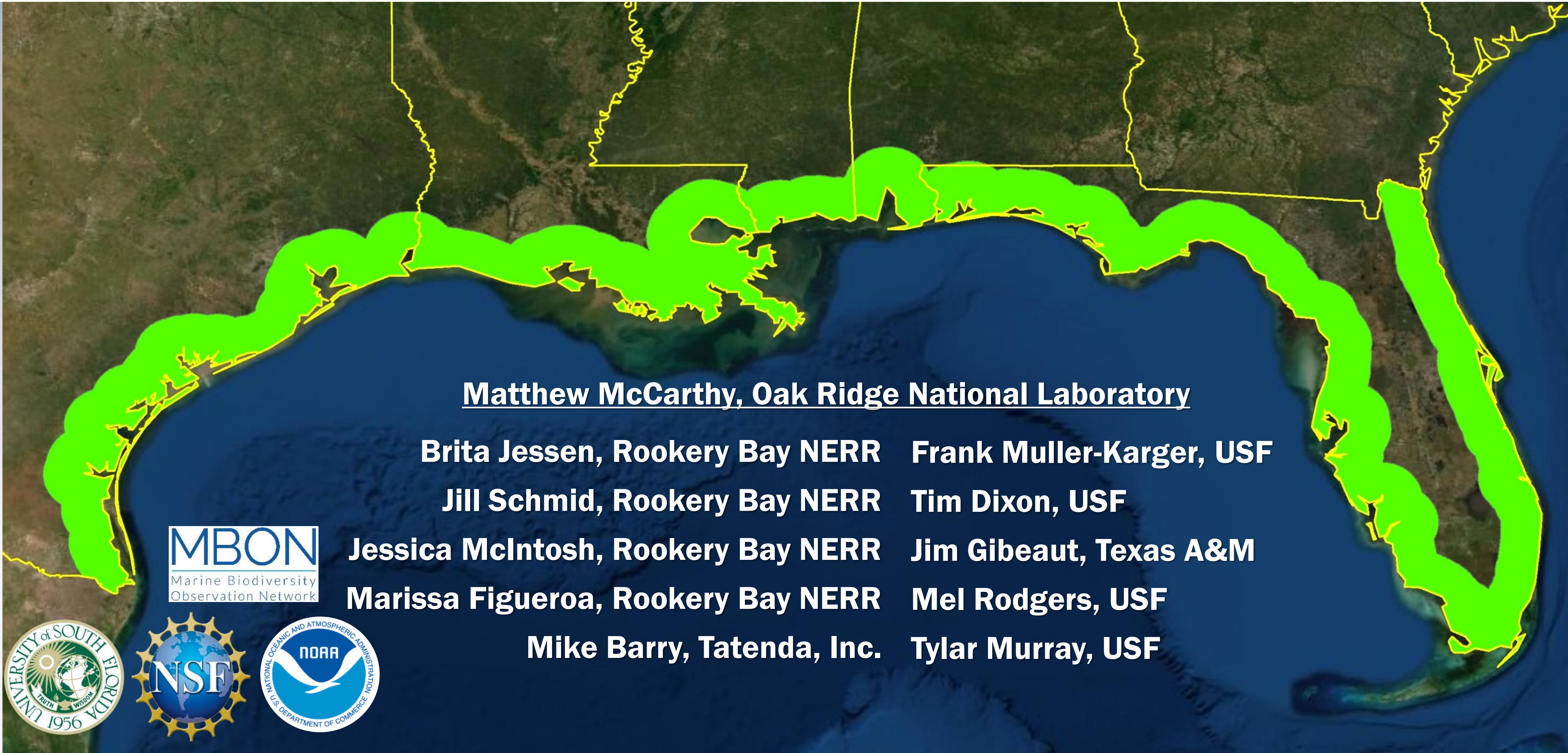
Coastal 3-D High-Resolution Maps for Floods, Wetlands, and Biodiversity

SECOORA 2020



Matthew McCarthy, Oak Ridge National Laboratory

Brita Jessen, Rookery Bay NERR
Jill Schmid, Rookery Bay NERR
Jessica McIntosh, Rookery Bay NERR
Marissa Figueroa, Rookery Bay NERR
Mike Barry, Tatenda, Inc.

Frank Muller-Karger, USF
Tim Dixon, USF
Jim Gibeaut, Texas A&M
Mel Rodgers, USF
Tylar Murray, USF

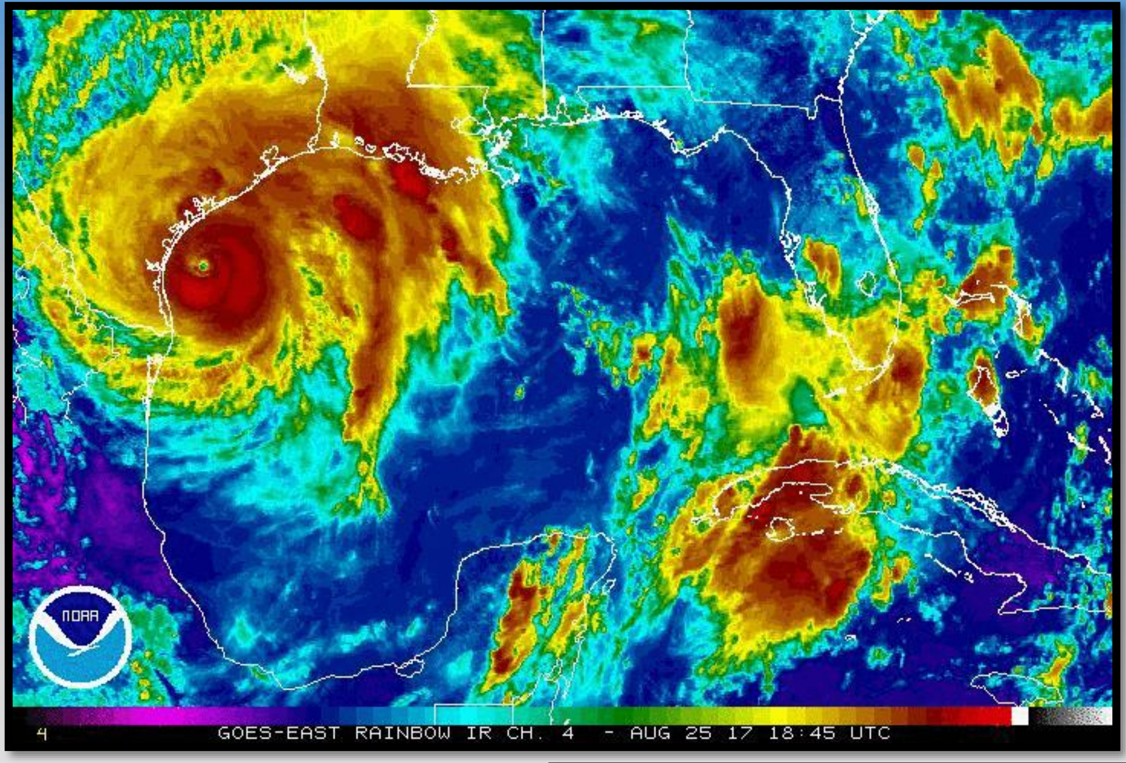
MBON Marine Biodiversity Observation Network

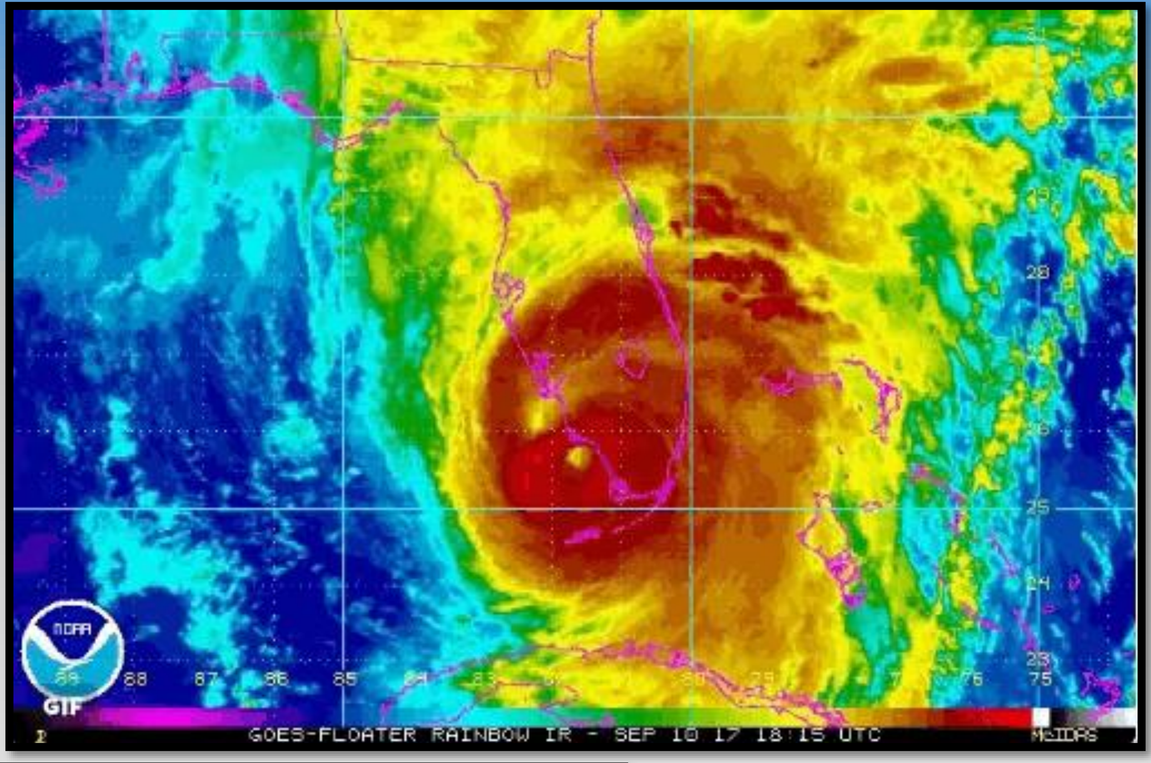
Motivation

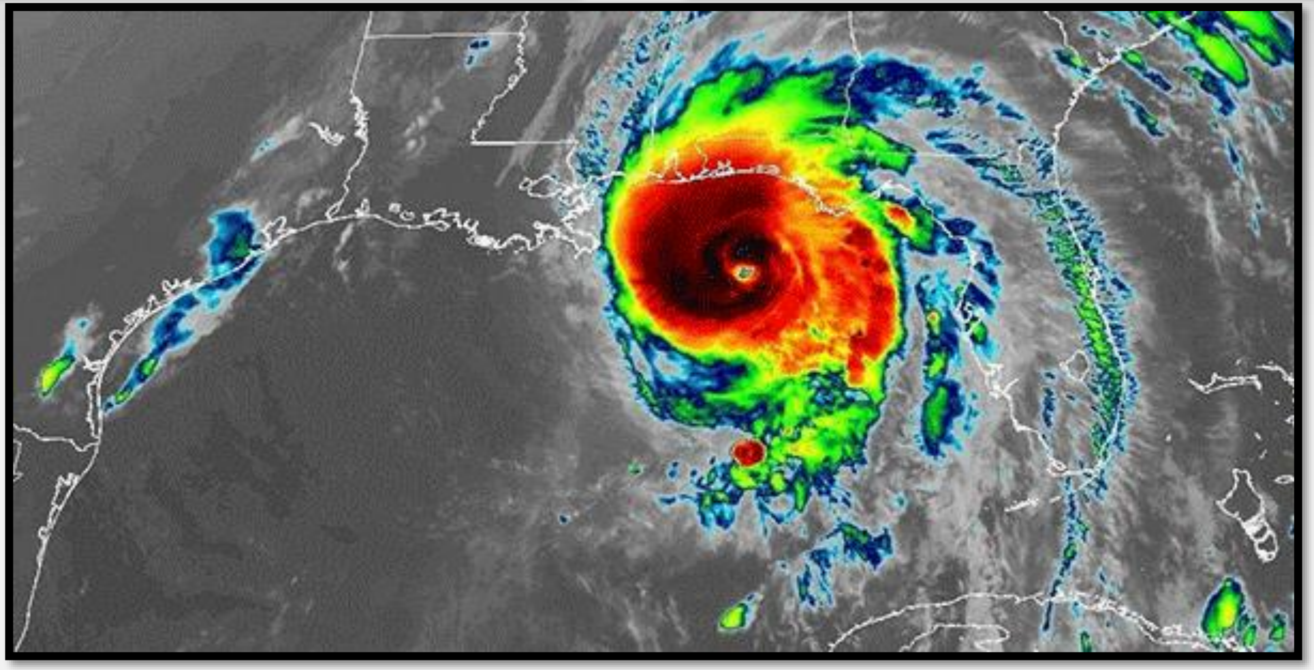
- Rapid coastal population growth
  - Texas and Florida > 1,000 new resident per day each
  - 50% of built environment needed exists today
- Sustainable development
- Improved and updated flood maps
- Compliment and improve NOAA C-CAP maps
- Evaluate first-order biodiversity

Project Overview

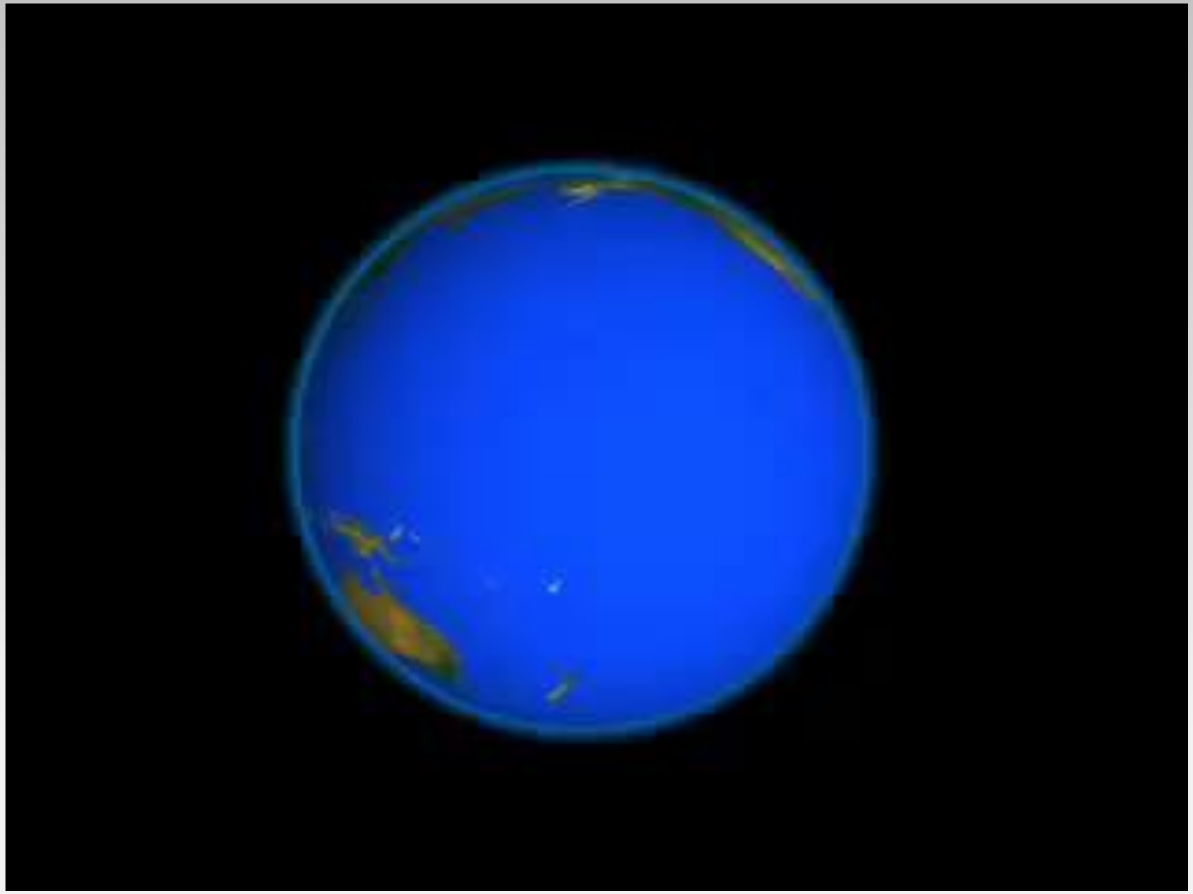
- Research Questions
  - What are the types and extent of different wetland and other land cover classes, their geomorphology, composition, and vulnerability at local and regional scales?
  - What is the relationship between topography and land cover across scales of meters?
  - Which areas are particularly prone to flooding across the region?
  - What are major changes observed in land cover pre- and post-severe storms and specifically Hurricanes Harvey, Irma and Michael?

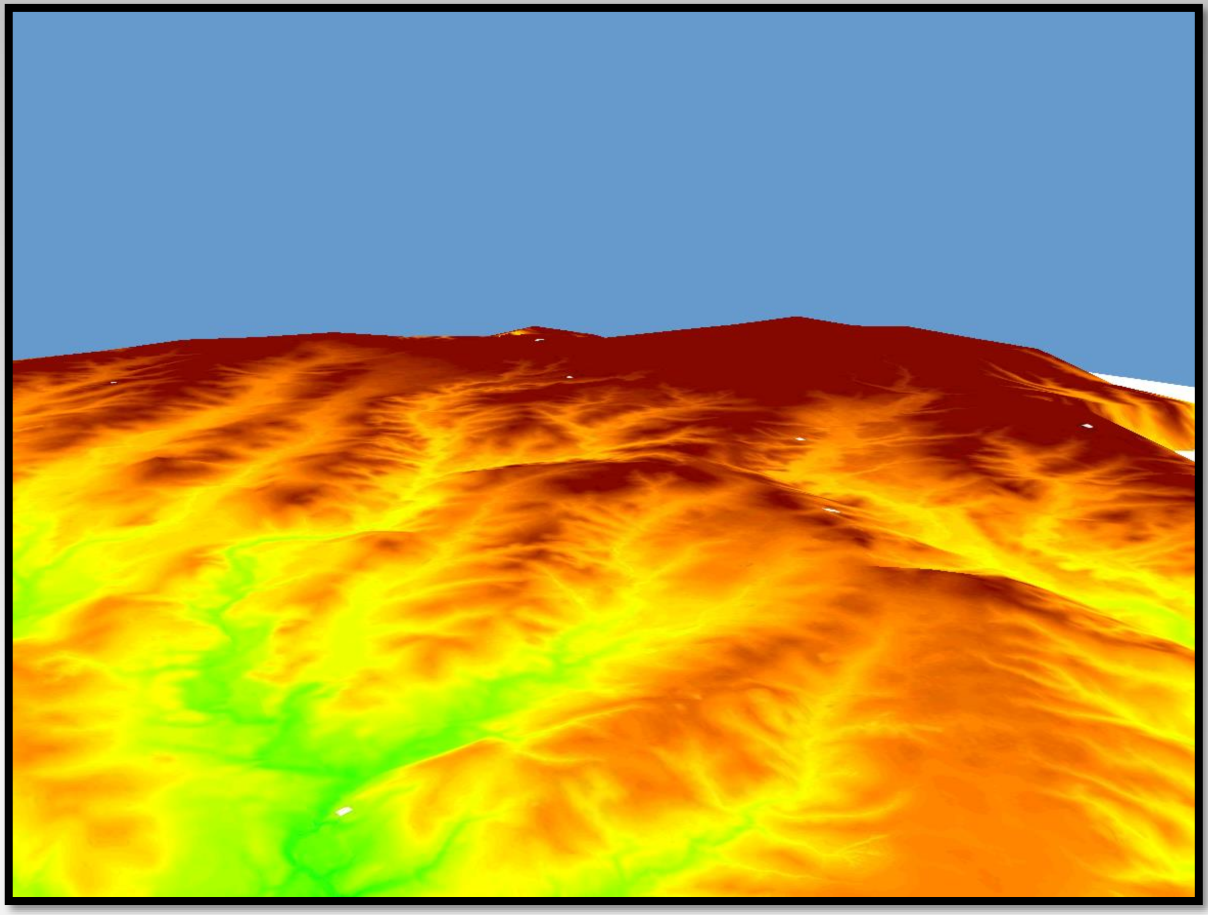

NOAA
GOES-EAST RAINBOW IR CH. 4 - AUG 25 17 18:45 UTC


NOAA
GIF
GOES-FLOATER RAINBOW IR - SEP 10 17 18:15 UTC
McIDAS

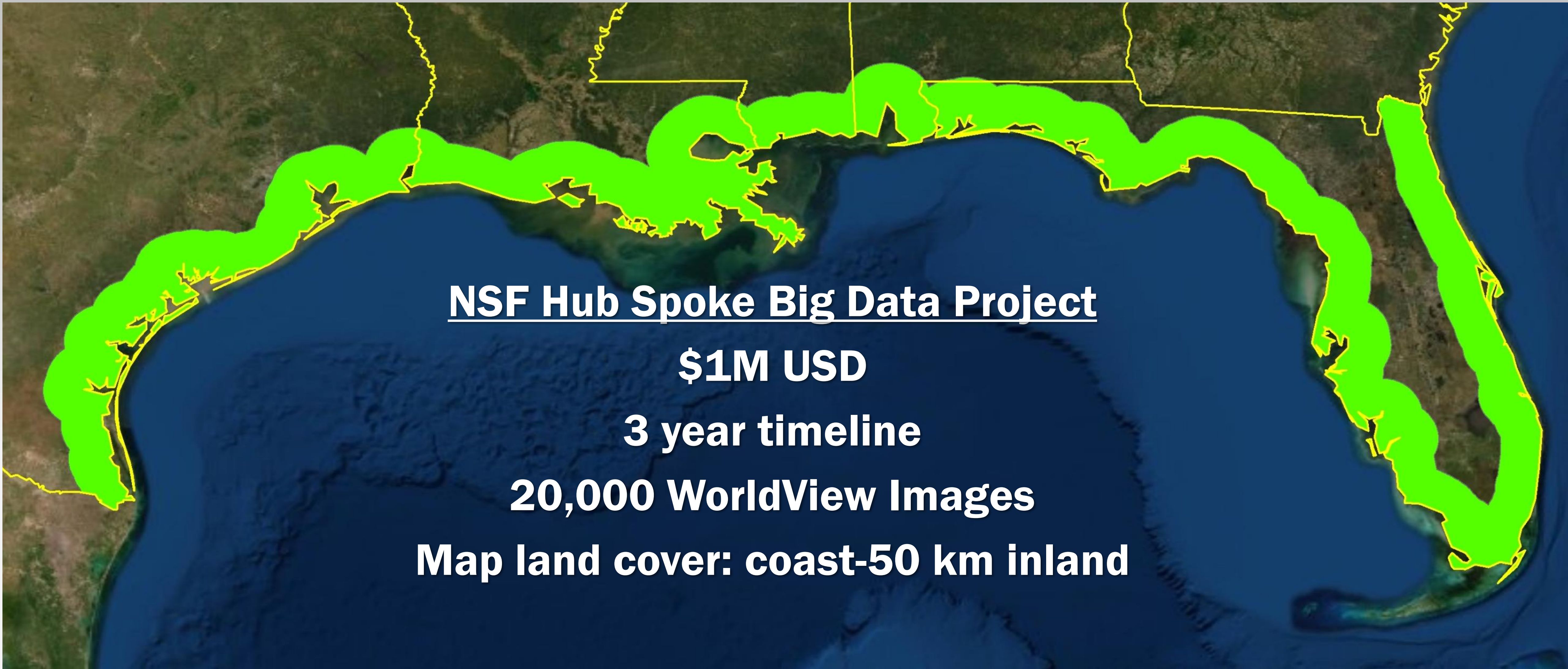


Methodology: WorldView Imagery + Lidar





Coastal 3-D High-Resolution Mapping



NSF Hub Spoke Big Data Project

$1M USD

3 year timeline

20,000 WorldView Images

Map land cover: coast-50 km inland

Objective: Large-scale mapping

Problem	Solution
Big Data processing efficiency	Automation
Automation issues • Consistency • Thresholding • Sunglint • Water column	Automation solutions • Standardized preprocessing • Scene-specific algorithms • Novel deglinting algorithm • Novel correction algorithm

Methodology: SOALCHI Workflow

WorldView-2&3 Images
Texas: 2,284

↓

Spectral and **O**bject-based **A**utomated **L**and cover **C**lassification of **H**igh-resolution **I**magery	Python code ↓ Matlab code

USF CIRCE Cluster:
419 nodes
9152 cores
46TB memory
222 GPUs

↓

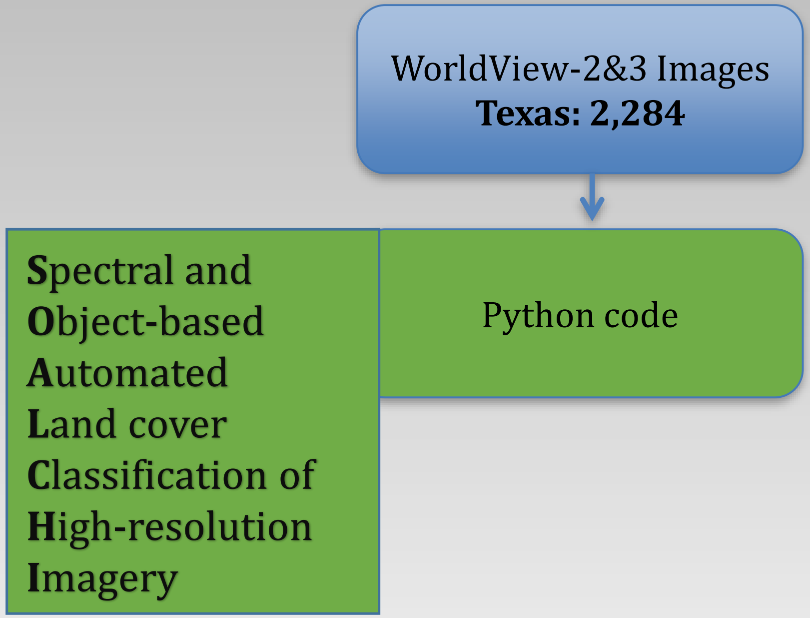
Mosaic

↓

Classified Map

Traditional Methods: 5.2 years
SOALCHI: 6.5 days

Methodology: SOALCHI Workflow




```
#!/bin/bash
#SBATCH --partition=bgfsqdr
#SBATCH --job-name ="SOALCHI_bgfs"
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#SBATCH --mem-per-cpu=20480
#SBATCH --time=10:00:00
#SBATCH --array=0-10000
```

Pgc_ortho.py

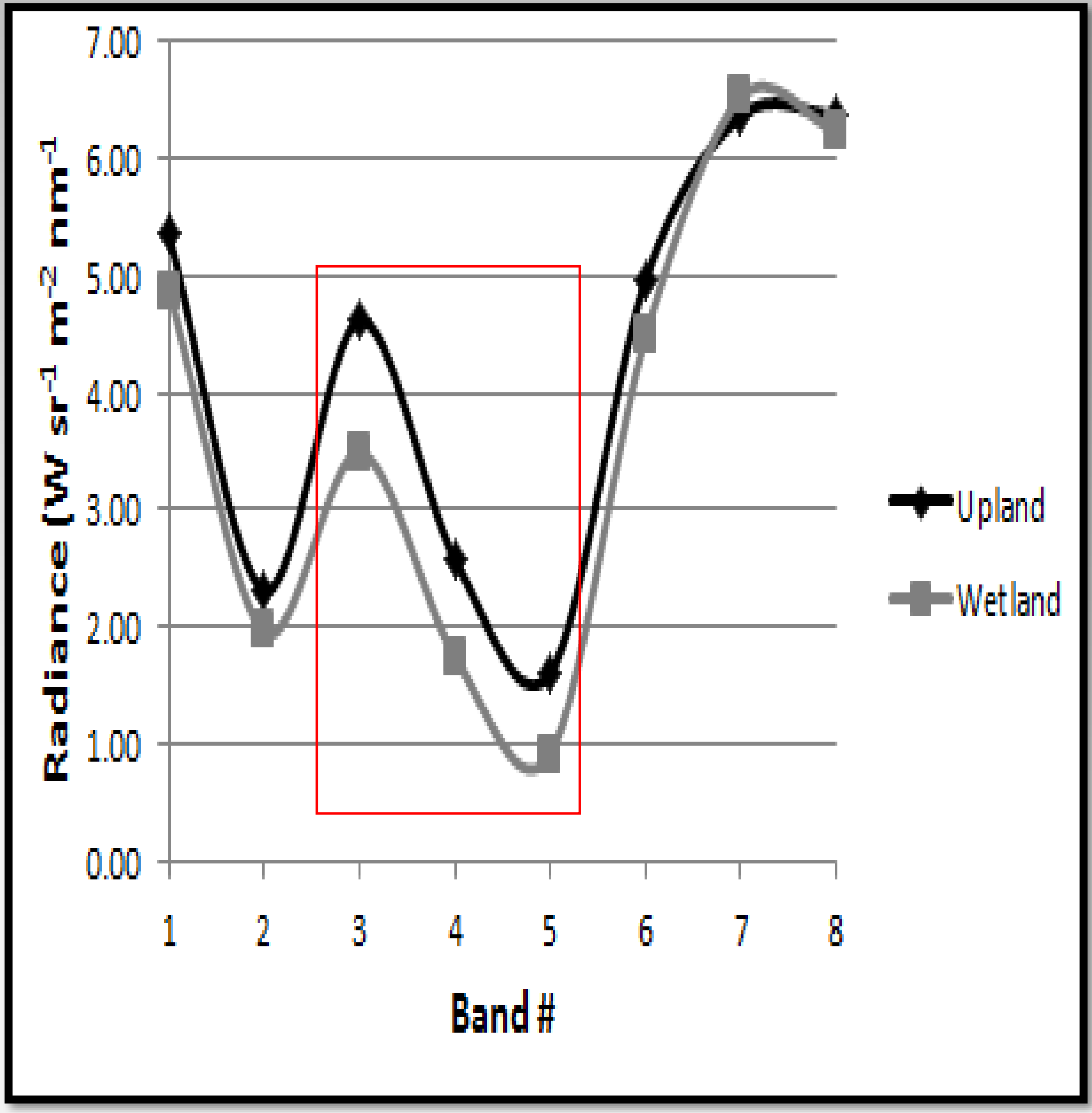
- Written by Polar Geospatial Center
- Steps
  - Ingest Level-1B WorldView NITF
  - Optional georectification using RPCs
  - Project to WGS 1984 (EPSG:4326)
  - Output Level-2B GeoTIFF
- Run time = 5-15 minutes per image

Methodology: SOALCHI Workflow

WV_Classify.m

- Written by M McCarthy
- Steps
  - Ingest Level-2B GeoTIFF + metadata XML
  - Convert DN to Radiance
  - Correct for Rayleigh scattering
  - Convert to Rrs
  - Decision Tree preparation
  - Decision Tree
  - Post-processing filter

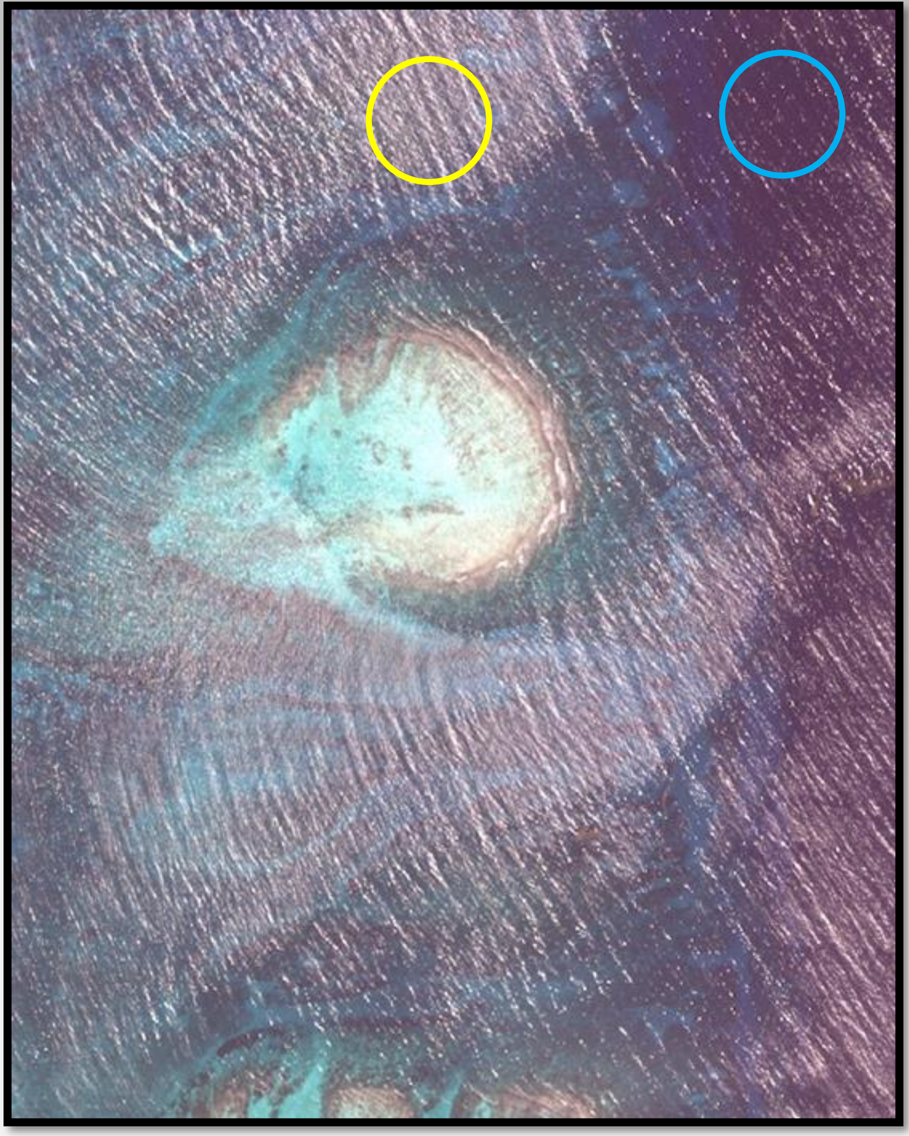
Methodology: SOALCHI Workflow



WV_Classify.m

- Written by M McCarthy
- Steps
  - Ingest Level-2B GeoTIFF + metadata XML
  - Convert DN to Radiance
  - Correct for Rayleigh scattering
  - Convert to Rrs
  - Decision Tree preparation
    - Upland vs Wetland
    - Scene-specific algorithm
      - Wetland < Average(sum(B3-B5))
  - Decision Tree
  - Post-processing filter

Methodology: SOALCHI Workflow



WV_Classify.m

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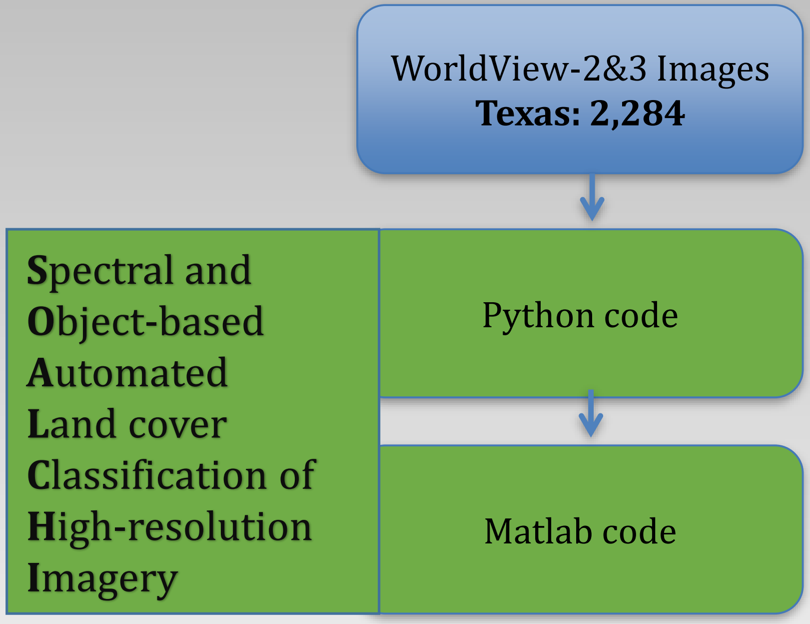
- Steps
  - Ingest Level-2B GeoTIFF + metadata XML
  - Convert DN to Radiance
  - Correct for Rayleigh scattering
  - Convert to Rrs
  - Decision Tree preparation
    - Deglint
      - Isolate glint pixels from ODW (novel algorithm)
      - Dual-array of WorldView imagery
      - Regress visible bands against NIR for slope
      - $Rrs_{dg,i} = Rrs_i - (Slope_i * (Rrs_{NIR} - Rrs_{NIRmin}))$
  - Decision Tree
  - Post-processing filter

Methodology: SOALCHI Workflow

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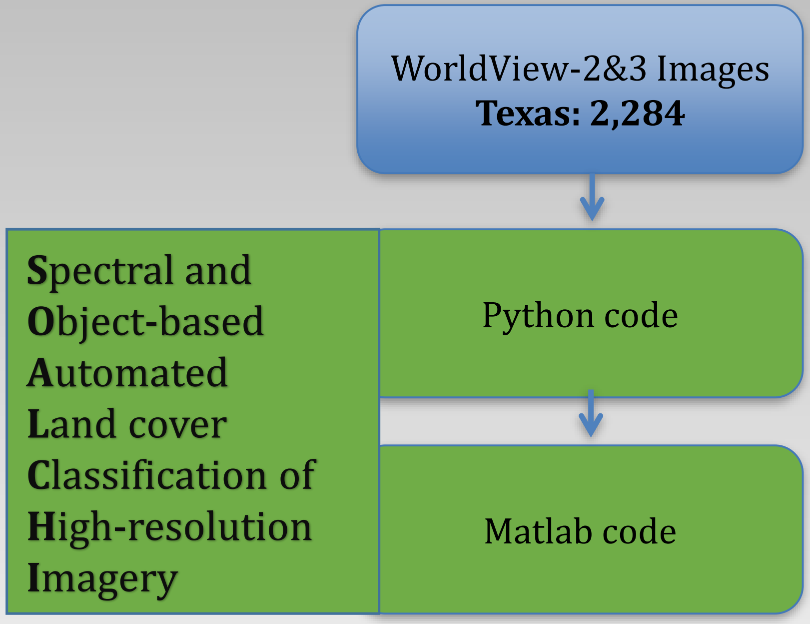
```

WV_Classify.m

- Written by M McCarthy
- Steps
    - Ingest Level-2B GeoTIFF + metadata XML
    - Convert DN to Radiance
    - Correct for Rayleigh scattering
    - Convert to Rrs
    - Decision Tree preparation
        - Estimate water column properties (Kd)
            - Calculate IOP index (Li 2019, Hu 2012)
                - Based on ODW
            - Estimate chlorophyll-a content (Hu 2012)
    - Decision Tree
    - Post-processing filter

Methodology: SOALCHI Workflow

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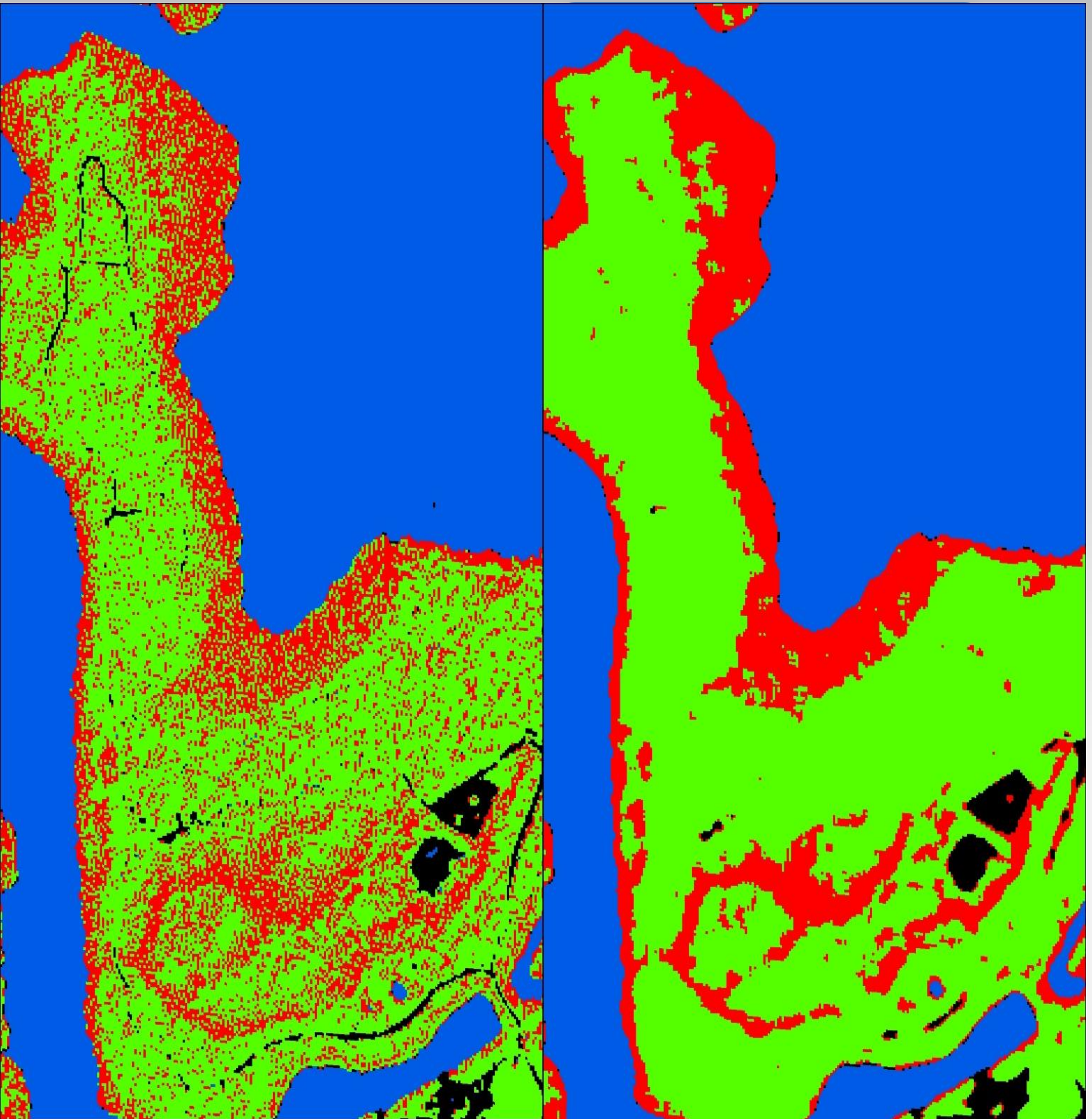
- Written by M McCarthy
- Steps
  - Ingest Level-2B GeoTIFF + metadata XML
  - Convert DN to Radiance
  - Correct for Rayleigh scattering
  - Convert to Rrs
  - Decision Tree preparation
  - Decision Tree
    - Calculate bathymetry (from Kd)
      - Revised from Li 2019 with exponential scalars derived from WorldView field data tuning parameters
  - Post-processing filter

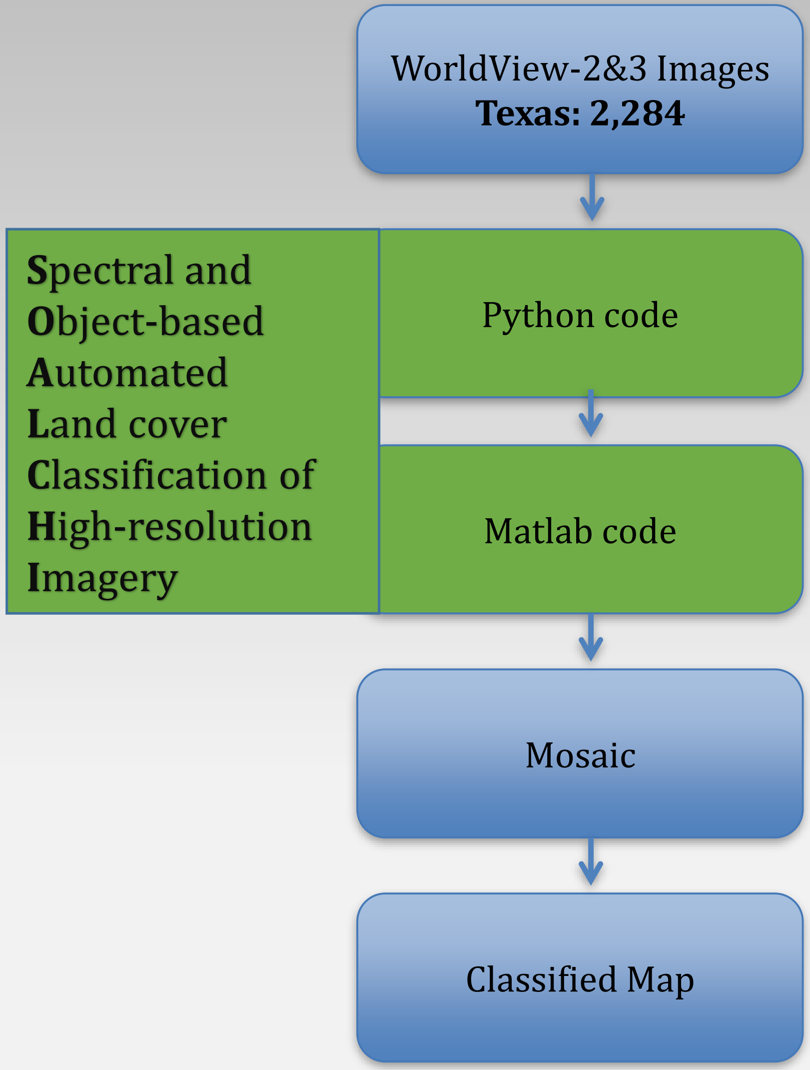
Methodology: SOALCHI Workflow



WV_Classify.m

- Written by M McCarthy
- Steps
  - Ingest Level-2B GeoTIFF + metadata XML
  - Convert DN to Radiance
  - Correct for Rayleigh scattering
  - Convert to Rrs
  - Decision Tree preparation
  - Decision Tree
  - Post-processing filter

Methodology: Mosaicking

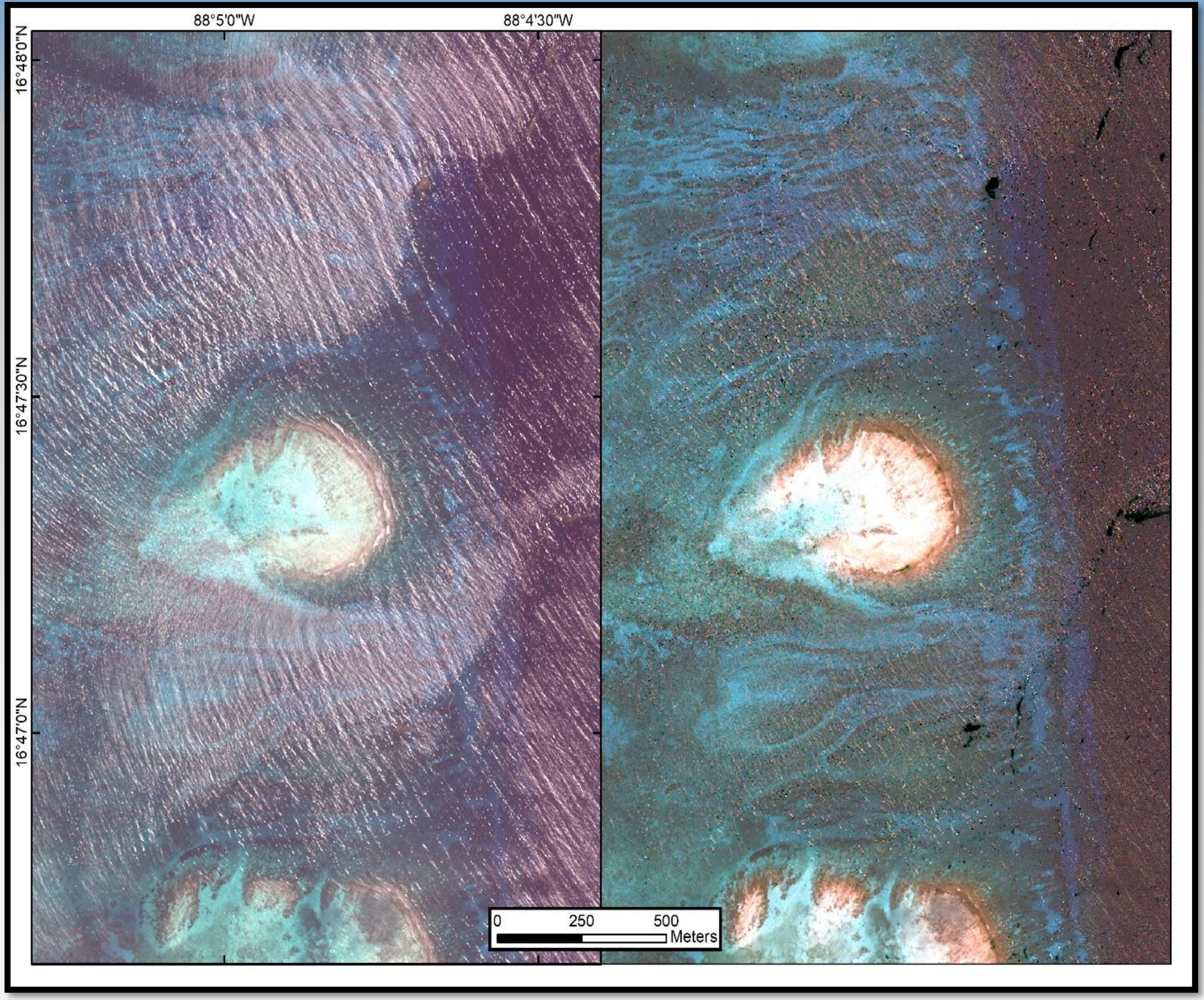


Mosaic

- Python
  - GDAL library
- Automated image-stitching

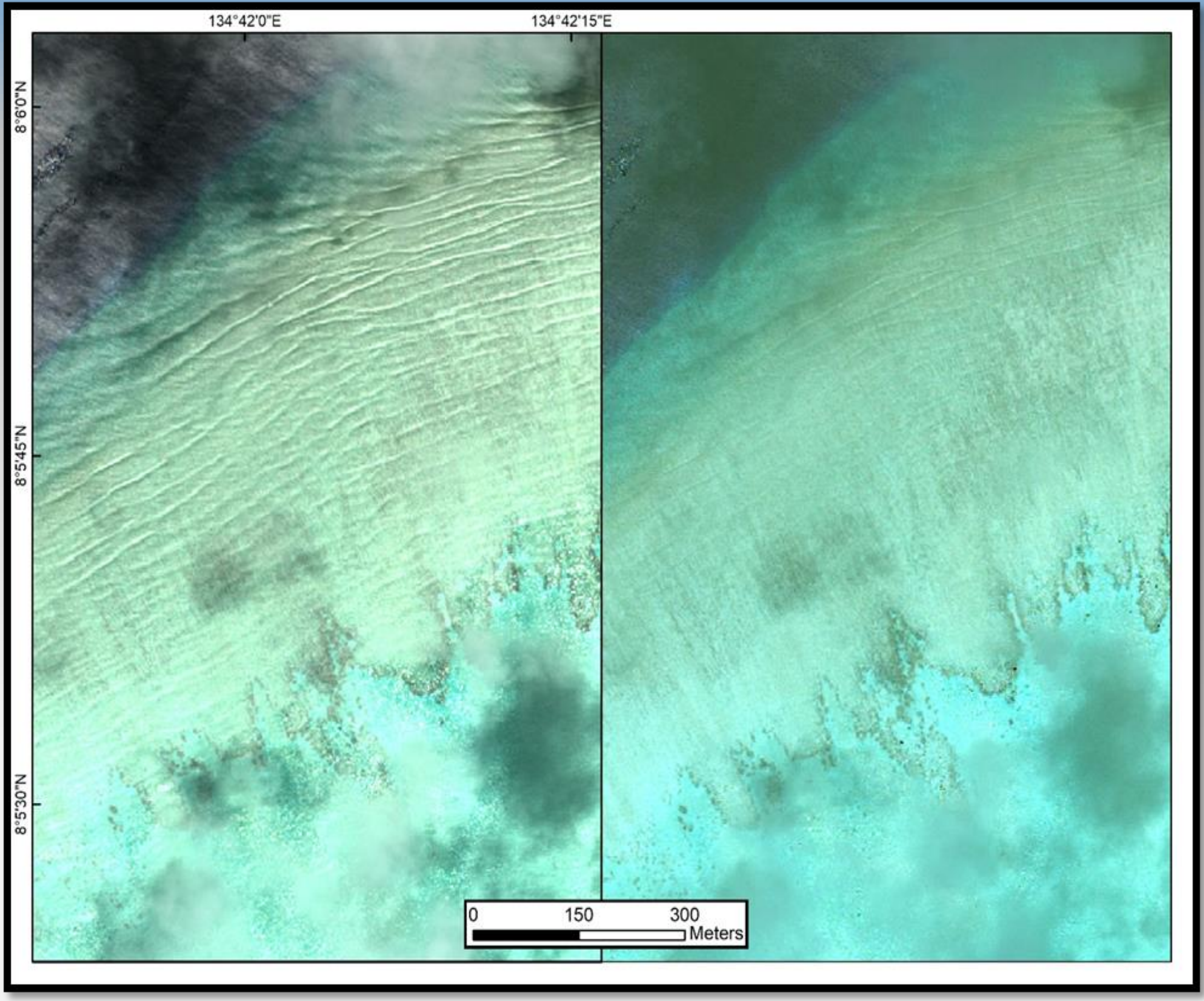
Examples

- Deglinting



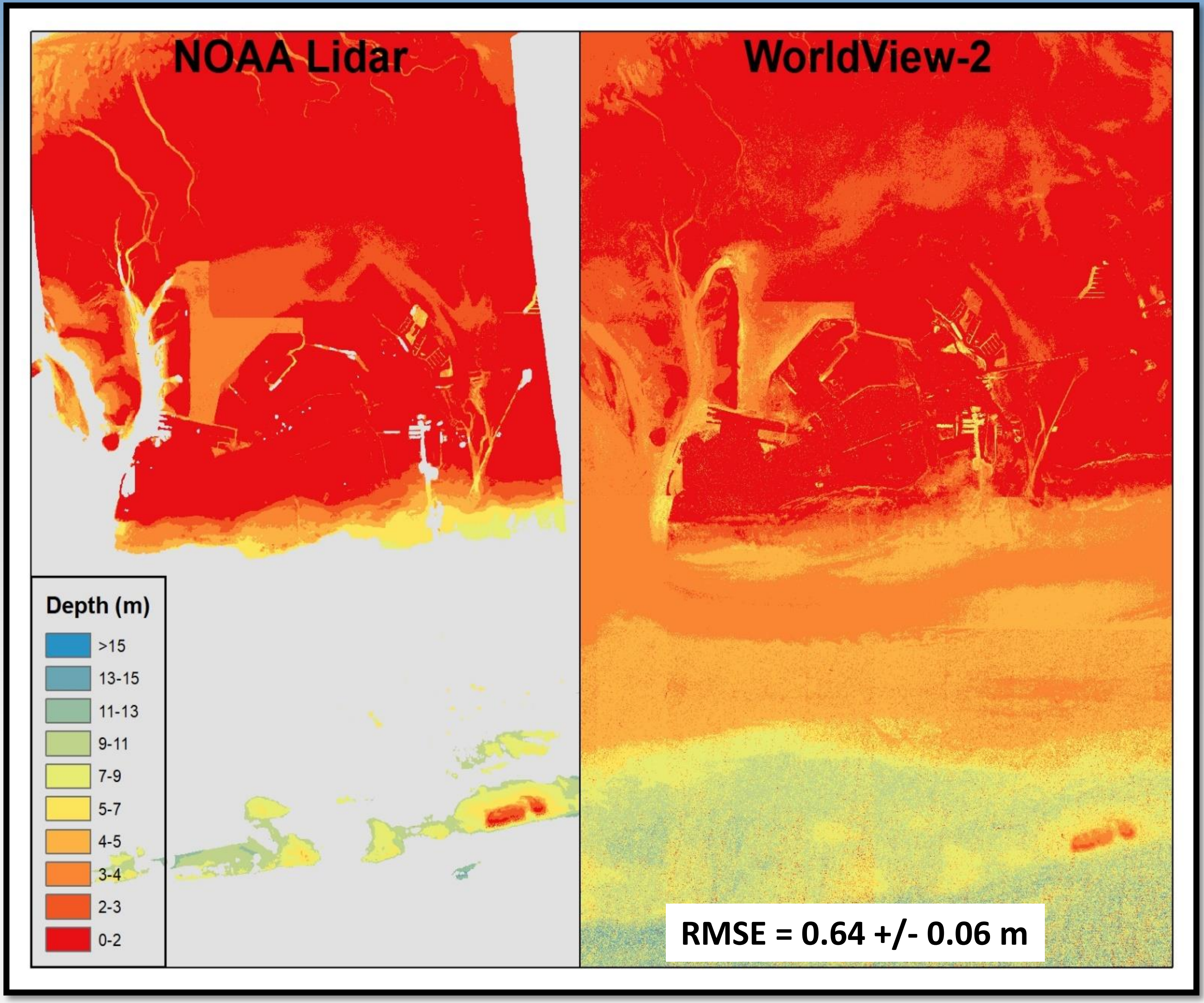
Examples

- **Deglinting**

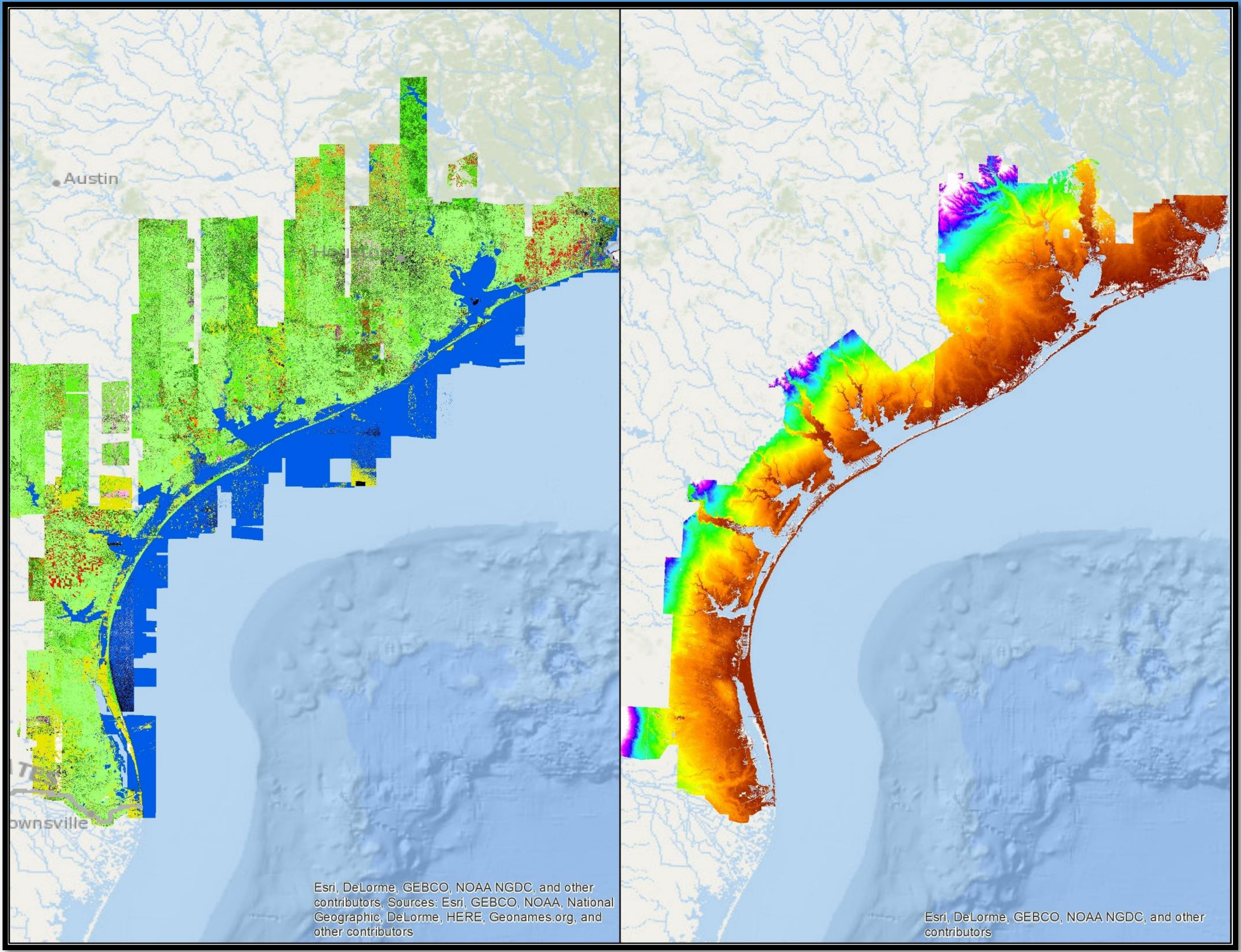


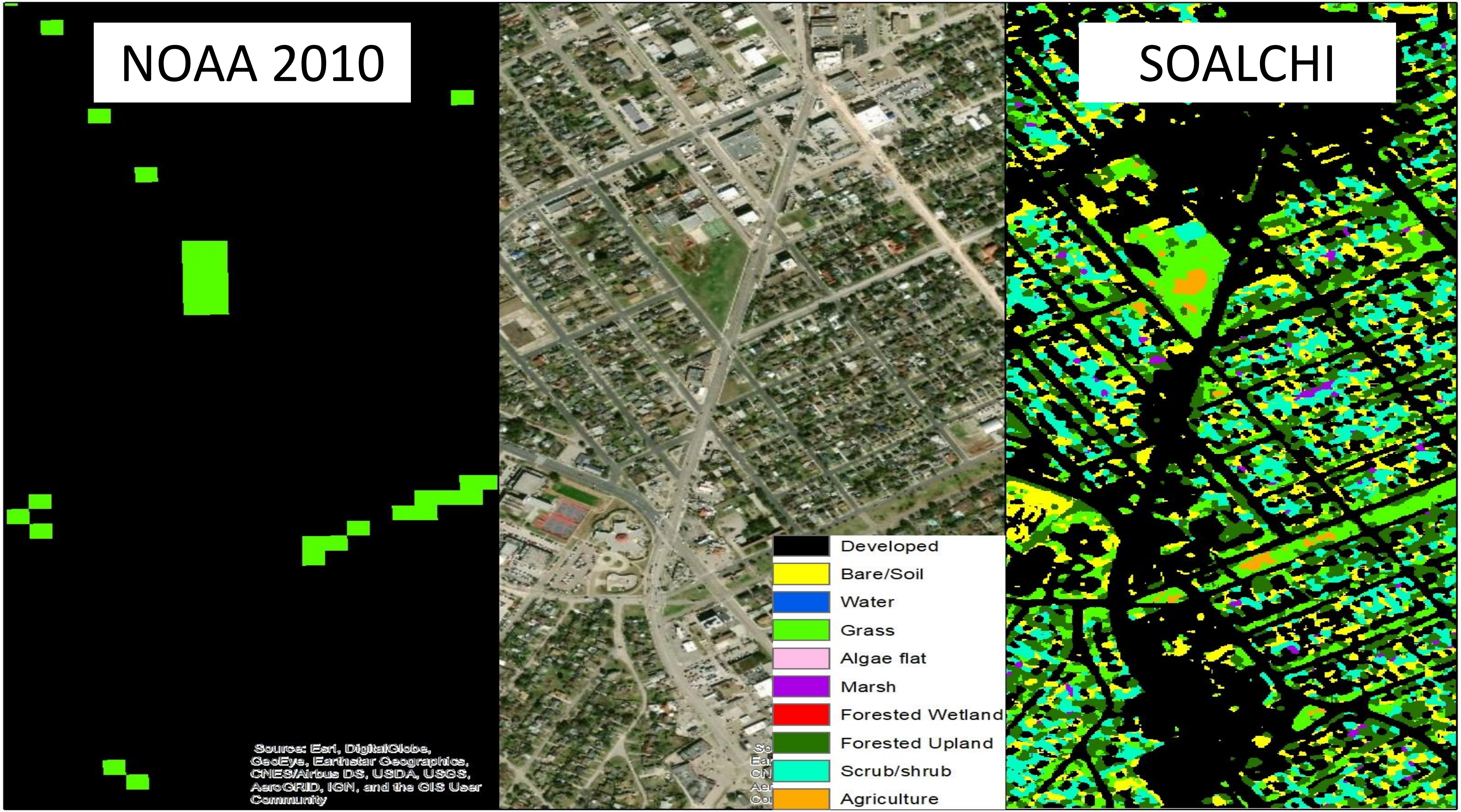
Examples

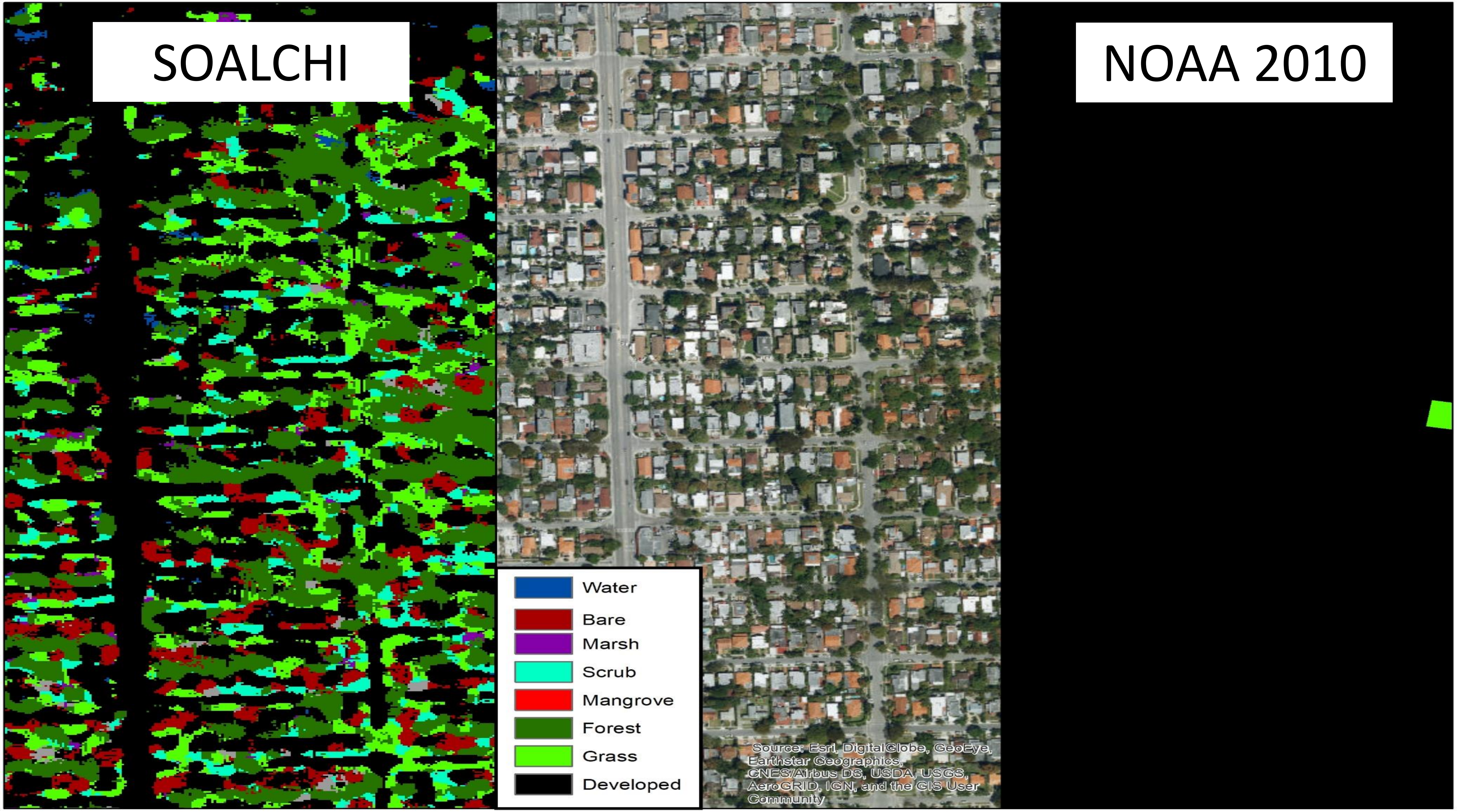
- **Bathymetry mapping**
  - **Key West**

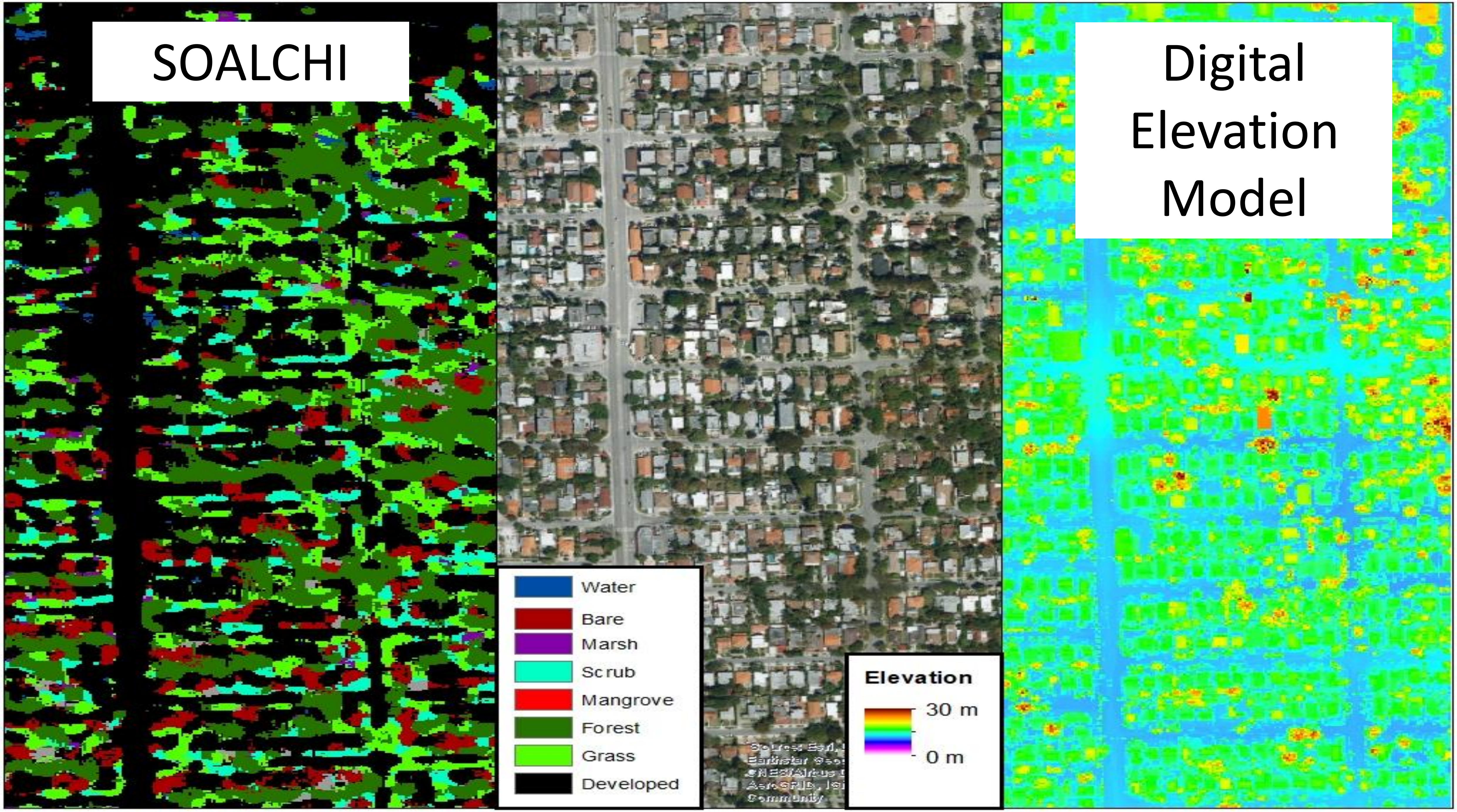


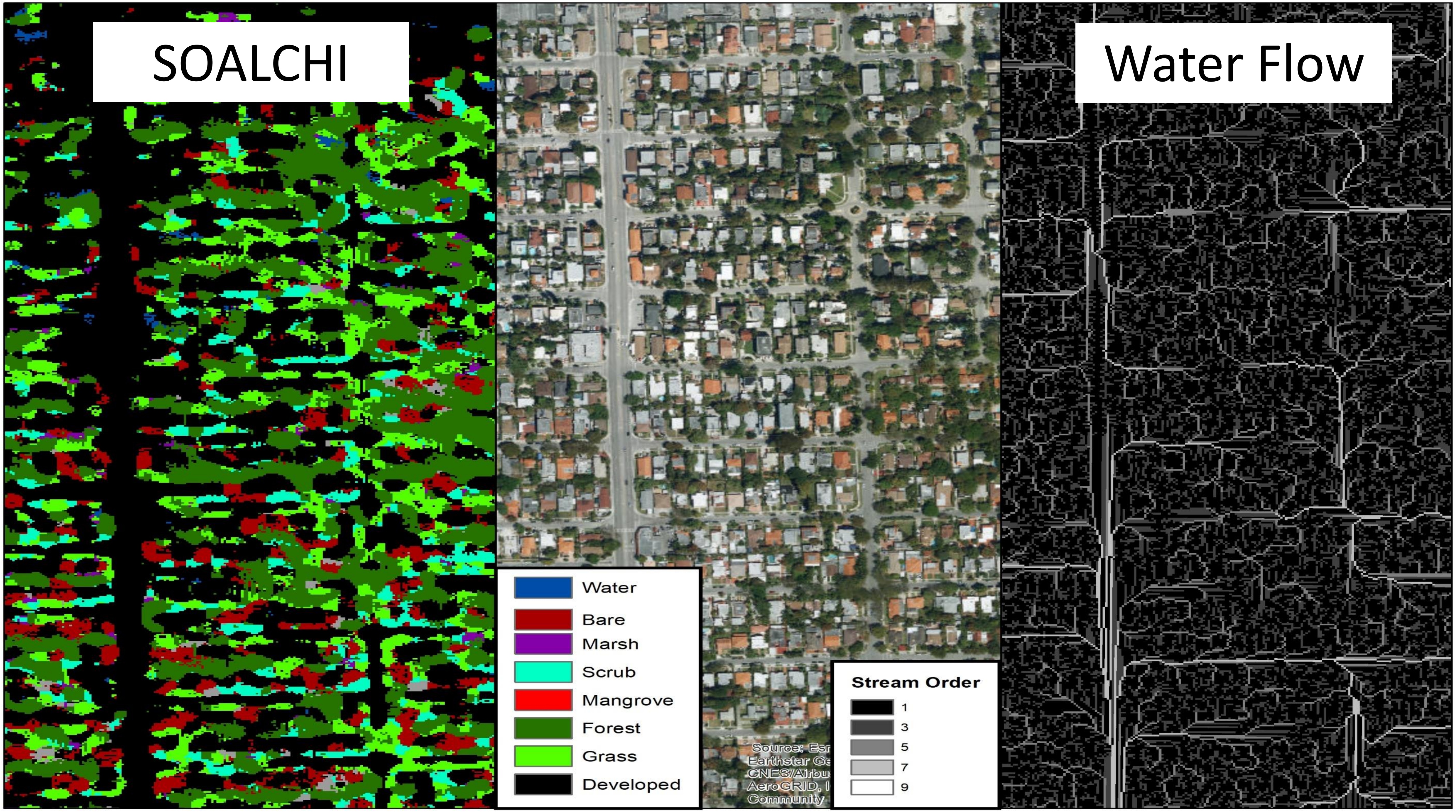
Results: Texas




NOAA 2010
SOALCHI
Developed
Bare/Soil
Water
Grass
Algae flat
Marsh
Forested Wetland
Forested Upland
Scrub/shrub
Agriculture
Source: Esri, DigitalGlobe, GeoEye, Earthstar Geographics, CNES/Airbus DS, USDA, USGS, AeroGRID, IGN, and the GIS User Community


SOALCHI
NOAA 2010
Water
Bare
Marsh
Scrub
Mangrove
Forest
Grass
Developed
Source: Esri, DigitalGlobe, GeoEye, Earthstar Geographics, CNES/Airbus DS, USDA, USGS, AeroGRID, IGN, and the GIS User Community

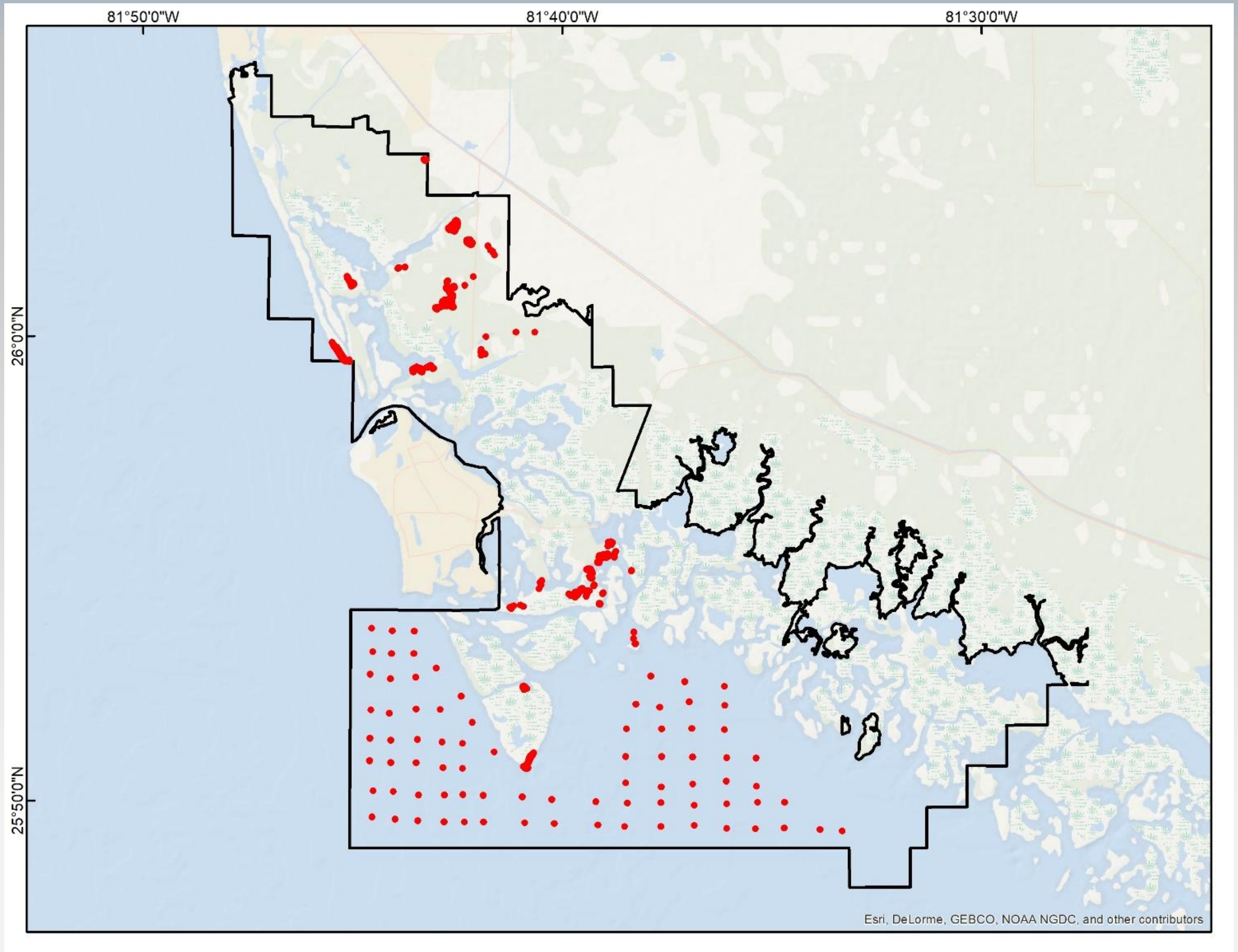

SOALCHI
Digital Elevation Model
Water
Bare
Marsh
Scrub
Mangrove
Forest
Grass
Developed
Elevation
30 m
0 m


SOALCHI
Water Flow
Water
Bare
Marsh
Scrub
Mangrove
Forest
Grass
Developed
Stream Order
1
3
5
7
9

Applications

- Sustainable Development
- Flood Hazards
  - Land cover + topography + SfM
- Machine Learning
  - Large training dataset

SOALCHI Method Validation



Purpose

- Map hurricane damage
- Compare pros and cons

Algorithms

- SOALCHI
- Support Vector Machine
- Neural Network

Data

- WorldView-2 (Nov 2018)

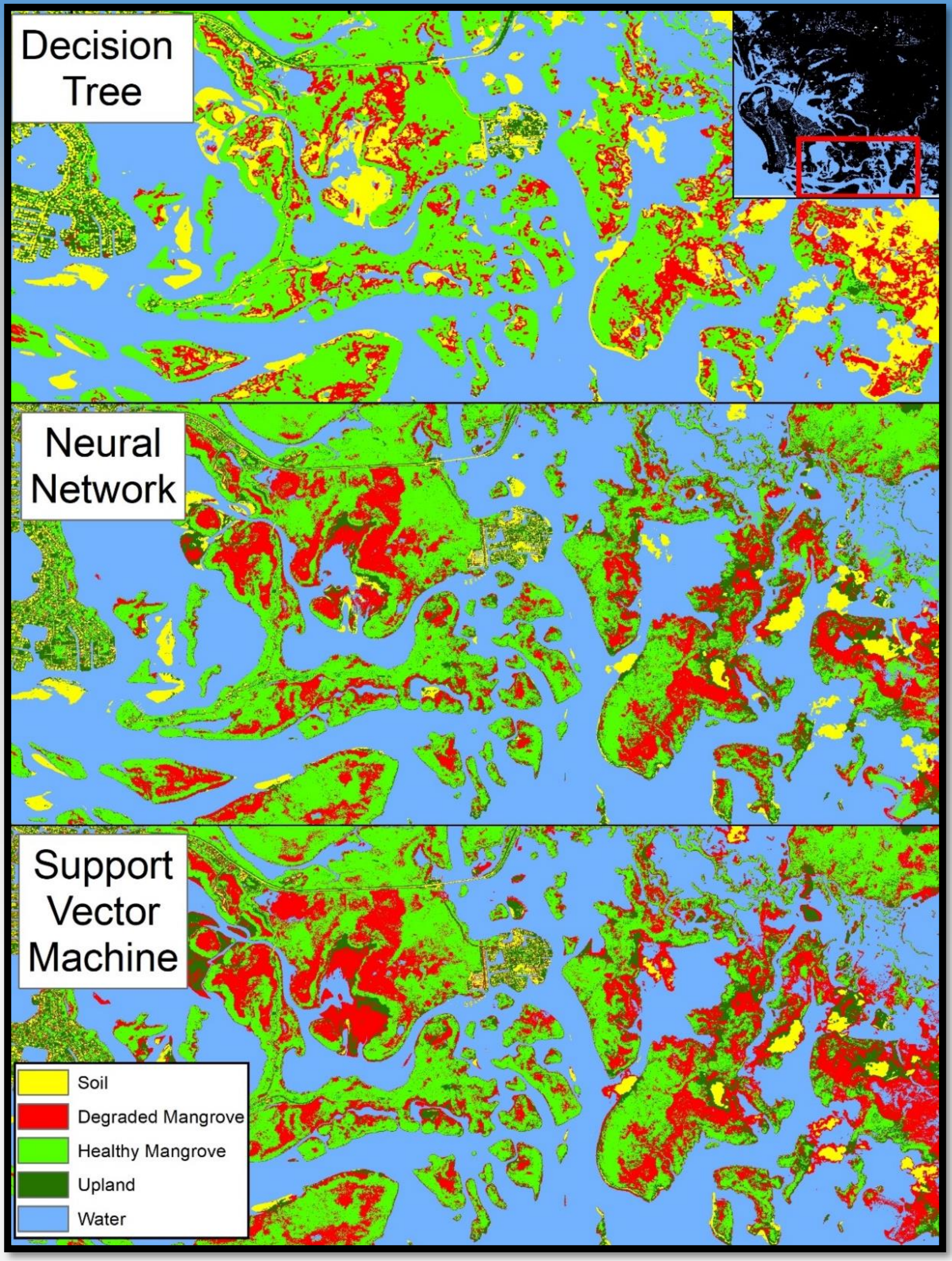
Training & Validation

- 714 field survey points

McCarthy et al. (2020) *International Journal of Applied Earth Observations and Geoinformation*

Results

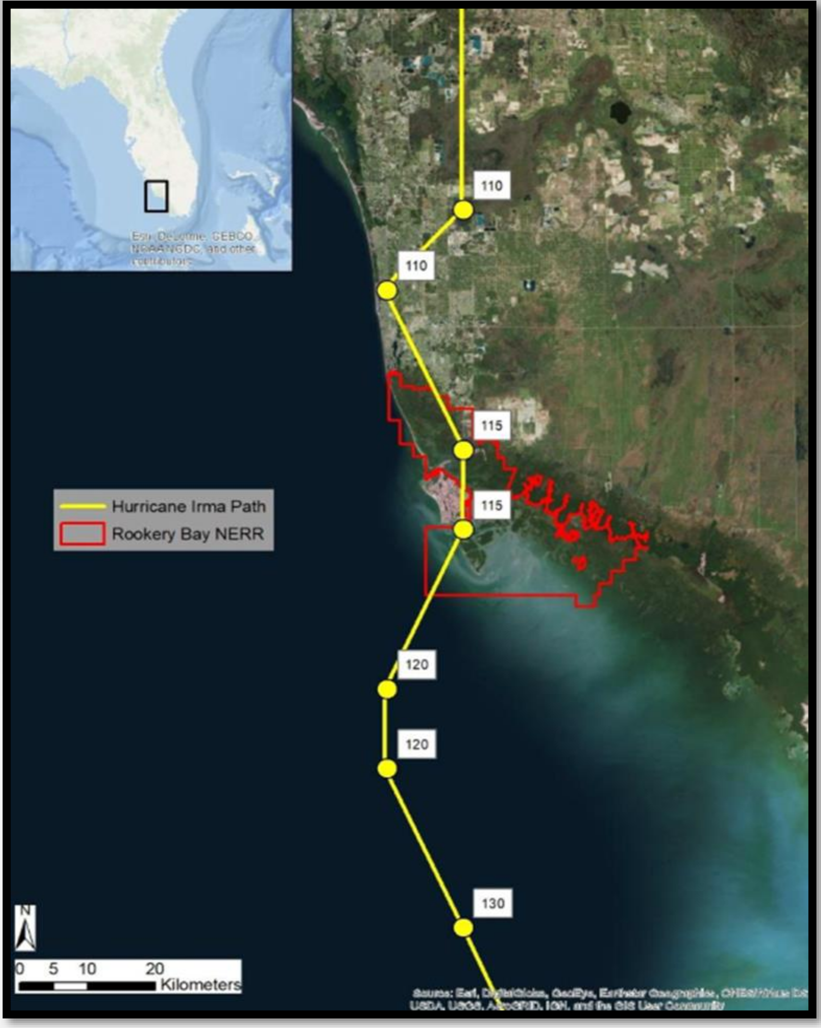
<u>Producer's Accuracy</u>	Decision Tree	Support Vector Machine	Neural Network
Soil	97%	92%	92%
Damaged Mangrove	38%	62%	57%
Healthy Mangrove	63%	69%	75%
Upland Vegetation	91%	86%	88%
Water	100%	100%	100%
Overall Accuracy (Kappa)	**83% (0.765)**	**83% (0.767)**	**85% (0.792)**



Conclusions

	Pros	Cons
Decision Tree	Fastest Automated Best Upland vs Mangrove accuracy	Least accurate damaged mangrove
Support Vector Machine	Most accurate damaged mangrove	Manual training Slowest
Neural Network	Most accurate overall Most accurate healthy mangrove	Manual training

Natural-disaster monitoring



Objective: Hurricane-damage assessment

Background

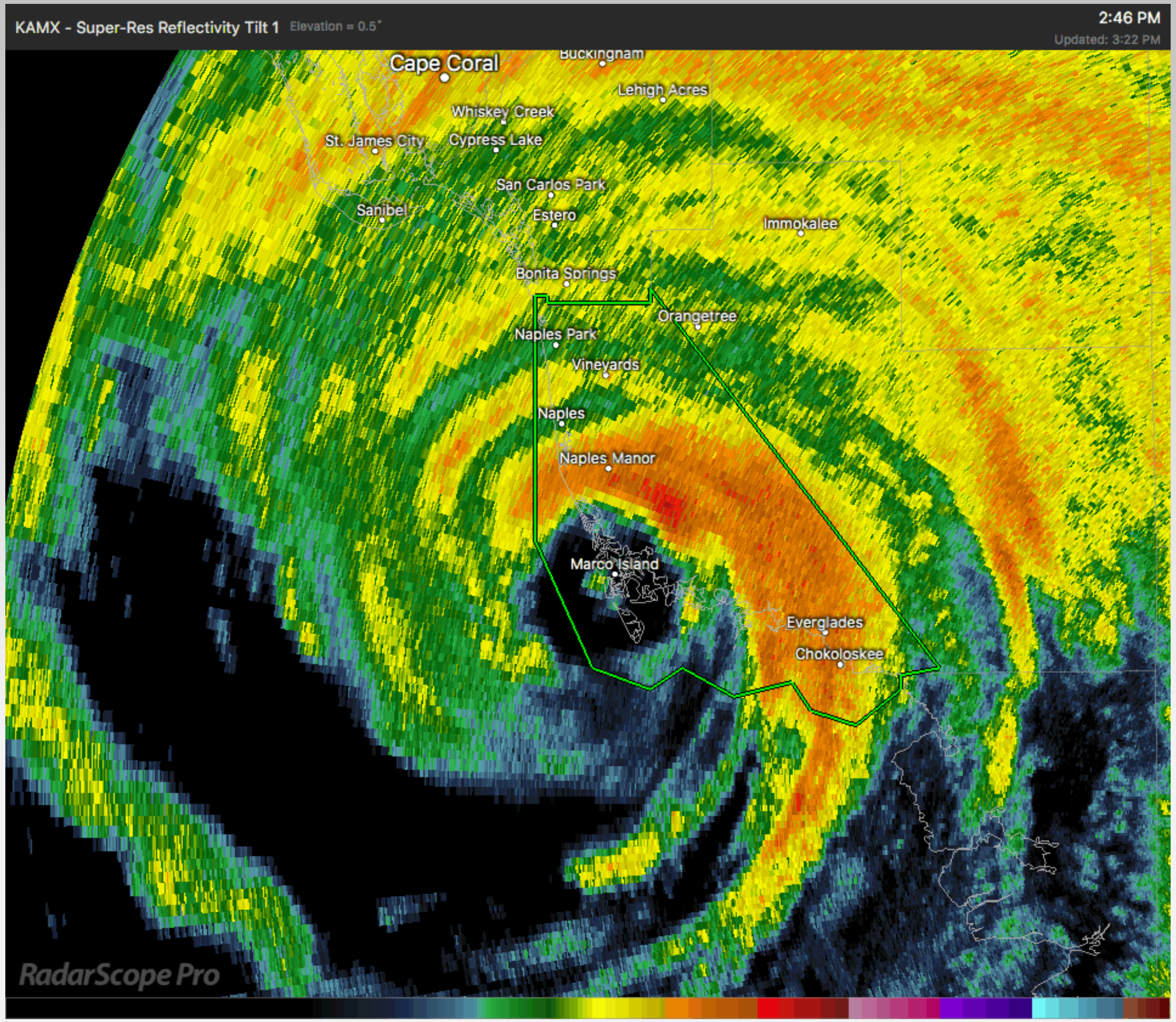
Hurricane Irma September 2017

Category 3: 120 mph winds

Mangrove damage

- Damaged vs undamaged
- Dead vs recovered

Existing map: 2010 (2 years to create)



Management Need

- Identify location, extent, and timeframe of coastal wetland degradation
  - Determine chronic vs acute drivers
  - Help managers determine how to mitigate loss, understand recovery, and improve resiliency

Project Goals

1. Map land and aquatic habitats for years 2010, 2013, 2016, 2017, 2018
2. Detect change location and extent
3. Attribute changes
4. Share information with regional resource managers through facilitated meetings and mapping products

Data

- High-resolution WorldView-2 satellite imagery
- Medium-resolution Landsat satellite imagery
- LiDAR data: 2007
- Field surveys (M. Barry)

Methodology

WorldView-2&3
91 images

Spectral and
Object-based
Automated
Land cover
Classification of
High-resolution
Imagery

Python code

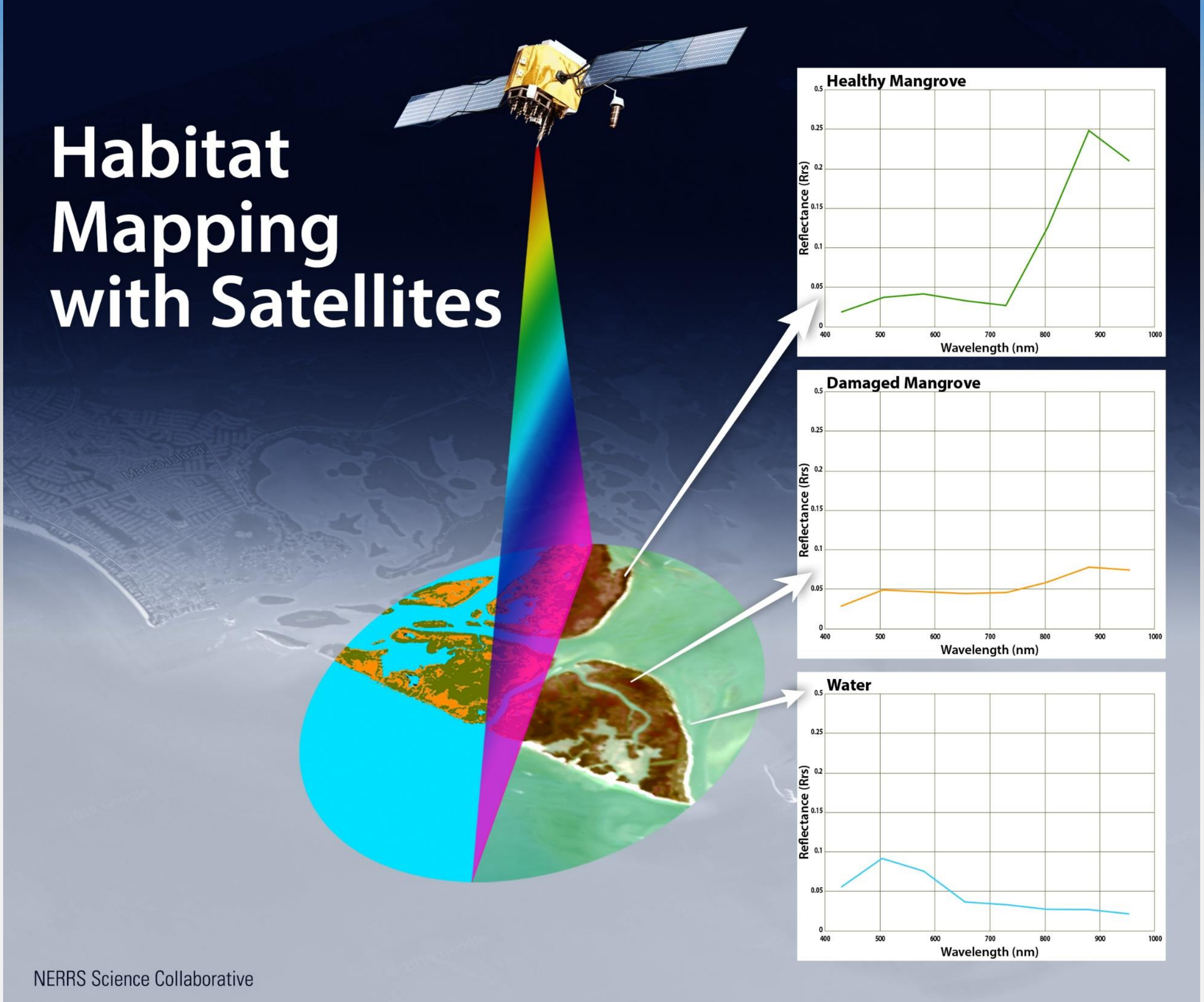
Matlab code

USF CIRCE Cluster:
419 nodes
9152 cores
46TB memory
222 GPUs

GDAL Mosaic

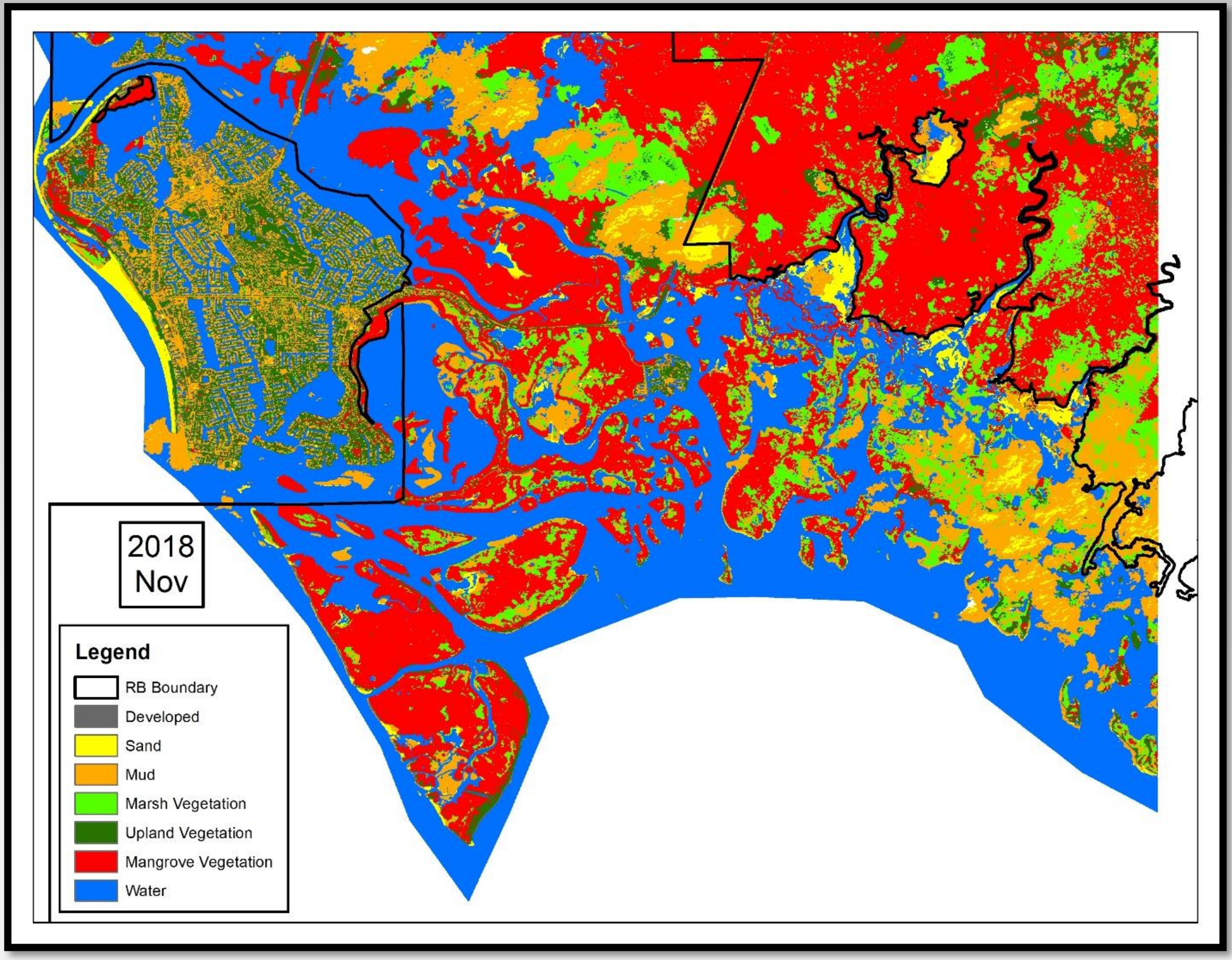
Classified Map

Existing Map: 2 years
SOALCHI: 4 hours


Habitat Mapping with Satellites
Healthy Mangrove
Reflectance (Rrs)
0.5
0.25
0.2
0.15
0.1
0.05
0
400
500
600
700
800
900
1000
Wavelength (nm)
Damaged Mangrove
Reflectance (Rrs)
0.5
0.25
0.2
0.15
0.1
0.05
0
400
500
600
700
800
900
1000
Wavelength (nm)
Water
Reflectance (Rrs)
0.5
0.25
0.2
0.15
0.1
0.05
0
400
500
600
700
800
900
1000
Wavelength (nm)
NERRS Science Collaborative

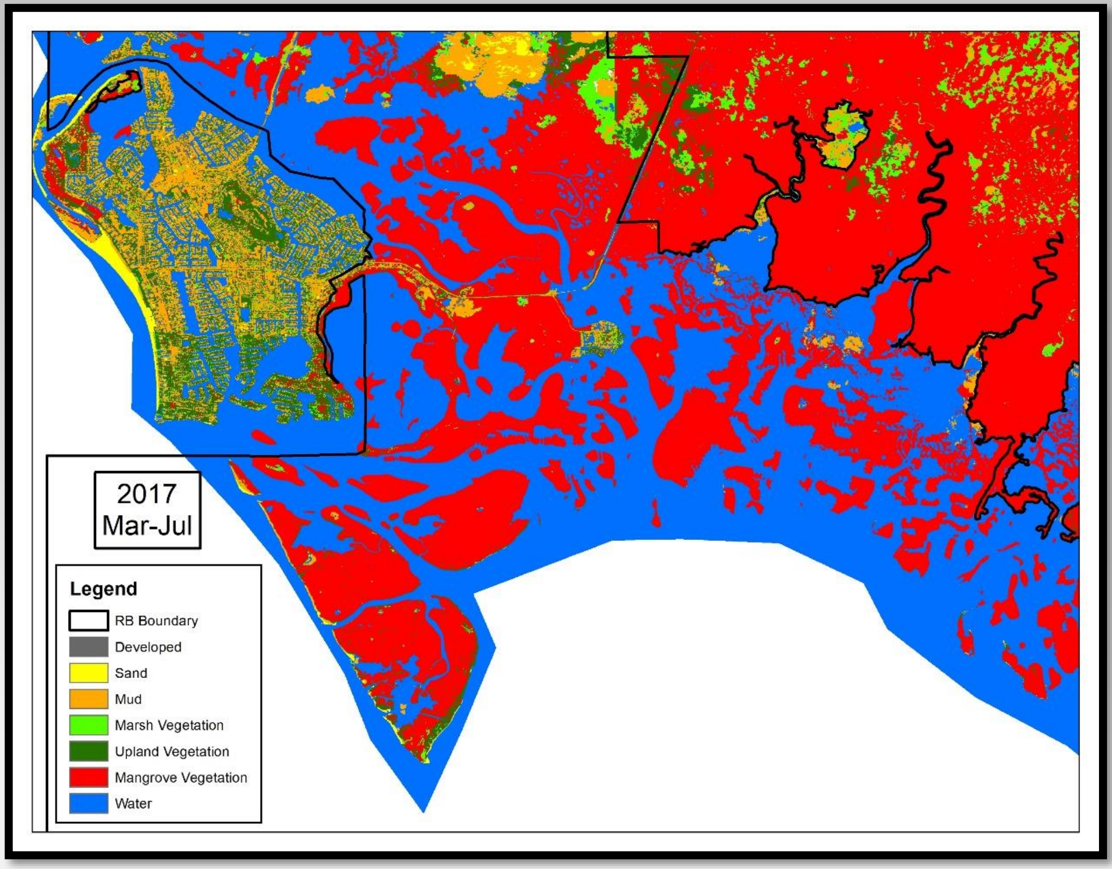
Accuracy Assessment: Worldview Nov 2018

- Soil: 95%
- Degraded mangrove: 56%
- Healthy mangrove: 78%
- Upland: 68%
- Water: 100%
- Overall accuracy: 82%

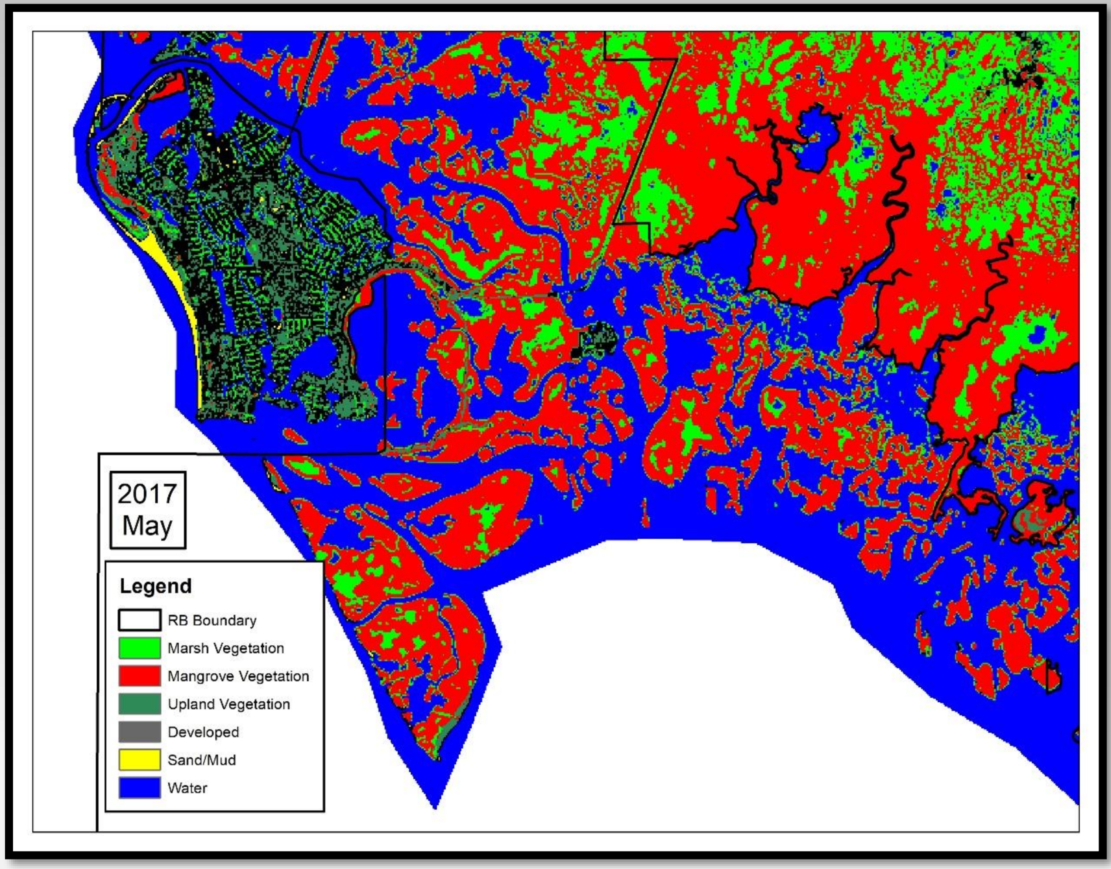


Results

WorldView

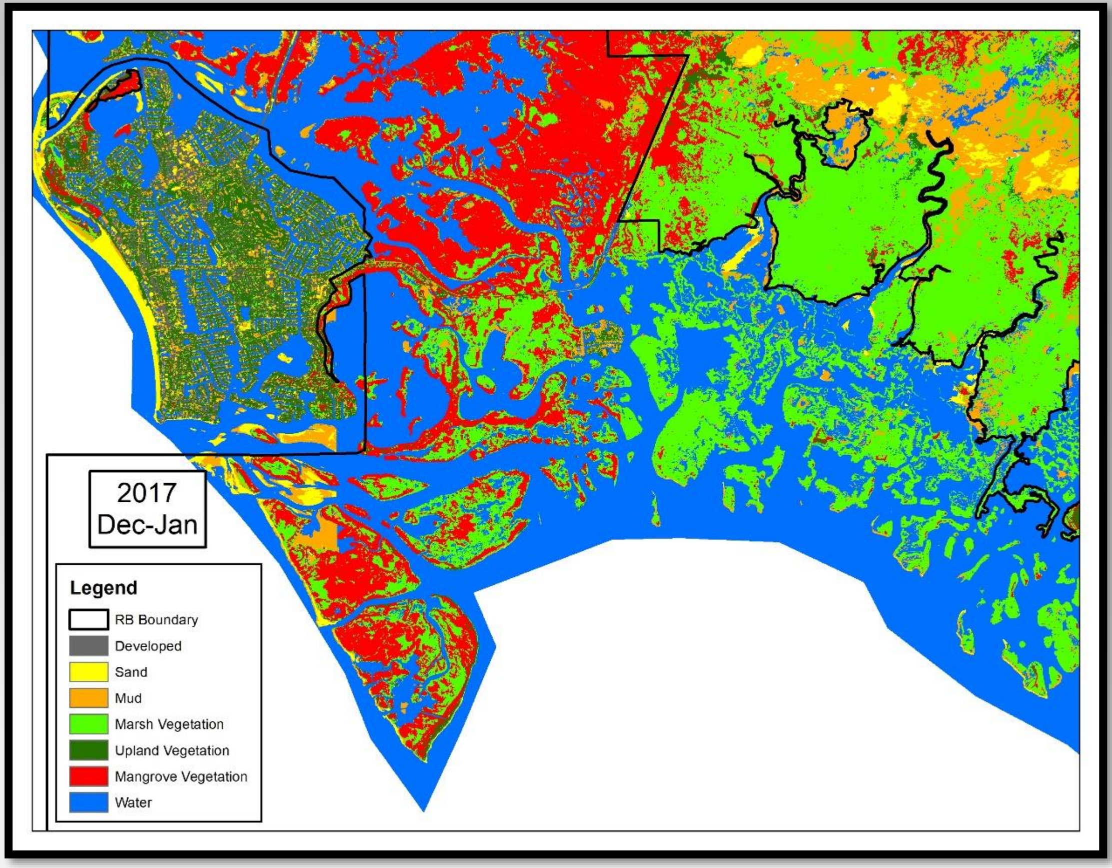


Landsat

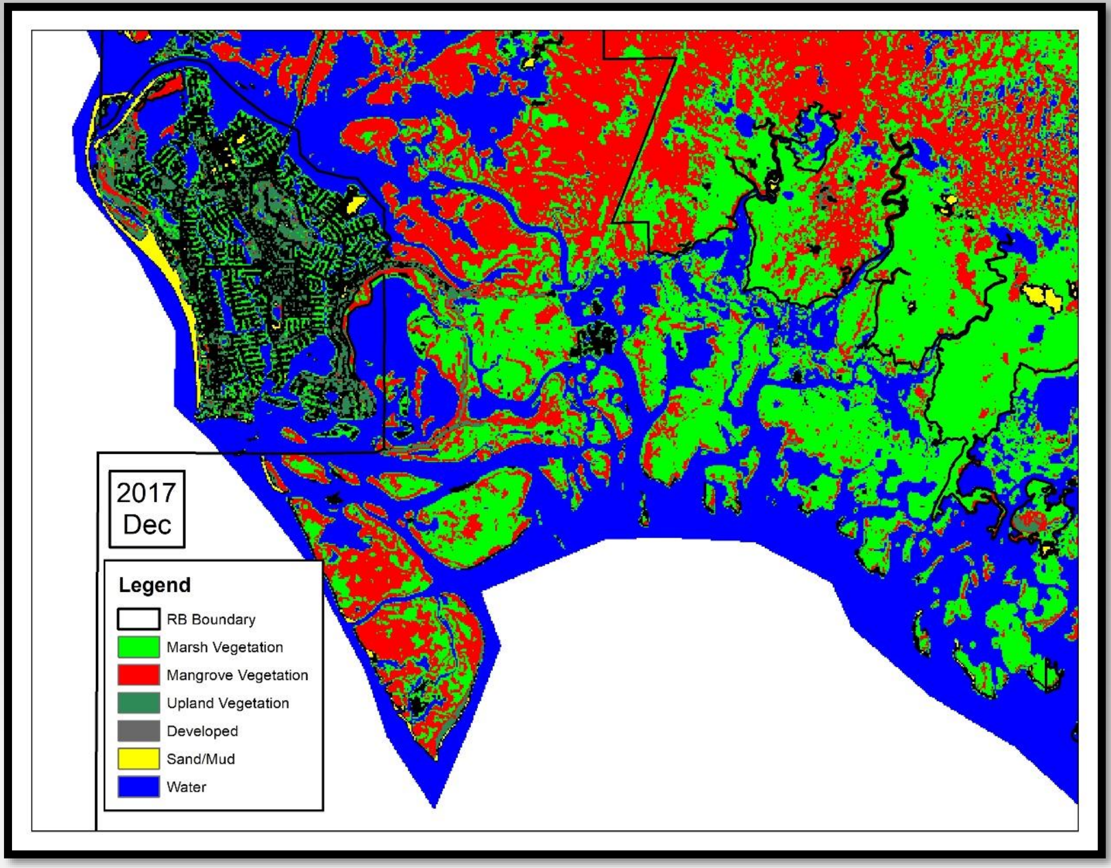


Results

WorldView

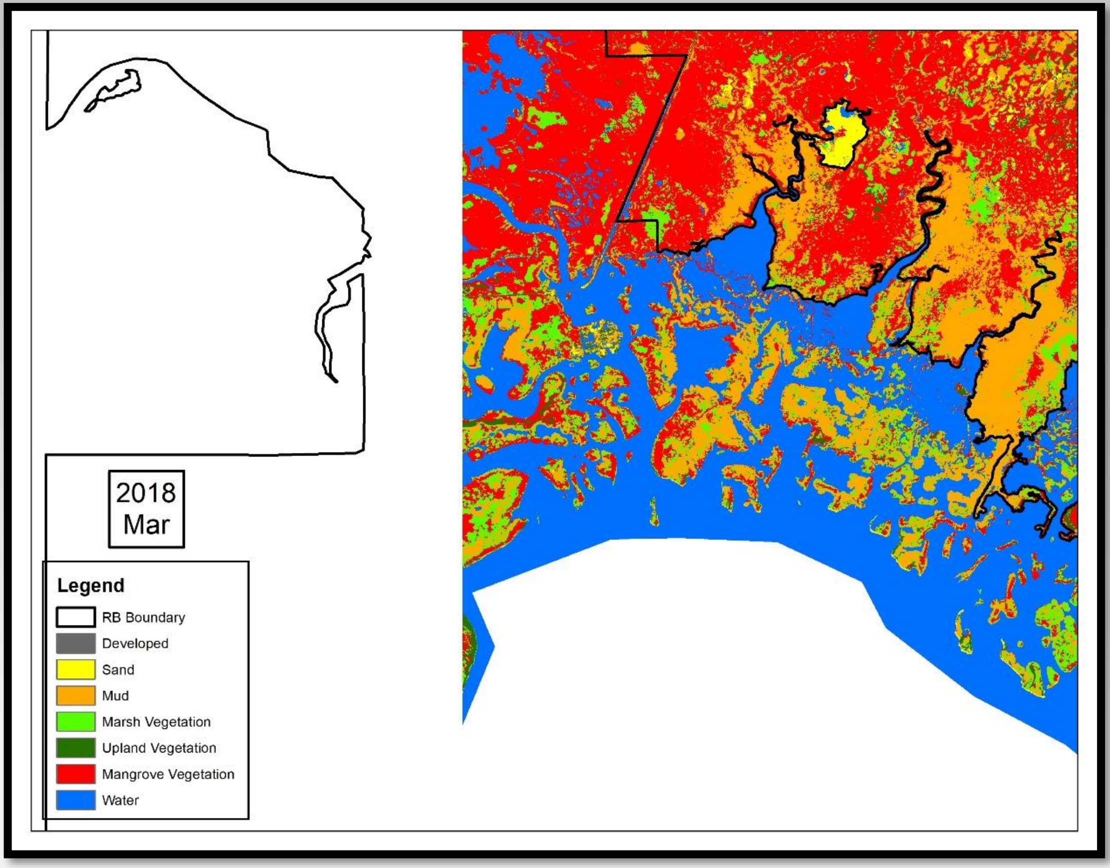


Landsat

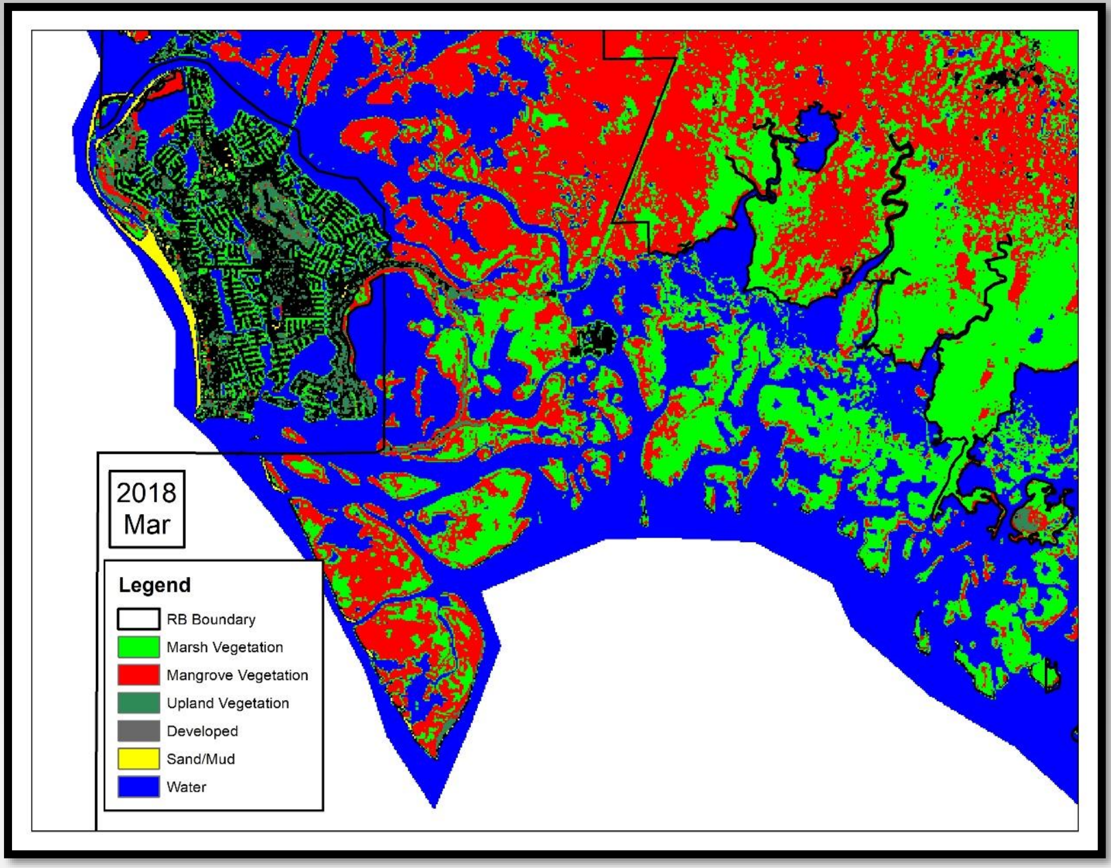


Results

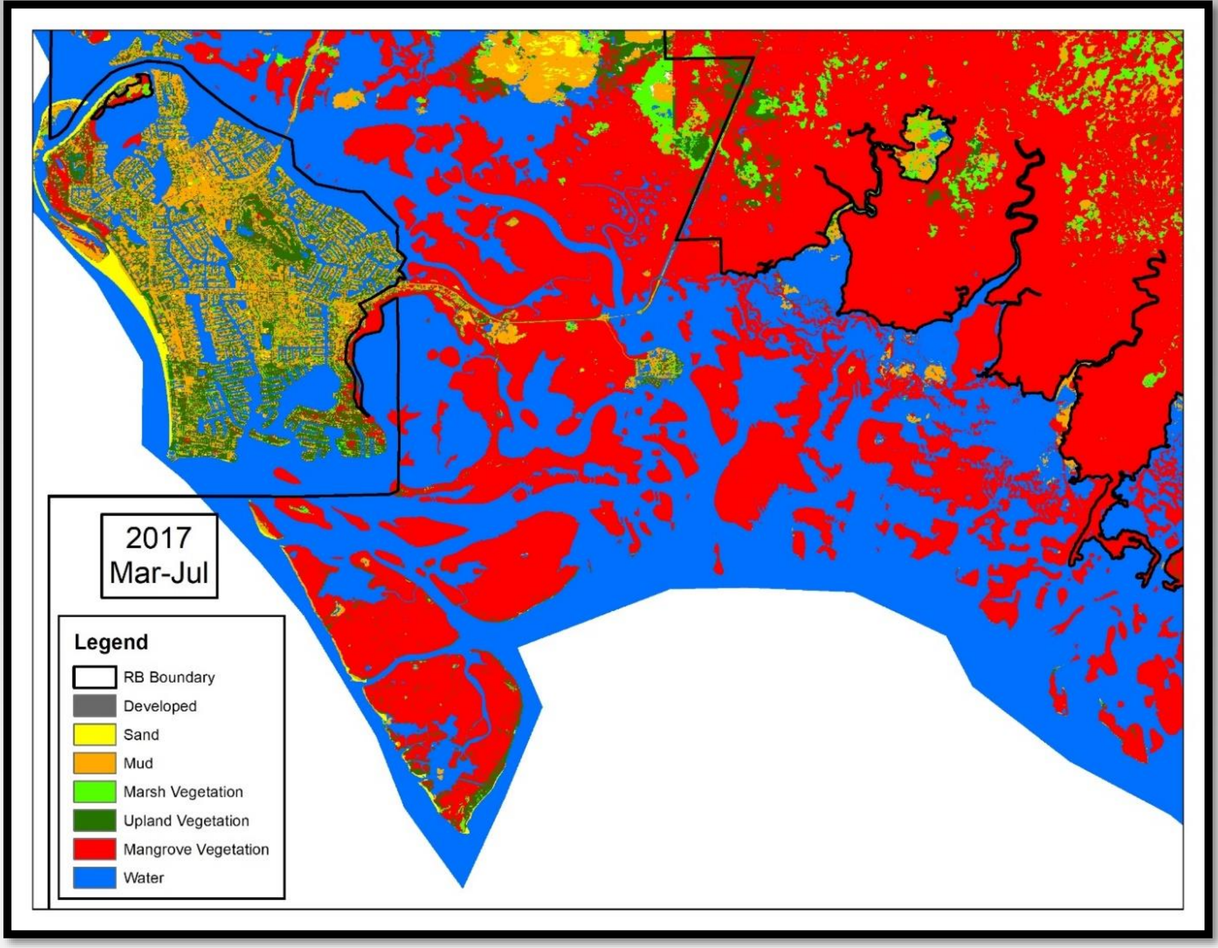
WorldView

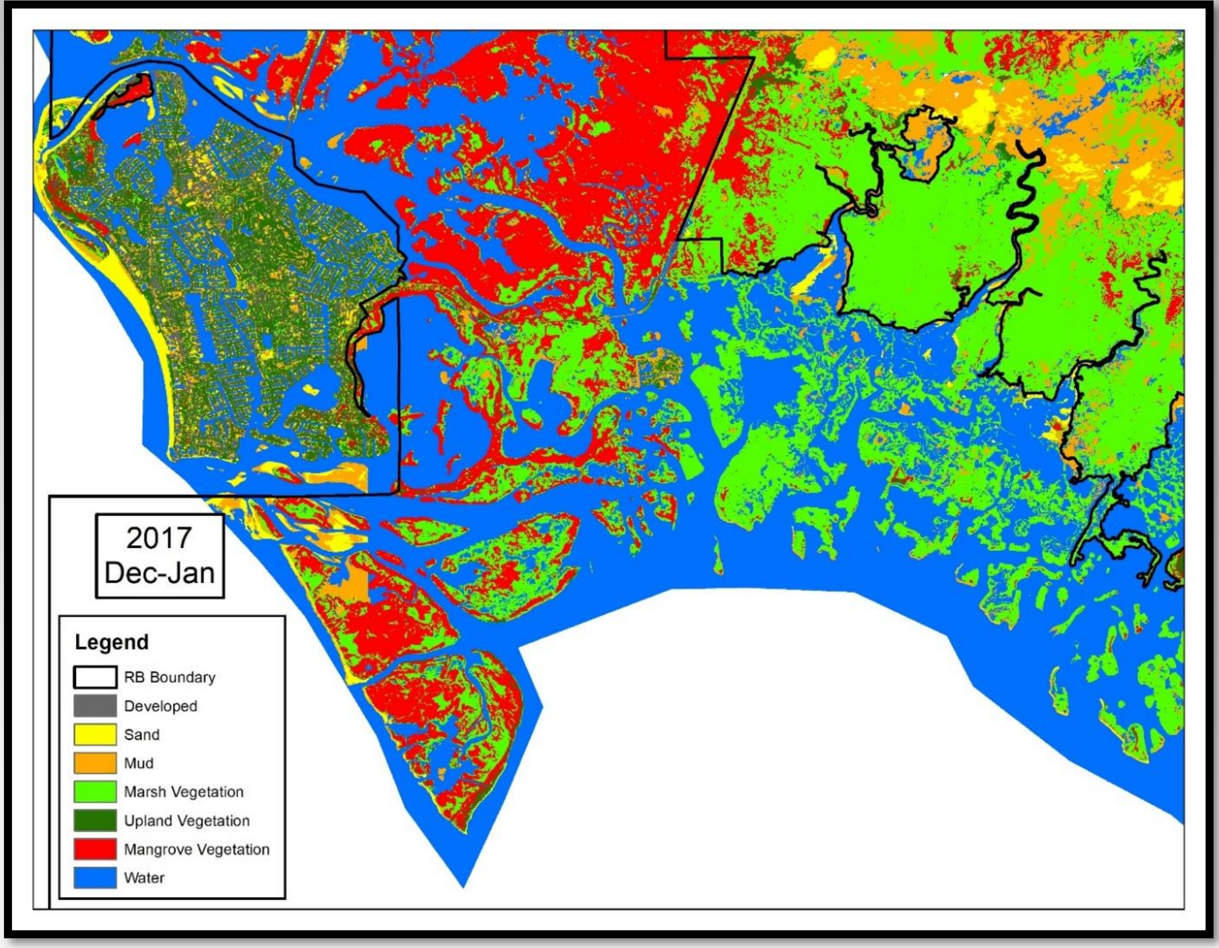


Landsat

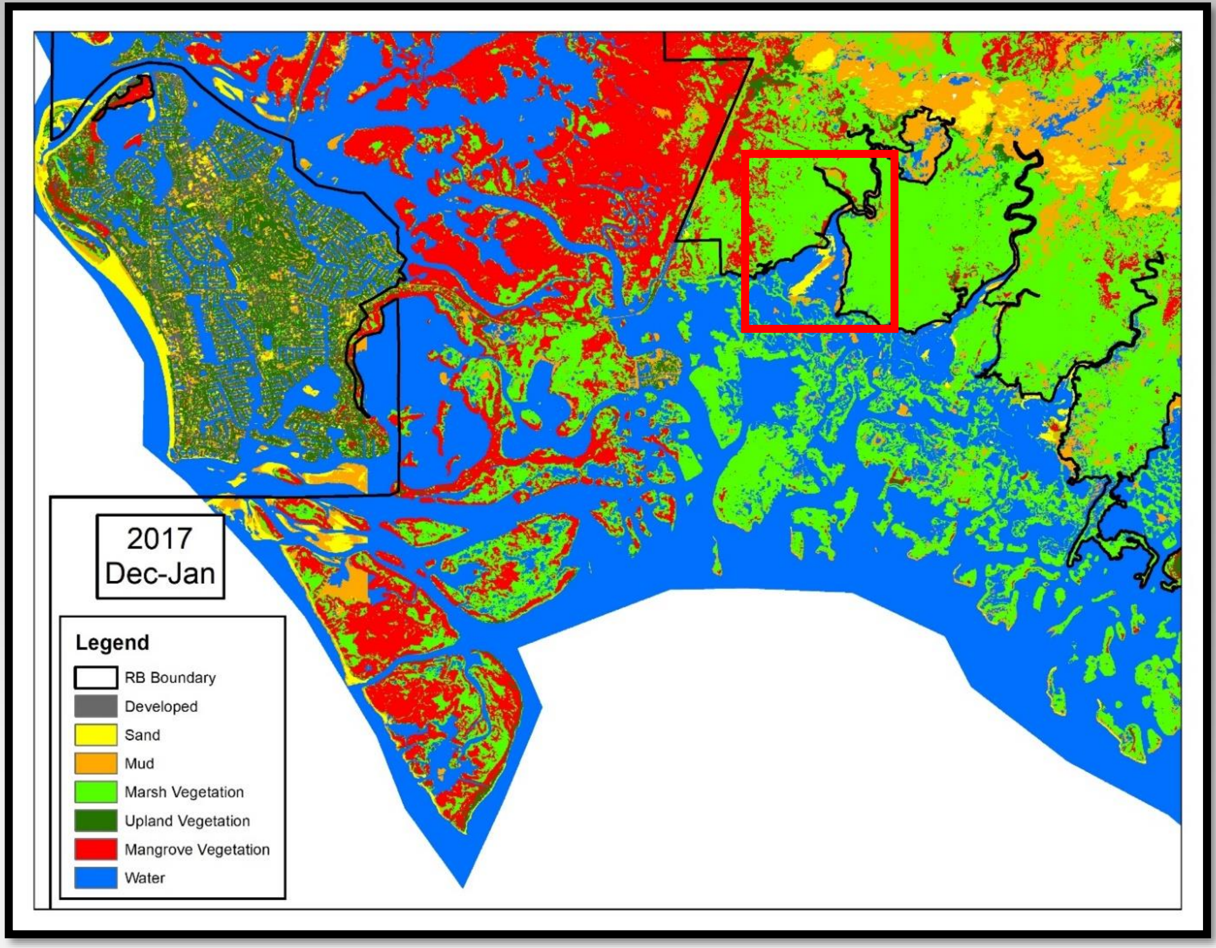


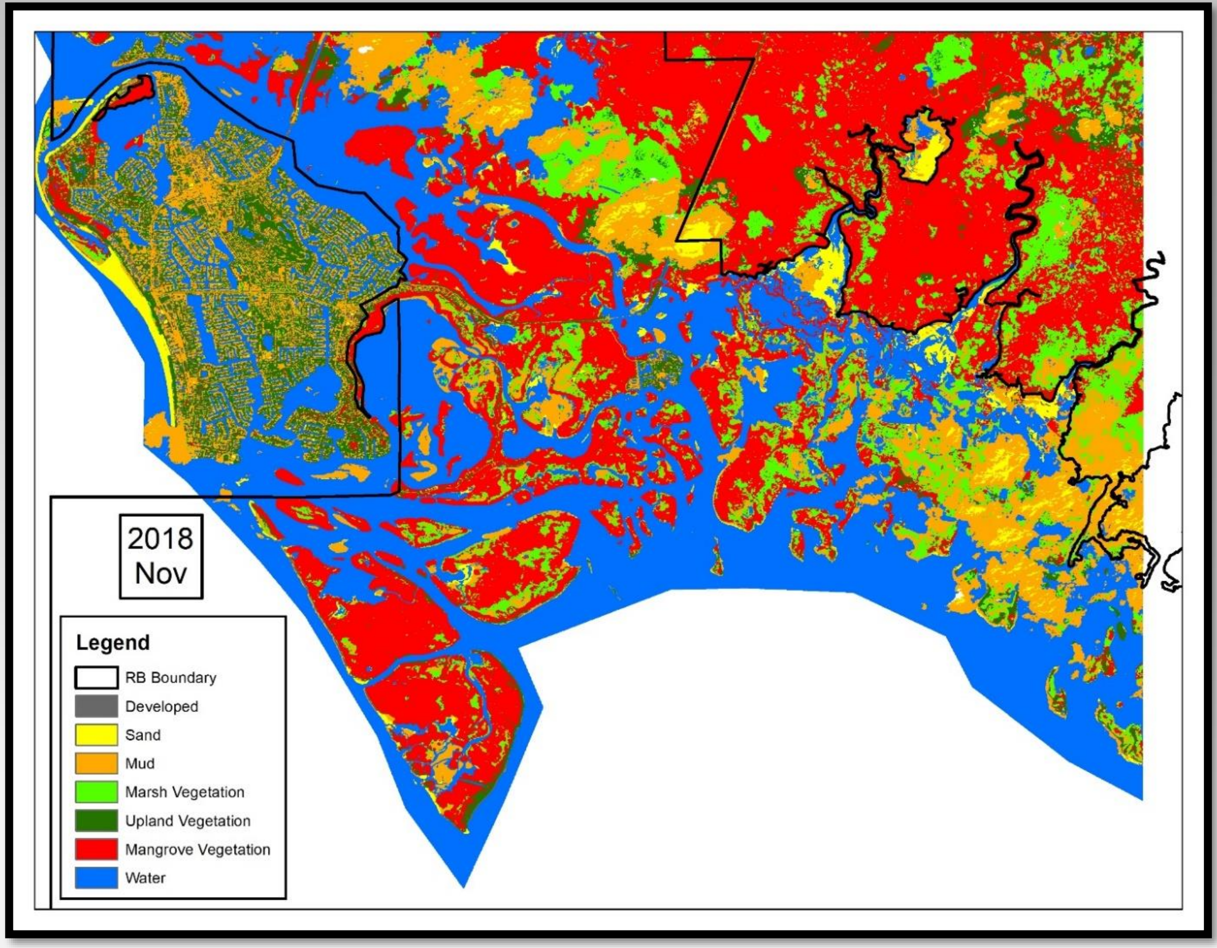
Results: Irma Damage



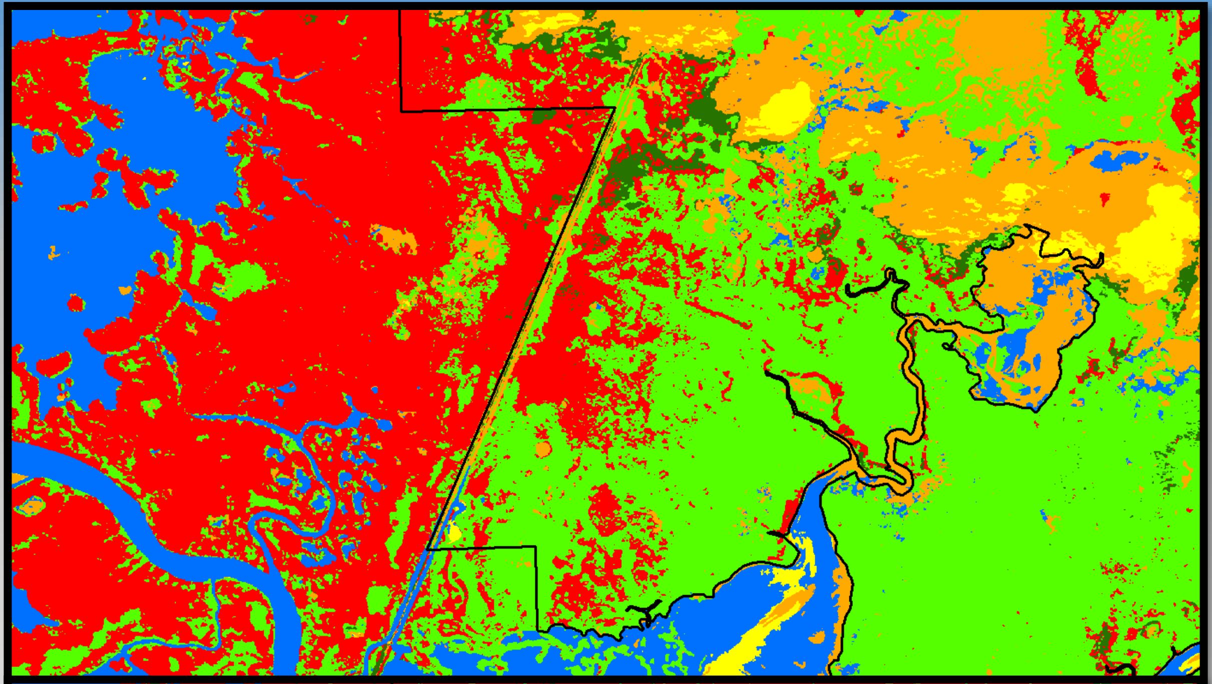


Results: Recovery

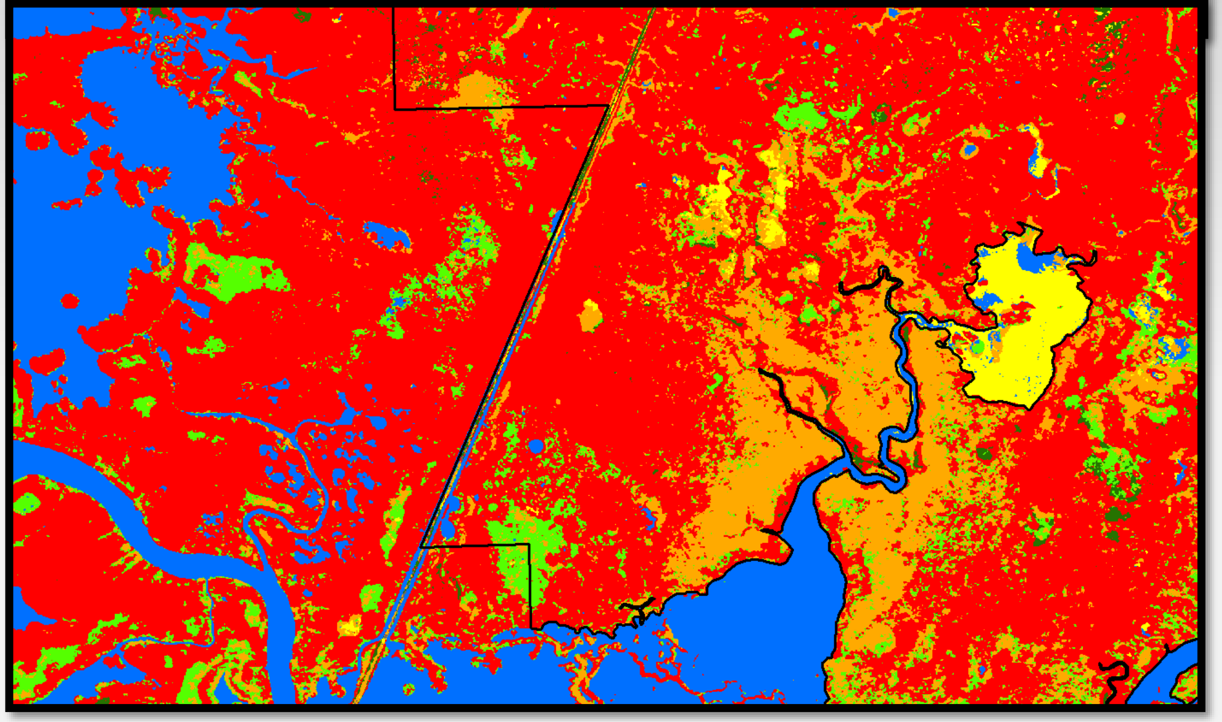




Three months post Irma
(WorldView)



Five months post Irma
(WorldView)



Recovery

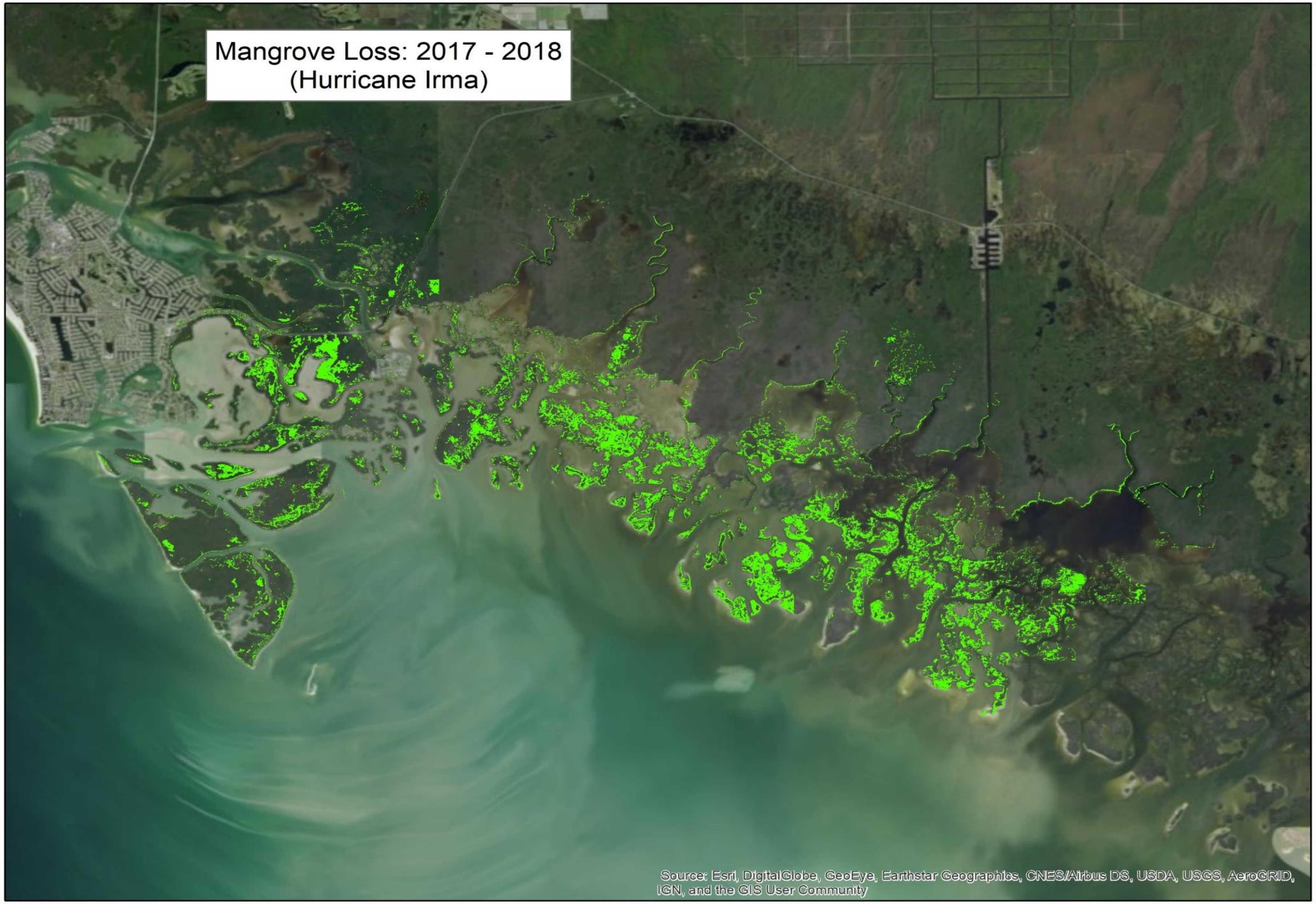
- Some mangrove rebound
- Some mangrove die-off

Net Change:
Pre-Irma to Recovery

Mangrove to Marsh
7.1 km^2
~1,750 acres

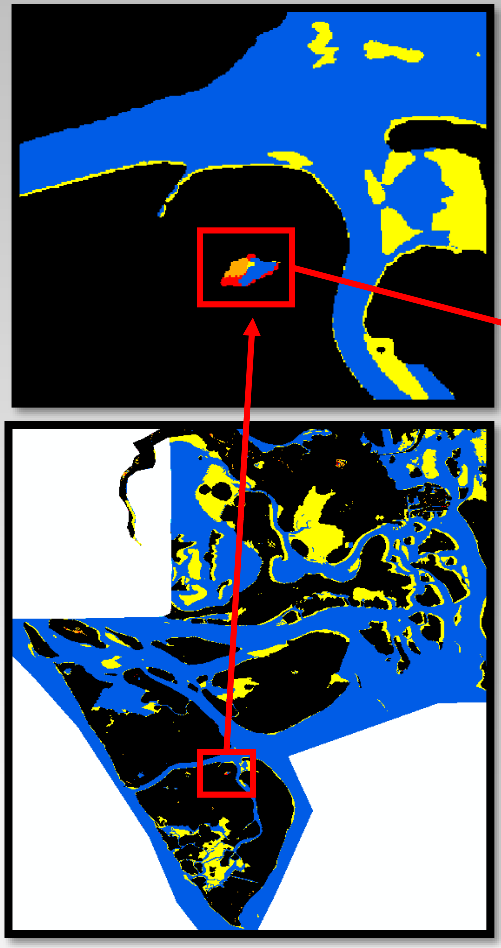
Mangrove to Bare Soil
1.6 km^2
~395 acres

Total Mangrove Decline
10.6 km^2
~2,600 acres



McCarthy et al. (2020) *Remote Sensing*

Mangrove Loss

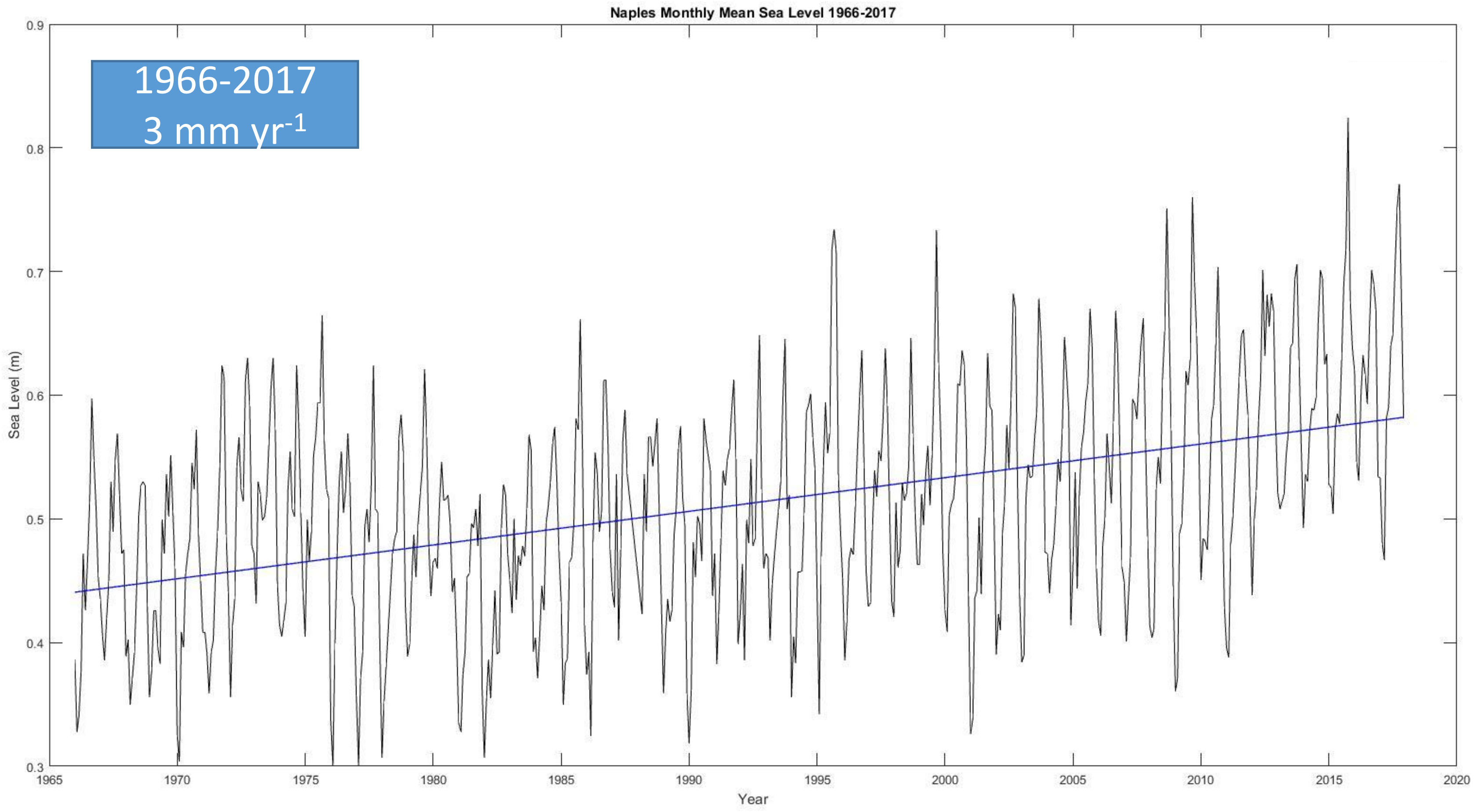


Acute Drivers of Loss

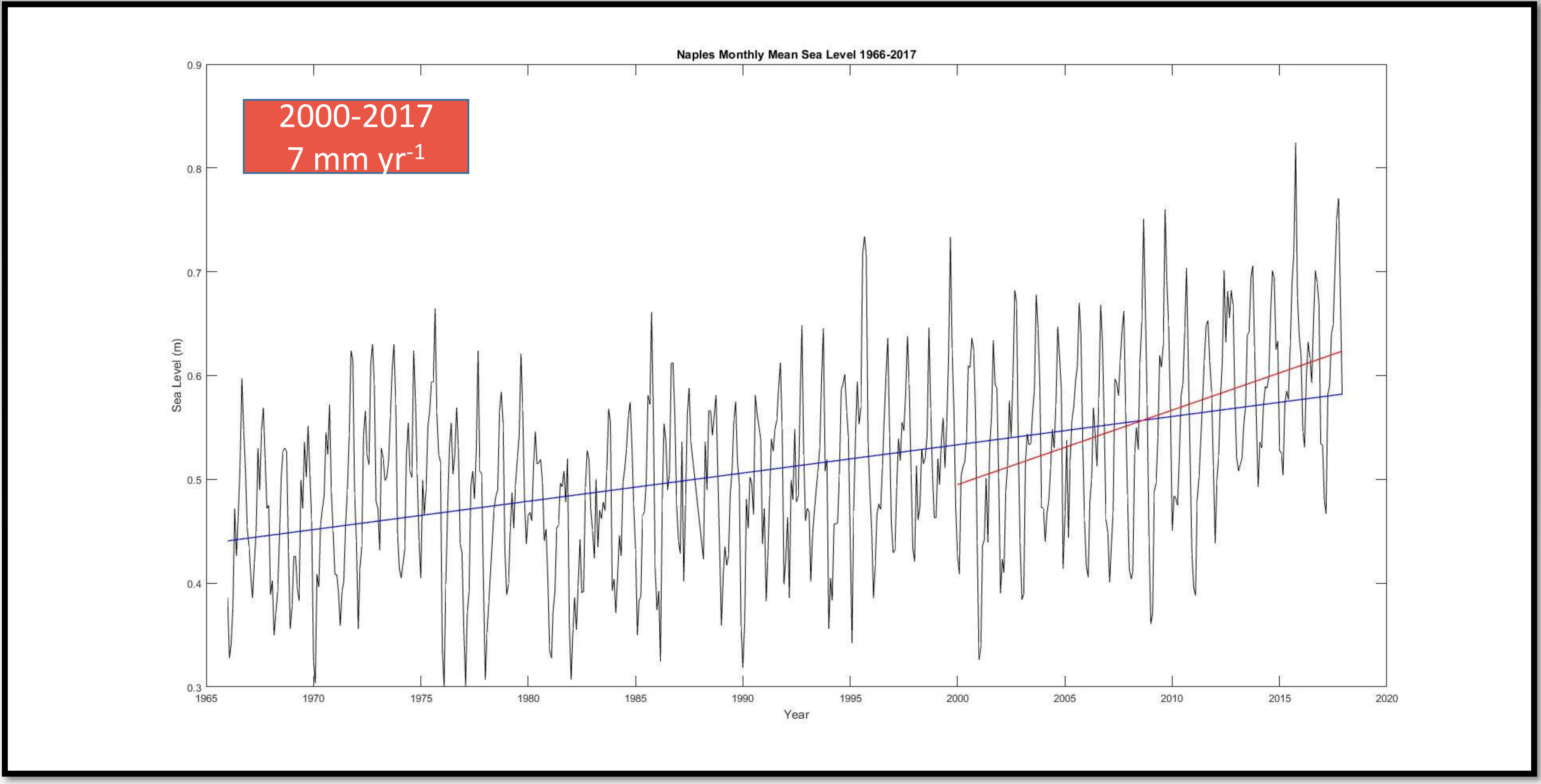
Maerl overwash starving mangroves

- *Radabaugh et al. 2019*
    - 11% mortality 2-3 months post-Irma
    - 20% mortality 9 months post-Irma

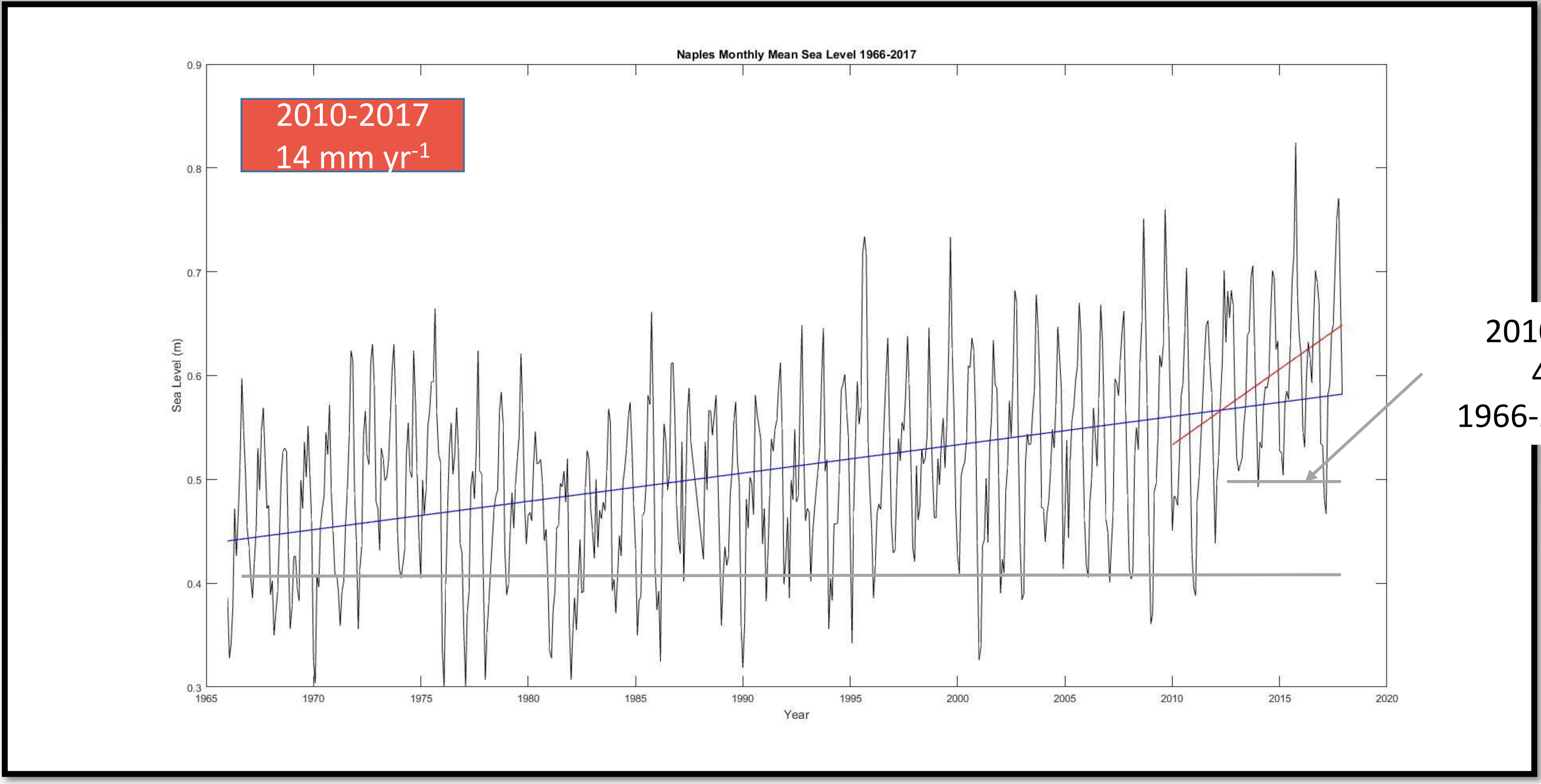
Local Sea Level



Local Sea Level



Local Sea Level



2010-2017
40% ⇧
1966-2017 avg

Mangrove Recovery

Radabaugh et al. 2019

60% canopy cover 3 to 9 months post-Irma

Sunlight reaching seedlings

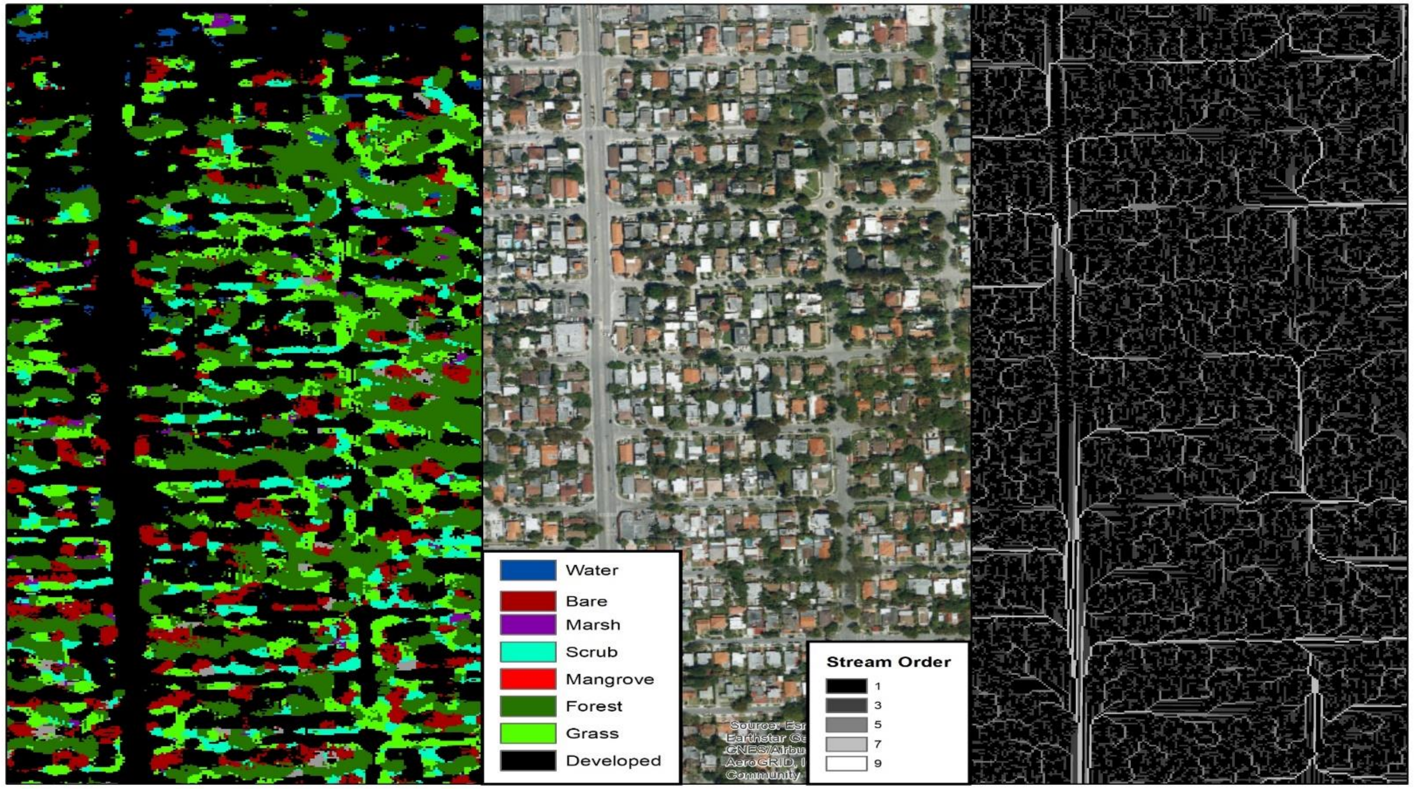
Next Steps

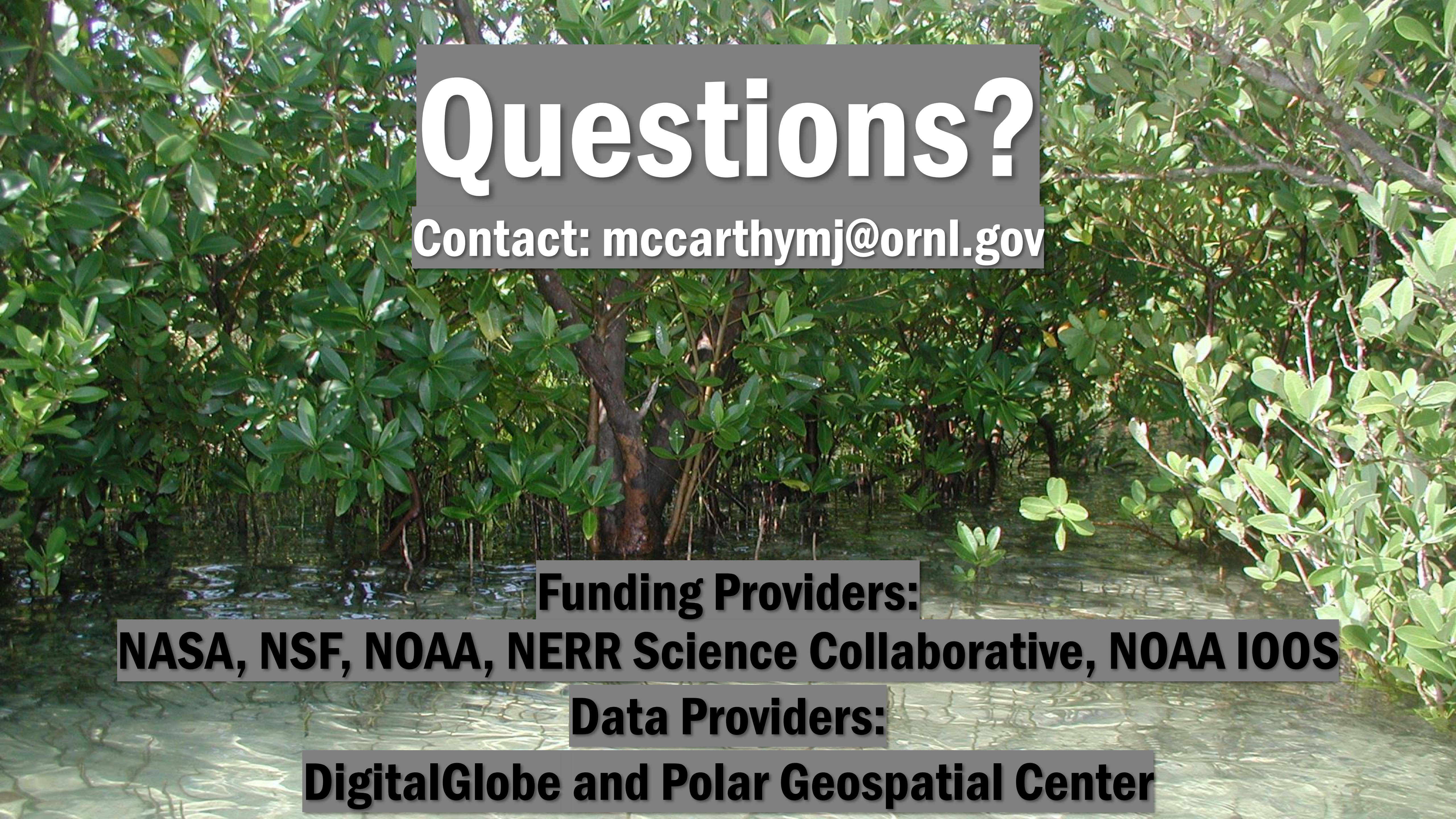
Complete Florida mapping

Conduct flood risk mapping

Disseminate results

- SECOORA
- Digital Coast





Questions?

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