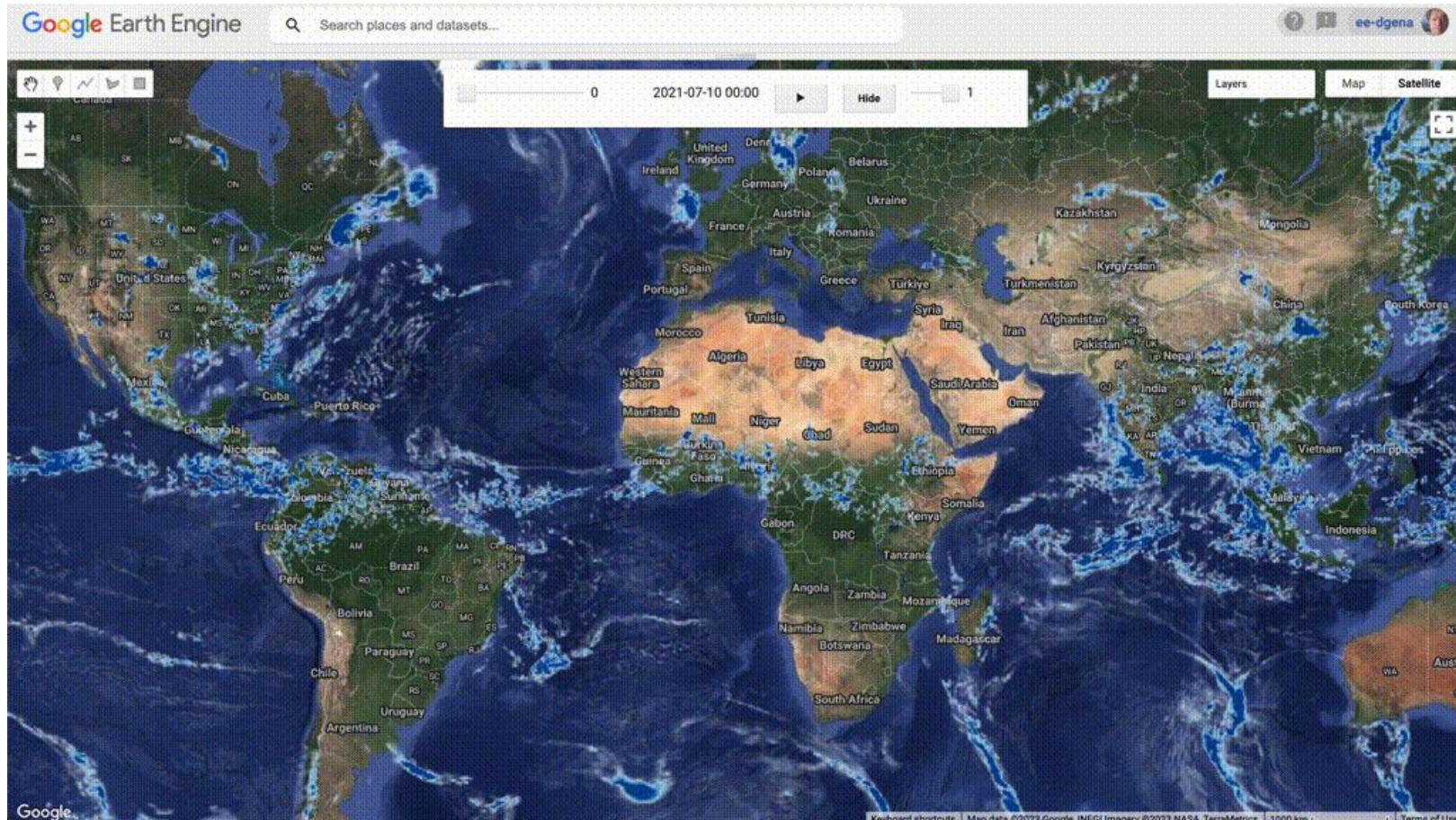
Field View

New Here? Take a Tour

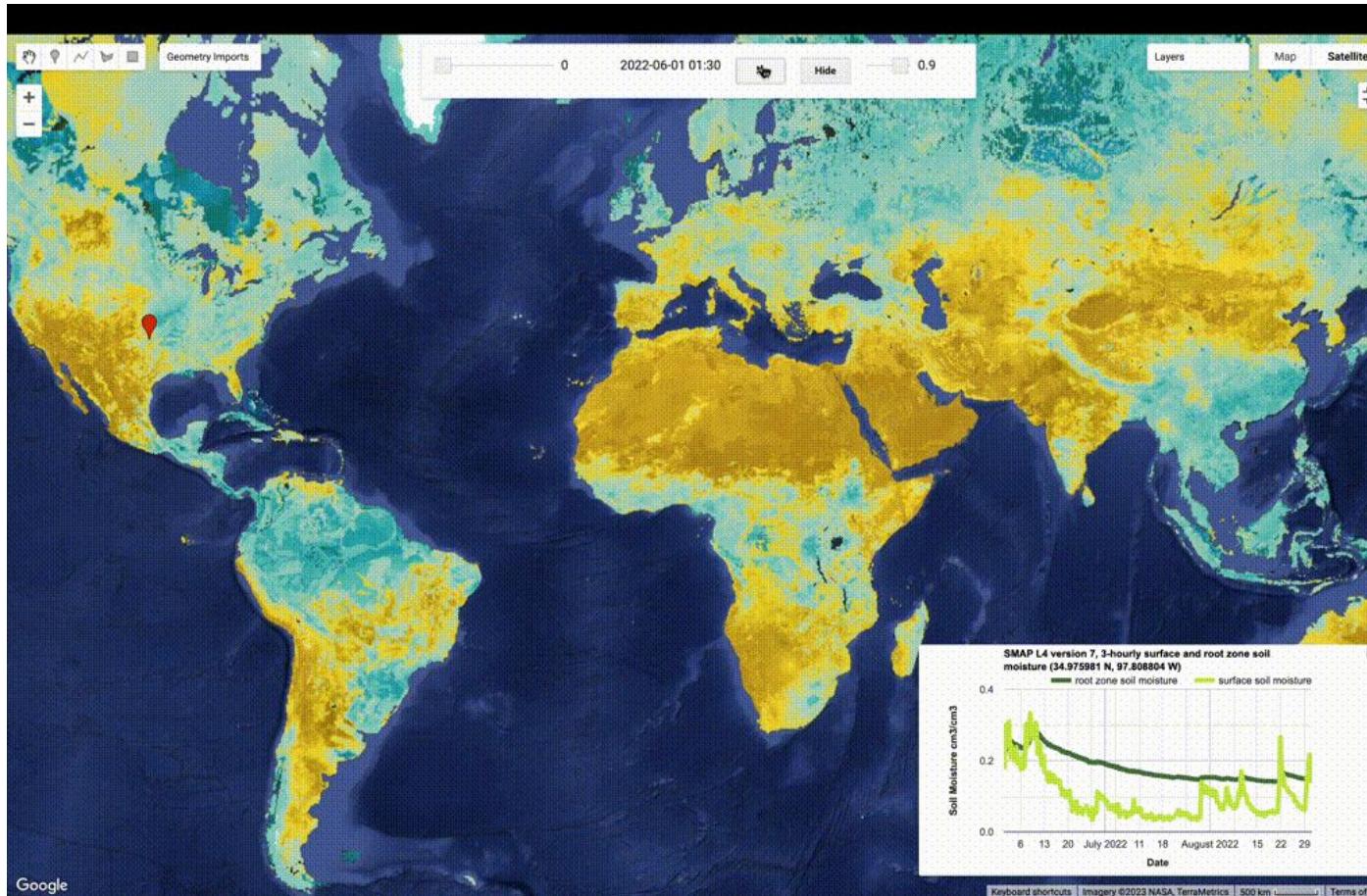
 Cities mm in? About Crop Type
and Field BoundariesOpacity



Precipitation (GFS)



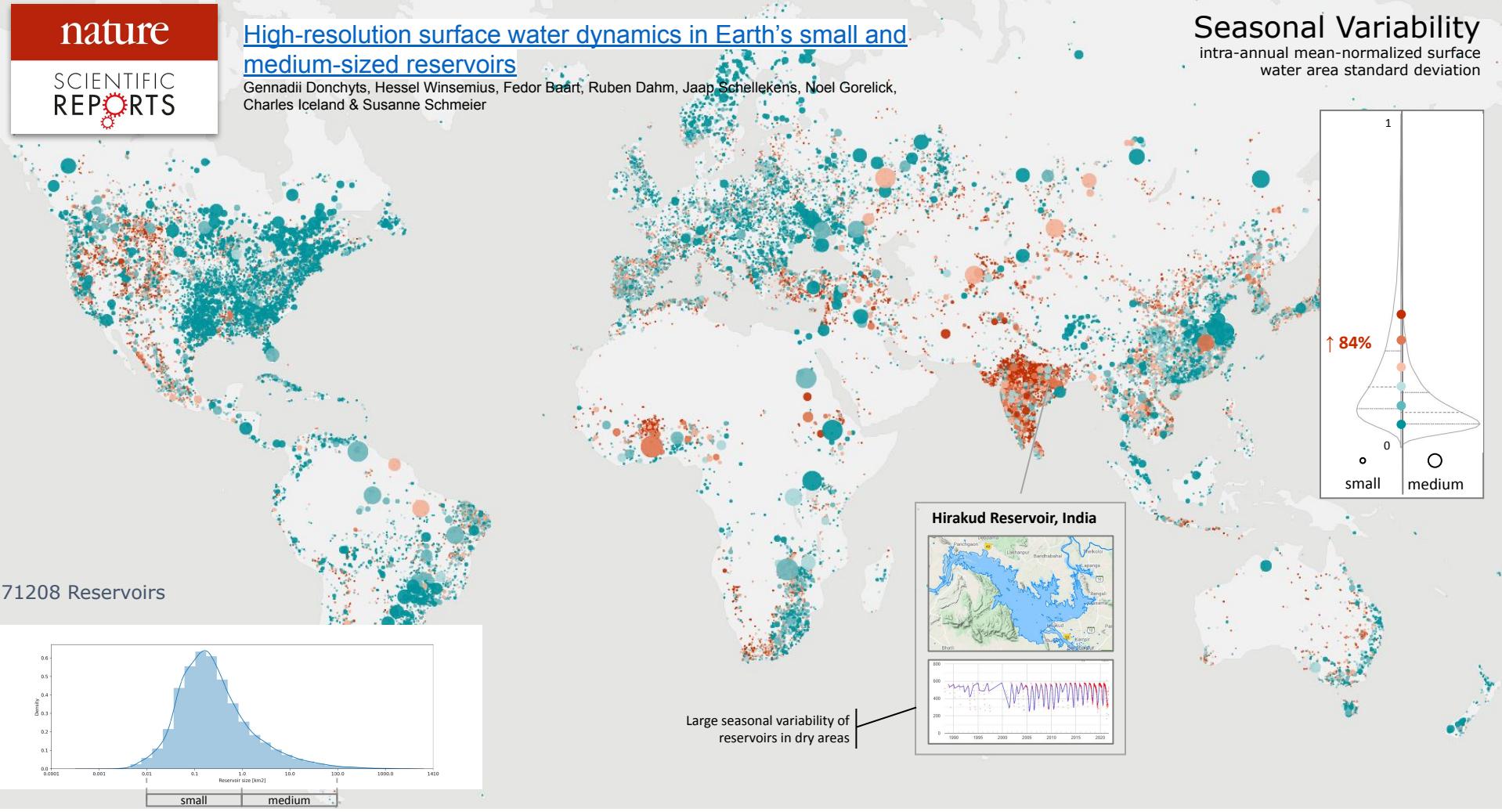
SMAP (<https://developers.google.com/earth-engine/tutorials/community/smap-soil-moisture>)



High-resolution surface water dynamics in Earth's small and medium-sized reservoirs

Gennadii Donchyts, Hessel Winsemius, Fedor Baart, Ruben Dahm, Jaap Schellekens, Noel Gorelick, Charles Iceland & Susanne Schmeier

Seasonal Variability
intra-annual mean-normalized surface
water area standard deviation

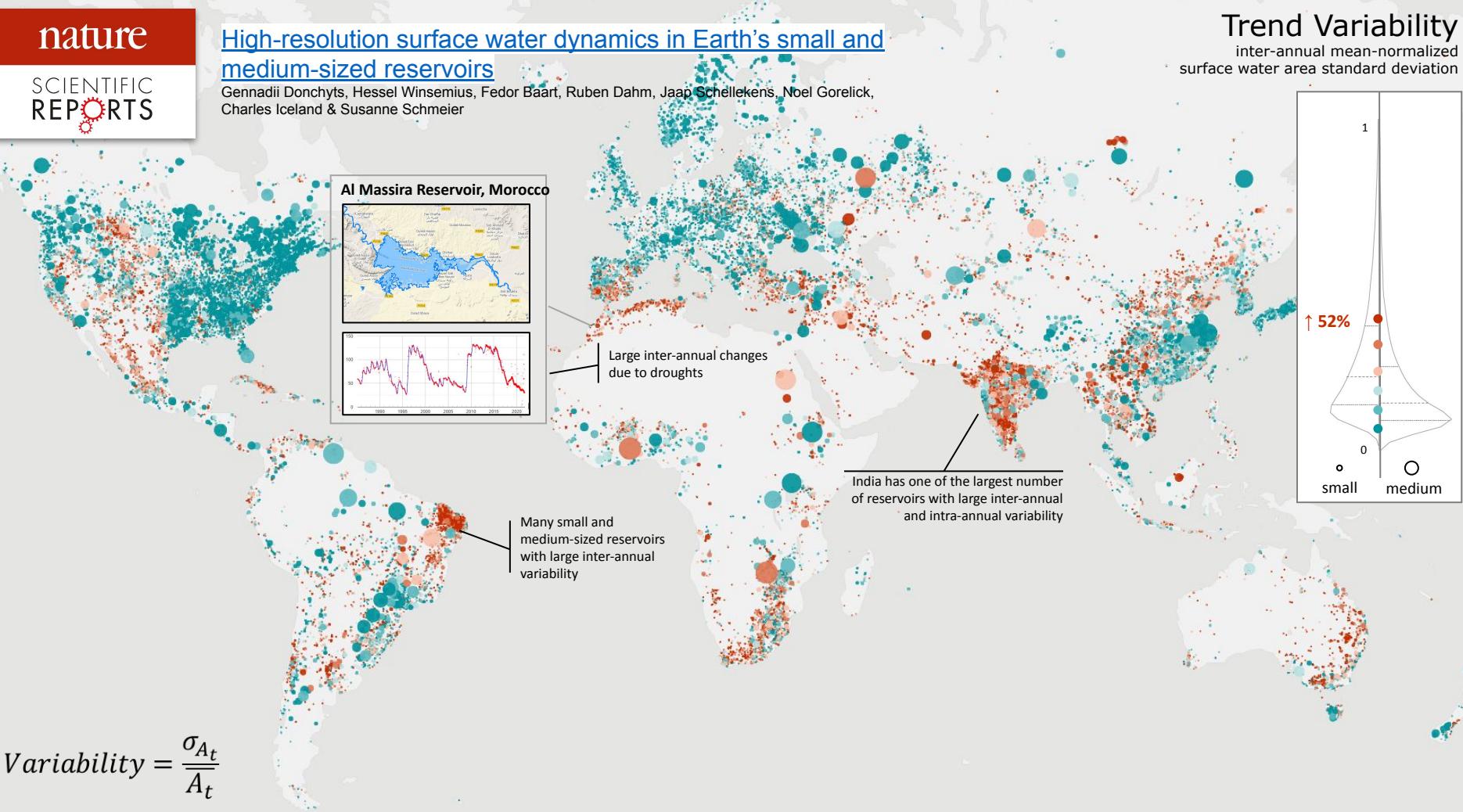


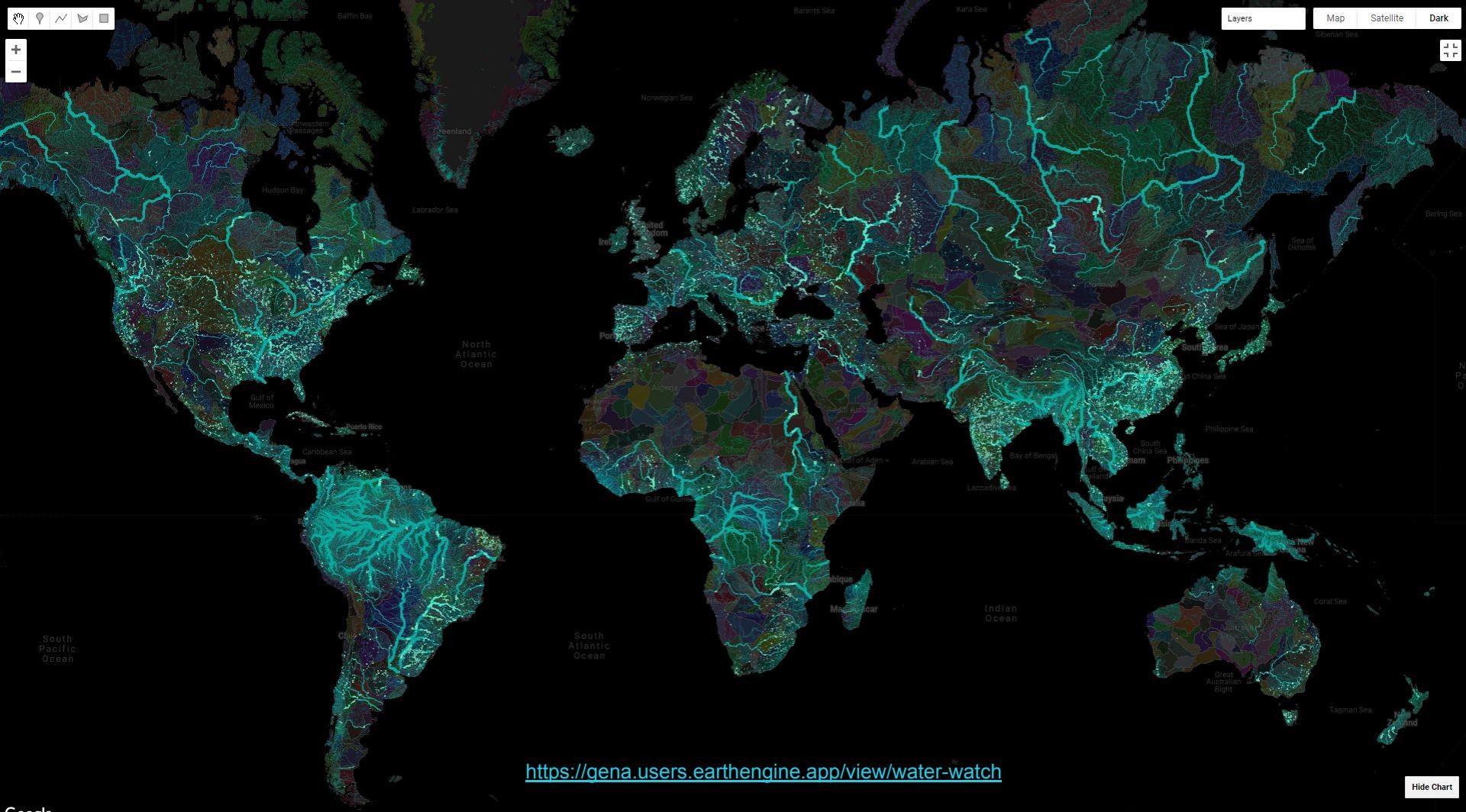
High-resolution surface water dynamics in Earth's small and medium-sized reservoirs

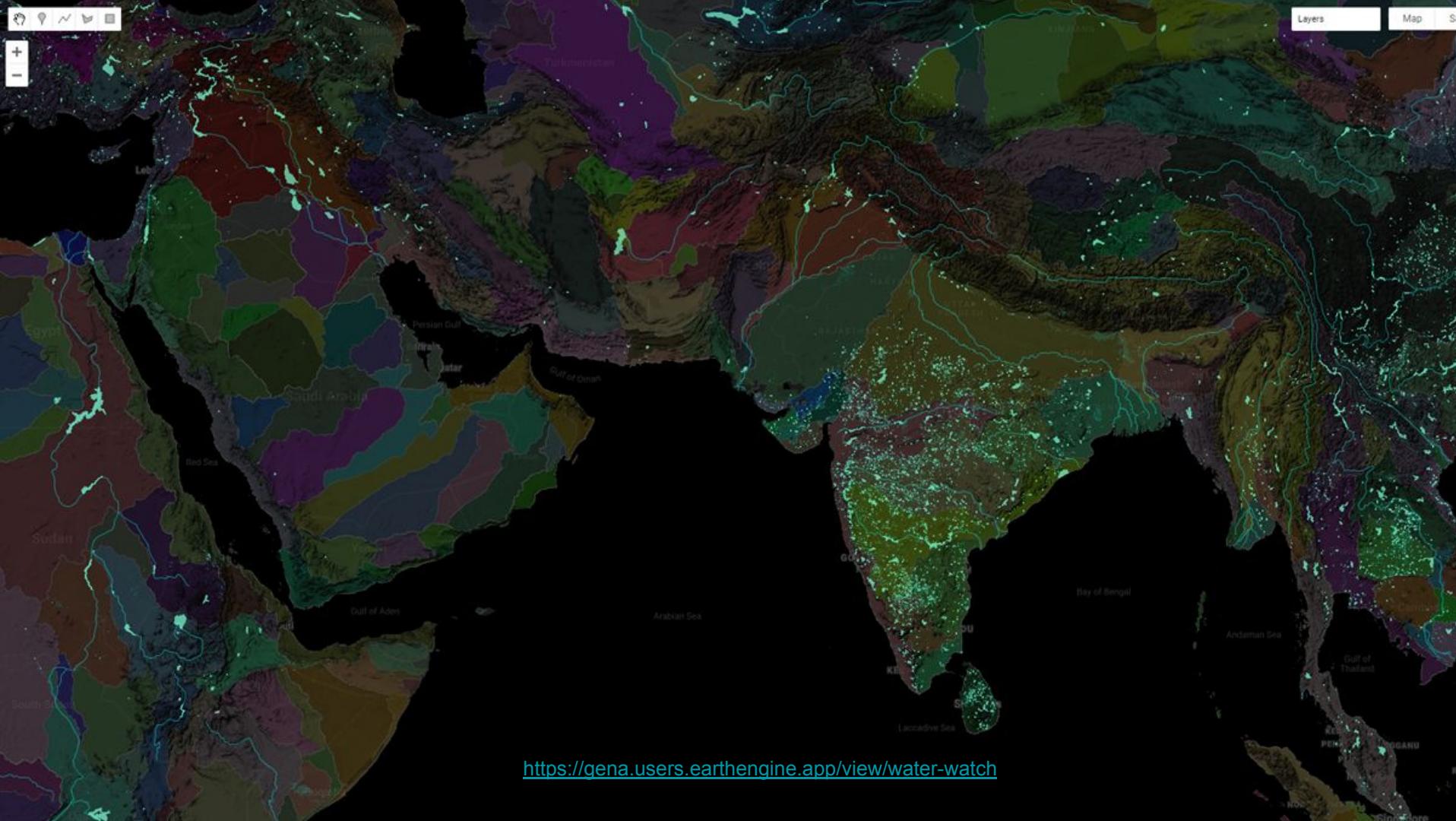
Gennadii Donchyts, Hessel Winsemius, Fedor Baart, Ruben Dahm, Jaap Schellekens, Noel Gorelick, Charles Iceland & Susanne Schmeier

Trend Variability

inter-annual mean-normalized
surface water area standard deviation

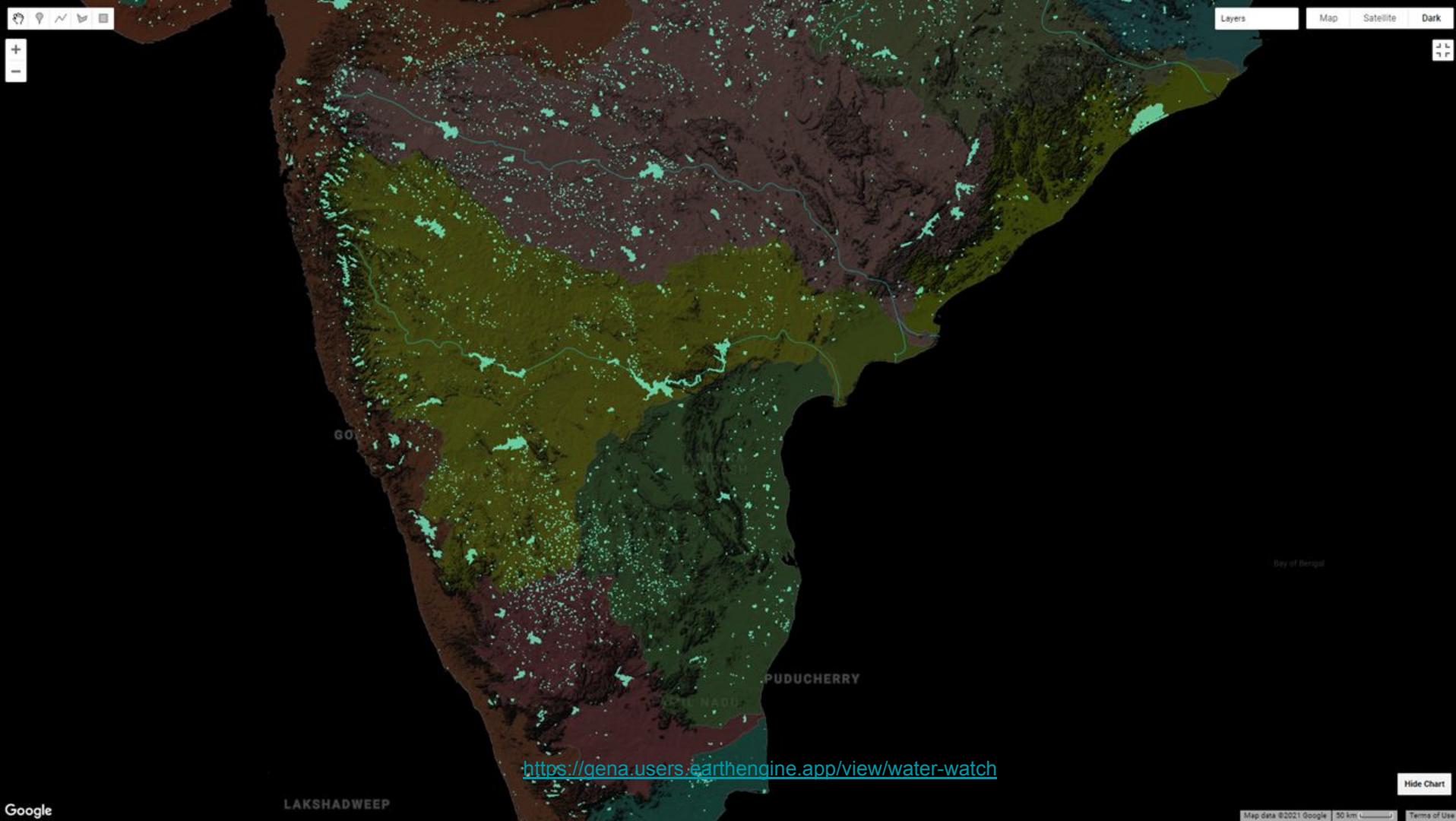






<https://qena.users.earthengine.app/view/water-watch>



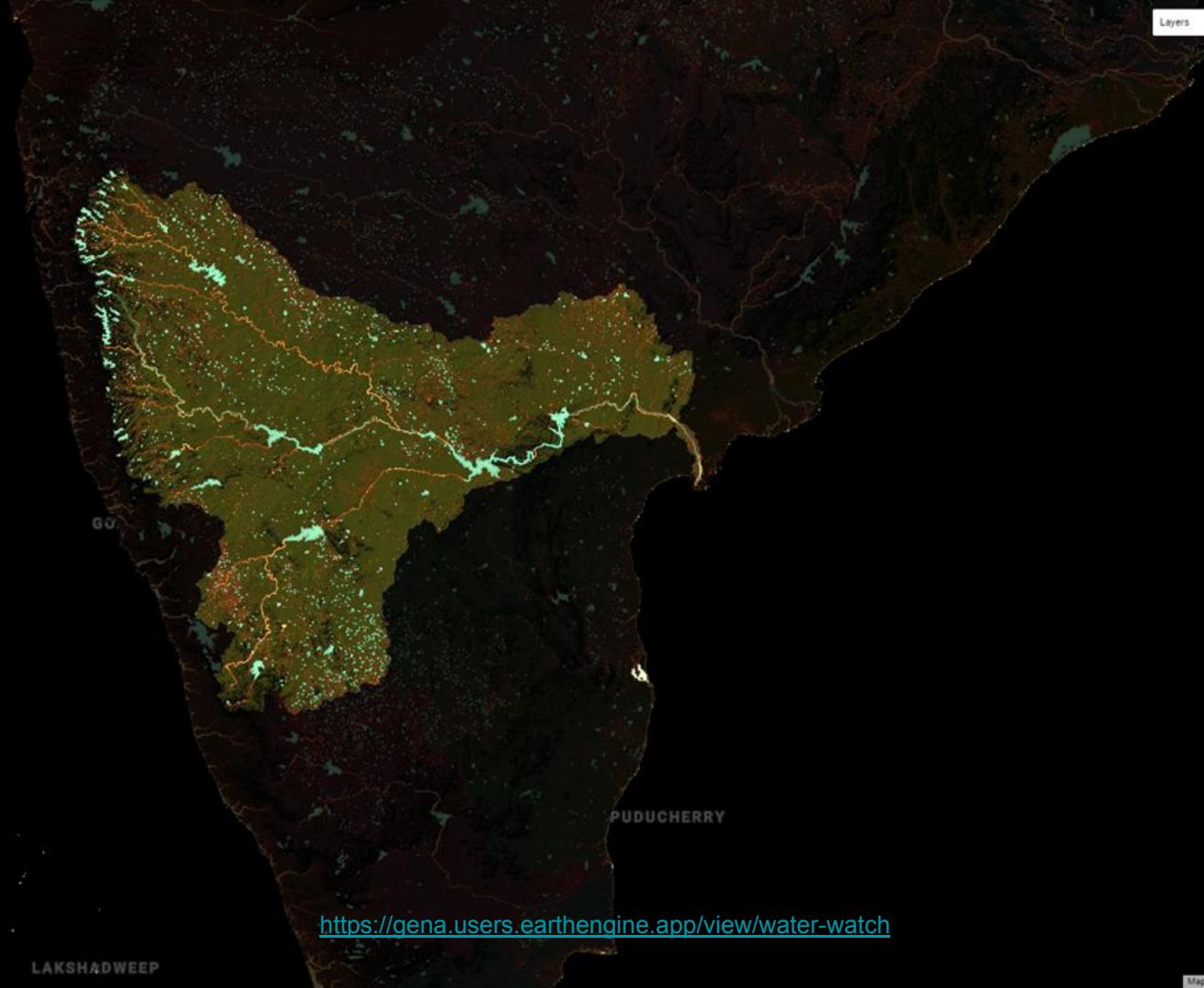




Layers Map Satellite Dark

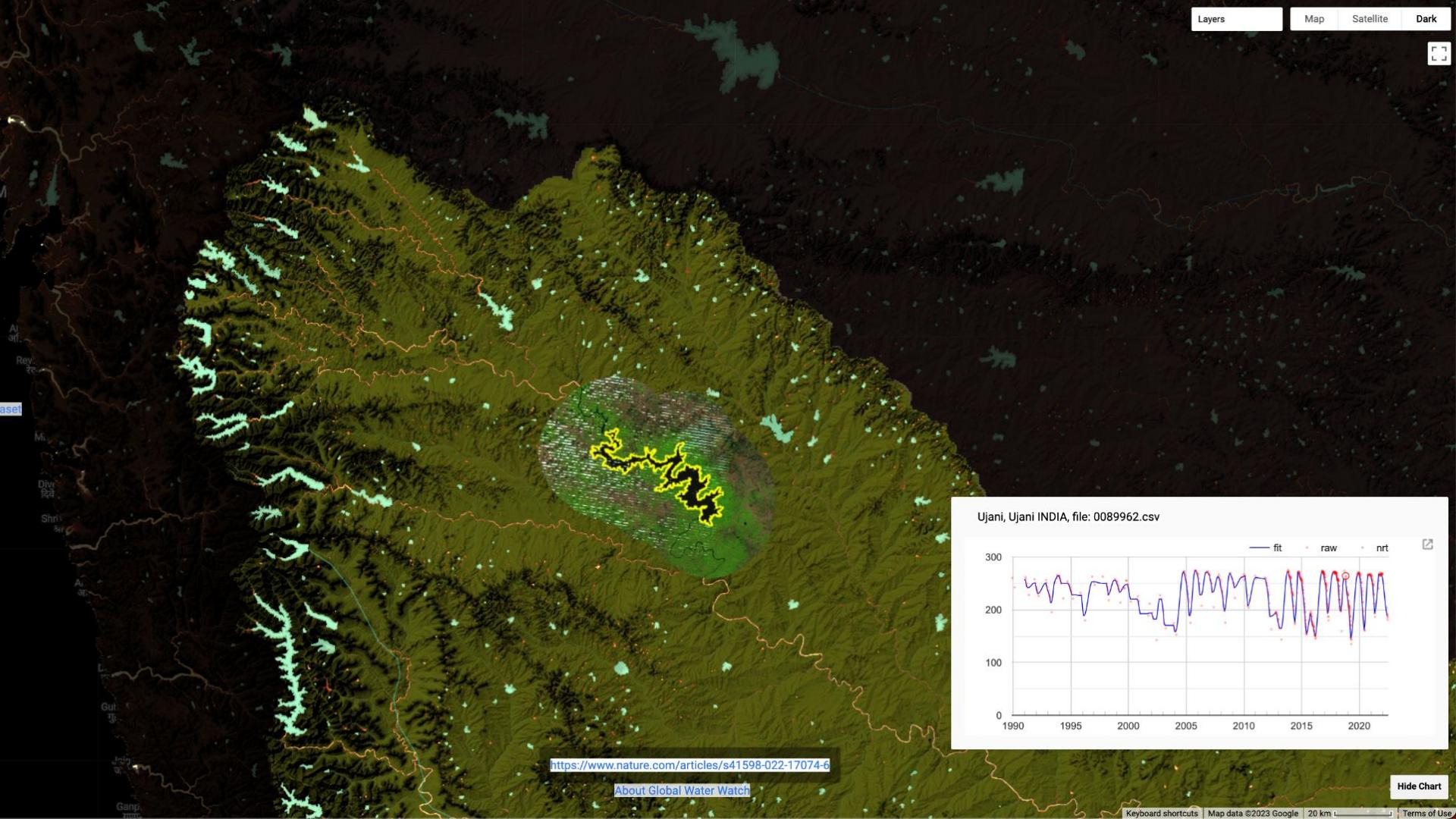
+

-

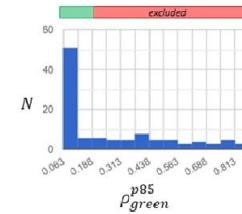
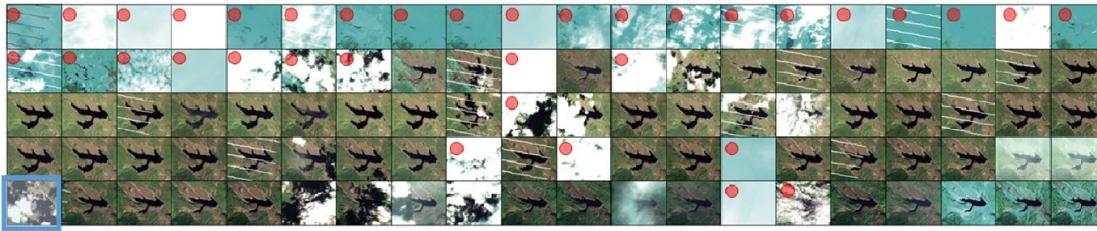


<https://qena.users.earthengine.app/view/water-watch>

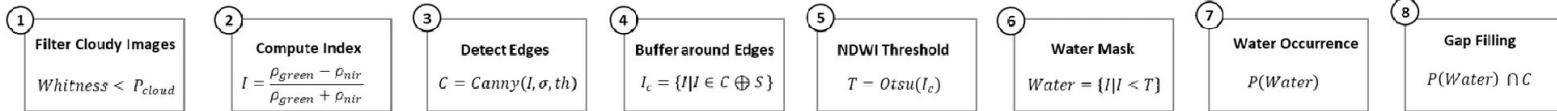
Hide Chart



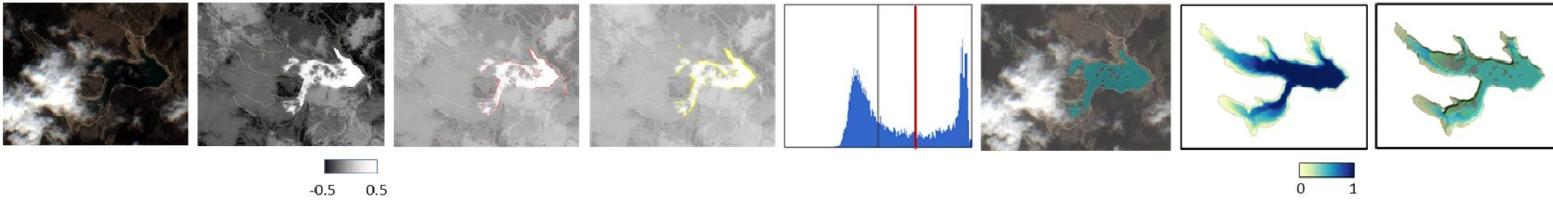
All Landsat 7, 8 and Sentinel-2 images for 2017 which overlap with the reservoir geometry



WATER DETECTION



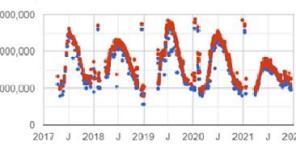
RGB



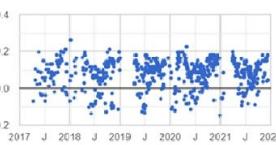
Gap-filled water mask



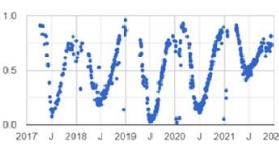
Gap-filled and detected water area



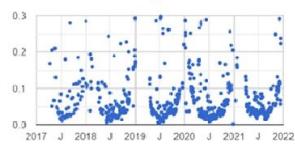
NDWI thresholds



Water occurrence values

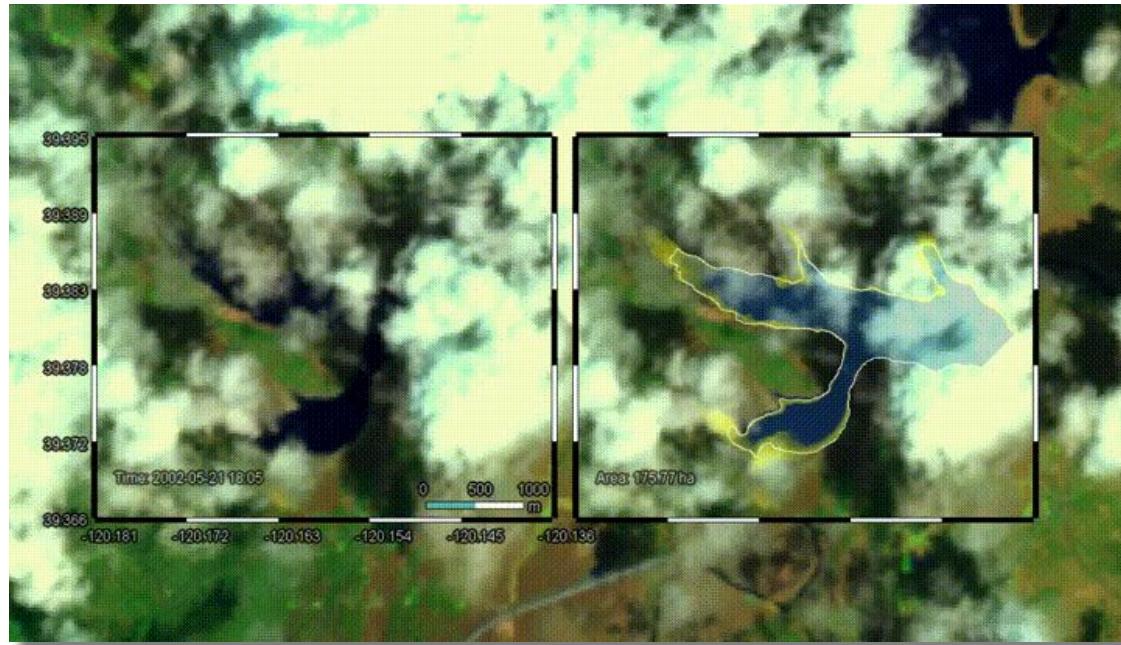


Filled fraction (% of detected area)



[Code](#)

[Paper](#)



02

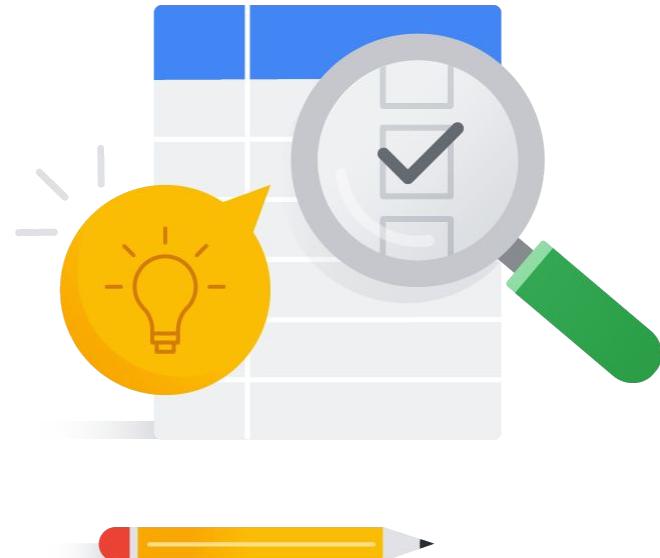
Water dynamics mapping (JRC)

 10 min Individual**Steps**

visualize water occurrence

explore monthly water occurrence

compute and plot monthly surface water area



Water occurrence (1985-2022)

exploring JRC water occurrence dataset

The screenshot shows the Google Earth Engine interface. In the top left, it says "Google Earth Engine". Below that is a map of the Western United States. On the left side of the map is a sidebar with various tools and a search bar containing "jrc water". The search results are listed under "PLACES" and "RASTERS". Under "RASTERS", several items are listed, with three highlighted by red boxes: "JRC Global Surface Water Mapping Layers, v1.4", "JRC Monthly Water History, v1.4", and "JRC Monthly Water Recurrence, v1.4". Under "TABLES", there are two entries: "LUCAS Copernicus (Polygons with attributes, 2018) V1" and "LUCAS Harmonized (Theoretical Location, 2006-2018) V1".

API Tutorials

Overview

- ▶ Introduction to JavaScript for Earth Engine
- ▶ The Earth Engine API
- ▶ Global Forest Change
- ▶ Global Surface Water

Introduction

Water Occurrence (1984-2015)

Water Occurrence Change Intensity

Water Class Transition

Video Tutorials

Link 6807701ce2188f2a89cb03644d752d6f *

Get Link

Save

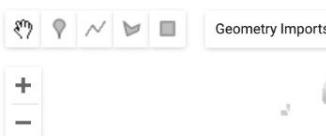
Run

Reset

Apps



```
Imports (1 entry) ↴  
↳ var geometry: Polygon, 4 vertices ⚖️ ⚒️  
1 Map.setOptions('TERRAIN')  
2  
3 Map.addLayer(ee.Image(1), { palette: ['white'] })  
4  
5 // JRC water occurrence  
6 var waterOccurrence = ee.Image("JRC/GSW1_3/GlobalSurfaceWater").select('occurrence')  
7 Map.addLayer(waterOccurrence, { min: 0, max: 100 }, 'water occurrence (raw)')  
8  
9 // JRC water occurrence (remask, transparent only when less than 2%)  
10 waterOccurrence = waterOccurrence  
11   .unmask(0).resample('bilinear')  
12   .divide(100)  
13   .rename('occurrence')  
14  
15 waterOccurrence = waterOccurrence.updateMask(waterOccurrence.unitScale(0, 0.02))  
16 Map.addLayer(waterOccurrence, { min: 0, max: 1 }, 'water occurrence')
```



Geometry Imports



Inspector Console Tasks

Point (-4.24107, 39.40158) at 19m/px

Pixels

- ↳ Layer 1: Image (1 band)
constant: 1
- ↳ water occurrence (raw): Image (1 band)
occurrence: 17 (18%)
- ↳ water occurrence: Image (1 band)
occurrence: 0.17

Objects

Link 6807701ce2188f2a89cb03644d752d6f*

Get Link Save Run Reset Apps

Imports (1 entry) ↗
var geometry: Polygon, 4 vertices

```
1 Map.setOptions('TERRAIN')
2
3 Map.addLayer(ee.Image(1), { palette: ['white']})
4
5 // JRC water occurrence
6 var waterOccurrence = ee.Image("JRC/GSW1_3/GlobalSurfaceWater").select('occurrence')
7 Map.addLayer(waterOccurrence, { min: 0, max: 100 }, 'water occurrence (raw)')
8
9 // JRC water occurrence (remask, transparent only when less than 2%)
10 waterOccurrence = waterOccurrence
11   .unmask(0).resample('bilinear')
12   .divide(100)
13   .convolve(ee.Kernel.gaussian(45, 30, 'meters'))
14   .rename('occurrence')
15
16 waterOccurrence = waterOccurrence.updateMask(waterOccurrence.unitScale(0, 0.02))
17 Map.addLayer(waterOccurrence, { min: 0, max: 1}, 'water occurrence')
18
```

Inspector Console Tasks

Point (-4.24004, 39.40277) at 19m/px

Pixels

- Layer 1: Image (1 band)
constant: 1
- water occurrence (raw): Image (1 band)
occurrence: 14 (15%)
- water occurrence: Image (1 band)
occurrence: 0.1400000059604636

Objects

Geometry Imports

+ -



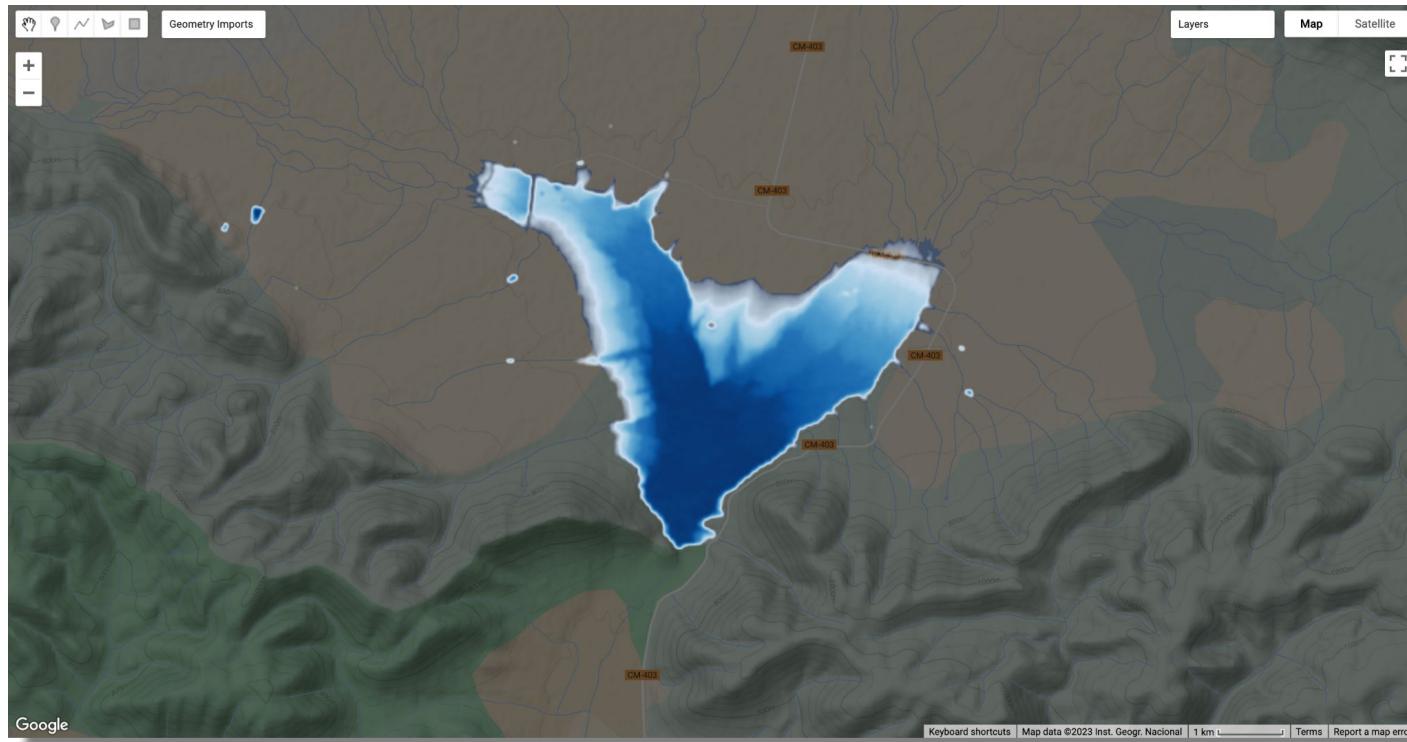
Layers

- water occurrence
- water occurrence (raw)
- Layer 1

Map Satellite

Water occurrence (1985-2022)

exploring JRC water occurrence dataset

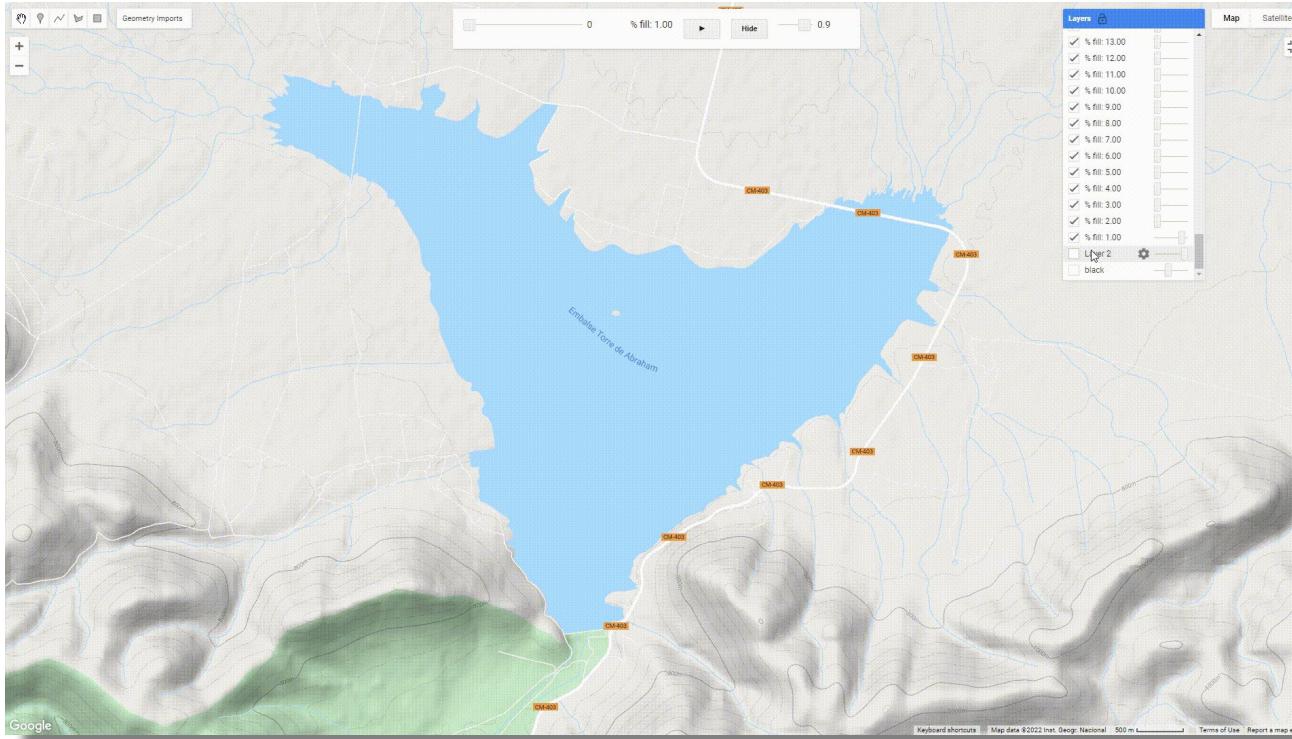


[Code](#)

Google Cloud

Water is dynamic

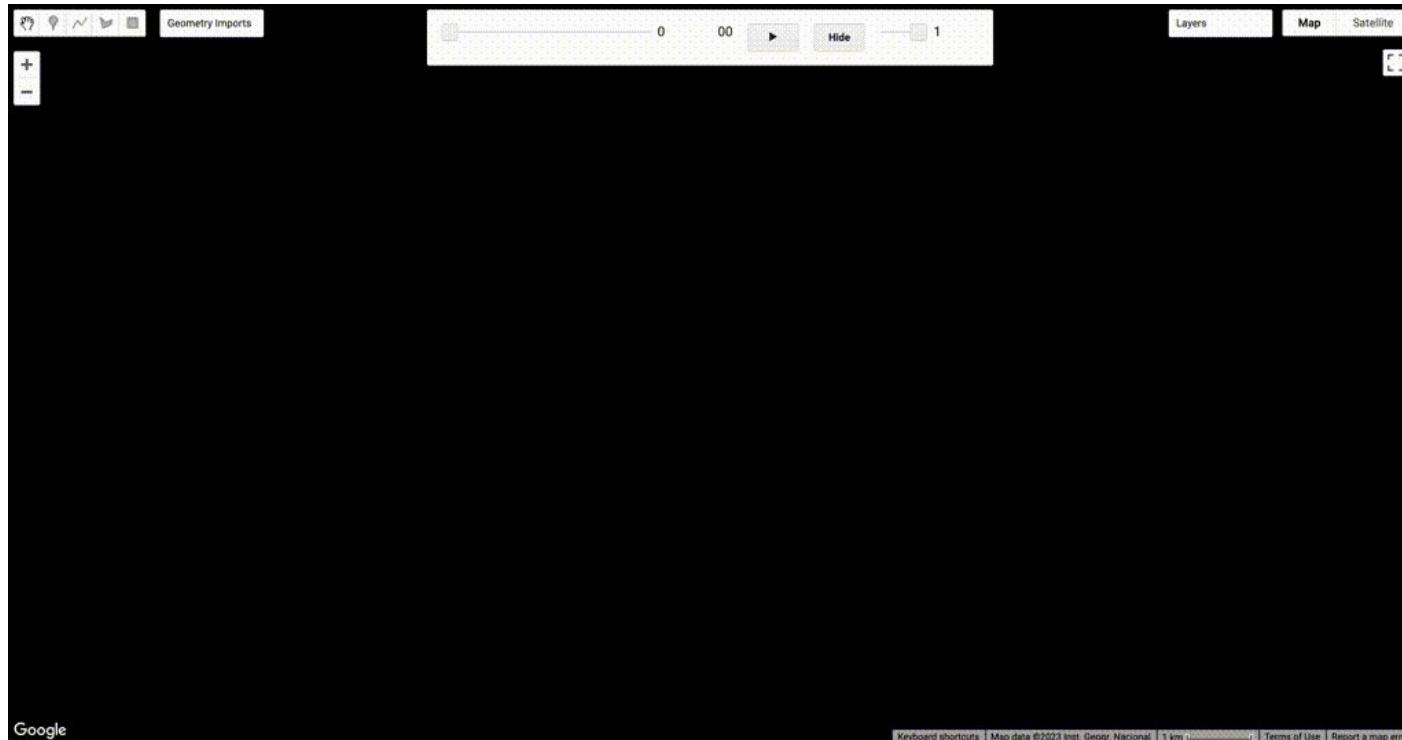
exploring JRC water occurrence dataset



[Code](#)

Google Cloud

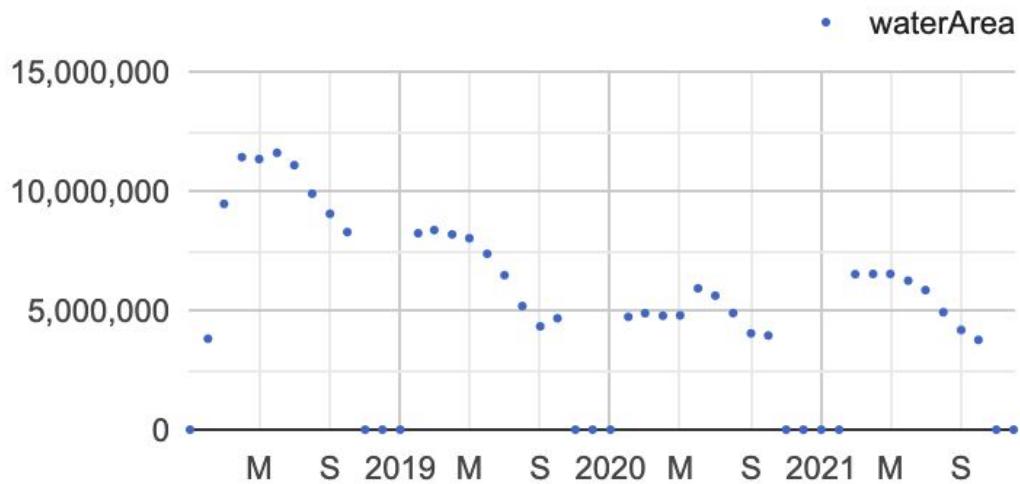
Monthly JRC water occurrence



Code To quantify surface water area changes, we will use monthly JRC water occurrence

Google Cloud

Monthly JRC water occurrence



```

var waterMonthlyMask = waterMonthly
  .map(function(i) {
    return i.eq(2).updateMask(i.gt(0))
      .copyProperties(i, ['system:time_start'])
  })

waterMonthlyMask = waterMonthlyMask.map(function(i) {
  var waterArea = ee.Image.pixelArea().updateMask(i)
    .reduceRegion(ee.Reducer.sum(), geometry,
scale).get('area')

  return i.set({ waterArea: waterArea })
})

var chart = ui.Chart.feature.byFeature(waterMonthlyMask,
  'system:time_start', ['waterArea'])
.setOptions({
  lineWidth: 0,
  pointSize: 1
})
print(chart)

```

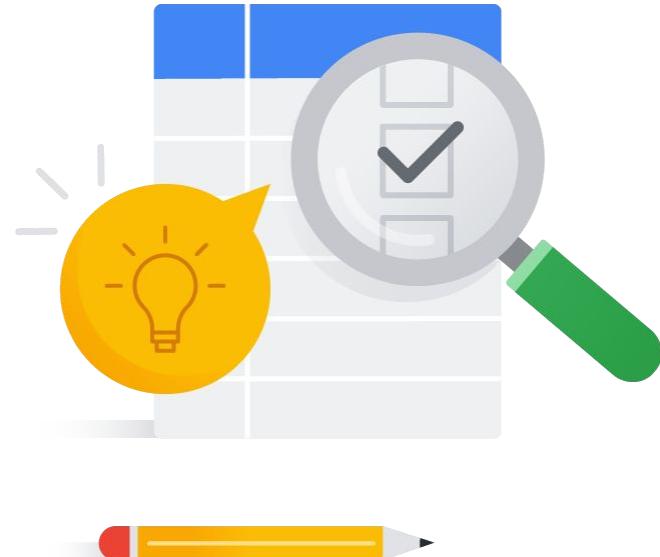
[Code](#)

03

Water detection with optical satellite imagery

 25 min Individual

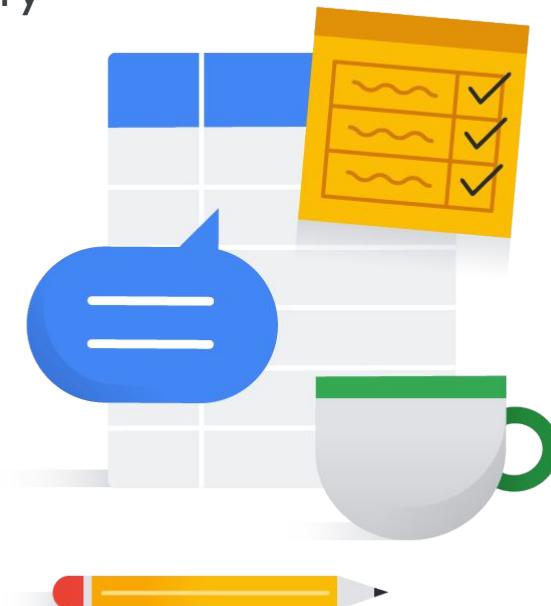
multispectral optical imagery (Sentinel-2)
compute NDWI, MNDWI, NDVI, ...
compute and plot surface water area
filter noisy (cloudy) images using cloud frequency
temporal smoothing

Code

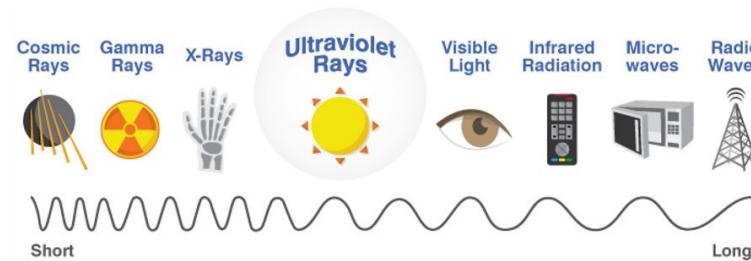
Quick overview of multi-spectral remote sensing theory

5 min

Group

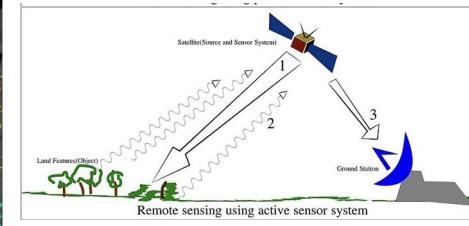
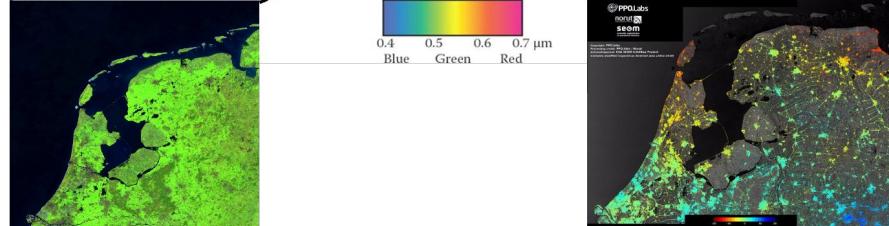
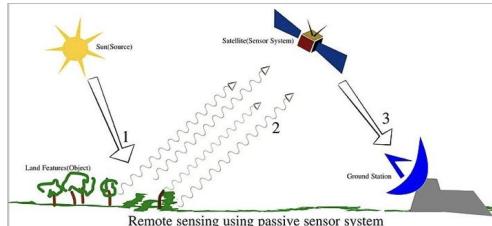
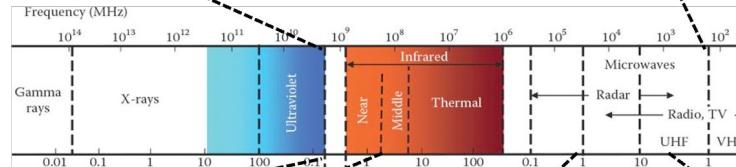
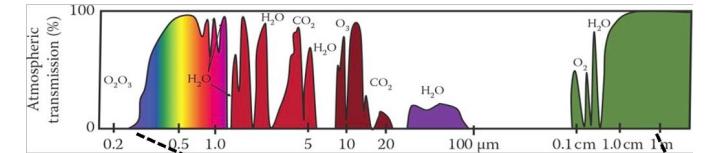


Earth Observations and Remote Sensing

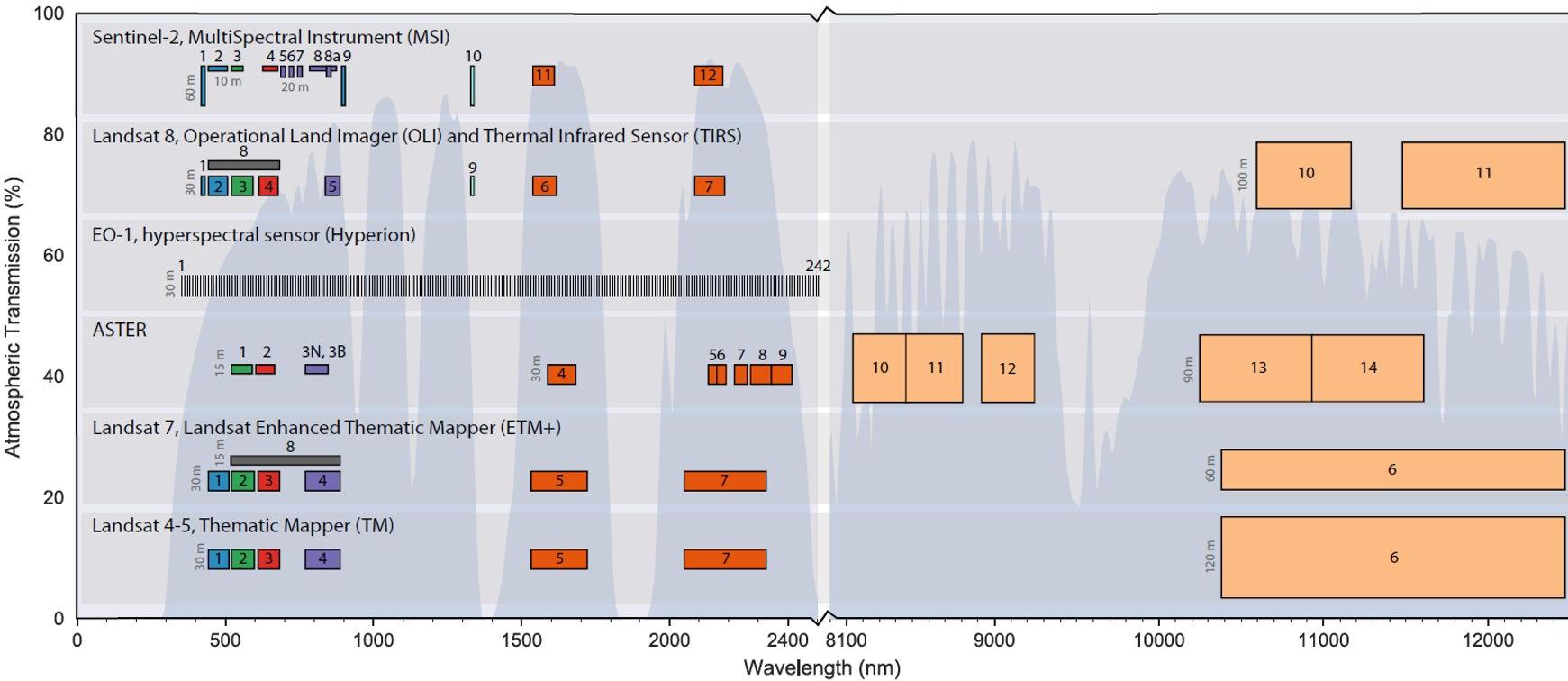


optical / passive

radar / active

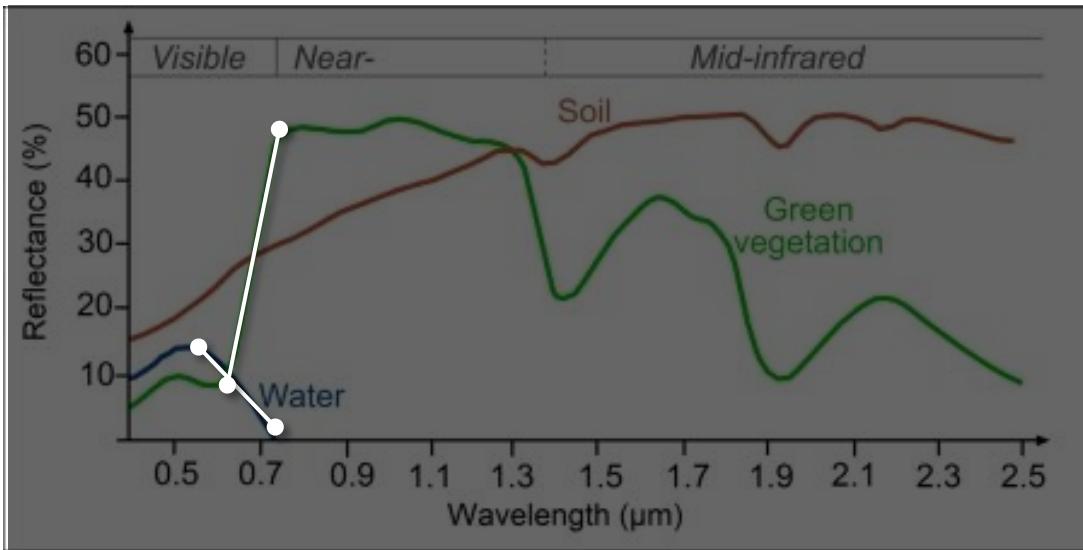


Spectral Bands



Spectral Signatures, Spectral Water Indices

Proprietary + Confidential

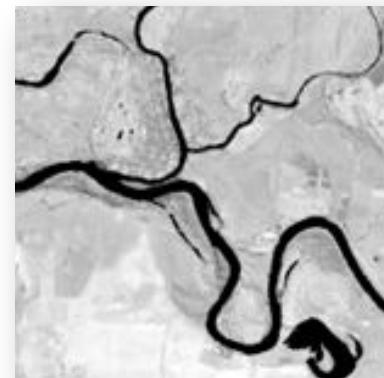


McFeeters, 1996

$$NDWI = \frac{\rho_{green} - \rho_{nir}}{\rho_{green} + \rho_{nir}} \quad \underline{\text{Code}}$$

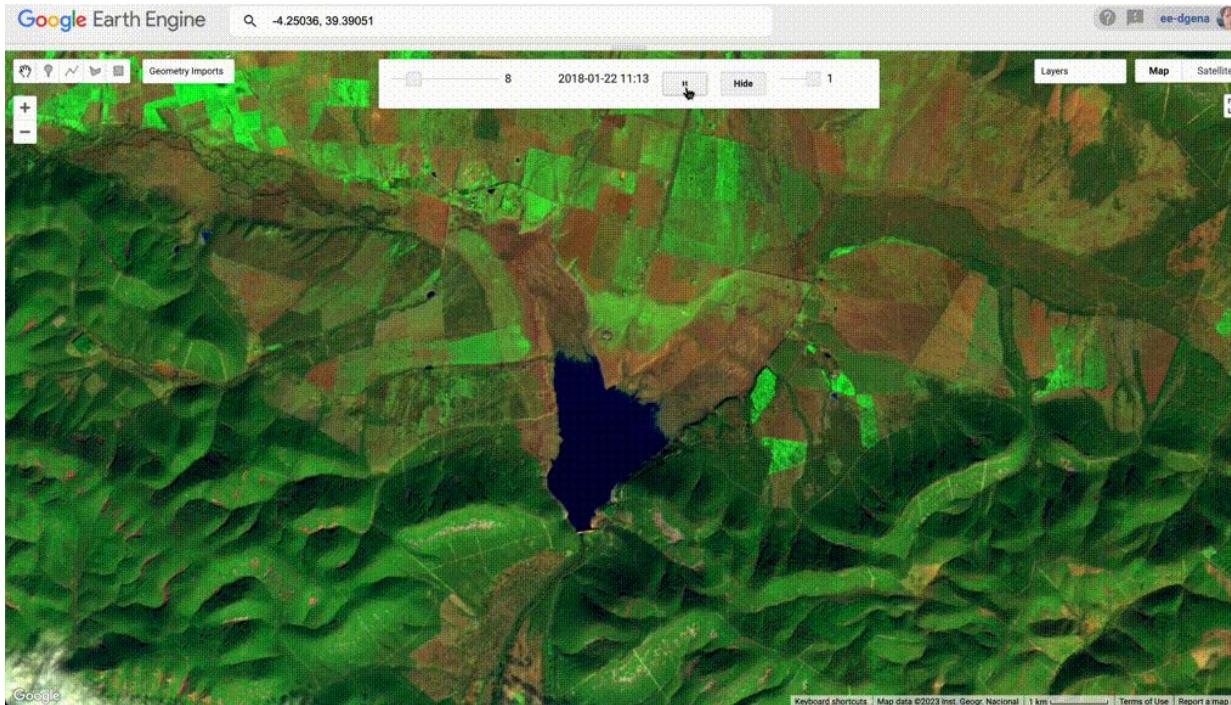
Rouse, 1974

$$NDVI = \frac{\rho_{nir} - \rho_{red}}{\rho_{nir} + \rho_{red}} \quad \underline{\text{Code}}$$

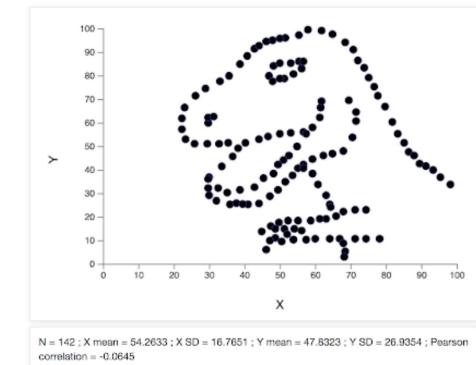


Google Cloud

Let's have a look at our images (Sentinel-2)



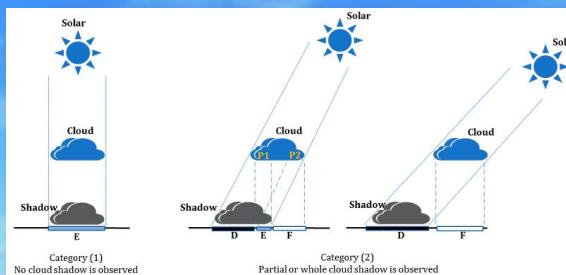
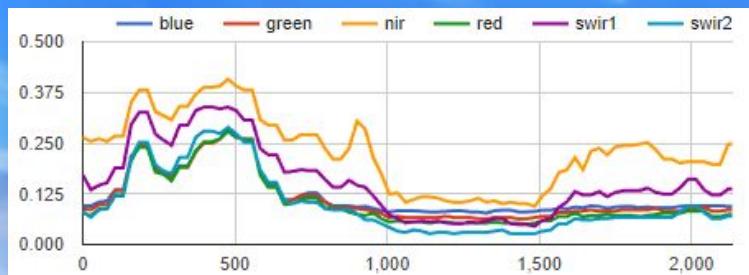
Always visualize your data,
never trust statistics-only!



Code

... a lot of noise from clouds and shadows

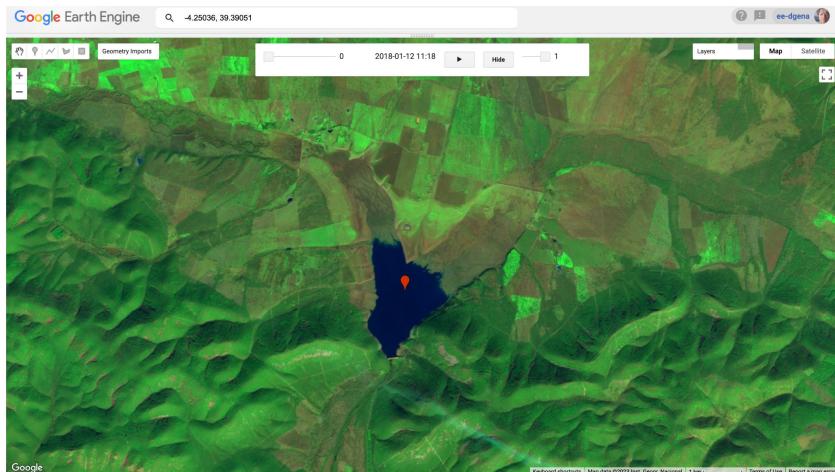
Cloud and cloud shadow masking, many algorithms exist today for cloud masking



<https://code.earthengine.google.com/f0d60d5c0070a54aa074f69fb77536f9>

Simple masking: [Code](#) (Landsat), [Code](#) (Sentinel-2)

Let's first inspect all values of a single (NIR) band, as well as compute a histogram

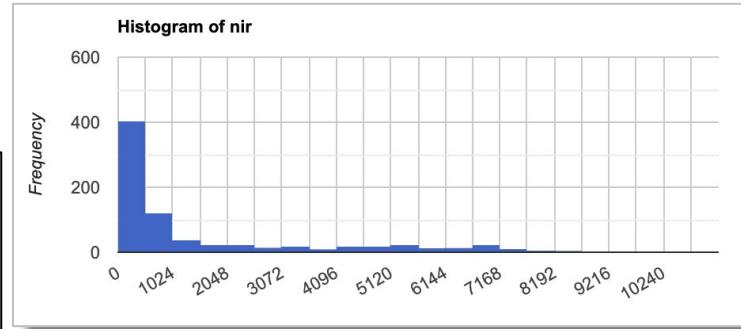
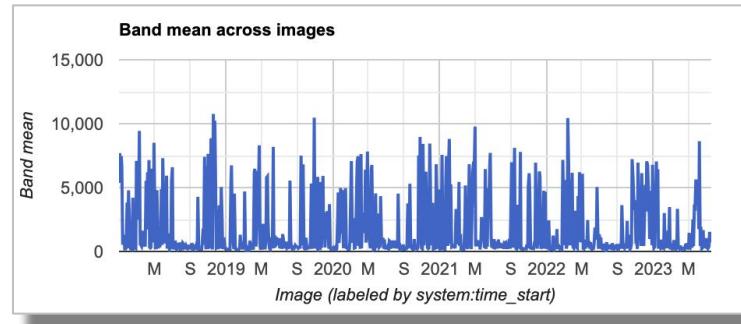


```
images = images.map(function(i) {
  return i.set({
    nir: i.select(['B8']).reduceRegion(ee.Reducer.mean(), pt,
scale).values().get(0),
  })
})

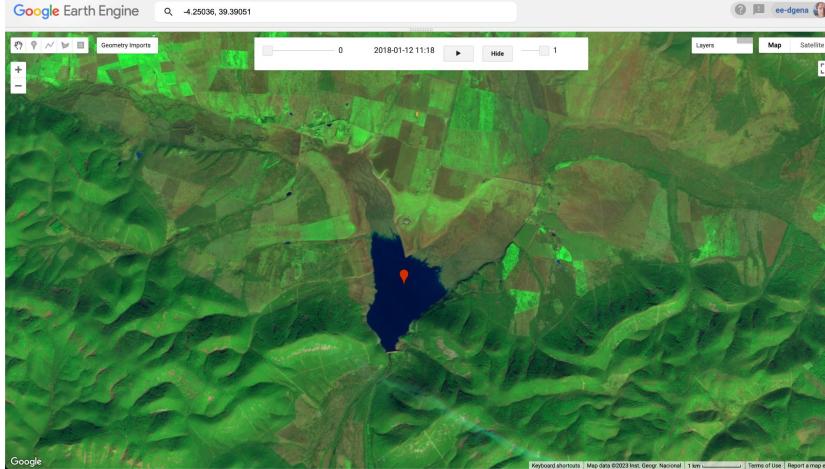
print(ui.Chart.feature.byFeature(images, 'system:time_start', ['nir']))

print(ui.Chart.feature.histogram(images, 'nir', 30))
```

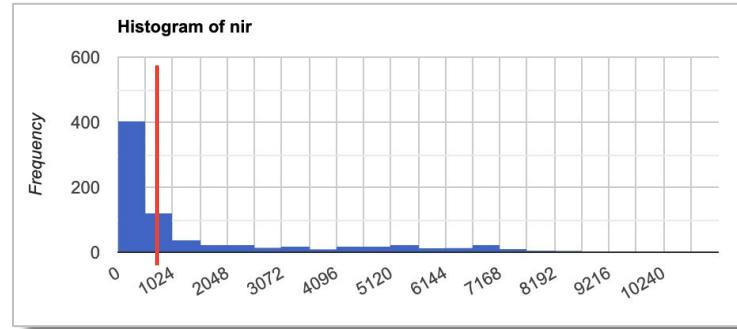
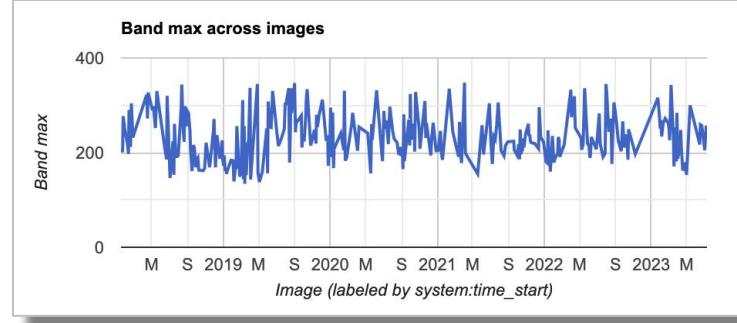
[Code](#)



Let's skip the top brightest images



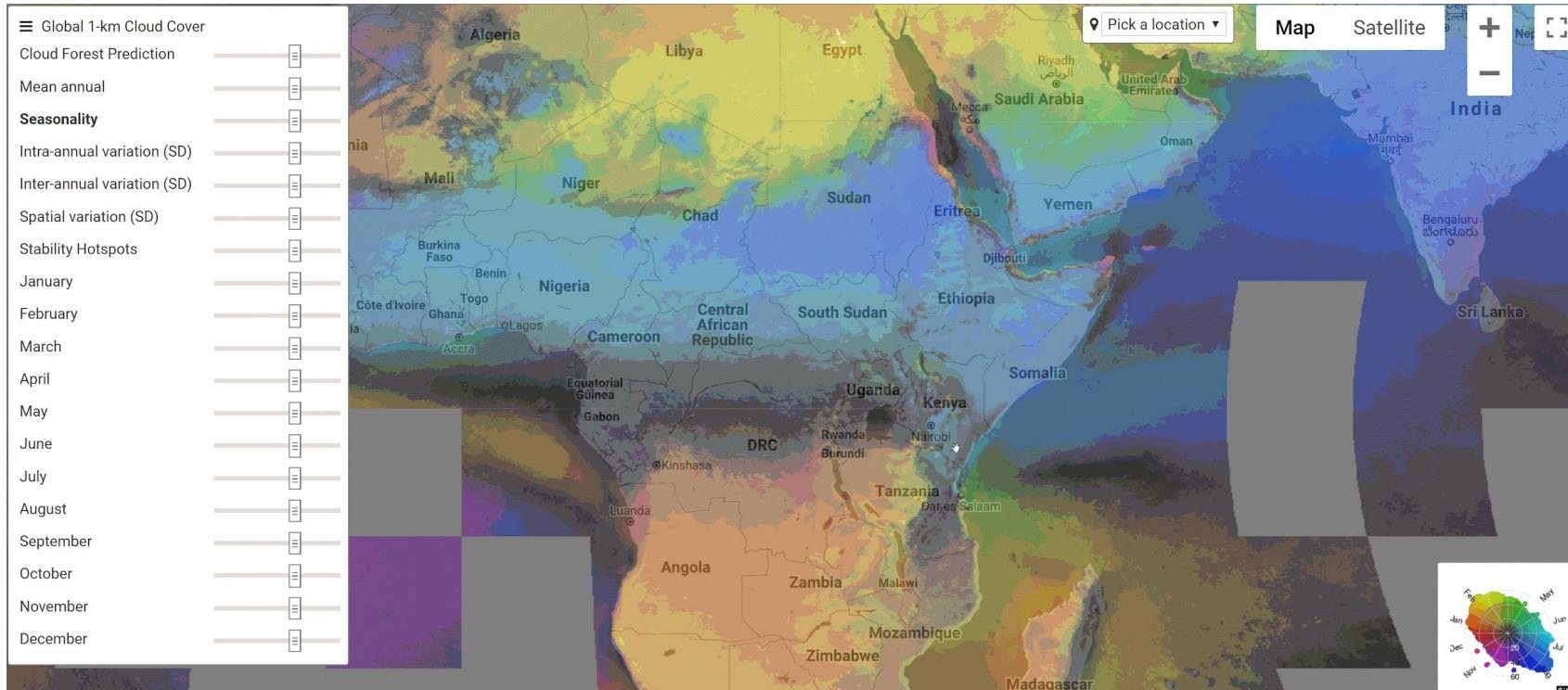
```
images = images.filter(ee.Filter.lt('nir', 350))
```



Global 1-km Cloud Cover

Proprietary + Confidential

Wilson AM, Jetz W (2016) Remotely Sensed High-Resolution Global Cloud Dynamics for Predicting Ecosystem and Biodiversity Distributions. PLoS Biol 14(3)



<https://www.earthenv.org/cloud>, or <https://gee-community-catalog.org/projects/gcc>

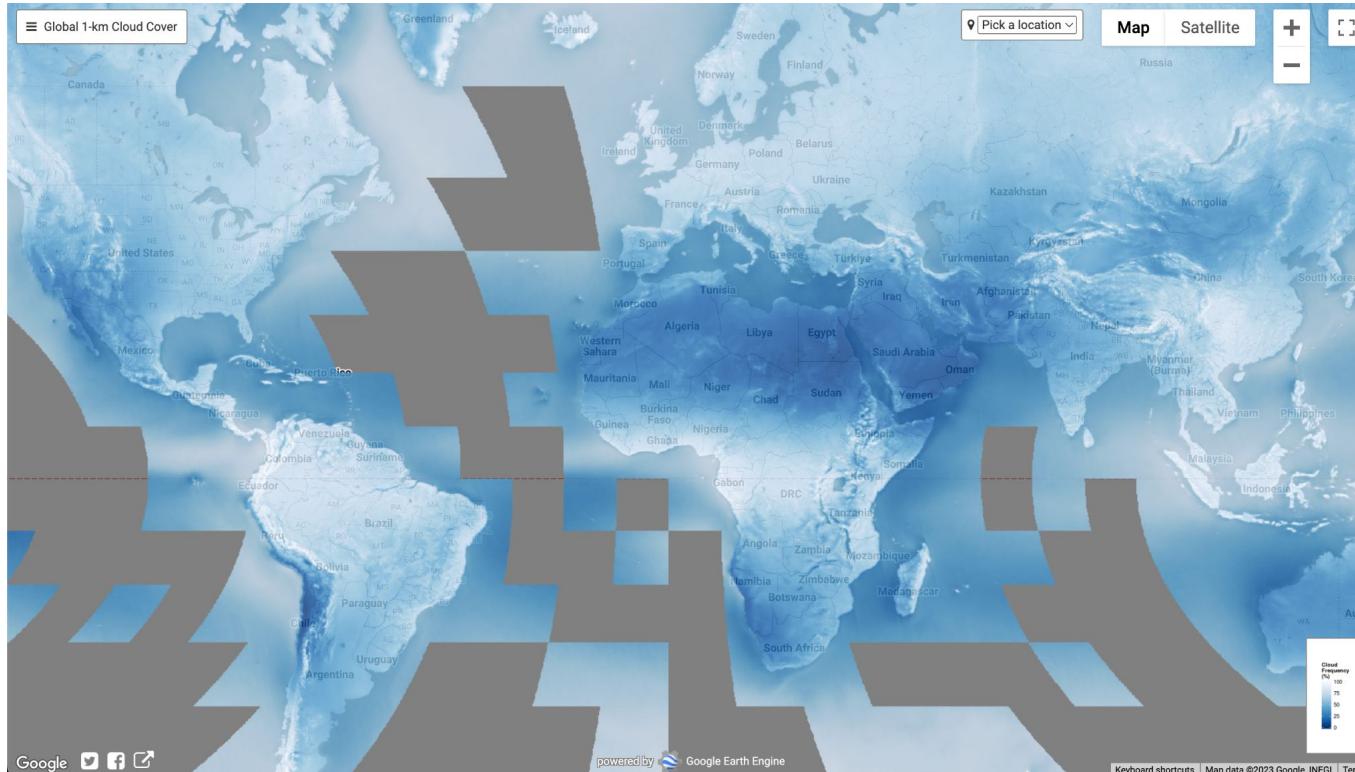
Instead of a fixed band brightness value, we can parametrize it using cloud frequency statistics

Google Cloud

Global 1-km Cloud Cover

Proprietary + Confidential

Wilson AM, Jetz W (2016) Remotely Sensed High-Resolution Global Cloud Dynamics for Predicting Ecosystem and Biodiversity Distributions. PLoS Biol 14(3)

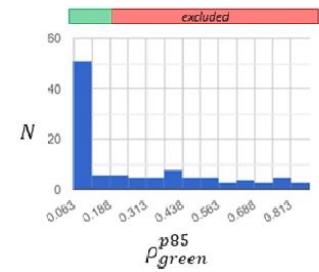
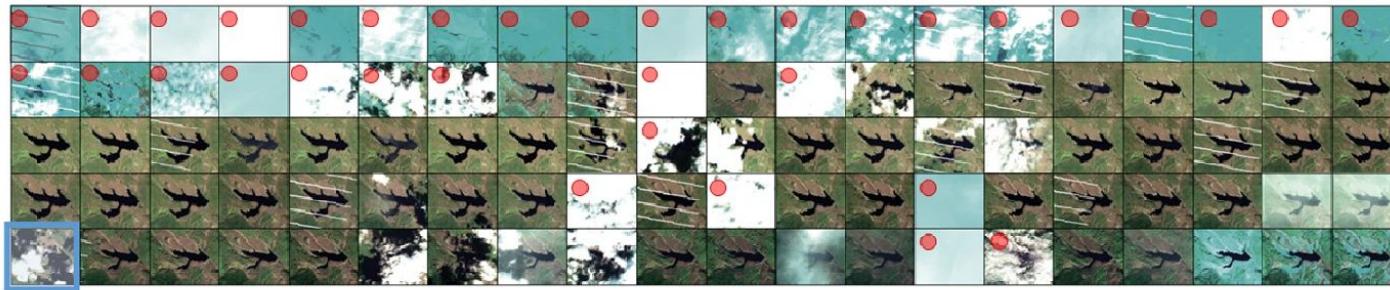


<https://www.earthenv.org/cloud>, or <https://gee-community-catalog.org/projects/gcc>

Instead of a fixed band brightness value, we can parametrize it using cloud frequency statistics

Google Cloud

All Landsat 7, 8 and Sentinel-2 images for 2017 which overlap with the reservoir geometry

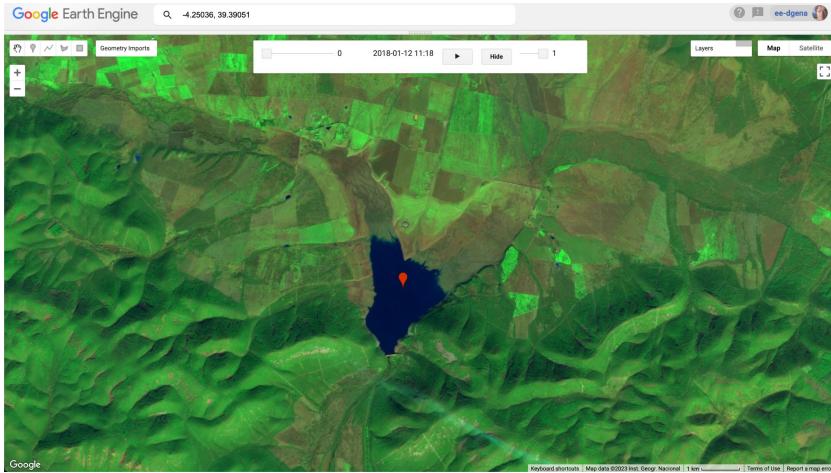


1. Compute statistic over the area of interest indicating image cloudiness
2. Skip top N of brightest images with N computed from the cloud frequency for this area

$$N = 100 * 0.35 = 35 \text{ in the above example}$$

Use mean annual cloud frequency instead of hardcoding the threshold

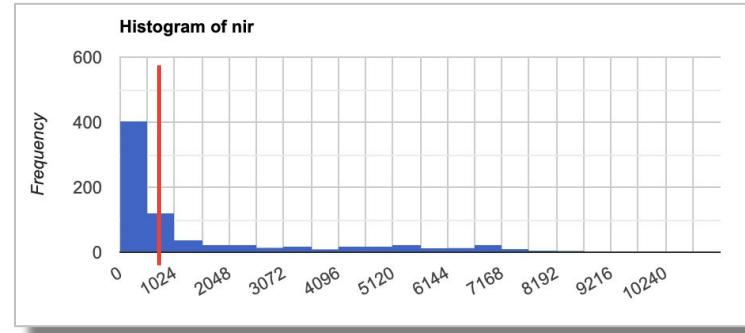
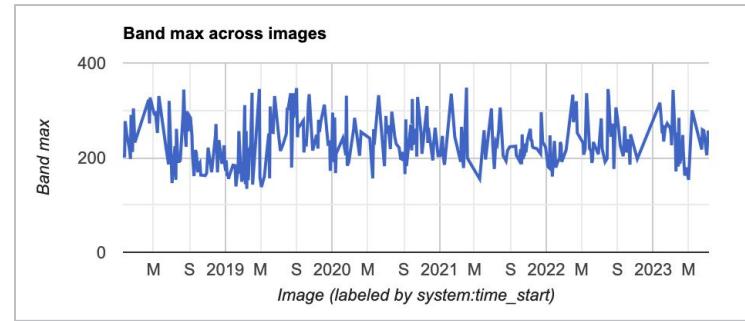
Proprietary + Confidential



```
// compute threshold from mean cloud frequency
var cloudFrequency =
ee.Image("projects/sat-io/open-datasets/gcc/MODCF_meanannual")
.divide(100)
.reduceRegion(ee.Reducer.first(), pt, scale).values().get(0)
print('Mean cloud frequency: ', cloudFrequency)

var percentile = ee.Number(cloudFrequency).int()
var threshold =
ee.List(images.aggregate_array('nir')).reduce(ee.Reducer.percentile([percentile]))
print('NIR threshold: ', threshold)
images = images.filter(ee.Filter.lt('nir', threshold))
```

Code



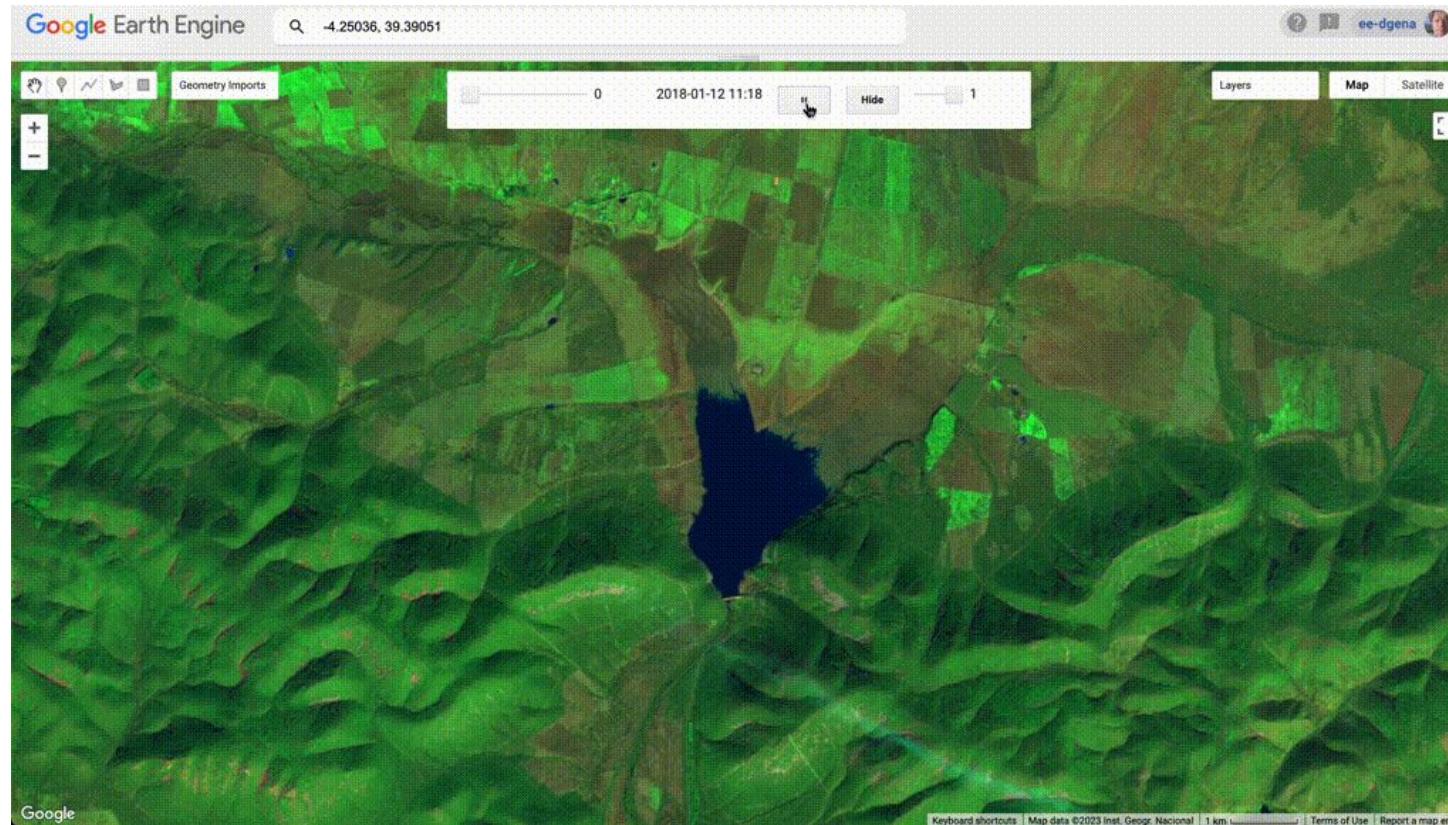
Mean cloud frequency:
47.74

NIR threshold:
410.3478260869565

Google Cloud

Let's see how our images look like after filtering

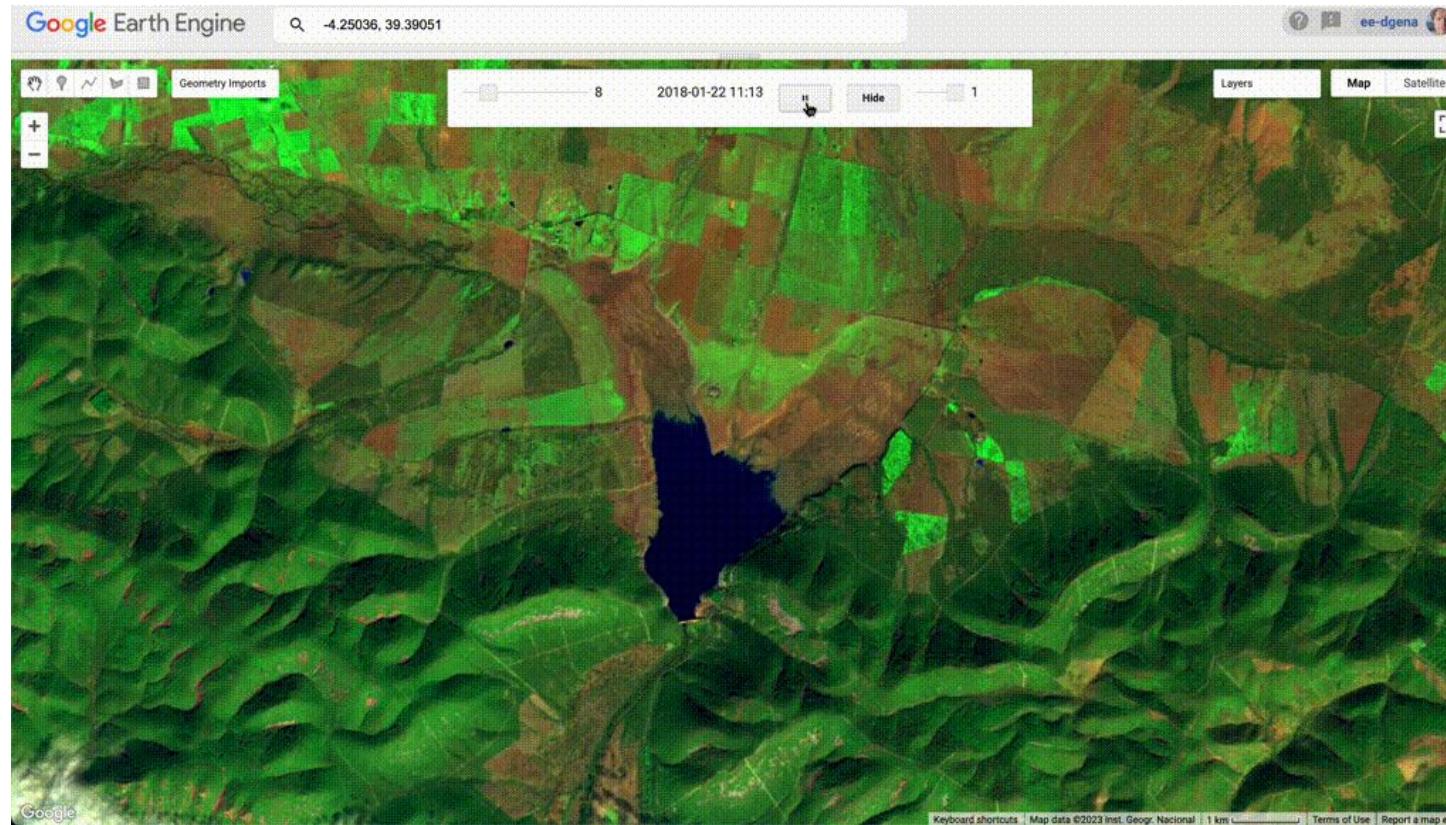
Proprietary + Confidential



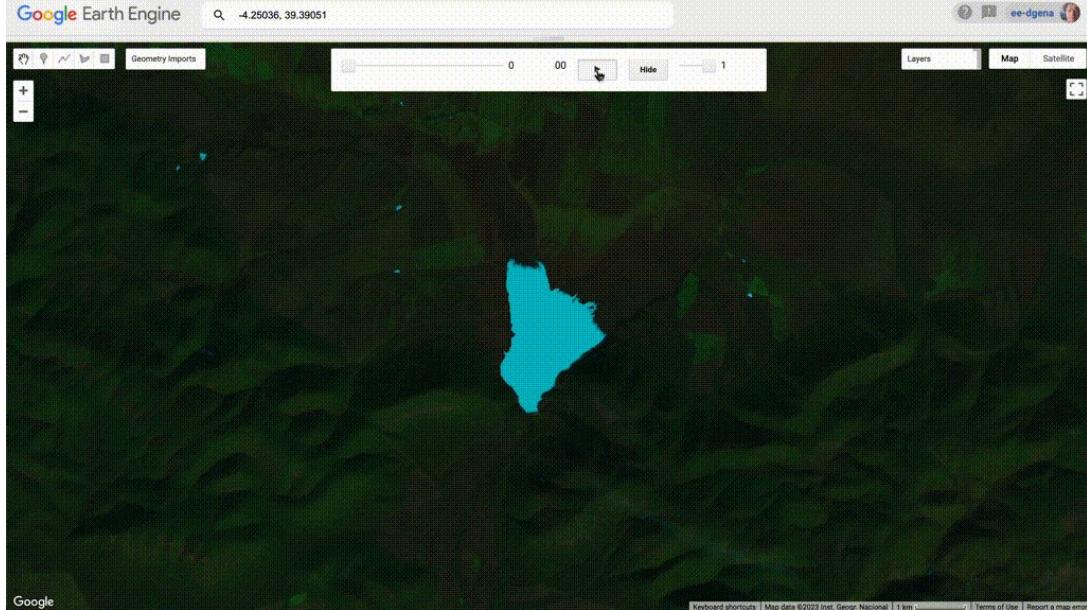
Code

Fewer cloudy images!

Google Cloud



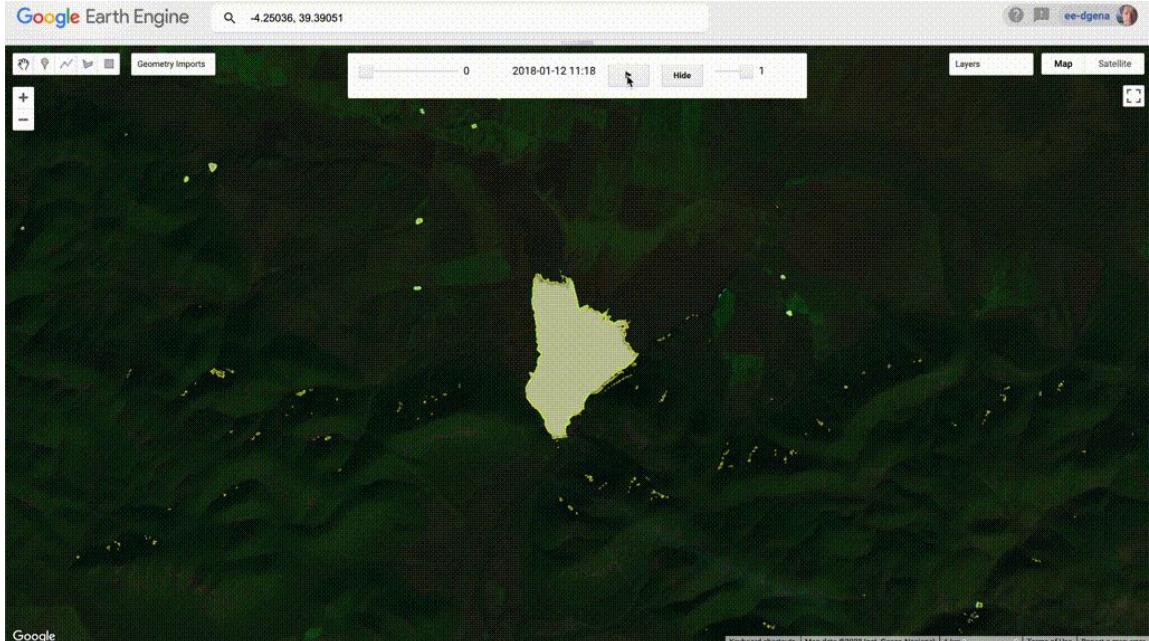
Let's compute and visualize NDWI



Code

```
var imagesRGB = images.map(function(i) {  
  var ndwi = i.normalizedDifference(['B3', 'B8']);  
  
  var ndwiRGB = ndwi.visualize({  
    min: 0,  
    max: 0.3,  
    palette: ['black', 'cyan'],  
    opacity: 0.7  
  })  
  
  return i.visualize(vis)  
    .blend(ndwiRGB)  
    .set({ label: i.get('label') })  
})
```

Let's add naive thresholding (NDWI > 0)



Code

```
var imagesRGB = images.map(function(i) {  
  var ndwi = i  
    .normalizedDifference(['B3', 'B8'])  
  
  var ndwiRGB = ndwi.visualize({  
    min: 0,  
    max: 0.3,  
    palette: ['black', 'white'],  
    opacity: 0.7  
  })  
  
  var ndwiEdgeRGB = ee.Algorithms.CannyEdgeDetector(ndwi, 0.9)  
    .selfMask()  
    .visualize({  
      palette: ['cyan']  
    })  
  
  var water = ndwi.gt(0).selfMask()  
  
  var waterRGB = water.visualize({  
    palette: ['yellow'],  
    opacity: 0.2  
  })  
  
  var waterEdgeRGB = ee.Algorithms.CannyEdgeDetector(water, 0.9)  
    .selfMask()  
    .visualize({  
      palette: ['yellow']  
    })  
  
  return i.visualize(vis)  
    .blend(ndwiRGB)  
    .blend(ndwiEdgeRGB)  
    .blend(waterRGB)  
    .blend(waterEdgeRGB)  
})
```

Google Cloud

Proprietary + Confidential

Experiment with different spectral indices (NDWI, MNDWI, ...) when one does not work

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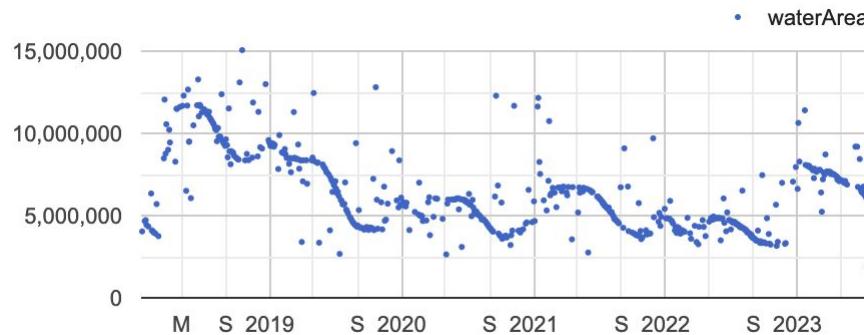
```
var imagesRGB = images.map(function(i) {  
  var waterIndices = ee.Image([  
    i.normalizedDifference(['B4', 'B8']).unitScale(0, 0.3),  
    i.normalizedDifference(['B3', 'B12']).unitScale(0.3, 1),  
    i.normalizedDifference(['B3', 'B8']).unitScale(0, 0.3)  
  ])  
  .visualize({ min: 0, max: 1, opacity: 1 })  
  
  return i.visualize(vis)  
    .blend(waterIndices)  
})
```

E.g., [Ma, Shengfang, et al.](#) "Application of the water-related spectral reflectance indices: A review." *Ecological indicators* 98 (2019): 68-79.

Code

Google Cloud

Let's compute and plot surface water area time series using a simple thresholding method



```
images = images.map(function(i) {  
  var ndwi = i.normalizedDifference(['B3', 'B8'])  
  
  var waterArea = ee.Image.pixelArea().updateMask(ndwi.gt(0))  
    .reduceRegion(ee.Reducer.sum(), geometry, scale).values().get(0)  
  
  return i.set({ waterArea: waterArea })  
})
```

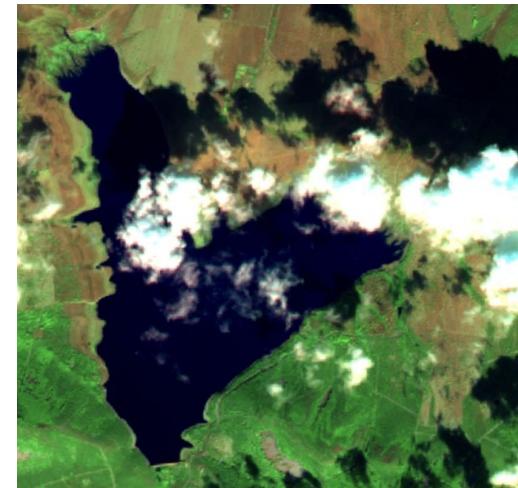
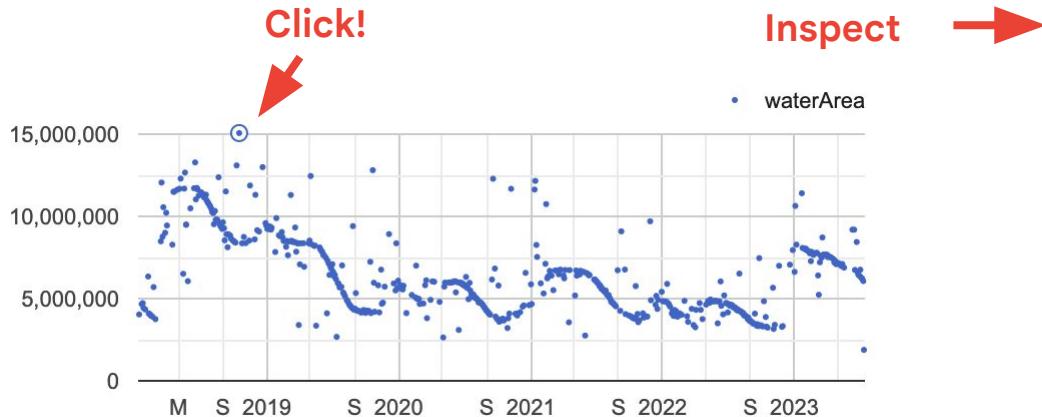
... we have some noise, but we can already clearly see reservoir dynamics

Code

let's add custom chart/image inspector for more visualization:

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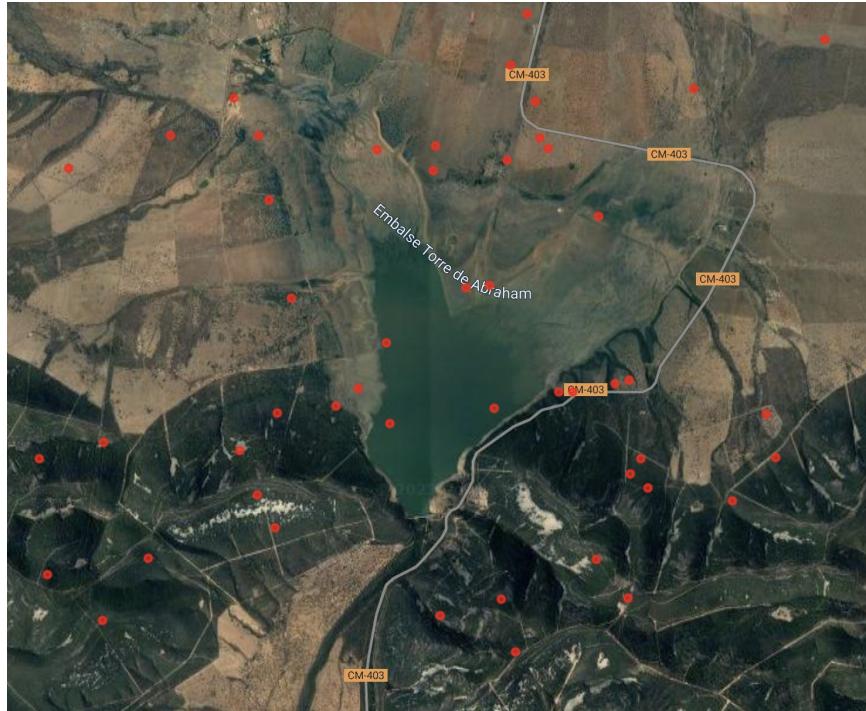
```
var inspectLayer = ui.Map.Layer(ee.Image(), {}, 'inspector')
Map.layers().add(inspectLayer)
function addChartInspector(v) {
  var image = images.filterDate(v).first()
  image = image.visualize(yis)
  inspectLayer.setEeObject(image)
}
chart01.onClick(addChartInspector)
```



Code

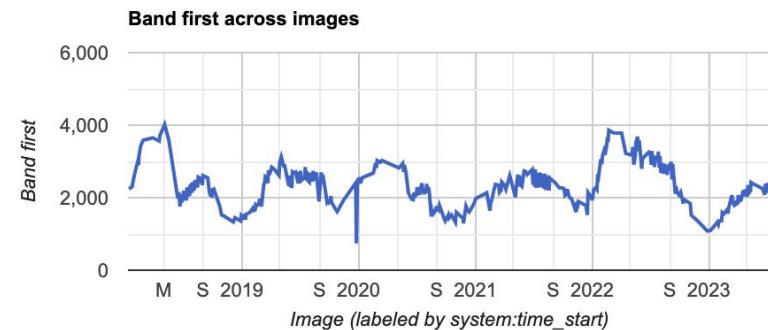
Google Cloud

Let's sample random points in our AOI instead of a single one to skip noisy images



```
pt = ee.Image().sample({  
  region: geometry,  
  scale: 10,  
  numPixels: 50,  
  seed: 42,  
  dropNulls: false,  
  geometries: true  
}).geometry()
```

... cleaner max nir time series:

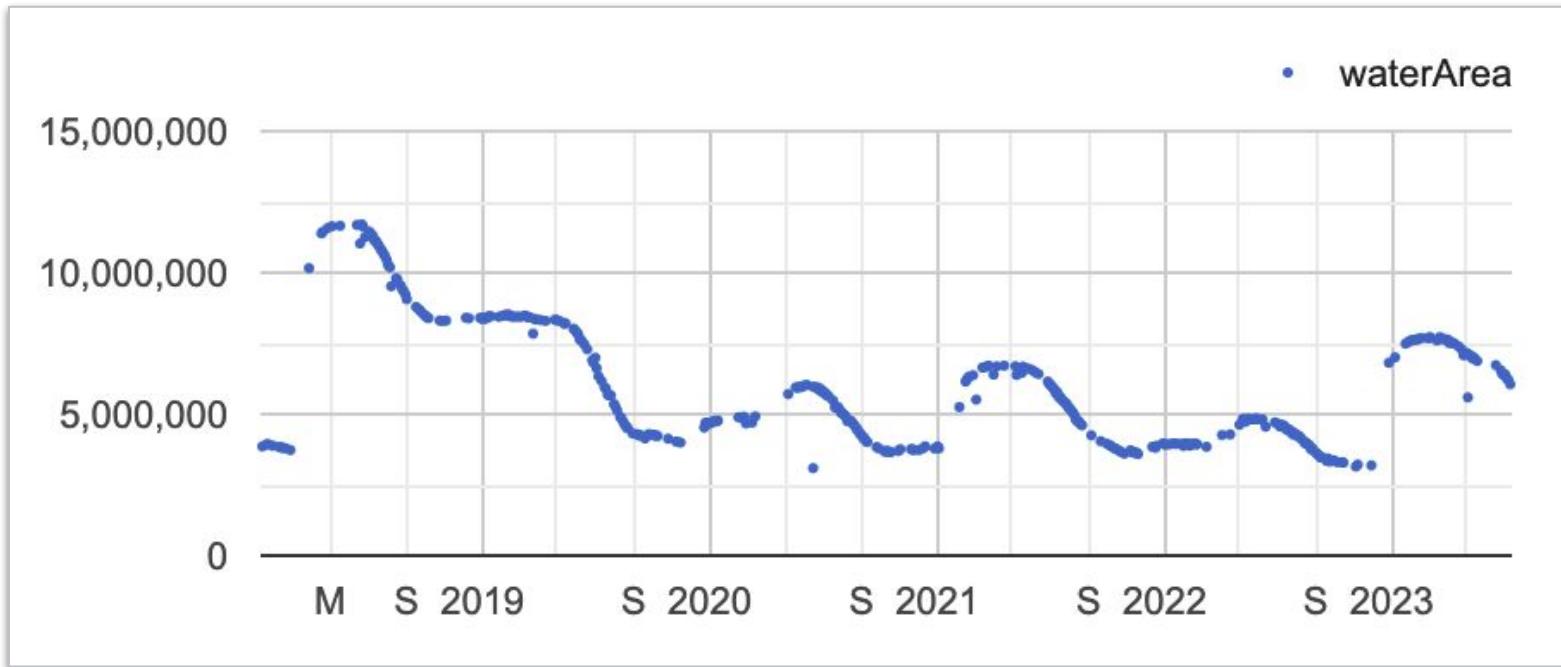


Code

Google Cloud

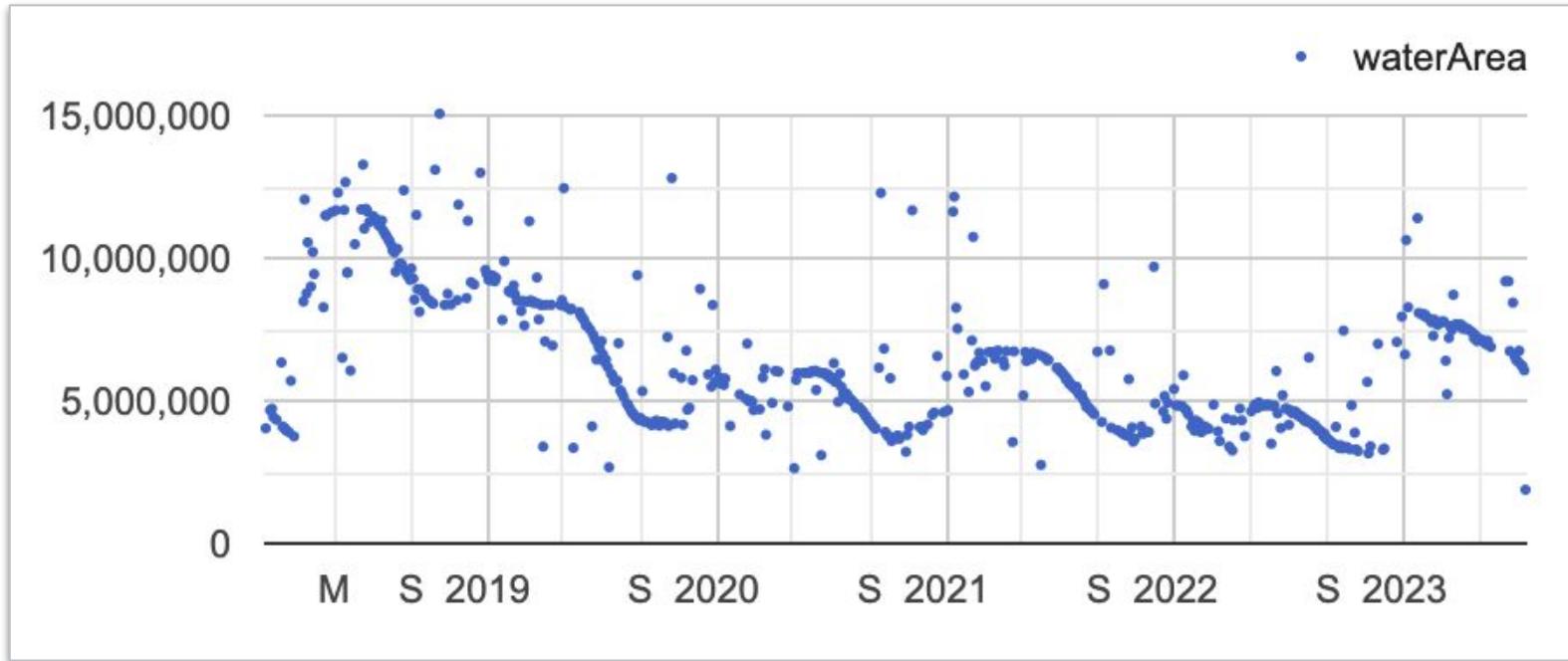
Whoa! That's looks much better, the noise is almost gone!

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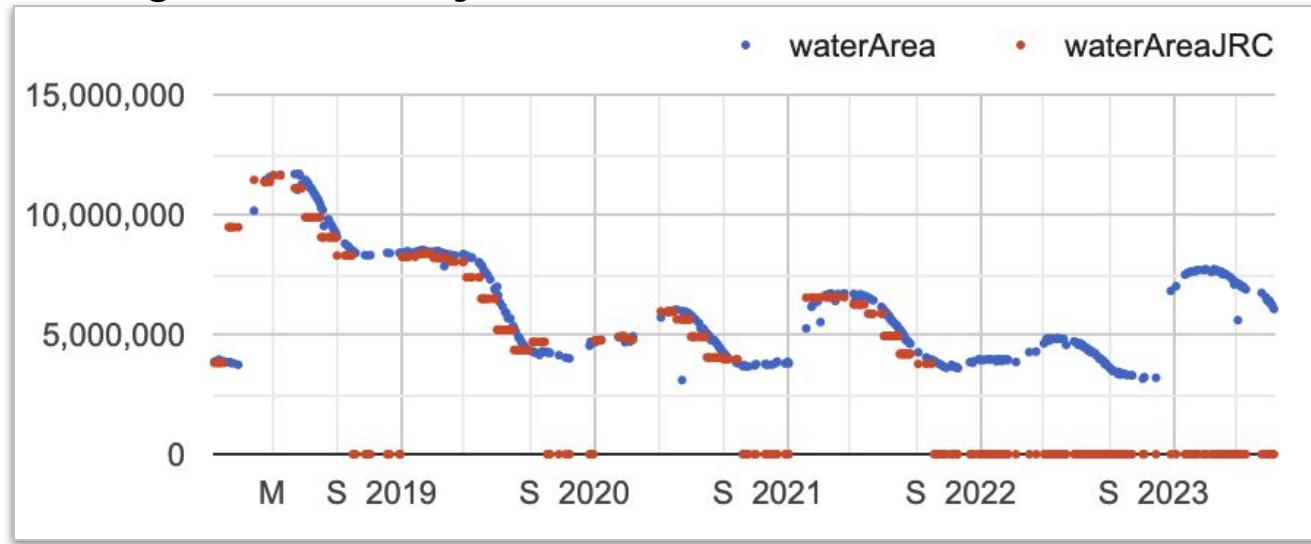


Old values

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Adding JRC monthly water occurrence



```

var images03 = images.map(function(i) {
...
  var empty = ee.ImageCollection([ee.Image.constant(0).float().rename('water')])
  var waterMonthly = empty.merge(ee.ImageCollection("JRC/GSW1_4/MonthlyHistory")
    .filterDate(i.date(), i.date().advance(1, 'month')).mosaic().eq(2)

  var waterAreaJRC = ee.Image.pixelArea().mask(waterMonthly)
    .reduceRegion(ee.Reducer.sum(), geometry, scale).get('area')

  return i.set({ waterArea: waterArea, waterAreaJRC: waterAreaJRC })
})
...
  
```

[Code](#)

Discussion and Questions

⌚ 5 min

👥 Group



Thank you!



Basins, rivers, and water

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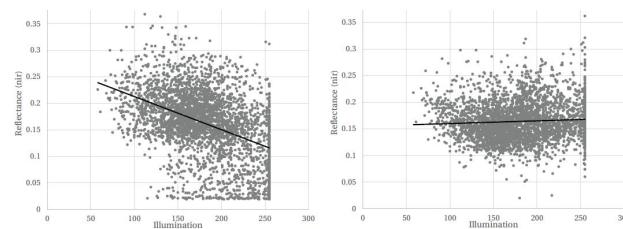
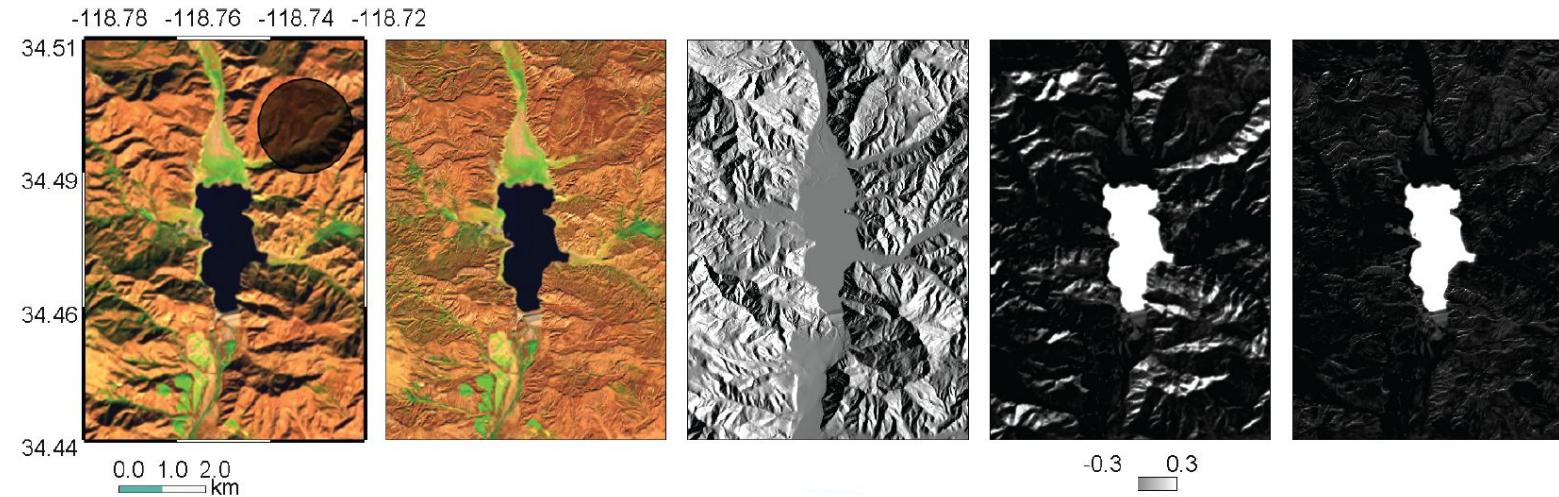


[Code](#)

Google Cloud

Topographic correction

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$$L_n(\lambda) = L(\lambda) \frac{\cos(\theta) + C(\lambda)}{IC + C(\lambda)}$$

Tan et. al., 2013, Source:

<https://code.earthengine.google.com/9e96c0046aa0881552406ba6e4cb63b1>

$$L(\lambda) = a(\lambda) \cdot IC + b(\lambda)$$

$$C = b/a$$

Google Earth Engine for Water Resources Management (Full Course Material)

Application-focused Introduction to Google Earth Engine.

Ujaval Gandhi