PECORA22

Opening the Aperture to Innovation: Expanding Our Collective Understanding of a Changing Earth

Near Real-time Agricultural Flood Monitoring and Crop Impact Assessment under Google Earth Engine

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Celebrating 50 YEARS Landsat 1972-2022

USDA

AGRICULTURE COUNTS

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- Methodology
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- Flood Extent Detection Applications
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- Flood Depth Algorithm and Applications
  - Hurricane Fiona
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Disclaimer: The findings and conclusions in this publication are those of the authors and should not be construed to represent any official USDA or U.S. Government determination or policy.

Background and Objectives

- Near real-time agricultural flood monitoring is critical to government agencies, farmers, ag business decision makers, and other stakeholders for rapid crop impact assessment.
- Google Earth Engine (GEE) is an ideal platform to develop web-based applications for rapid processing and visualization of flood inundation.
- In this study, a GEE app was implemented and different algorithms for flood detection were evaluated.
- Current existing remote sensing-based algorithms for flood detection are limited to the estimation of flood extent only, without depth.
- To fill this gap, a new algorithm was developed in the GEE application to estimate flood depth throughout the flood extent.

Methodology

- Open water bodies typically exhibit lower backscattering than other ground features. The flood can thus be detected by comparing SAR's images captured before and after a flood event.

- A common method for flood identification is to detect changes in backscattering from SAR's polarization bands acquired before and after a flood event.

Methodology - Flood extent detection algorithms

Absolute Threshold Differencing (ATD)

- Water bodies on both pre and post event images are identified using a threshold of $\beta_{vh} < -20$ or $\beta_{vv} < -14$
- Flood pixels identified by image differencing between pre and post event water

z-score

$$\text{z-score} = (x_i - \mu) / \sigma$$

Pixels on the post-event image with a z-score < -1.96 are considered as “floods”, as they are statistically significantly different from the mean values of the specified time period at a 95% confidence level.

Relative Threshold Differencing (RTD)

Pixels on the post-event image with a β_{vh} value 30% lower than normal are considered as “floods”

Modified z-score (Robust z-score)

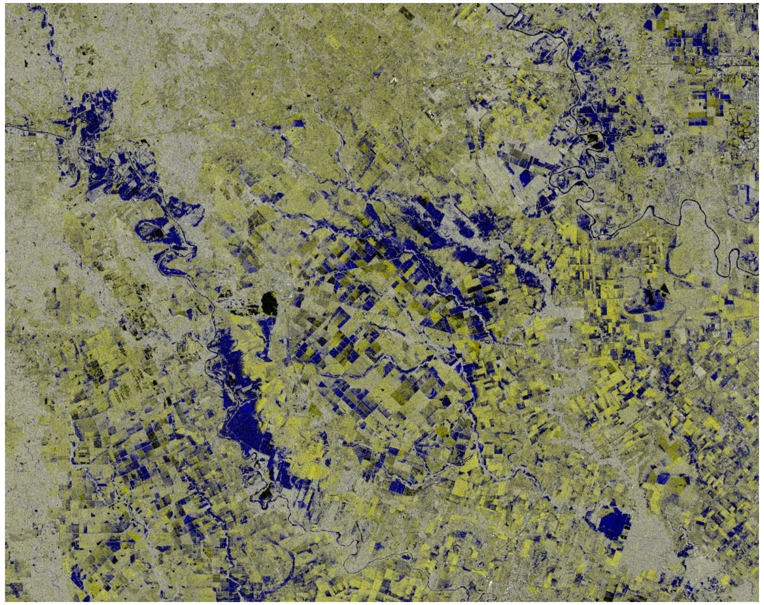
$$\text{Modified z-score} = (X_i - \text{median})/(1.4826 * \text{MAD})$$

- MAD is defined as the median of the absolute deviations from the data's median

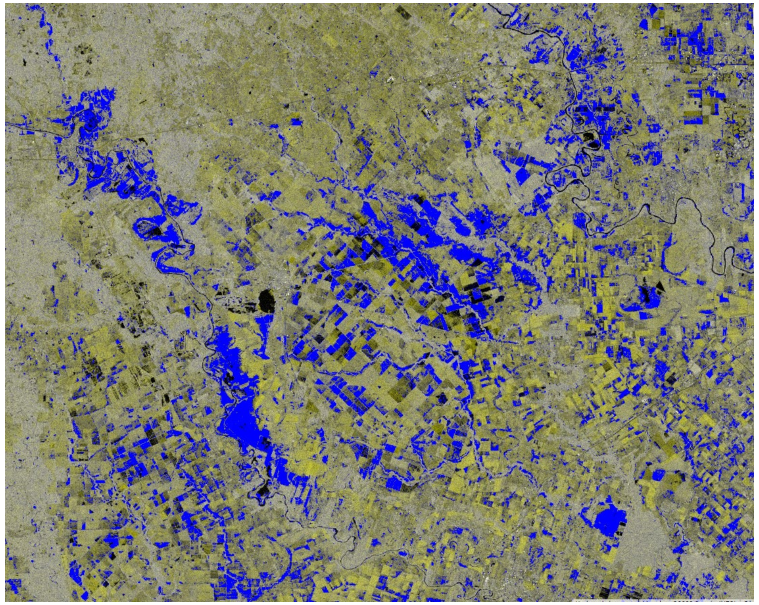
$$\text{MAD} = \text{median}(|X_i - \tilde{X}|)$$

- 1.4826 is a scalar constant linked to the assumption of normality of the data.
- 1.4826*MAD is conceptually equivalent to standard deviation.
- In this case, pixels on the post-event image with a modified z-score < -1.96 are considered as “floods”.

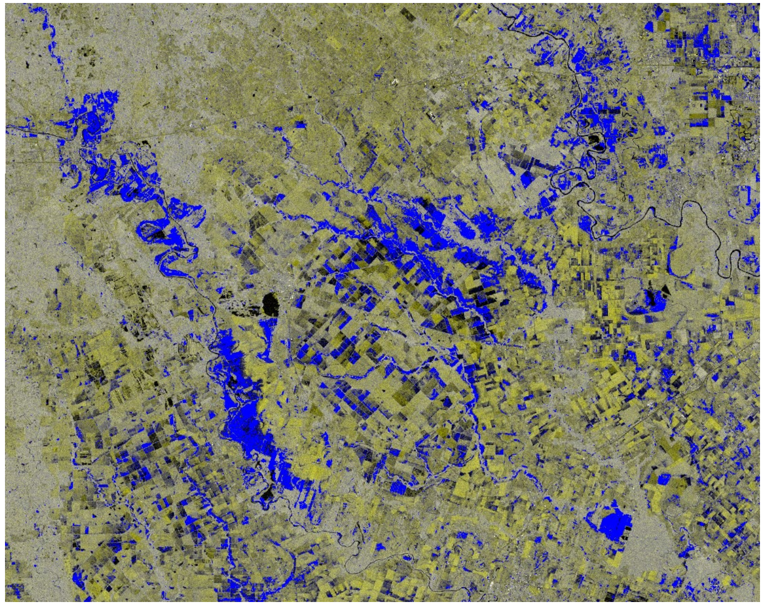
Flood detection using different methods for Hurricane Harvey (Aug 27- Sep 05, 2017)



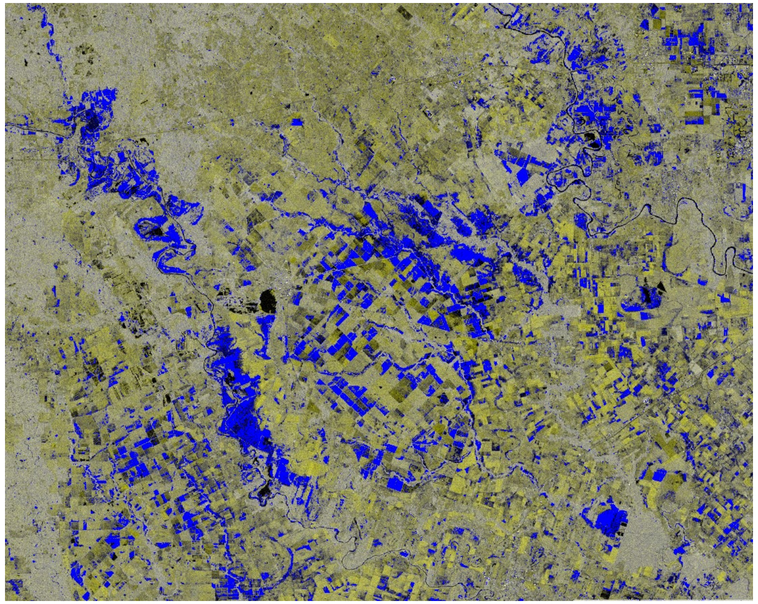
Sentinel-1 SAR false color composite (R: post-event VH, G: post-event VH, B: post-event VH) showing anomaly



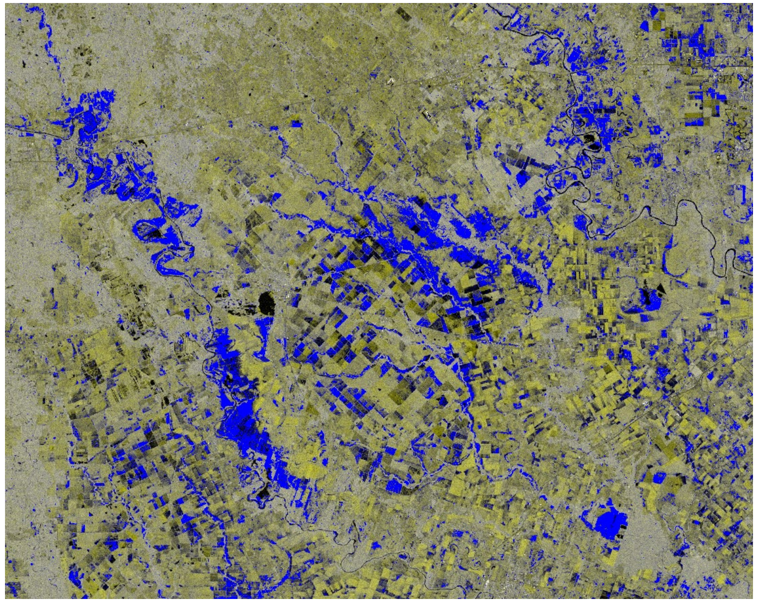
Absolute Threshold Differencing ($\beta_{vh} < -20$)



z-score ($z < -1.96$)

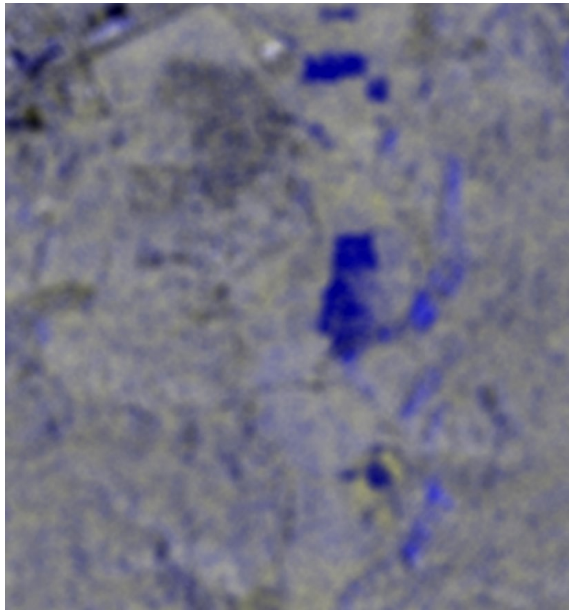


Relative Threshold Differencing (post-event β_{vh} 30% lower than normal)

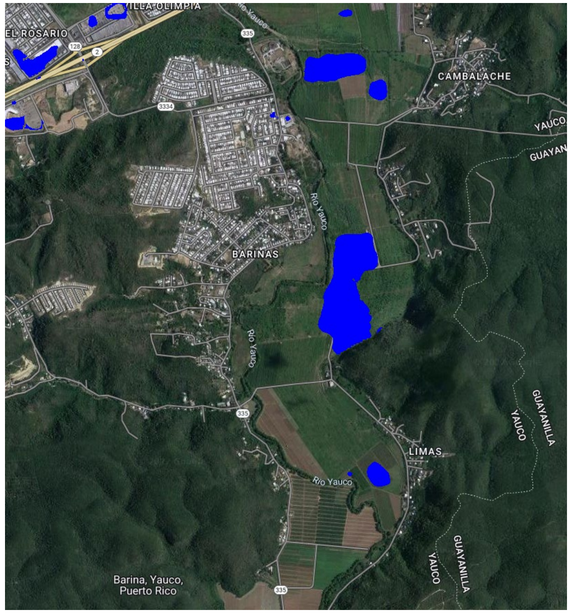


Modified z-score ($z < -1.96$)

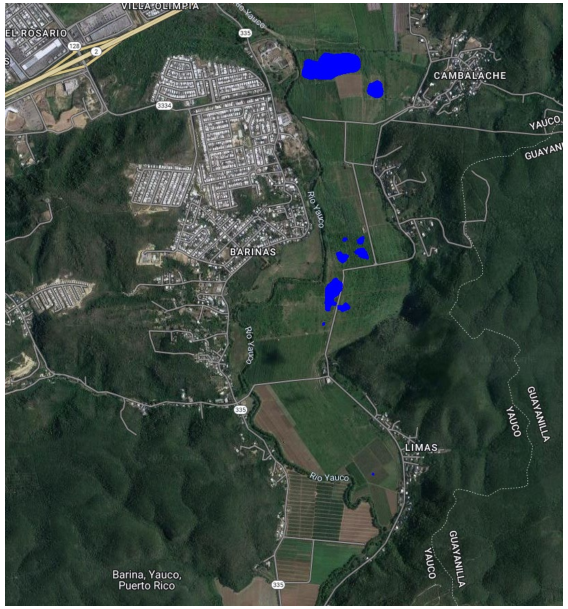
Flood detection using different methods for **Hurricane Fiona Puerto Rico (Sep 18 - 28, 2022)**



Sentinel-1 SAR false color composite (R: post-event VH, G: post-event VH, B: post-event VH) showing anomaly

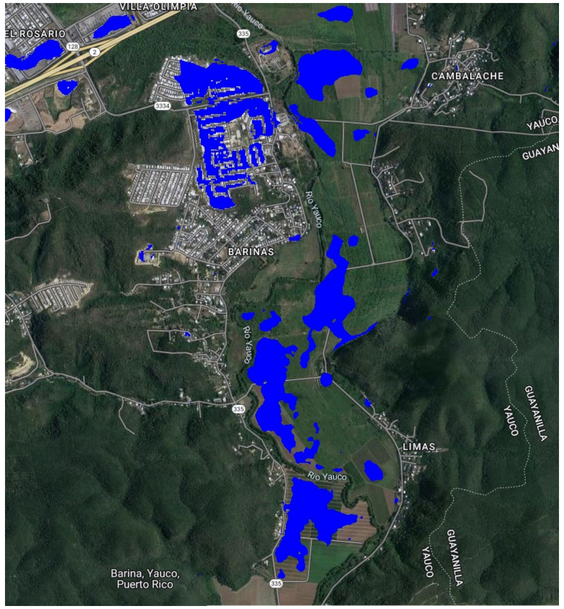


Absolute Threshold Differencing ($\beta_{vh} < -20$)

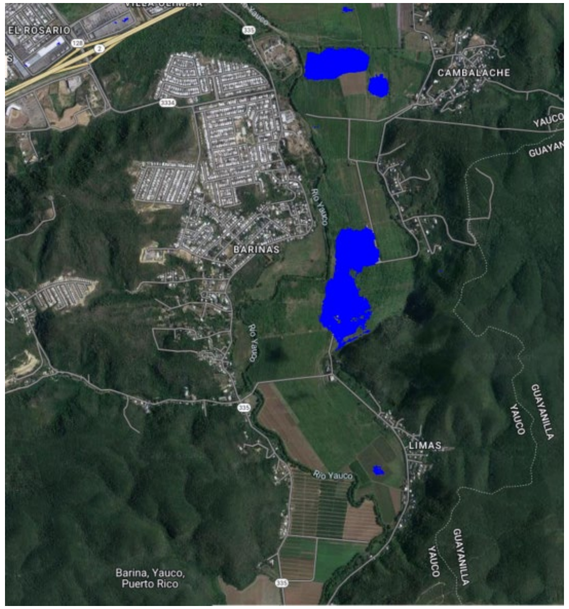


z-score ($z < -1.96$)

The maps show inundated plantain fields in a tropical farm, Yauco, Puerto Rico



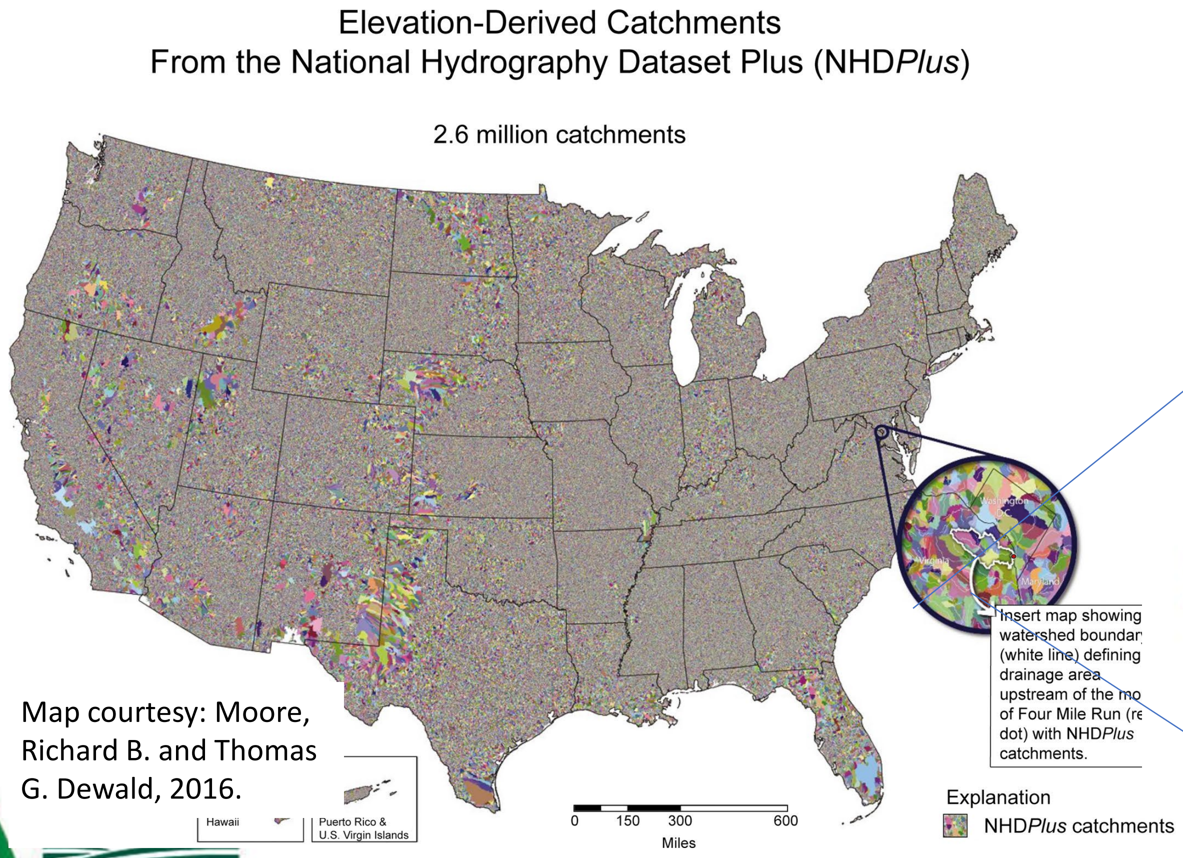
RTD (post-event β_{vh} 30% lower than normal)



Modified z-score ($z < -1.96$)

Methodology - Flood depth estimation algorithms

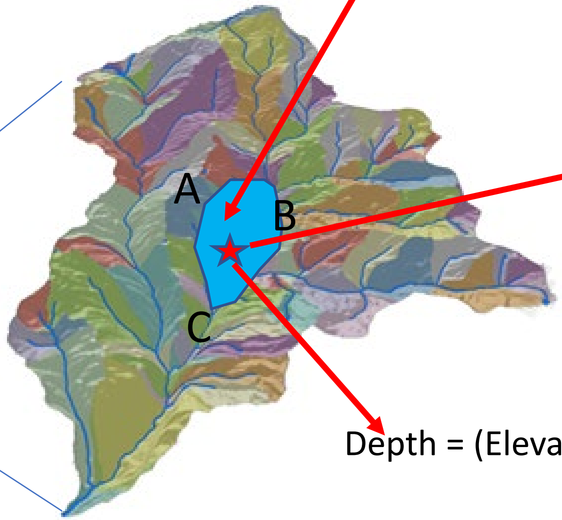
- A **flood depth** estimation algorithm was developed and implemented by integrating USGS 3DEP National Map Seamless 1/3 Arc-Second (10m) DEM, and NHDPlusV2 catchment geospatial products.

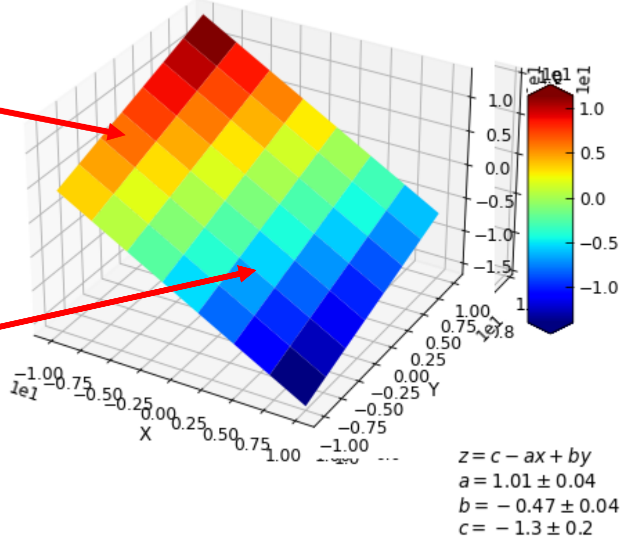


Map courtesy: Moore, Richard B. and Thomas G. Dewald, 2016.

$ax + by + cz + d = 0$,

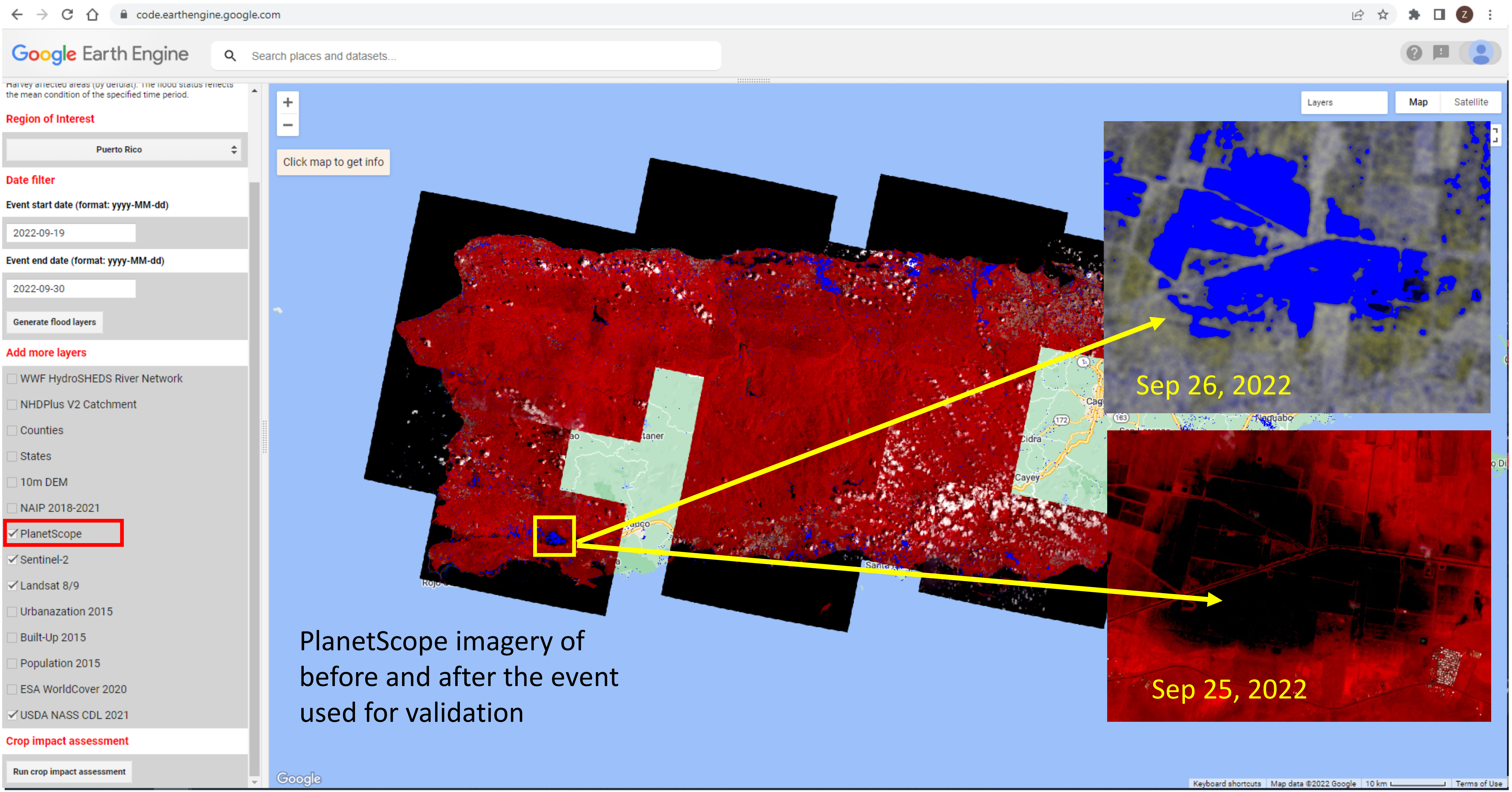
Flood water surface



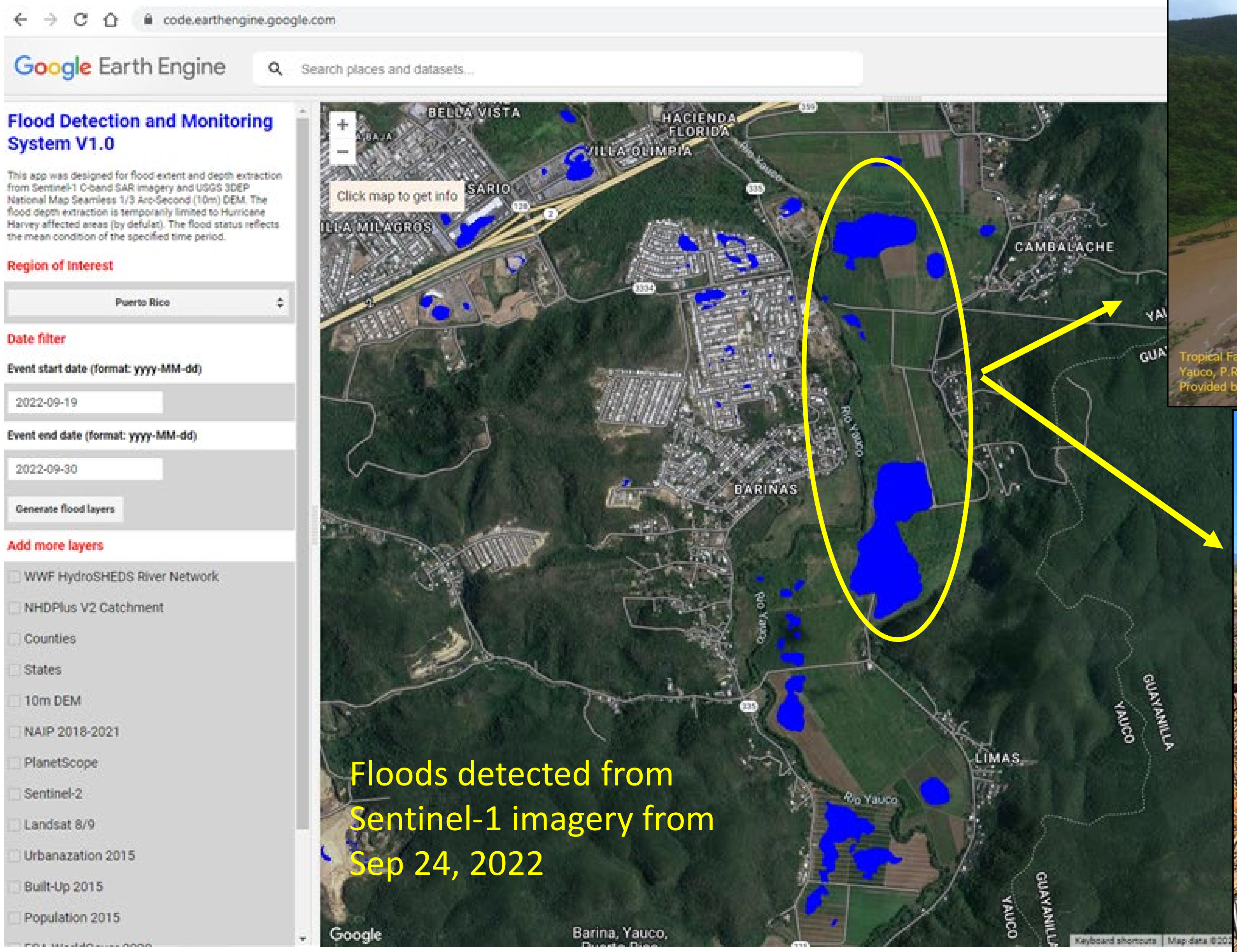


Depth = (Elevation_water_surface – Elevation_terrain)

Flood Detection and Monitoring System v1.0 – A Google Earth Engine Web App for rapid visualization and assessment

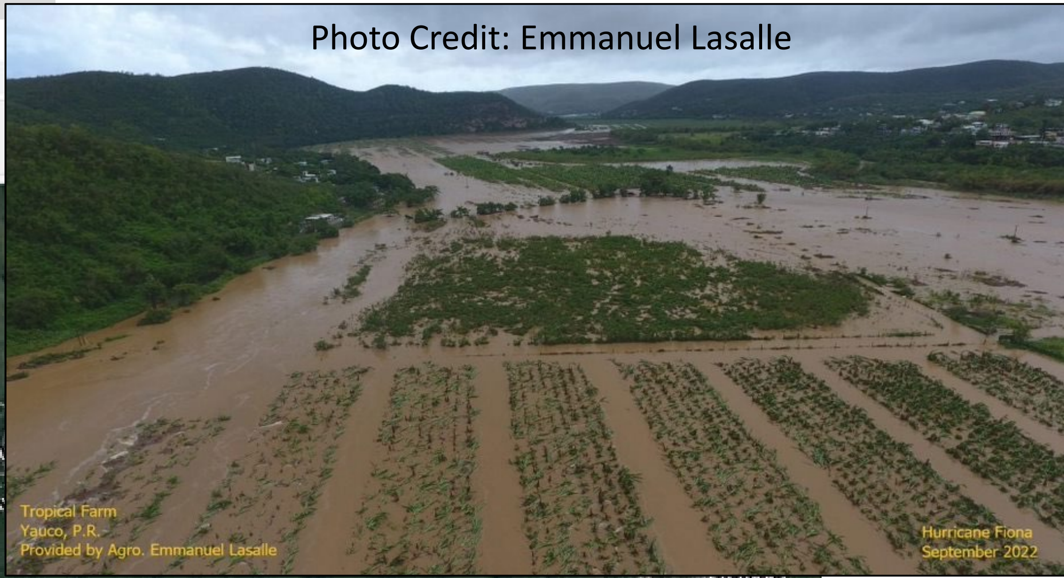


Hurricane Fiona Puerto Rico, Sep 18 - 28, 2022



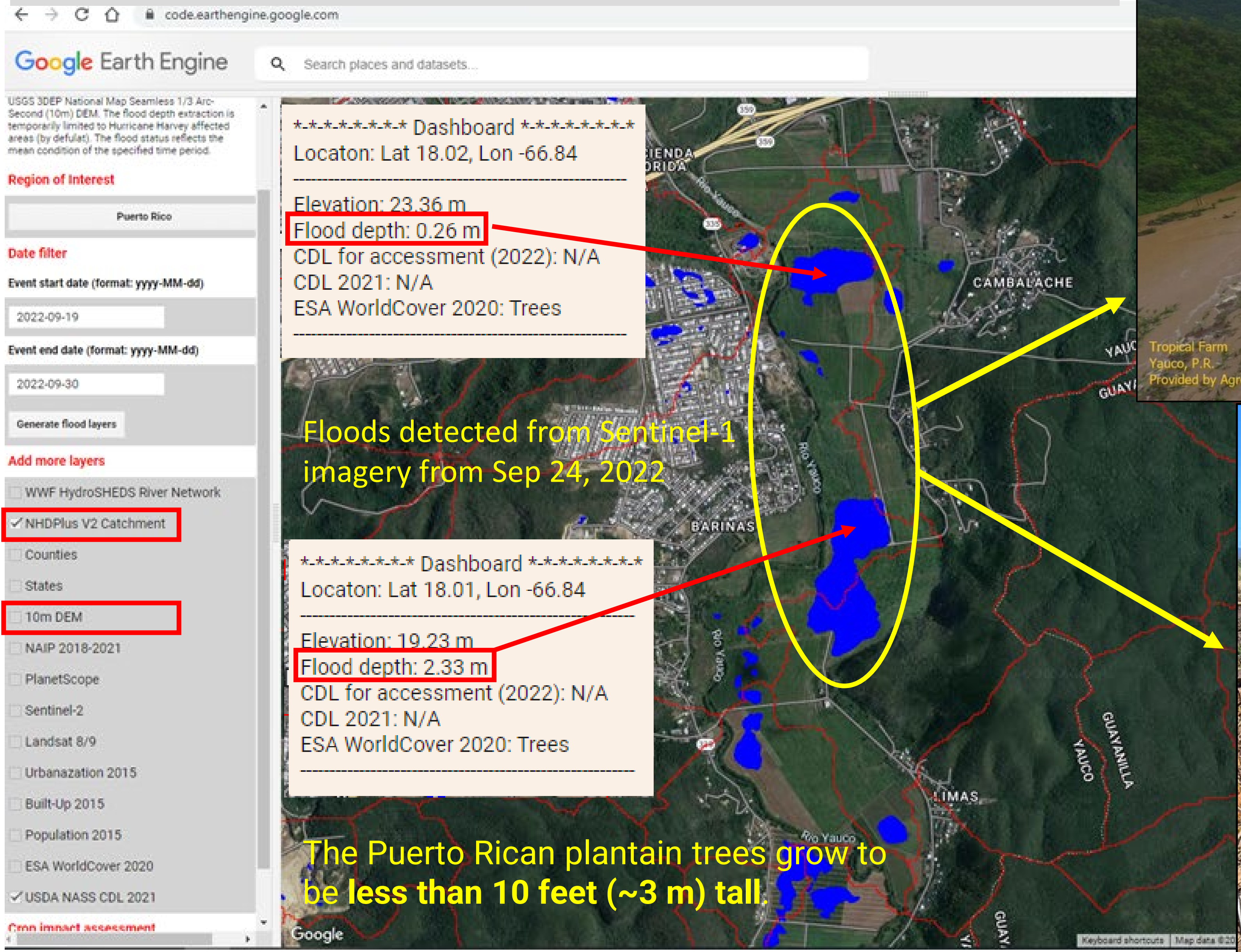
Floods detected from Sentinel-1 imagery from Sep 24, 2022

Plantain fields in Tropical Farm, Yauco, Puerto Rico, Sep 19, 2022



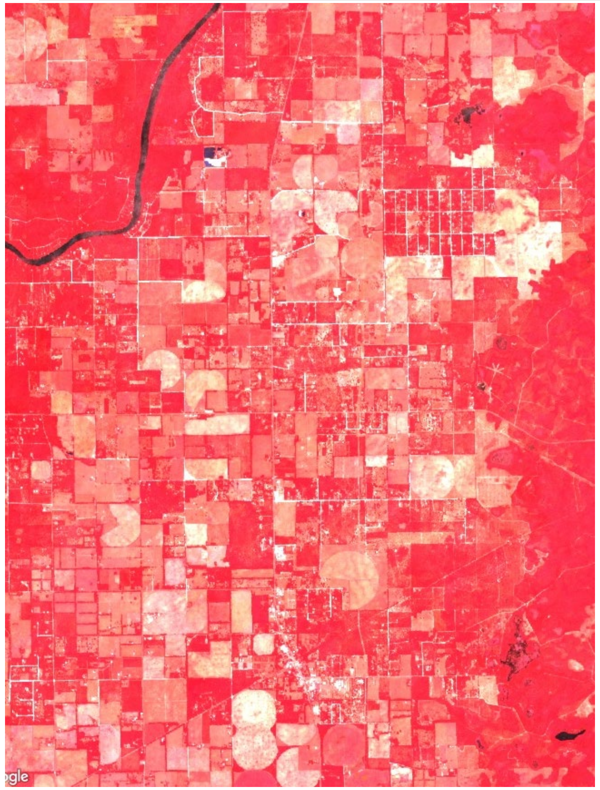
Plantain fields in Tropical Farm, Yauco, Puerto Rico, Sep 26, 2022

Using USGS 10m DEM and NHDPlusV2 catchment geospatial products for flood depth estimation

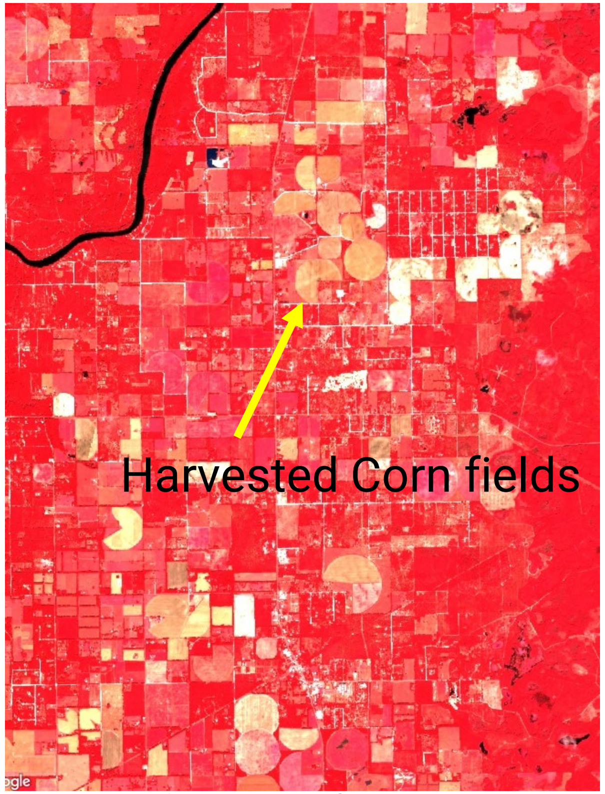


Inundated plantain in Tropical Farm, Yauco, Puerto Rico, Sep 19, 2022

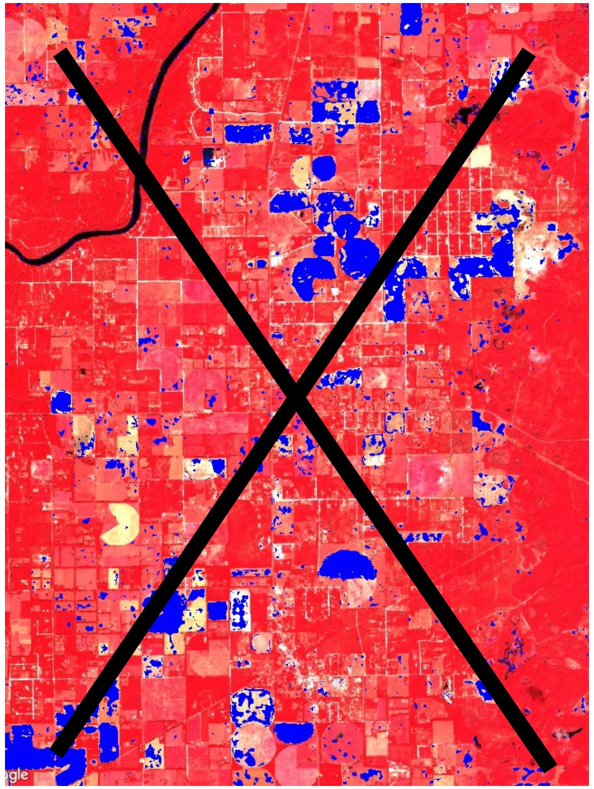
Removal of false alarm flooding detected from Sentinel-1 SAR imagery



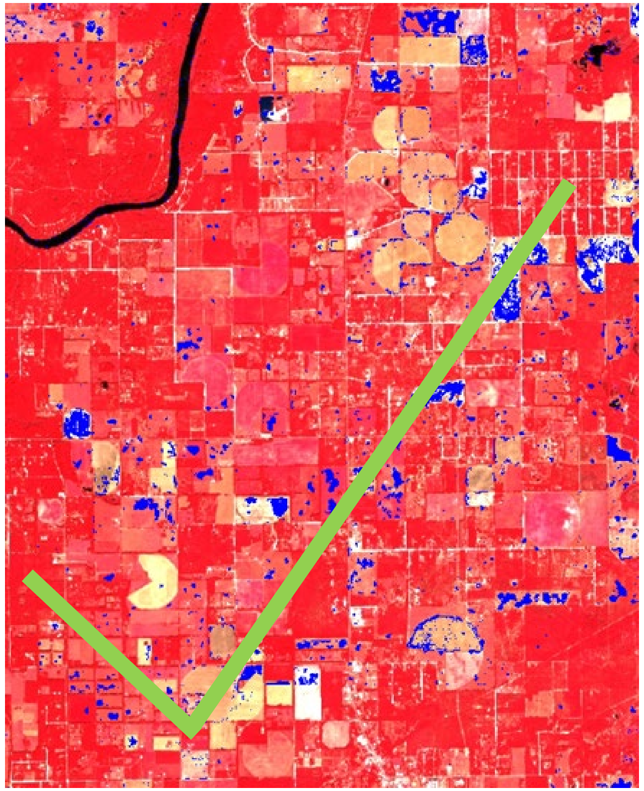
Sentinel-2 image before event



Sentinel-2 image after event



False floods detected from Sentinel-1 SAR imagery

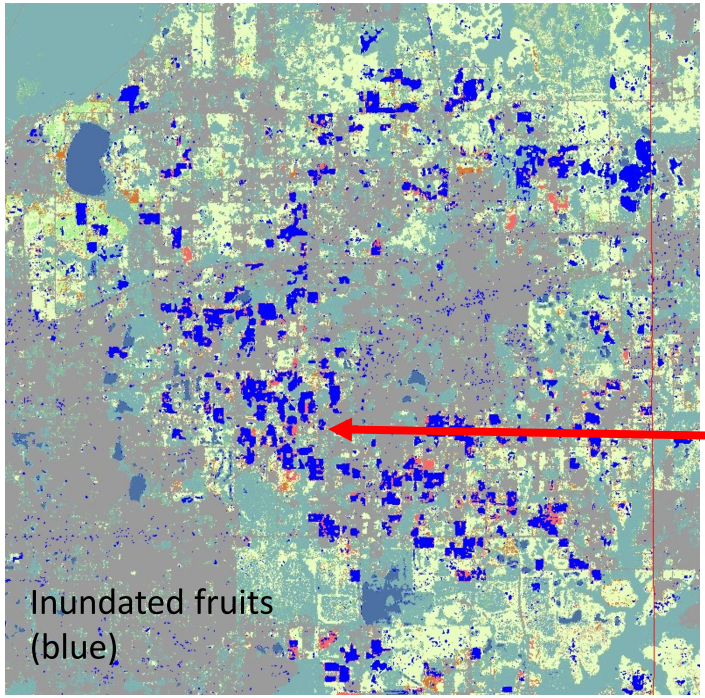


False floods eliminated by applying MNDWI

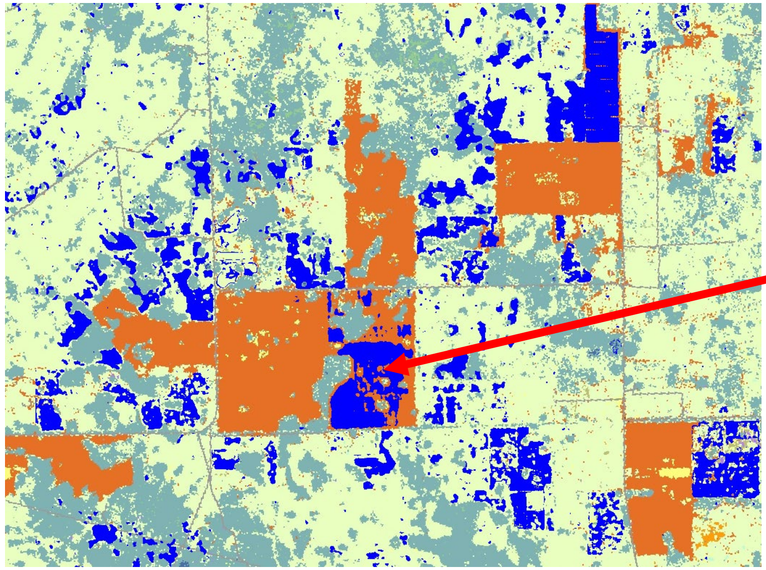
```
▾Sentinel-2 pre-event NDVI: Image (1 band)
   NDVI: 0.707317054271698
▾Sentinel-2 post-event NDVI: Image (1 band)
   NDVI: 0.16485686600208282
```

```
▾Sentinel-2 pre-event MNDWI true: Image (1 band)
   MNDWI: -0.2868894636631012
▾Sentinel-2 post-event MNDWI true: Image (1 band)
   MNDWI: -0.49059560894966125
```

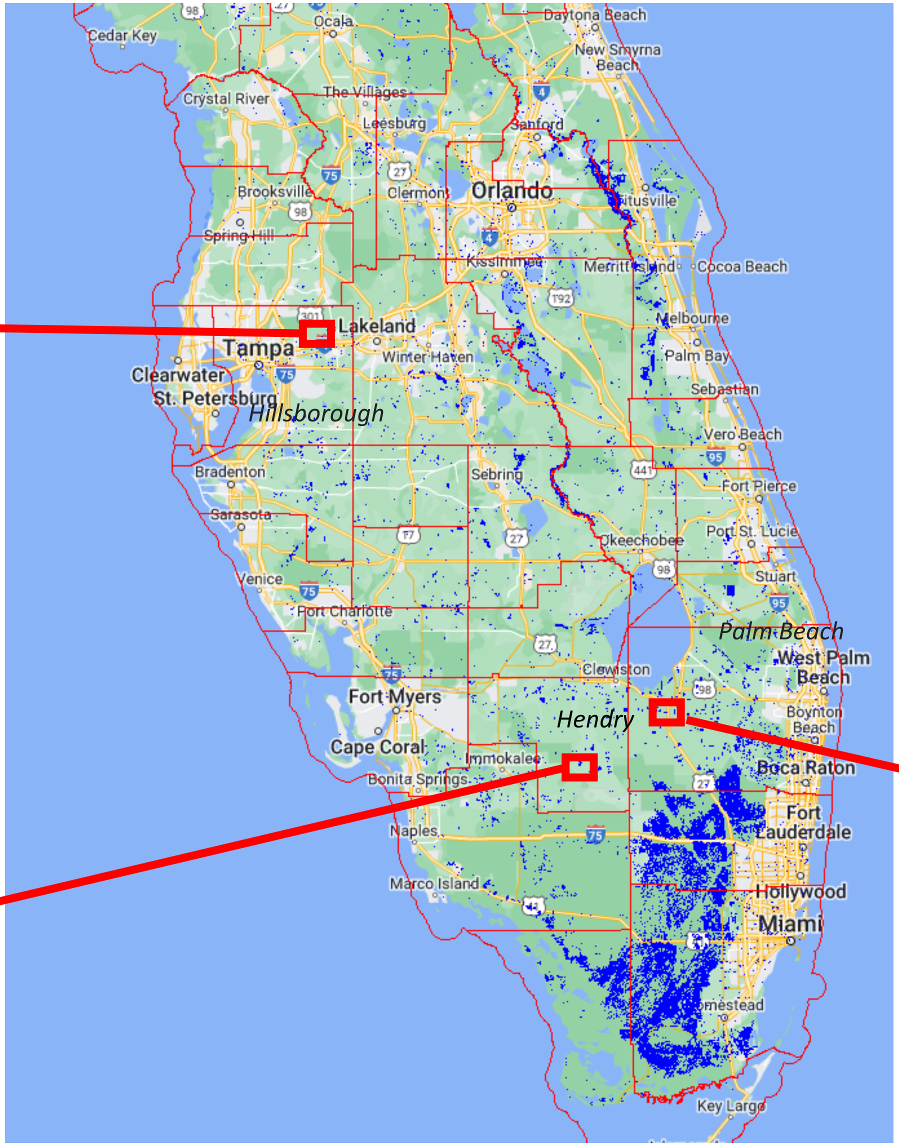
Flood detection with “harvested land filter” applied



Inundated fruits (blue)

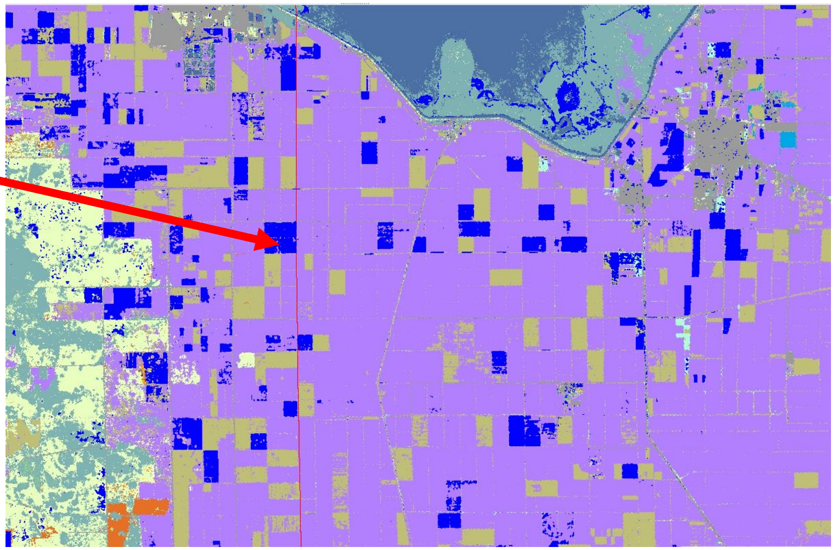


Inundated oranges (blue)



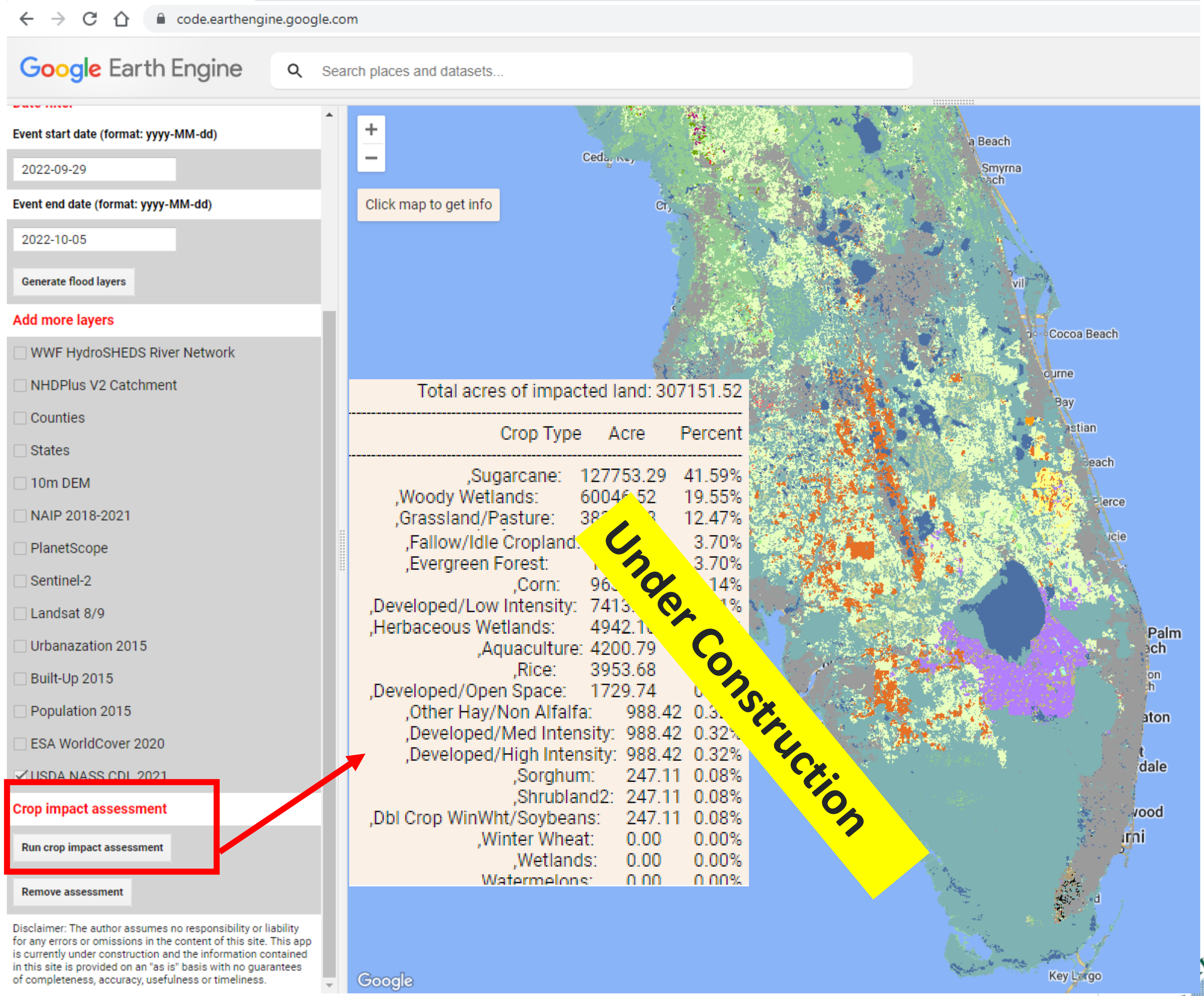
Inundated land in Florida after Hurricane Ian (blue)

Inundated croplands (blue) during Hurricane Ian Florida (Sep 2022) based on 2021 NASS CDL



Inundated sugarcane (blue)

Crop Impact Assessment



Summary and Future Work

- A GEE app was developed using four algorithms for flood extent detection and applied to major flood events for near real-time monitoring and assessment.
- Initial results indicate that all four algorithms can effectively capture major floods. However, ATD is most reliable and the default in this app.
- The Modified z-score method outperformed standard z-score for the Hurricane Fiona test. Further, the RTD method captured more “floods” than other algorithms and will be evaluated further.
- The Z-score, modified z-score and RTD methods can serve as ancillary anomaly detection tools to complement floods omitted by ATD. Further validation will be conducted when more ground reference data are available.

Summary and Future Work cont.

- When integrating MNDWI, this app can minimize the effects caused by false inundation alarms such as harvested croplands.
- By integrating DEM and NHD catchments, this app can provide reasonable flood depth estimates.
- To better characterize flood extents and depths, the L-band SAR data from the upcoming NISAR mission, and the observables (i.e., water level, water extent, etc.) from the upcoming satellite altimeter - the Surface Water and Ocean Topography mission (SWOT) will be integrated into the GEE flood monitoring app.

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Thank you and Questions

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