



SAR for Flood Mapping using Google Earth Engine

Erika Podest, Ph.D., Jet Propulsion Laboratory, California Institute of Technology Sean McCartney, NASA Goddard Space Flight Center

Dec. 3, 2019

Learning Objectives



By the end of this presentation, you will be able to understand:

- the information content in SAR images relevant to flooding
- how to generate a flood map using Google Earth Engine
- how to integrate socioeconomic data to your flood map to identify areas at risk



Flooding Definition from a Radar Perspective:

The presence of a water surface:

- beneath a vegetation canopy (tall or short standing vegetation)
- without any standing vegetation (referred to as open water)



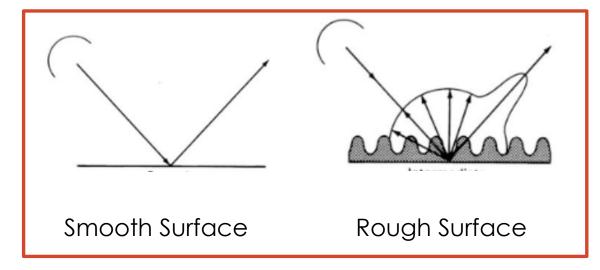


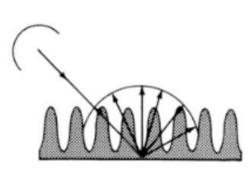




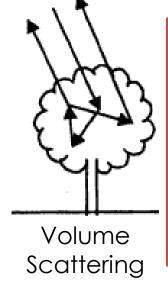
SAR Signal Scattering Over Inundated Regions











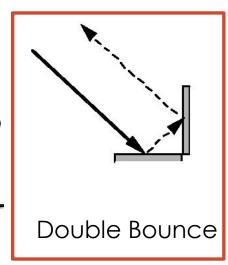
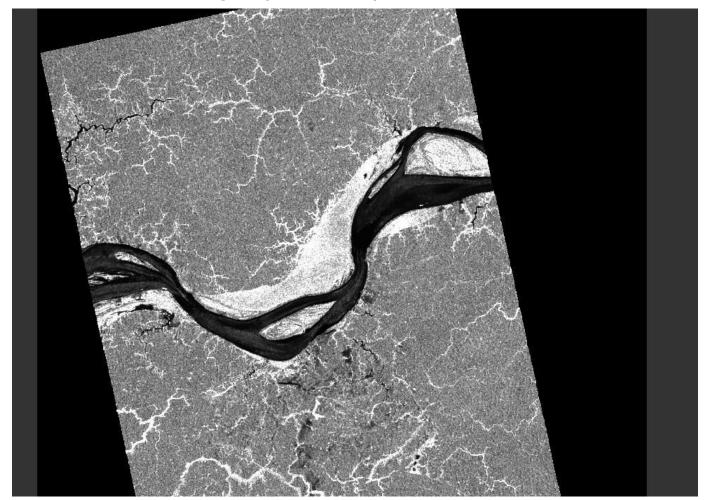


Image Credits: top: Ulaby et al. (1981a)



SAR Signal Scattering Over Inundated Vegetation and Open Water

PALSAR Image (L-band) near Manaus, Brazil



Wavelength and SAR Signal Response Over Flooded Vegetation

- Penetration is the primary factor in wavelength selection
- Generally, the longer the wavelength, the greater the penetration into the target

Vegetation			
Dry Alluvium	* * * *	* * * *	
	X-band 3 cm	C-band 5 cm	L-band 23 cm

Band Designation*	Wavelength (λ), cm	Frequency (v), GH _z (10 ⁹ cycles·sec ⁻¹)
Ka (0.86 cm)	0.8 – 1.1	40.0 – 26.5
K	1.1 – 1.7	26.5 – 18.0
Κυ	1.7 – 2.4	18.0 – 12.5
X (3.0 cm, 3.2 cm)	2.4 – 3.8	12.5 – 8.0
C (6.0)	3.8 – 7.5	8.0 – 4.0
S	7.5 – 15.0	4.0 – 2.0
L (23.5 cm, 25 cm)	15.0 – 30.0	2.0 – 1.0
P (68 cm)	30.0 – 100.0	1.0 – 0.3

^{*}wavelengths most frequently used in SAR are in parenthesis



Polarization

- The radar signal is polarized
- The polarizations are usually controlled between H and V:
 - HH: Horizontal Transmit, Horizontal Receive
 - HV: Horizontal Transmit, Vertical Receive
 - VH: Vertical Transmit, Horizontal Receive
 - VV: Vertical Transmit, Vertical Receive
- Quad-Pol Mode: when all four polarizations are measured
- Different polarizations can determine physical properties of the object observed

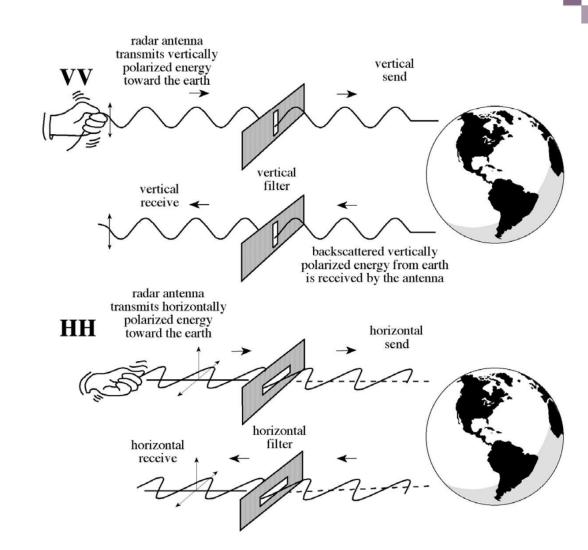
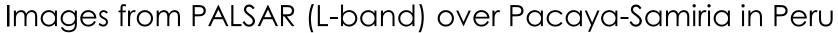
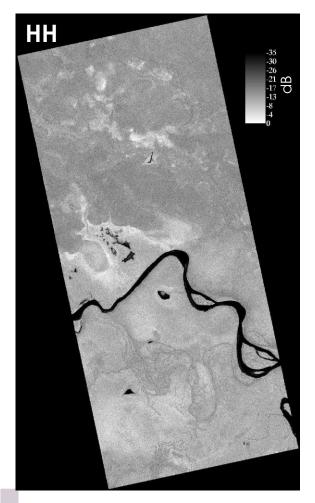


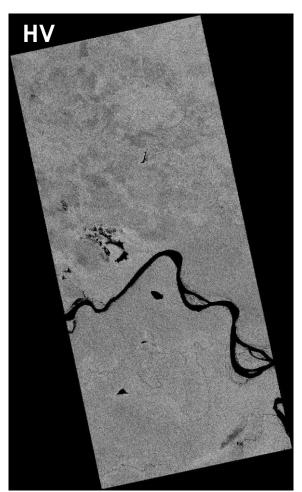
Image Credit: J.R. Jensen, 2000, Remote Sensing of the Environment

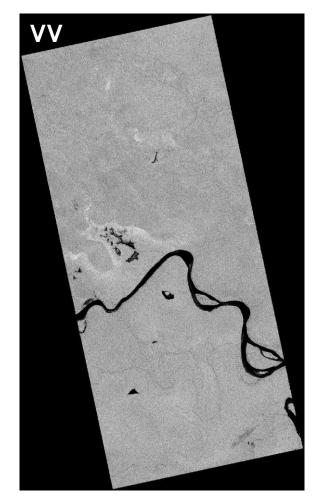


Multiple Polarizations for Detection of Inundated Vegetation





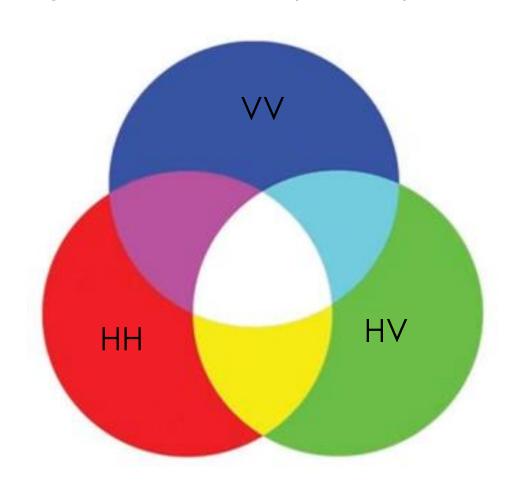


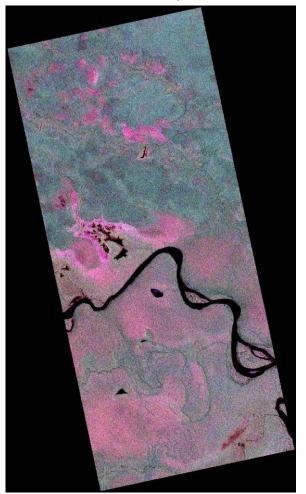




Multiple Polarizations for Detection of Inundated Vegetation

Images from PALSAR (L-band) over Pacaya-Samiria in Peru (HH-HV-VV)

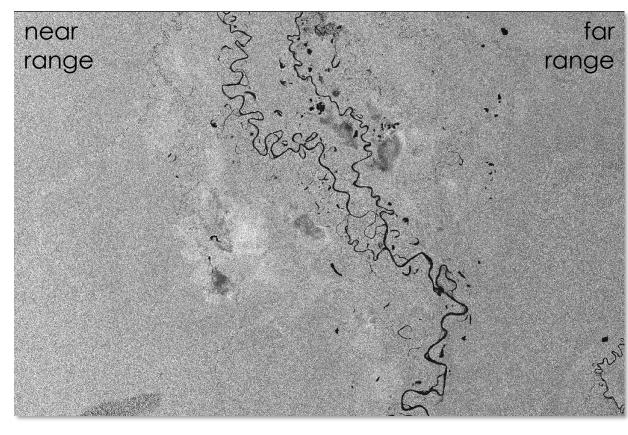


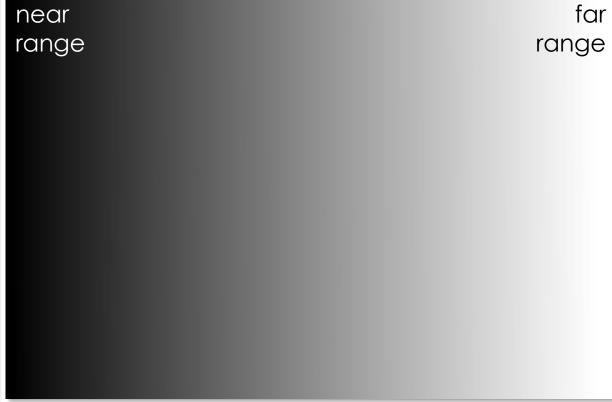




Effect of Incidence Angle Variation







Sentinel-1

30 Incidence Angle (degrees)

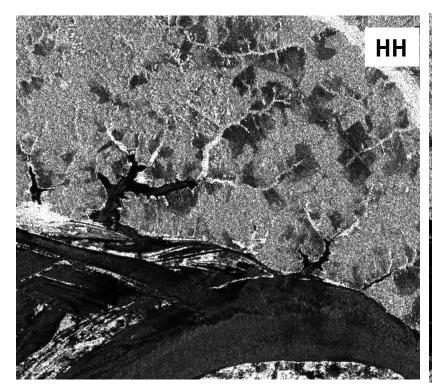
45

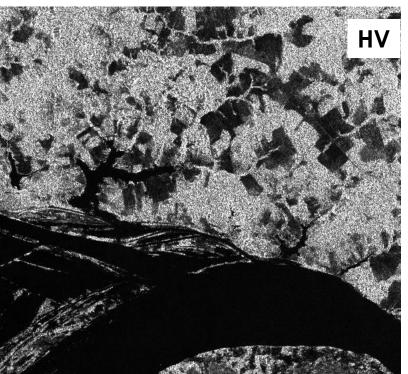


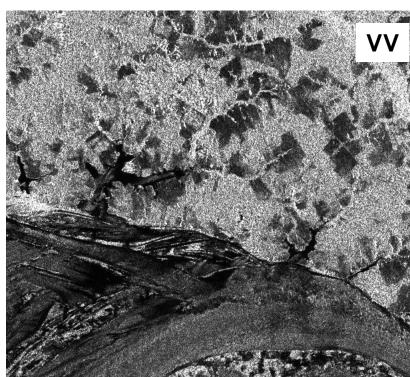


Source of Confusion: Open water and low vegetation

Images from PALSAR (L-band) near Manaus, Brazil



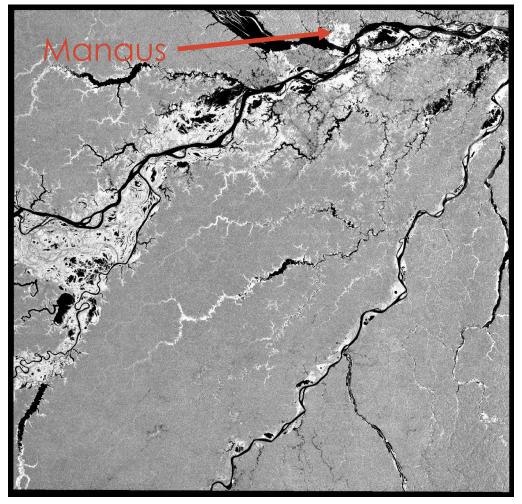






Source of Confusion: Urban Areas

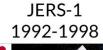
Images from PALSAR (L-band) near Manaus, Brazil



Radar Data Available

Legacy:







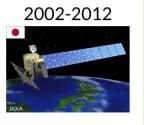
ERS 1/2 1991-2011



ENVISAT 2002-2012



ALOS-1



Radarsat-1 1995-2013



Current:

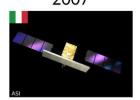


TanDEM-X

Radarsat-2 2007



COSMO-SkyMed 2007



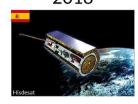
ALOS-2 2014



Sentinel-1 2014



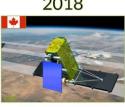
PAZ SAR 2018



SAOCOM 2018



RCM 2018



Future:

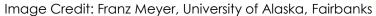


Biomass 2021



freely accessible







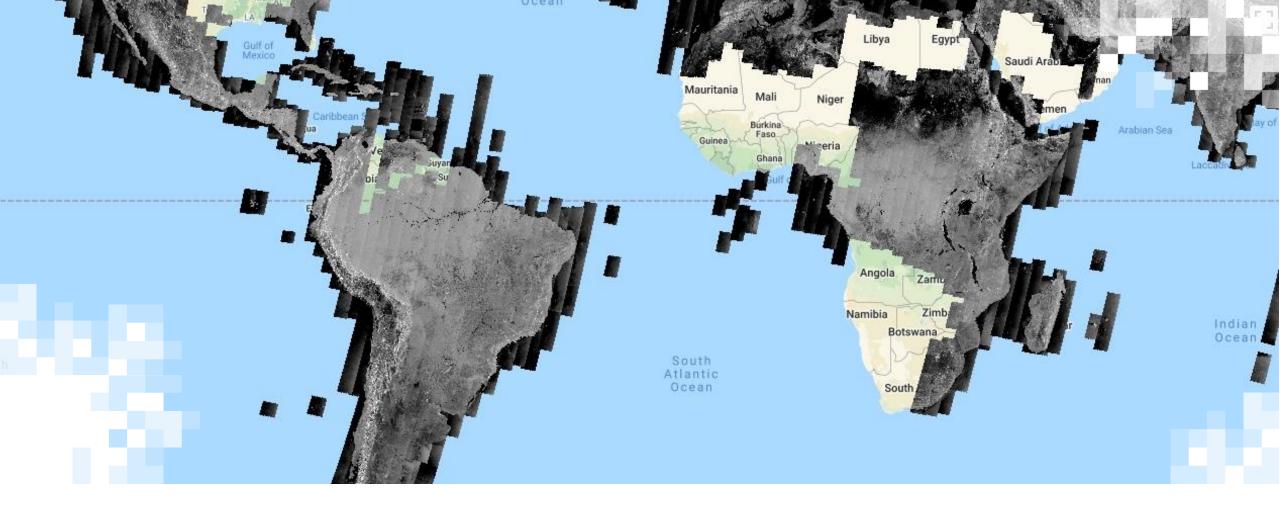
NASA-ISRO SAR Mission (NISAR)

- High spatial resolution with frequent revisit time
- Expected launch date: beginning of 2022
- Dual frequency L- and S-band SAR
 - L-band SAR from NASA and S-band SAR from ISRO
- 3 years science operations (5+ years consumables)
- All science data will be made available free and open

NISAR Characteristic:	Would Enable:	
L-band (24 cm wavelength)	Low temporal decorrelation and foliage penetration	
S-band (12 cm wavelength)	Sensitivity to light vegetation	
SweepSAR technique with Imaging Swath >240 km	Global data collection	
Polarimetry (Single/Dual/Quad)	Surface characterization and biomass estimation	
12-day exact repeat	Rapid Sampling	
3-10 meters mode-dependent SAR resolution	Small-scale observations	
3 years since operations (5 years consumables)	Time-series analysis	
Pointing control < 273 arcseconds	Deformation interferometry	
Orbit control < 500 meters	Deformation interferometry	
>30% observation duty cycle	Complete land/ice coverage	
Left/Right pointing capability	Polar coverage, North and South	
Noise Equivalent Sigma Zero ≤ -23 db	Surface characterization of smooth surfaces	

Slide Courtesy of Paul Rosen (JPL)



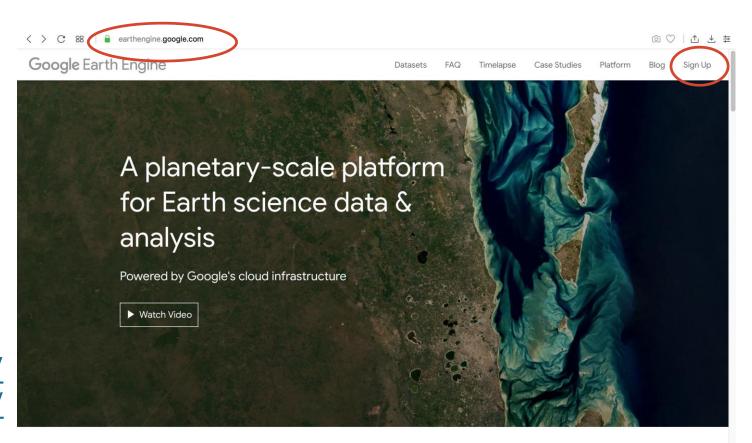


Hands-on Exercise Using Google Earth Engine

Google Earth Engine

https://earthengine.google.com

- Cloud based geospatial processing platform
- Available to scientists, researchers, and developers for analysis of the Earth's surface
- Contains a catalog of satellite imagery and geospatial datasets (including Sentinel-1):
- https://developers.google.com/ earth-engine/datasets/catalog/
- Uses Javascript code editor
- Sign up for a (free) account

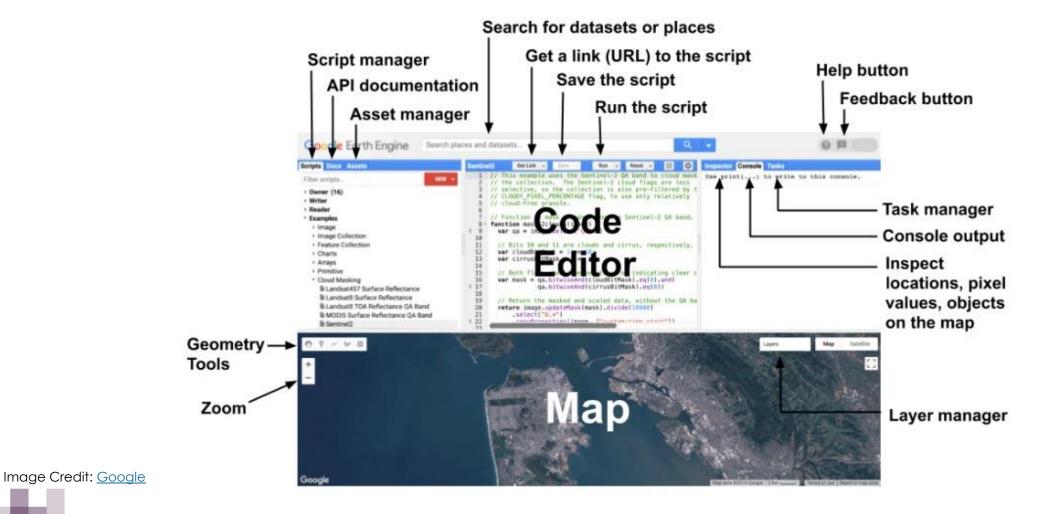


Meet Earth Engine



Google Earth Engine Code Editor

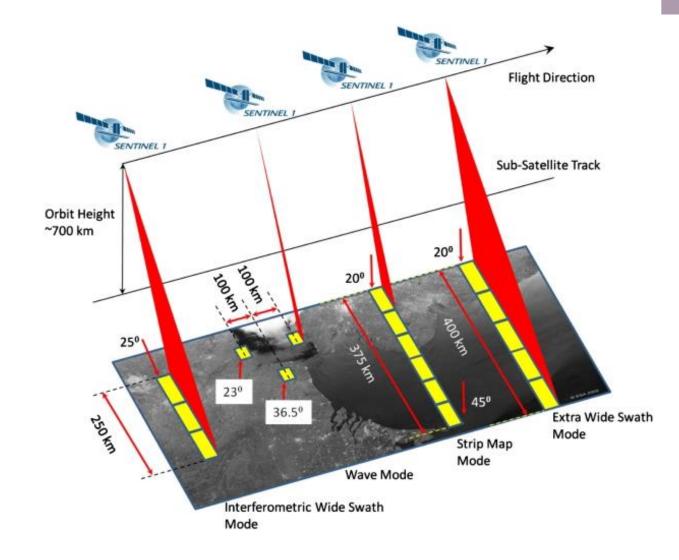
https://code.earthengine.google.com



Sentinel-1 Data

Two satellites: A & B

- C-band data
- Each satellite has global coverage every 12 days
- Global coverage of 6 days over the equator when using data from both satellites



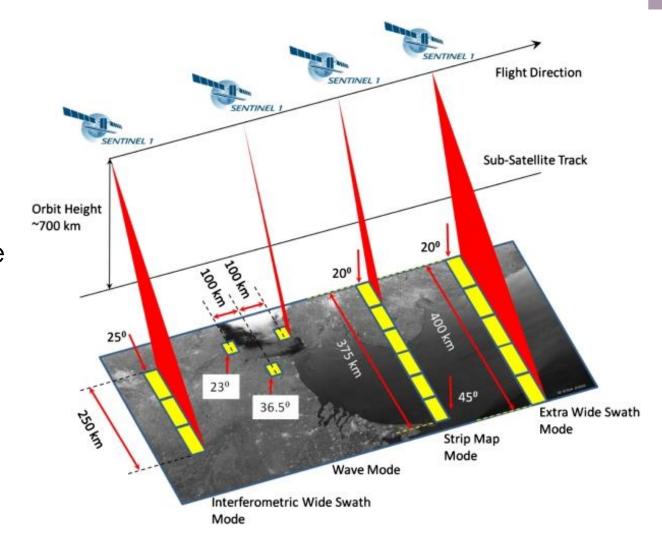




Sentinel-1 Data

Different Modes:

- Extra Wide Swath for monitoring oceans and coasts
- Strip Mode by special order only and intended for special needs
- Wave Mode routine collection for the ocean
- Interferometric Wide Swath routine collection for land (this is the one you want to use for flood mapping)







Sentinel-1 Catalog

https://developers.google.com/earth-engine/datasets/catalog/COPERNICUS_S1_GRD

The Sentinel-1 mission provides data from a dual-polarization C-band Synthetic Aperture Radar (SAR) instrument. This collection includes the S1 Ground Range Detected (GRD) scenes, processed using the Sentinel-1 Toolbox to generate a calibrated, ortho-corrected product. The collection is updated weekly.

This collection contains all of the GRD scenes. Each scene has one of 3 resolutions (10, 25 or 40 meters), 4 band combinations (corresponding to scene polarization) and 3 instrument modes. Use of the collection in a mosaic context will likely require filtering down to a homogenous set of bands and parameters. See this article for details of collection use and preprocessing. Each scene contains either 1 or 2 out of 4 possible polarization bands, depending on the instrument's polarization settings. The possible combinations are single band VV or HH, and dual band VV+VH and HH+HV:

- 1. VV: single co-polarization, vertical transmit/vertical receive
- 2. HH: single co-polarization, horizontal transmit/horizontal receive
- 3. VV + VH; dual-band cross-polarization, vertical transmit/horizontal receive
- 4. HH + HV: dual-band cross-polarization, horizontal transmit/vertical receive

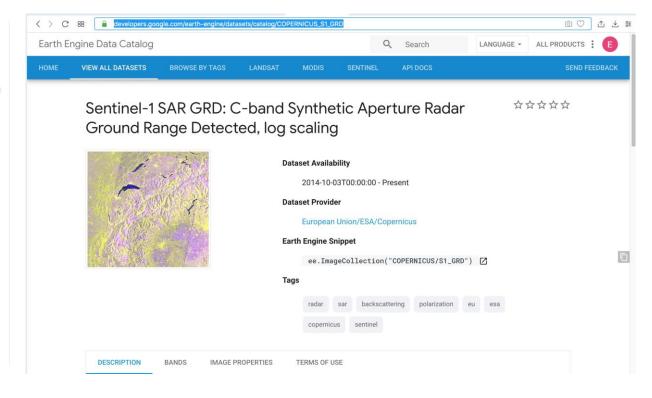
Each scene also includes an additional 'angle' band that contains the approximate viewing incidence angle in degrees at every point. This band is generated by interpolating the 'incidenceAngle' property of the 'geolocationGridPoint' gridded field provided with each asset.

Each scene was pre-processed with Sentinel-1 Toolbox using the following steps:

- 1. Thermal noise removal
- 2. Radiometric calibration
- 3. Terrain correction using SRTM 30 or ASTER DEM for areas greater than 60 degrees latitude, where SRTM is not available. The final terrain-corrected values are converted to decibels via log scaling (10*log10(x).

For more information about these pre-processing steps, please refer to the Sentinel-1 Pre-processing article.

This collection is computed on-the-fly. If you want to use the underlying collection with raw power values (which is updated faster), see COPERNICUS/S1_GRD_FLOAT.



Case Study

Hurricane Matthew - South Carolina

- October 7-8, 2016
- Hurricane Matthew was the most powerful storm of the 2016 Atlantic Hurricane Season
- It made its fourth and final landfall near McClellanville, South Carolina, as a Category 1 hurricane late in the morning of October 8th







Classification Window

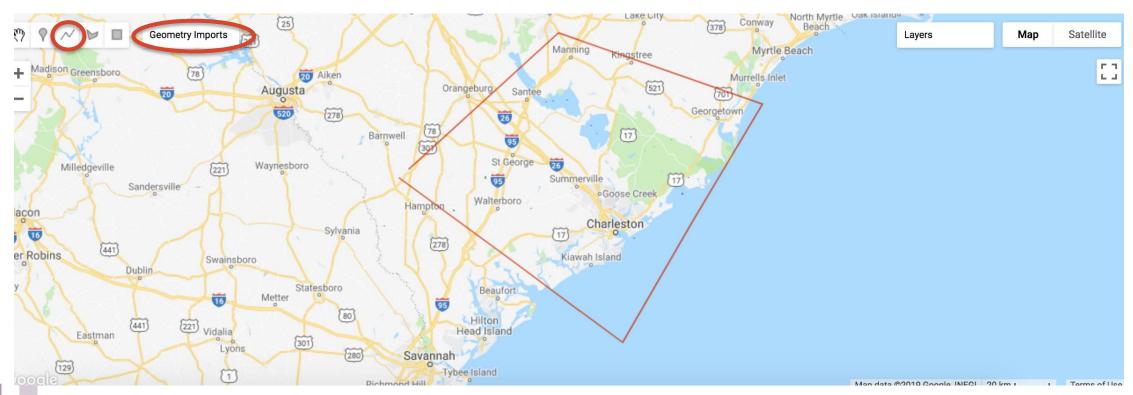
m

- Load the image or images to be classified
- 2. Gather the training data:
 - Collect training data to teach the classifier
 - Collect representative samples of backscatter for each landcover class of interest
- 3. Create the training dataset:
 - Overlay the training areas over the images of interest
 - Extract backscatter for those areas
- 4. Train the classifier and run the classification
- 5. Validate your results



Identify the Area of Interest

- 1. Select the **draw a line** icon on the upper left
- 2. Draw your area of interest
- 3. Under Geometry Imports in the upper left, select geometry and rename it to ROI



Load the Image or Images to Be Classified

```
m
```

```
// Load Sentinel-1 C-band SAR Ground Range collection (log scale, VV,
ascending)
var collection = ee.ImageCollection('COPERNICUS/S1_GRD')
    .filter(ee.Filter.eq('instrumentMode', 'IW'))
    .filter(ee.Filter.eq('orbitProperties_pass', 'ASCENDING'))
    .filterMetadata('resolution_meters', 'equals', 10)
    .filterBounds(roi)
    .select('VV', 'VH');
```



Filter by Date and Display

```
m
```

```
//Filter by date
var before = collection.filterDate('2016-10-04', '2016-10-05').mosaic();
var after = collection.filterDate('2016-10-16', '2016-10-17').mosaic();

// // Display map
Map.centerObject(roi, 7);
Map.addLayer(before, {min:-15,max:0}, 'Before flood', 0);
Map.addLayer(after, {min:-15,max:0}, 'After flood', 0);
```



Apply a Speckle Filter and Display



```
//Apply filter to reduce speckle
 var SMOOTHING_RADIUS = 50;
 var before_filtered = before.focal_mean(SMOOTHING_RADIUS, 'circle',
'meters');
var after_filtered = after.focal_mean(SMOOTHING_RADIUS, 'circle',
'meters');
//Display filtered images
 Map.addLayer(before_filtered, {min:-15,max:0}, 'Before Flood Filtered',0);
 Map.addLayer(after_filtered, {min:-15,max:0}, 'After Flood Filtered',0);
```



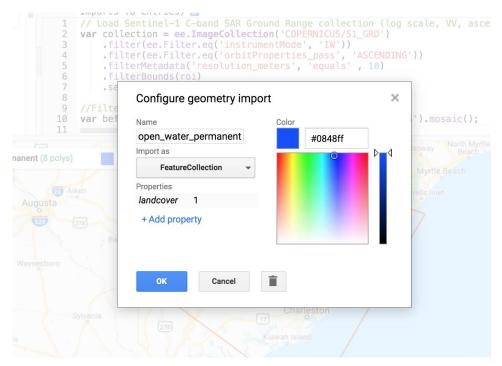
Selection of Training Data

- m
- The first step in running a supervised classification is to collect training data to "train" the classifier
 - This involves collecting representative samples of backscatter for each landcover class of interest
- 2. Display the after VV image and go to the **Geometry Imports** box next to the geometry drawing tools and click **+ new layer**
- 3. Next to it select the draw a polygon icon
- 4. Each new layer represents one class within the training data, for example open_water



Selection of Training Data

- 5. Define the first new layer as open_water
- 6. Locate areas in the new layer in rivers and lakes and click to collect them
- Collect a representative sample of polygons and rename the geometry as open_water
- 8. Configure the open_water geometry import (cog-wheel, top of the script in imports section)
- Click the cog-wheel icon to configure it, change Import as from Geometry to FeatureCollection
- 10. Use **Add property** landcover and set its value to 1. (Subsequent classes will be 2, 3, 4 etc.) when finished, click **OK**





Merge the Defined Classes

- We identified six classes. The next step is to merge them into a single collection, called a FeatureCollection.
- 11. Run the following line to merge the geometries into a single FeatureCollection:

```
//Merge Feature Collections

//Merge Feature Collections

var newfc =
open_water_permanent.merge(open_water_flooded).merge(flooded_vegetation).me
rge(urban).merge(flood_channel).merge(low_vegetation);
```



Geometry Imports

open_water_permanent (8 polys)

open_water_flooded (17 polys)

flooded_vegetation (17 polys)

✓ roi (1 line)

Create the Training Data

- m
- We will use the FeatureCollection created to extract backscatter values for each landcover class identified for all images that will be used in the classification.
- The training data is created by overlaying the training points on the image.

```
//Define the bands to be used to train your data
var final = ee.Image.cat(before_filtered,after_filtered)
var bands = ['VV'];
var training = final.select(bands).sampleRegions({
   collection: newfc,
   properties: ['landcover'],
   scale: 30 })
```



Train the Classifier

```
//Train the classifier
var classifier = ee.Classifier.cart().train({
   features: training,
   classProperty: 'landcover',
   inputProperties: bands
});
```



Run the Classification

 We run the classification by applying the knowledge from our training areas to the rest of the image:

```
//Run the Classification
var classified = final.select(bands).classify(classifier);
```

 Display the results using the mapping function below. The colors may need to be adjusted, however, if colors and numbers have been assigned to the training data, the result will be rendered with those class numbers and colors

```
//Display the Classification
Map.addLayer(classified,
{min: 1, max: 6, palette: ['0848ff', '00ffff', 'bf04c2', 'ff0000',
'00ff00', '0f874a']},
'classification');
```



Classification Accuracy

- Here were are only looking at the training area accuracy, which describes how well the classifier was able to correctly label resubstituted training data
- For true validation accuracy, we need to use new 'testing' data

Inspector Console Tasks

Use print(...) to write to this console.

```
RF error matrix:
▼List (7 elements)
  10,0,0,0,0,0,0
  1: [0,4801,0,0,0,0,0]
  2: [0,0,345,106,0,228,551]
  ▶ 3: [0,0,54,729,0,228,510]
  ▶ 4: [0,0,0,0,307,0,0]
  5: [0,0,61,89,0,494,304]
  ▶ 6: [0,0,119,57,0,224,5561]
```

```
RF accuracy:
0.8286159263271939
```

```
// Create a confusion matrix representing resubstitution accuracy.
print('RF error matrix: ', classifier.confusionMatrix());
print('RF accuracy: ', classifier.confusionMatrix().accuracy());
```



Overlaying Population Data



```
//Add Population Layer
var dataset = ee.ImageCollection('CIESIN/GPWv4/population-density');
var populationDensity = dataset.select('population-density')
var populationDensityVis = {
   min: 200.0,
   max: 1500.0,
   palette: ['ffffff', 'ffcdc6', 'ff0000', '950000'],
};
Map.addLayer(populationDensity, populationDensityVis, 'Population Density');
```



Overlaying Roads

```
77
```

```
//Add Road Layer
var dataset = ee.FeatureCollection('TIGER/2016/Roads');
var roads = dataset.style({color: '#4285F4', width: 1});
Map.addLayer(roads, {}, 'TIGER/2016/Roads');
```

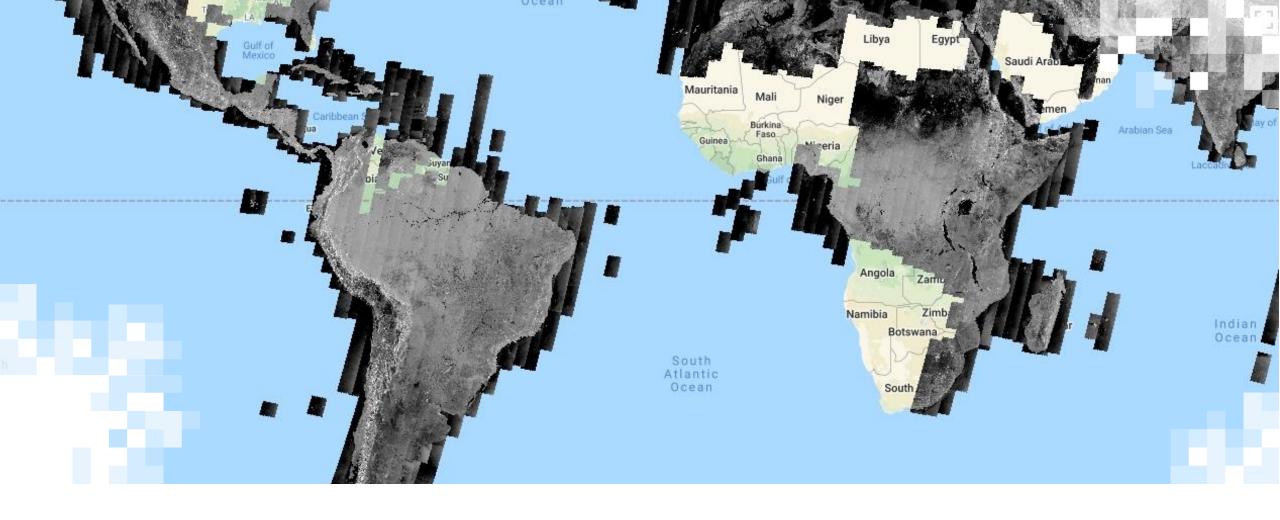


Export the Image to Google Drive

```
77
```

```
// Export the image, specifying scale and region.
Export.image.toDrive({
   image: classified,
   description: 'Flooding',
   scale: 100,
   region: roi,
   fileFormat: 'GeoTIFF',
});
```





THANK YOU

Contacts

- ARSET Disasters Contacts
 - Erika Podest: <u>erika.podest@jpl.nasa.gov</u>
 - Amita Mehta: <u>amita.v.mehta@nasa.gov</u>
 - Sean McCartney: sean.mccartney@nasa.gov
- General ARSET Inquiries
 - Ana Prados: <u>aprados@umbc.edu</u>
- ARSET Website:
 - http://arset.gsfc.nasa.gov

