Environmental Land Management and Compliance Using A

Moderator: Terry Watkins, Principal, Jacobs

Speakers:

- Brendan Brown, PWS, Nature-based Solutions Discipline Leader, CDM Smith
- Drew Reicks, Remote Sensing Specialist, CDM Smith

May 14, 2024, 3:00 PM

HOUSEKEEPING ITEMS

Take Note of Exits

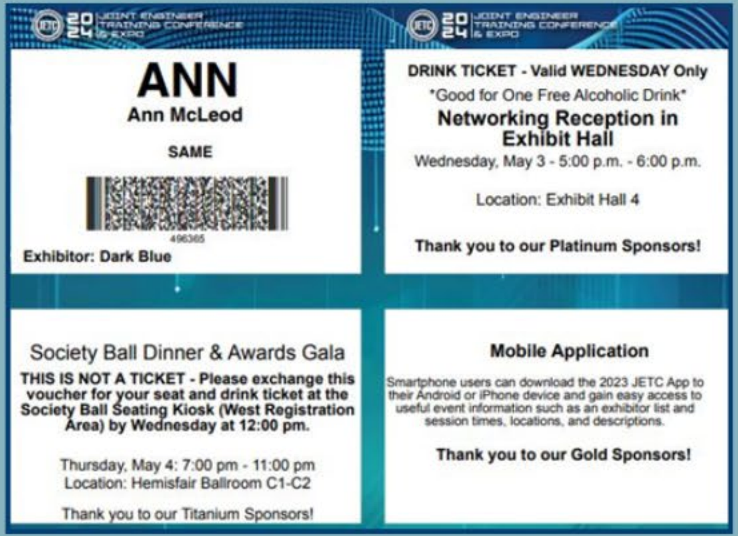
Silence Your Mobile Devices

Presentations and Audio Recordings will be available in the Attendee Service Center until August 30, 2024

Download your PDH record in the Attendee Service Center before August 30, 2024

Opening Reception at Universal CityWalk

(Minimum age 18 - No Children)



Bring Your Name Badge with Drink Tickets) + Your ID

Get Your Wrist Band TODAY at the Registration Help Desk or SAME Booth

Buses depart Gaylord & Caribe Royale, beginning at 6:00 p.m.

SAME Environmental Community of Interest (ECOI)

- The COI will support and engage SAME Posts, DOD and Federal Agencies by providing members with a wide range of programs, activities, and information to enable them to stay on the forefront of environmental technologies, management and regulatory developments facing the A/E/C community, and national security.
- SAME ECOI Website - SAME ECOI Webpage
- Webinars
- Networking
- Joint Engineering Training Conference (JETC)
- PFAS Industry and Government Engagement (IGE) Project
- Post Support and Interaction
- Monthly ECOI - LINK to monthly call is on SAME ECOI webpage - SAME ECOI Monthly Call
  - Call currently third Wednesday of the month 1500-1600 hrs. May Change in Future
- For more information contact ECOI Chair Ann Ewy annewysame@gmail.com

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Joint Engineer Training
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MAY 14-16, 2024
ORLANDO, FL

OPERATION: COLLABORATION

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MODERATOR

Terry Watkins, PMP
Jacobs Engineering
Principal

Fun Facts

- Sports Team: Green Bay Packers
- Vacation: Italy, Spain, Germany
- Competitive archer
- Hobbies include working out and shooting sports

Joint Engineer Training
JETC
Conference & Expo

MAY 14-16, 2024
ORLANDO, FL

OPERATION:
COLLABORATION

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SPEAKER

Brendan Brown, PWS

CDM Smith

Nature-based Solutions Discipline Leader

Fun Facts

- Surfed in Costa Rica
- Played tennis and cross country in high school
- Enjoys making art but is terrible at painting
- Eagle Scout

MAY 14-16, 2024
ORLANDO, FL

OPERATION: COLLABORATION

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SPEAKER

Drew Reicks, GISP, CFM

CDM Smith

Remote Sensing Specialist

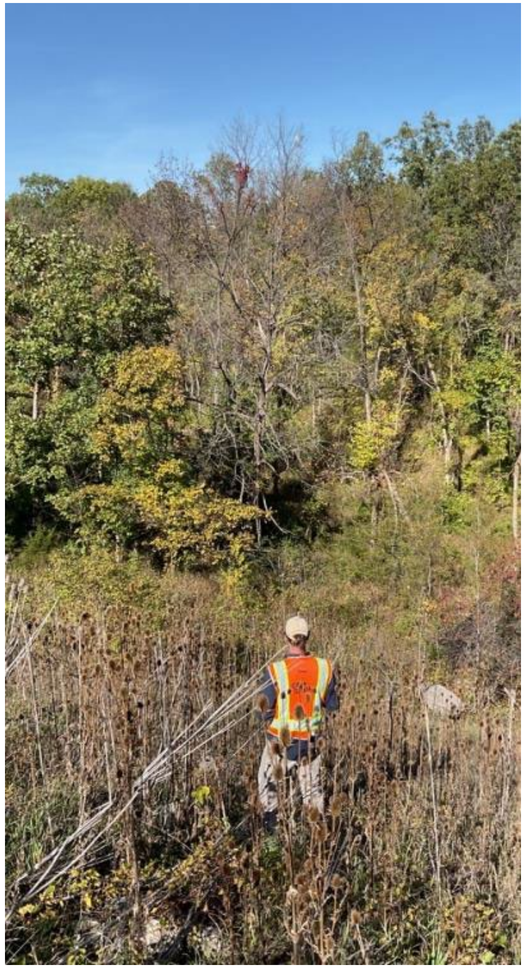
Fun Facts

- Placed 8^{th} in the Iowa High School Wrestling Tournament
- Grew up on the same farm as his dad
- Favorite team: Borussia Dortmund (BVB)
- Favorite game: Splendor

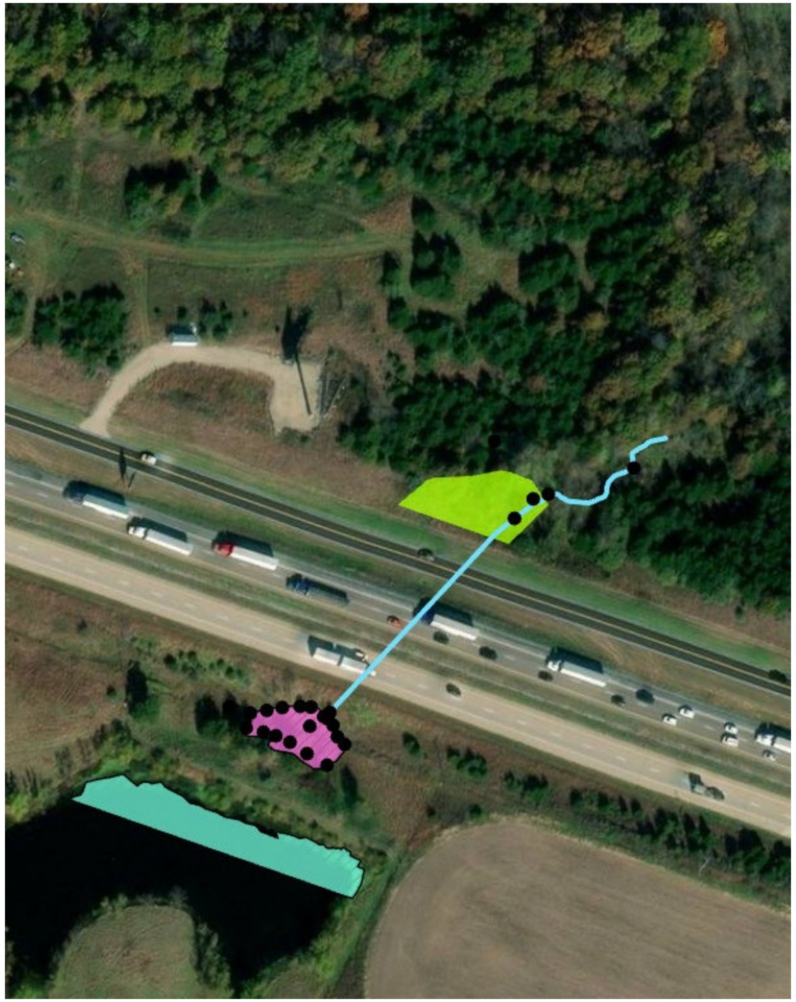
Agenda

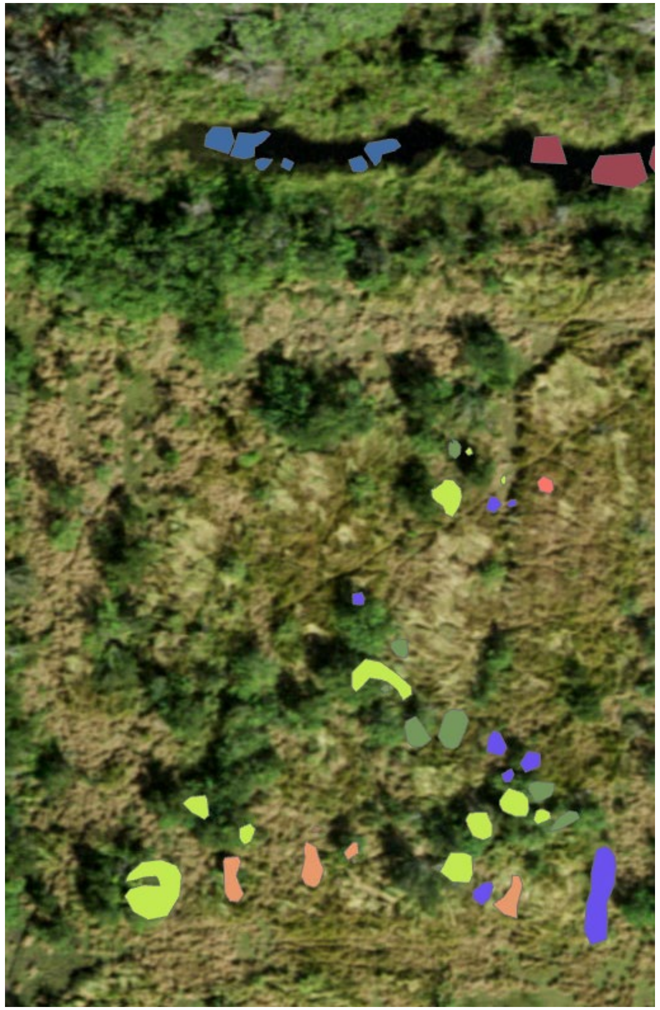
- Intro
- Remote Sensing Basics
- Machine Learning Basics
- Land Management: Invasive species
- Restoration and Resiliency: Marsh assessment
- Site Feasibility: Wetland Mapping
- Resiliency: New urban development

Field work is an invaluable, but limiting factor.

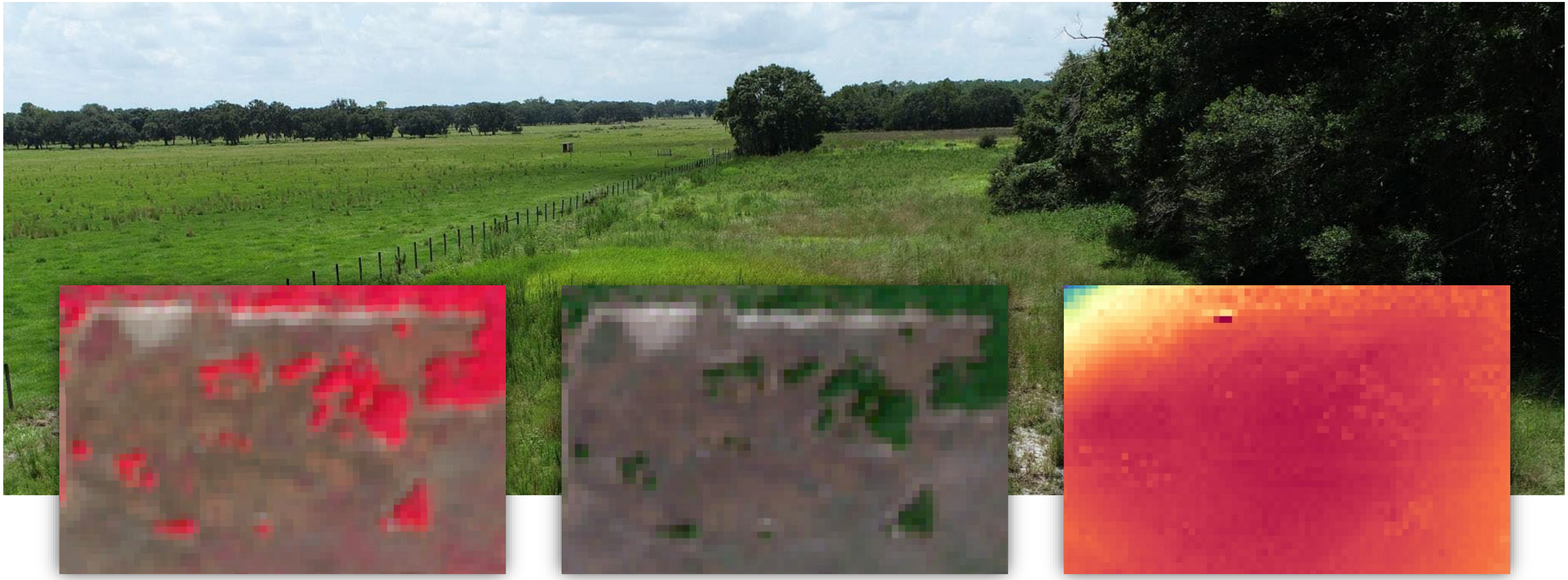


Explicit results, but a fraction of the site.

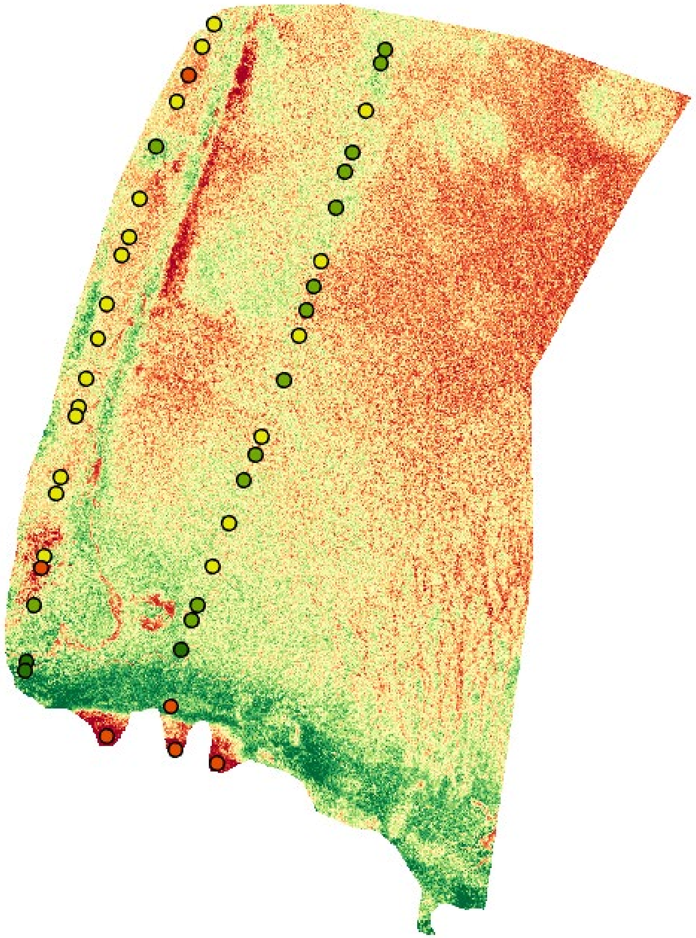


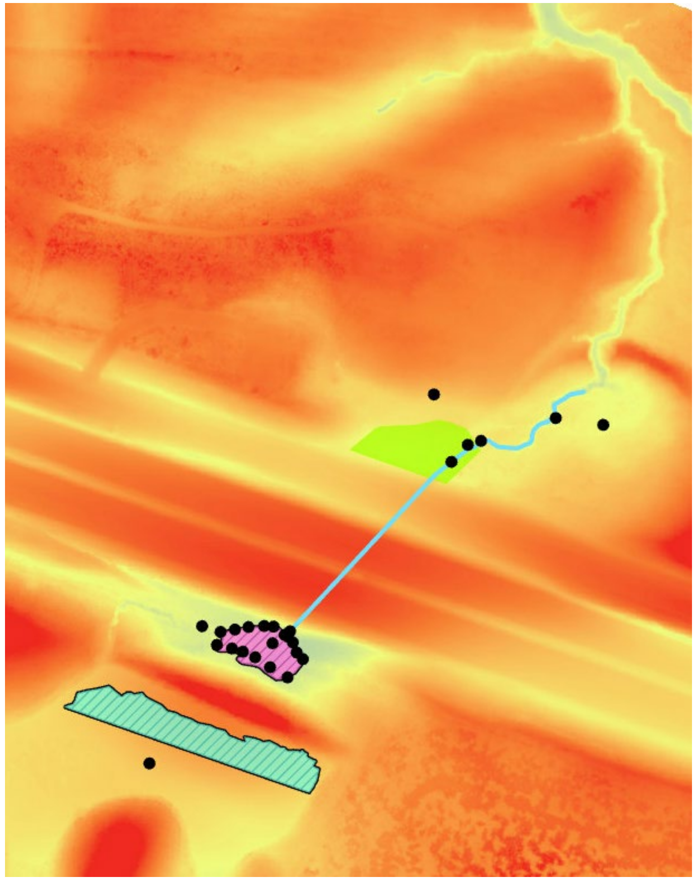


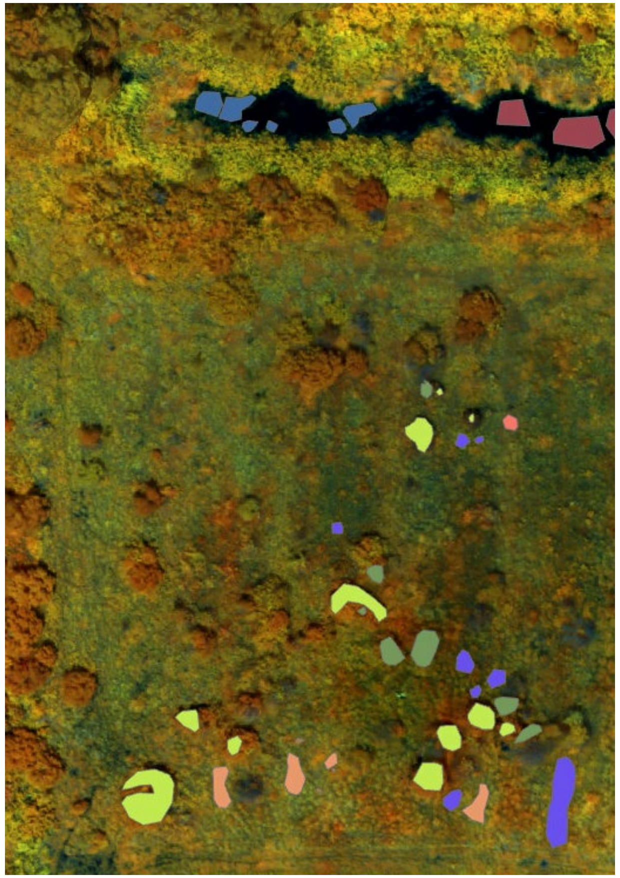
Satellite/plane data is widely available but low spatial or temporal resolution.



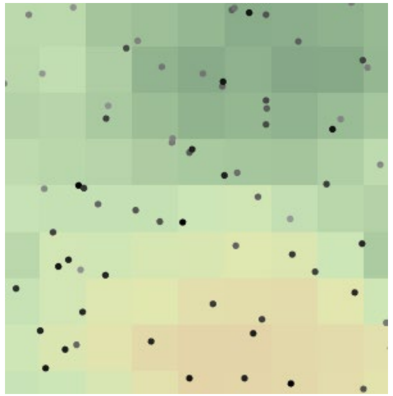
Comprehensive understanding, but lacking necessary details.

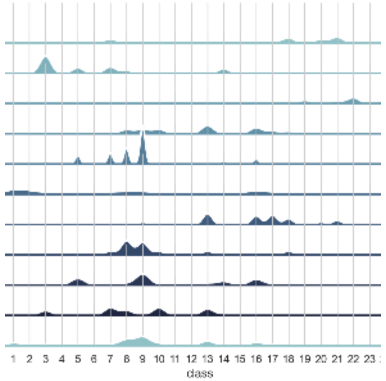


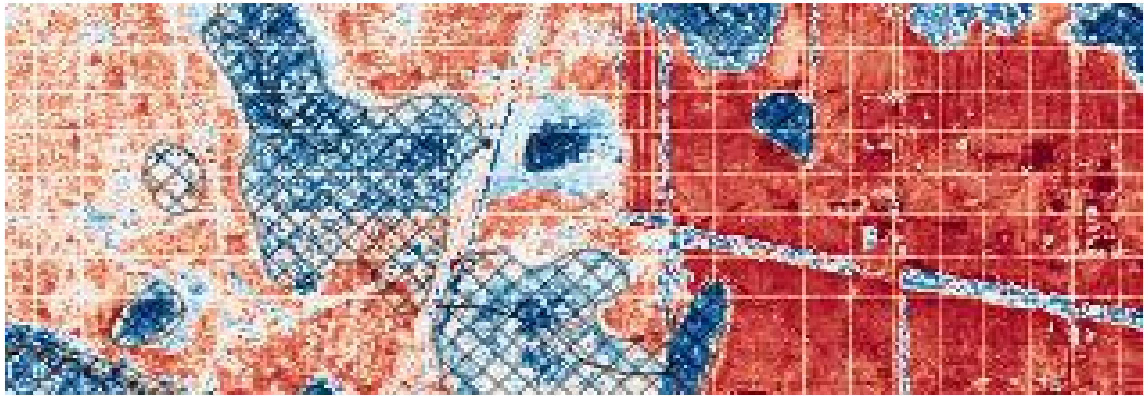


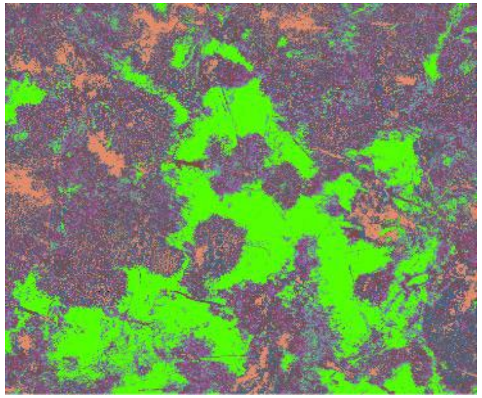


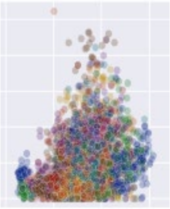
We are finally seeing the promise of machine learning being delivered, but environmental applications are lagging.

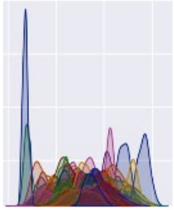


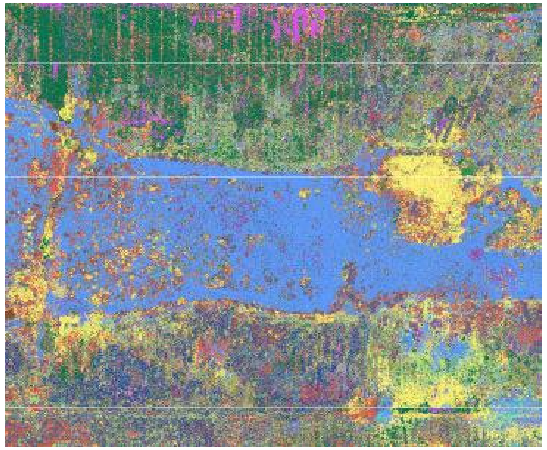


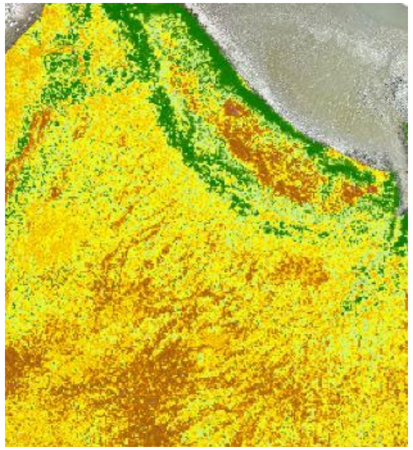


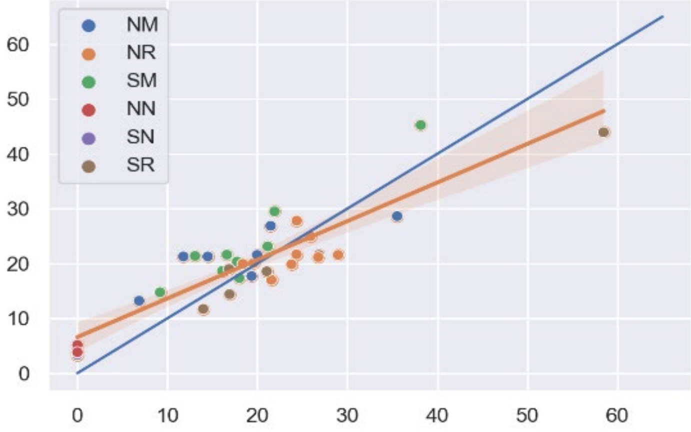


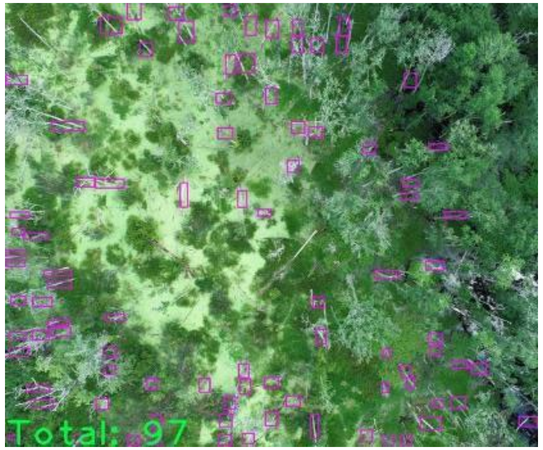




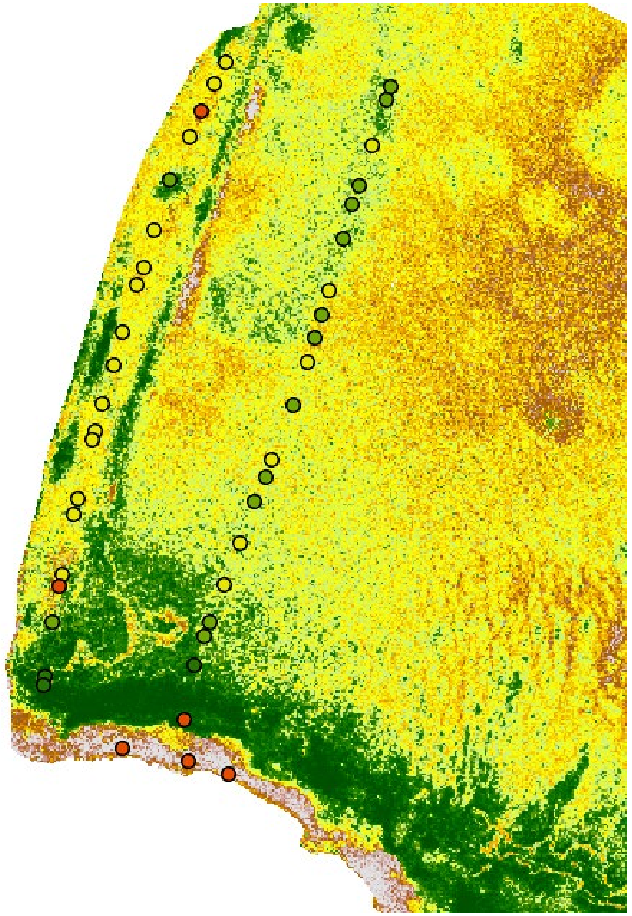


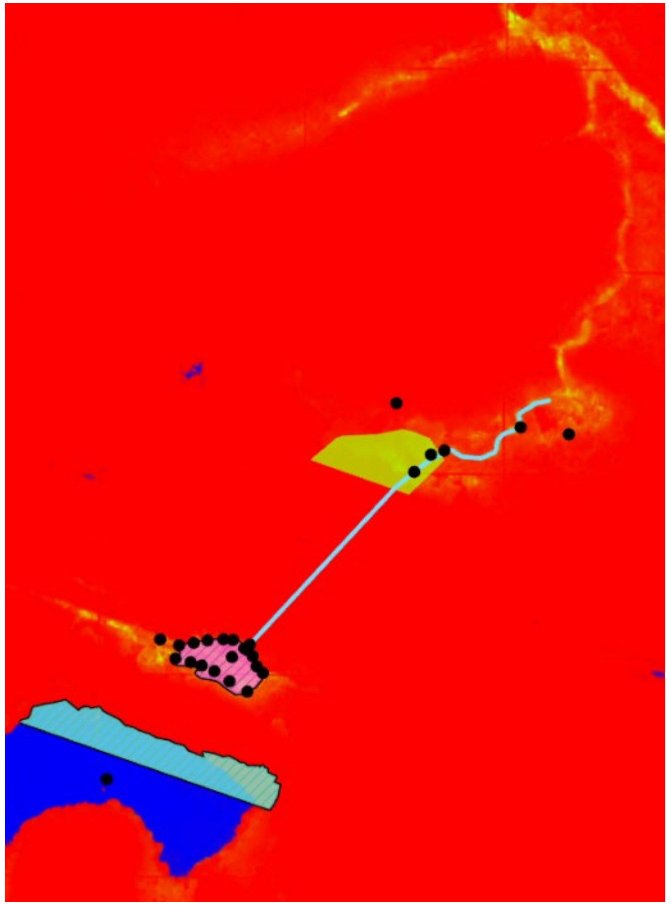


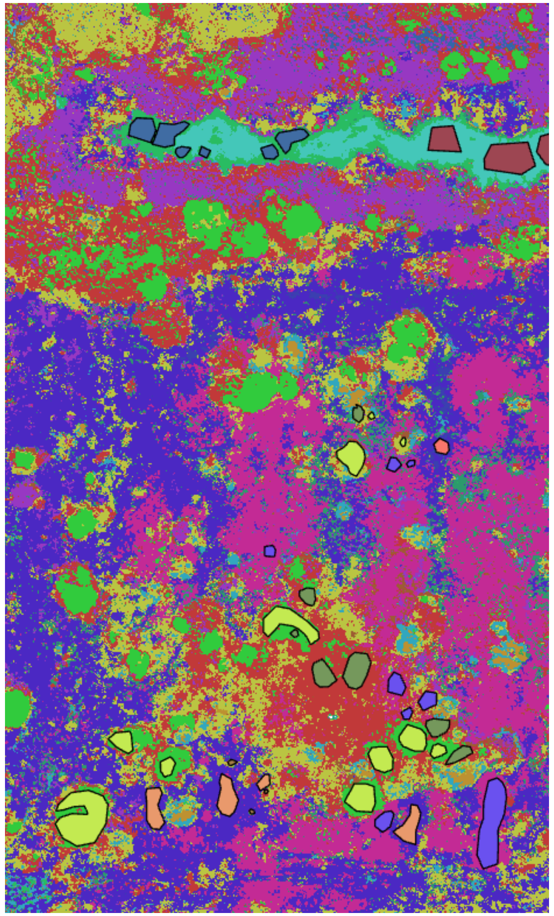




Full site, detailed results to drive data to decisions.

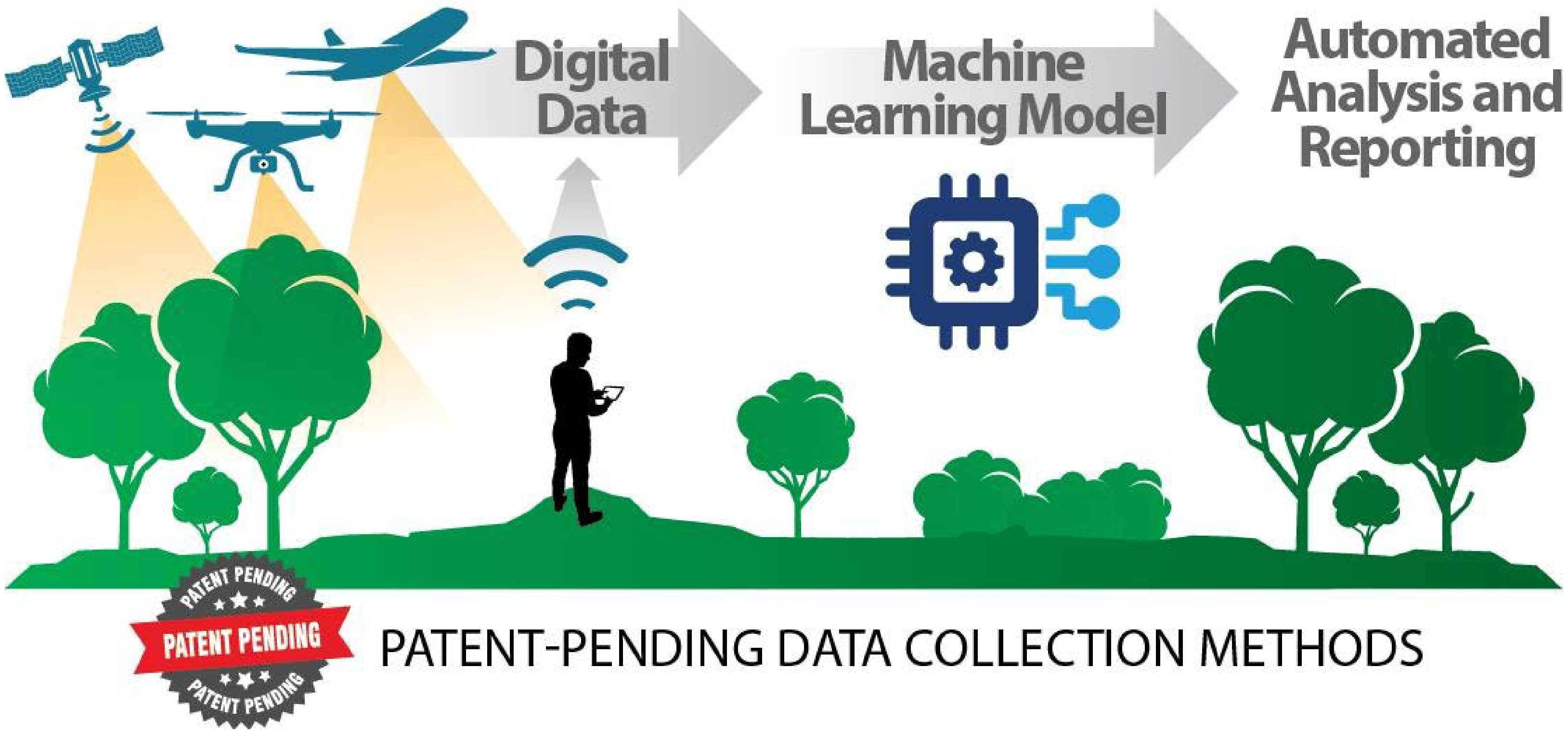






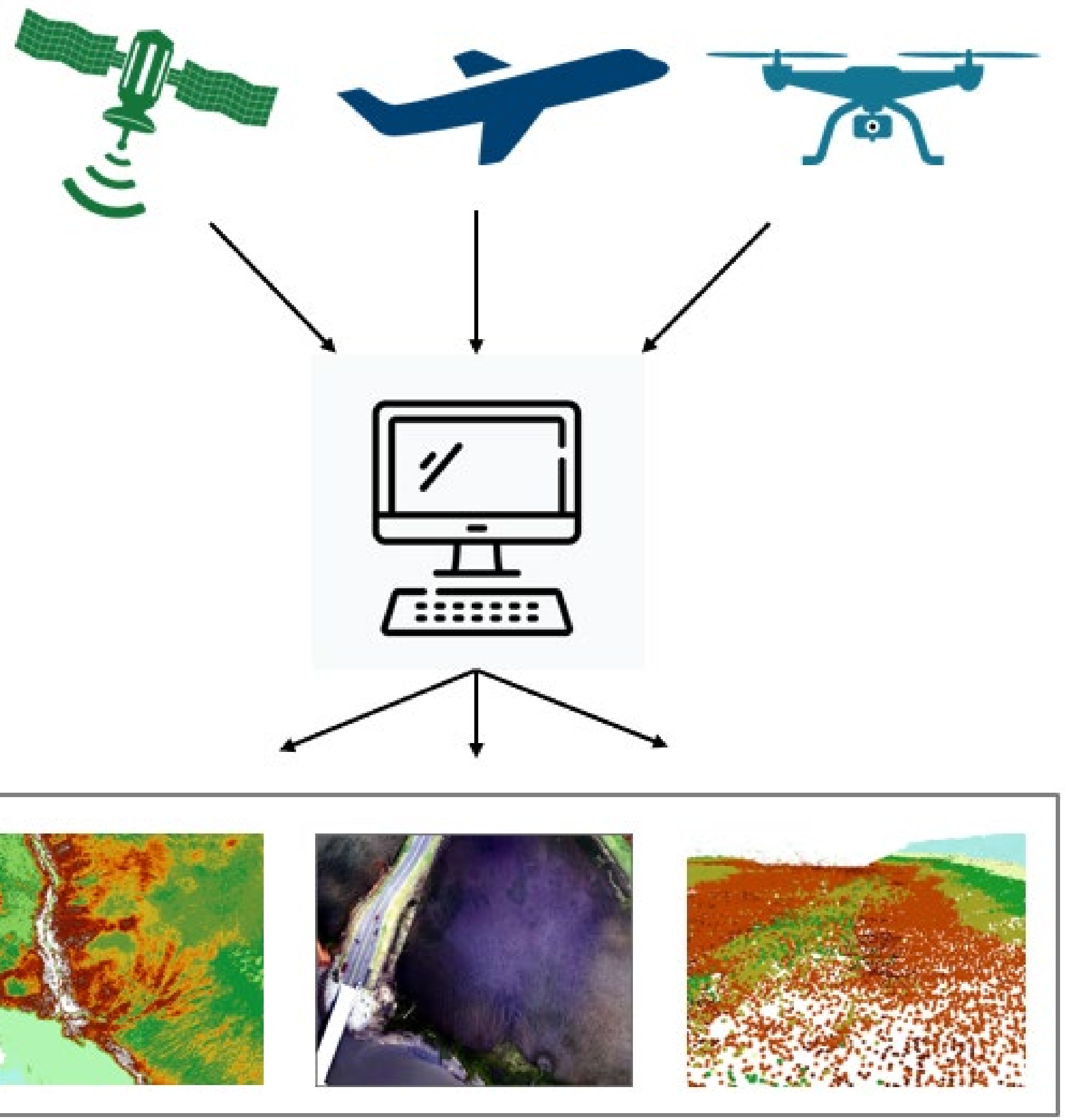
An expert-centered digital pipeline empowers better decisions.

- Surveyors
- Engineers
- Geologists
- Scientists
- FAA-certified drone pilots
- Remote sensing
- Machine learning



Remote Sensing

- **Common collection platforms**
  - Satellite, plane, UAVs/drones
- **Common sensors**
  - Camera, thermal, lidar multispectral, hyperspectral
- **Common products**
  - Imagery, elevation
- **Choosing the right tools**
  - Site size, project needs

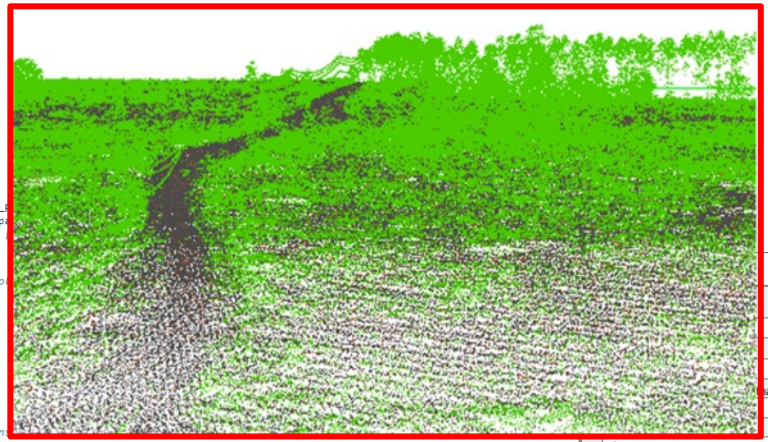


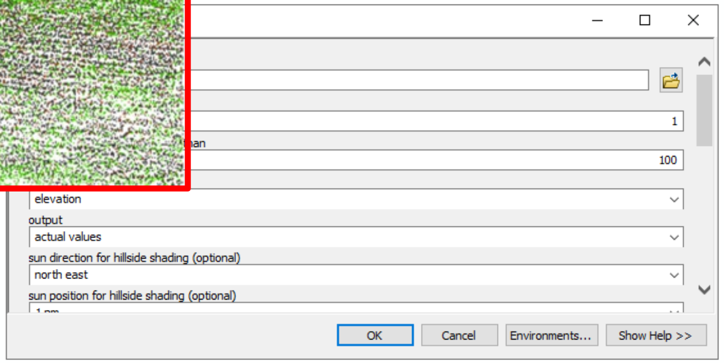
Automation

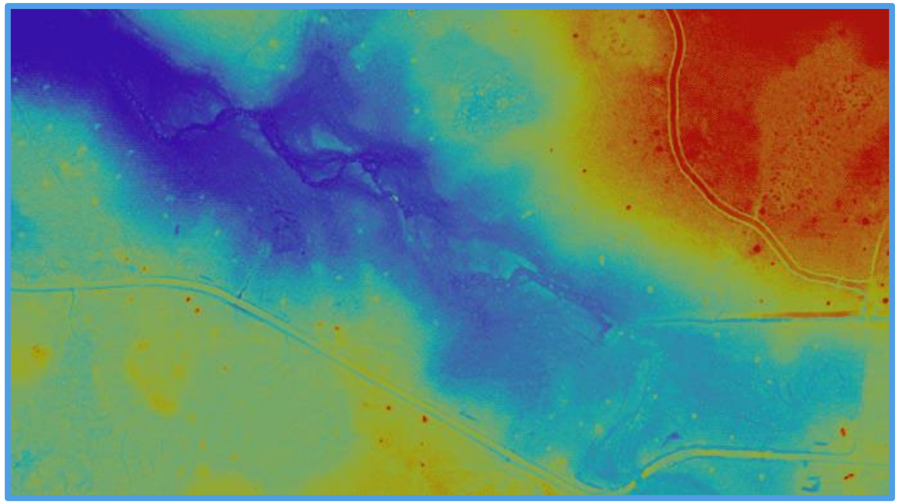
- Automation ≠ machine learning
- Automation is a pivotal part of the process
- How can we make things easier?

Automate it!

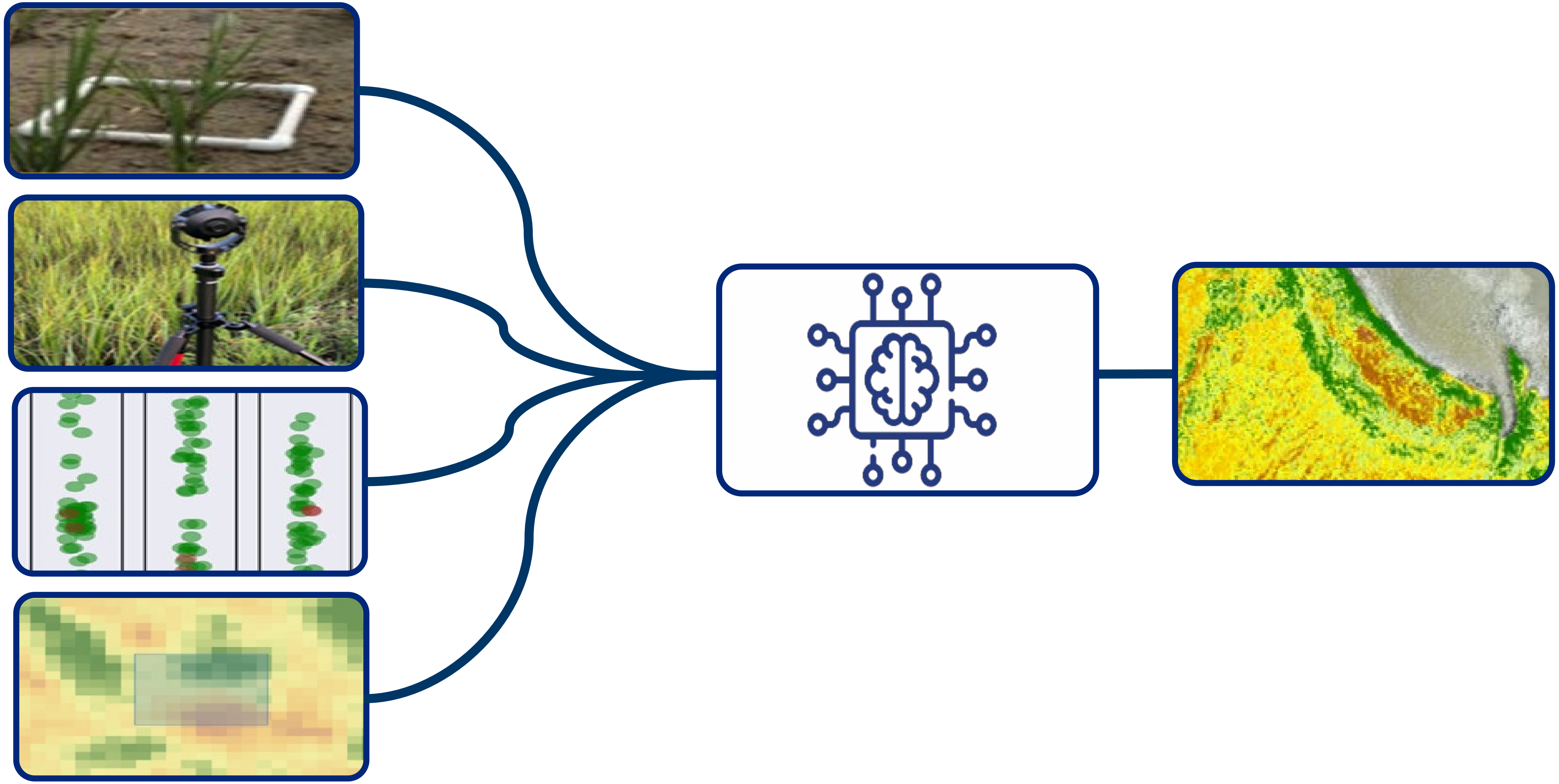
```python
###lasMerge###
def lasMerge(las, outLas, lasTools_p
    lasTool=os.path.join(lasTools_pa
    #create the command string for l
    command = ['"'+lasTool+'"']

    #use verbose, default in arctool
    command.append("-v")

    #add input LiDAR
    command.append("-i")
    command.append('"'+las+'"')

    #add output LiDAR
    command.append("-o")
    command.append('"'+outLas+'"')
    #additional command-line options
    #set max point limit
    command.append("-split")
    command.append(str(splitSize))

    #report command string
    command_length = len(command)
    command_string = str(command[0])
    command[0] = command[0].strip('"')
    for i in range(1, command_length):
        command_string = command_string + " " + str(command[i])
        command[i] = command[i].strip('"')

    #run command
    check_output(command, False)

###lasTile###
def lasTile(las, outNm, outP, lasTools_path, tileSize, buffSize):
    lasTool=os.path.join(lasTools_path, 'lastile.exe')
    #create the command string for lastile.exe
    command = ['"'+lasTool+'"']

    #use verbose, default in arctoolbox
    command.append("-v")

    #add input LiDAR
    command.append("-i")
    command.append('"'+las+'"')

    #tile size will only create squares
    command.append("-tile_size")
    command.append(str(tileSize))
```



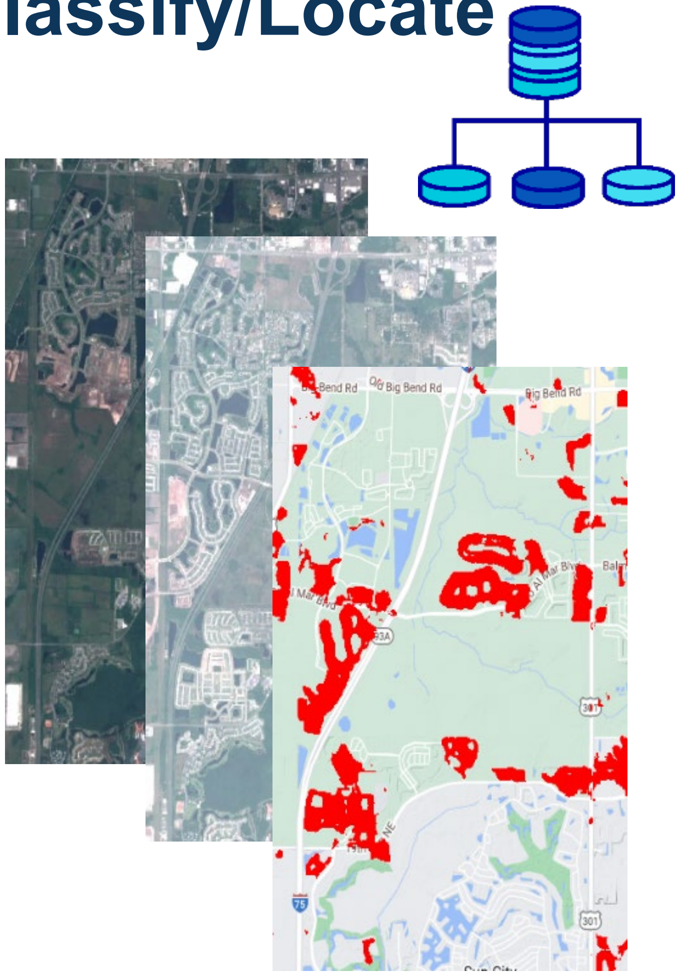




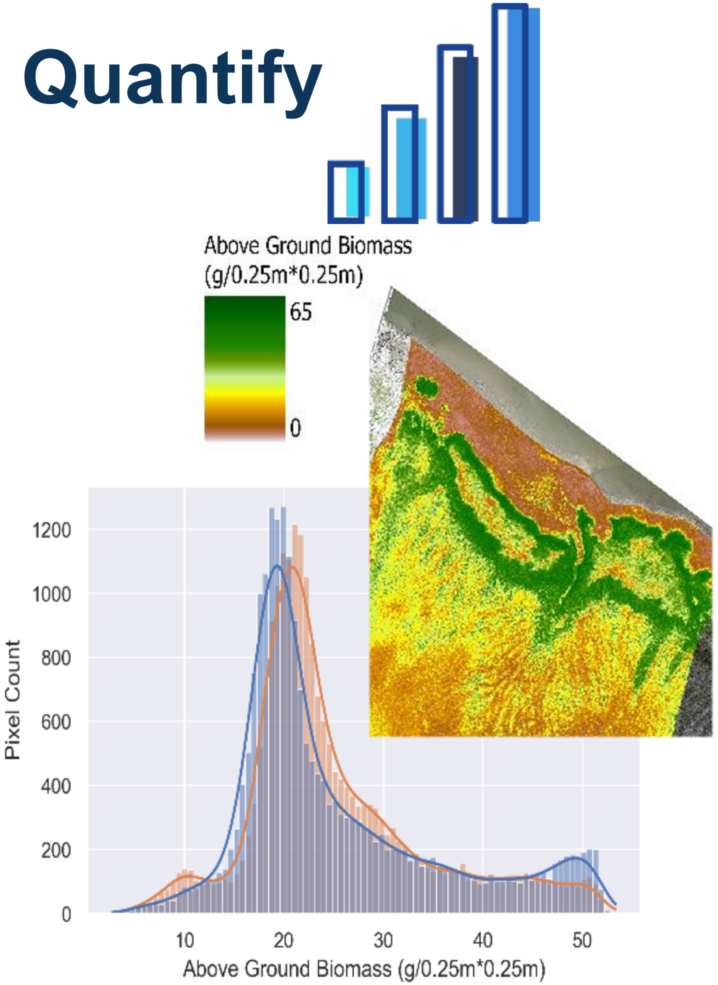
Automation's role in machine learning:



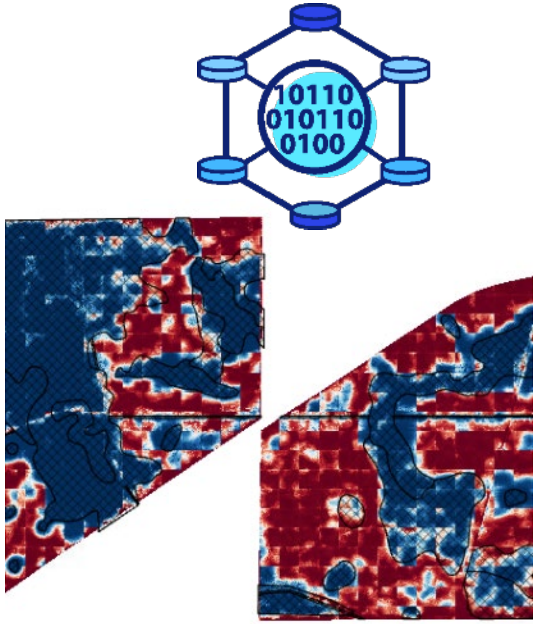
Classify/Locate



Quantify



Segment



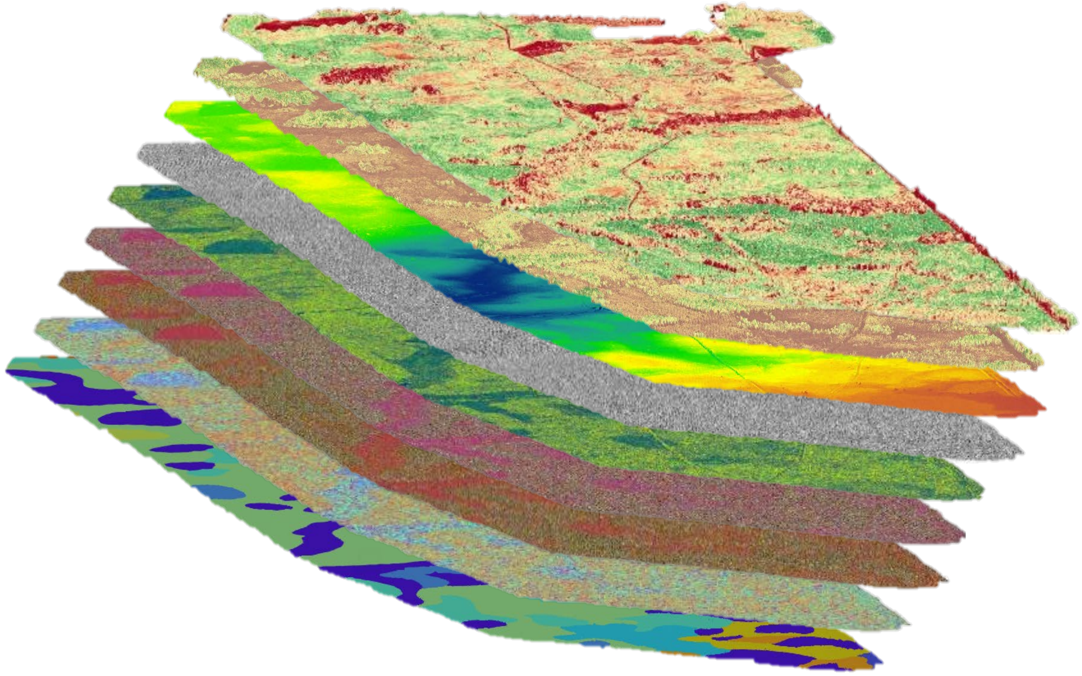
Machine Learning Basics

Multiple features

(easier/ cheaper/ faster to collect)

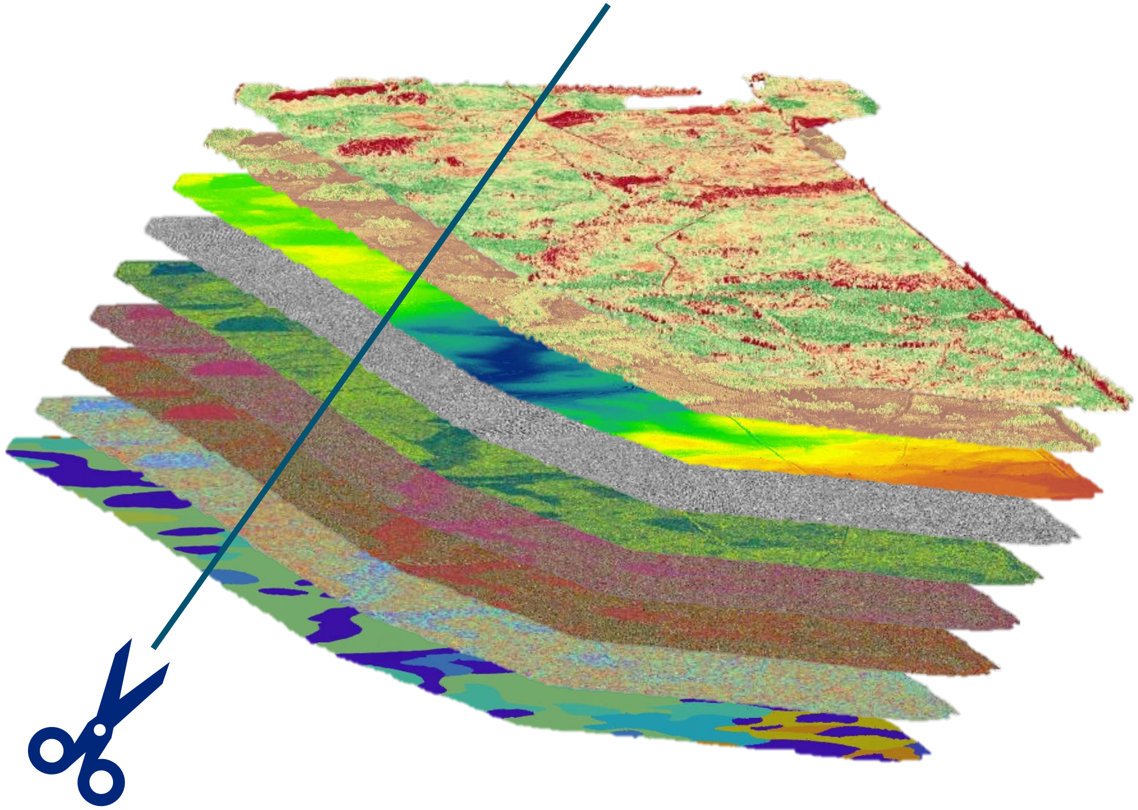
One property to classify or quantify

(difficult /expensive/slower to collect)

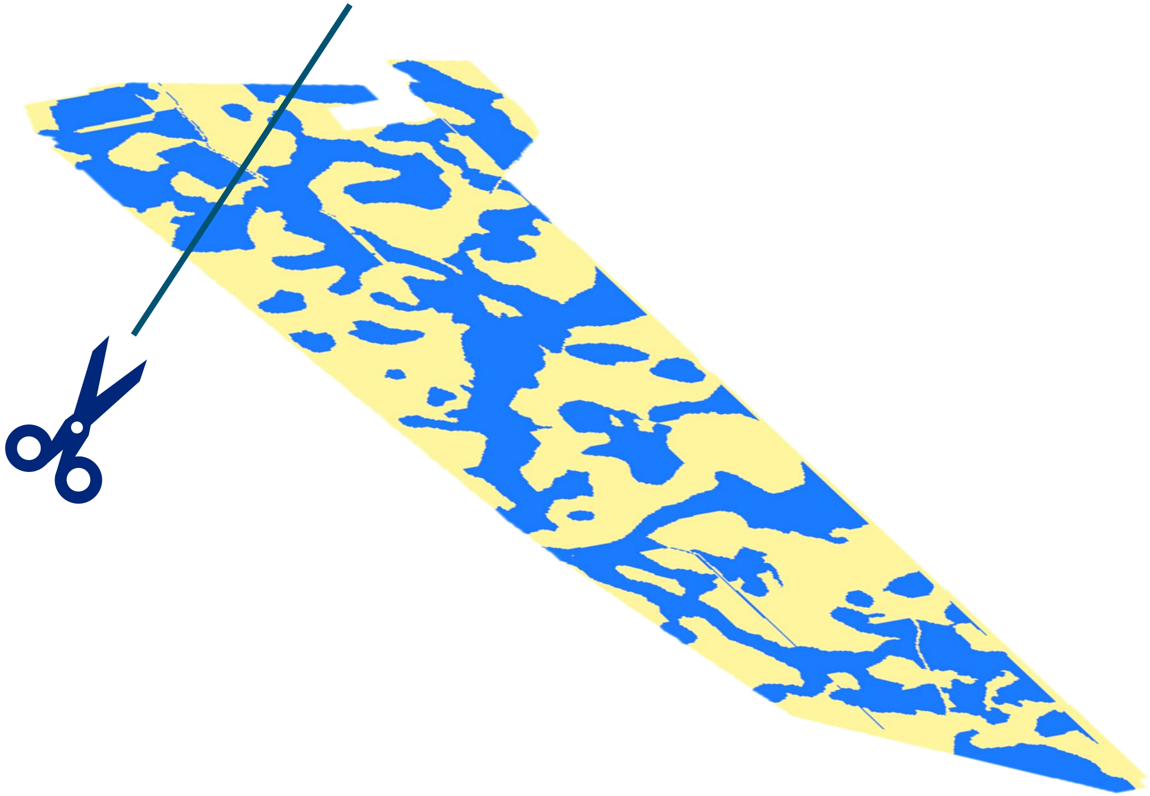


Machine Learning Basics

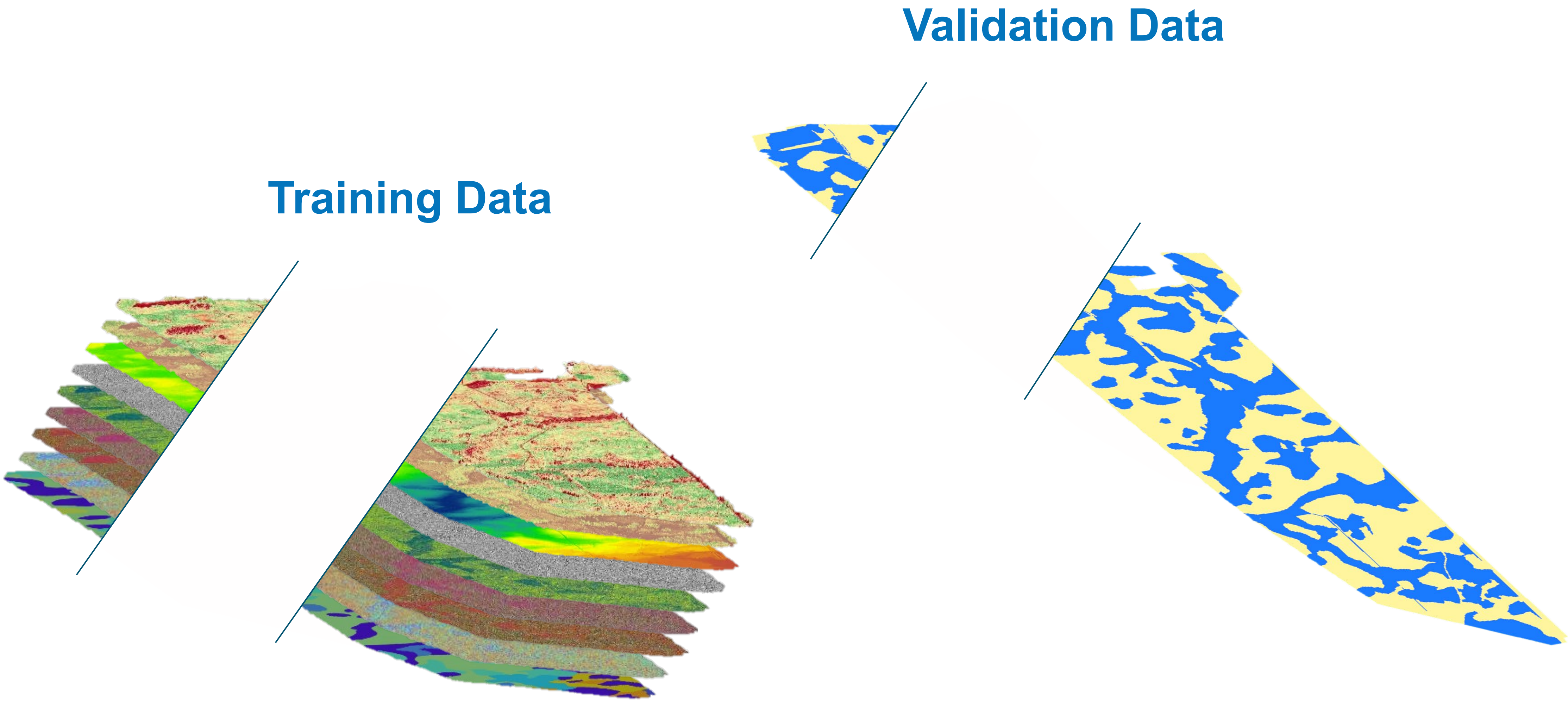
Model Variables



Target Class

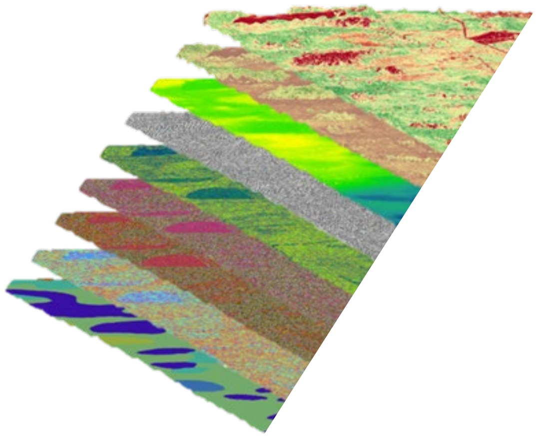


Machine Learning Basics



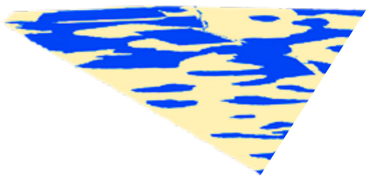
Train the Model

Data Inputs



+

Ground Truthing



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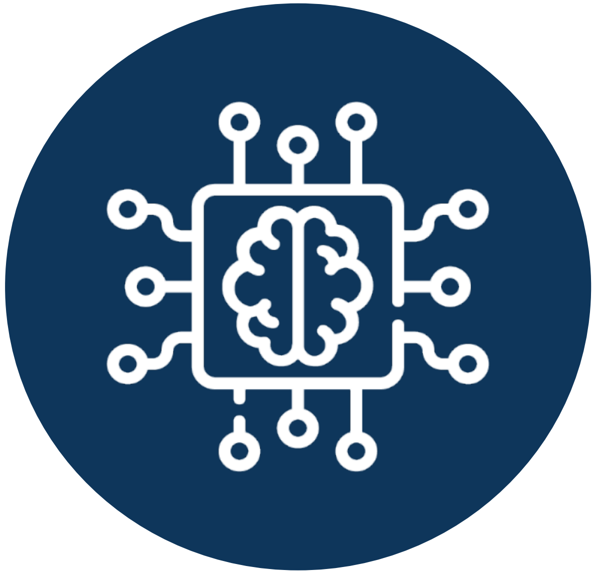
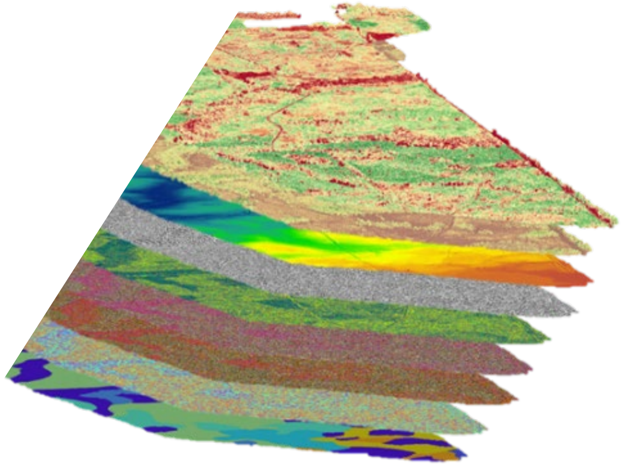
Machine Learning



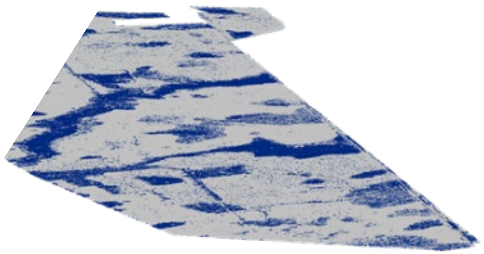
Model Accuracy

Data Inputs

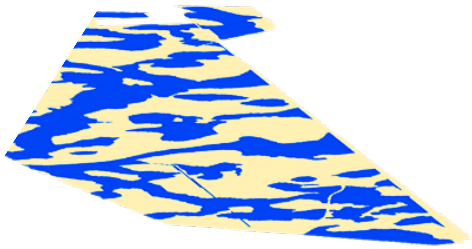


Machine Learning Model

Model Predictions



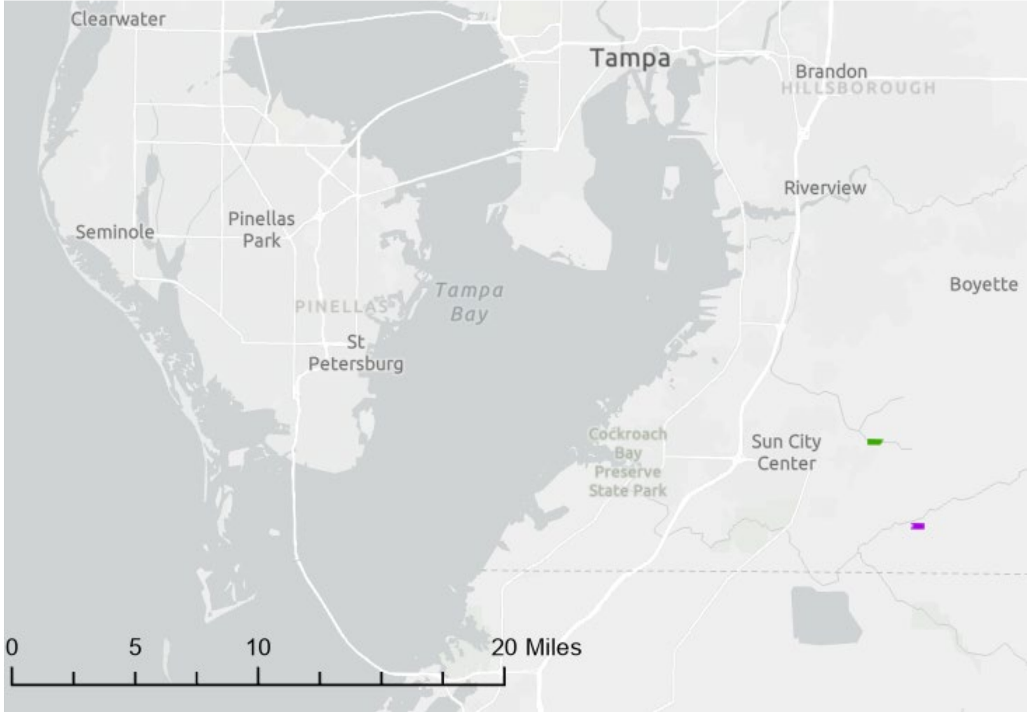
Measured Against



Ground Truthing

Land Management:
Invasive and native species identification

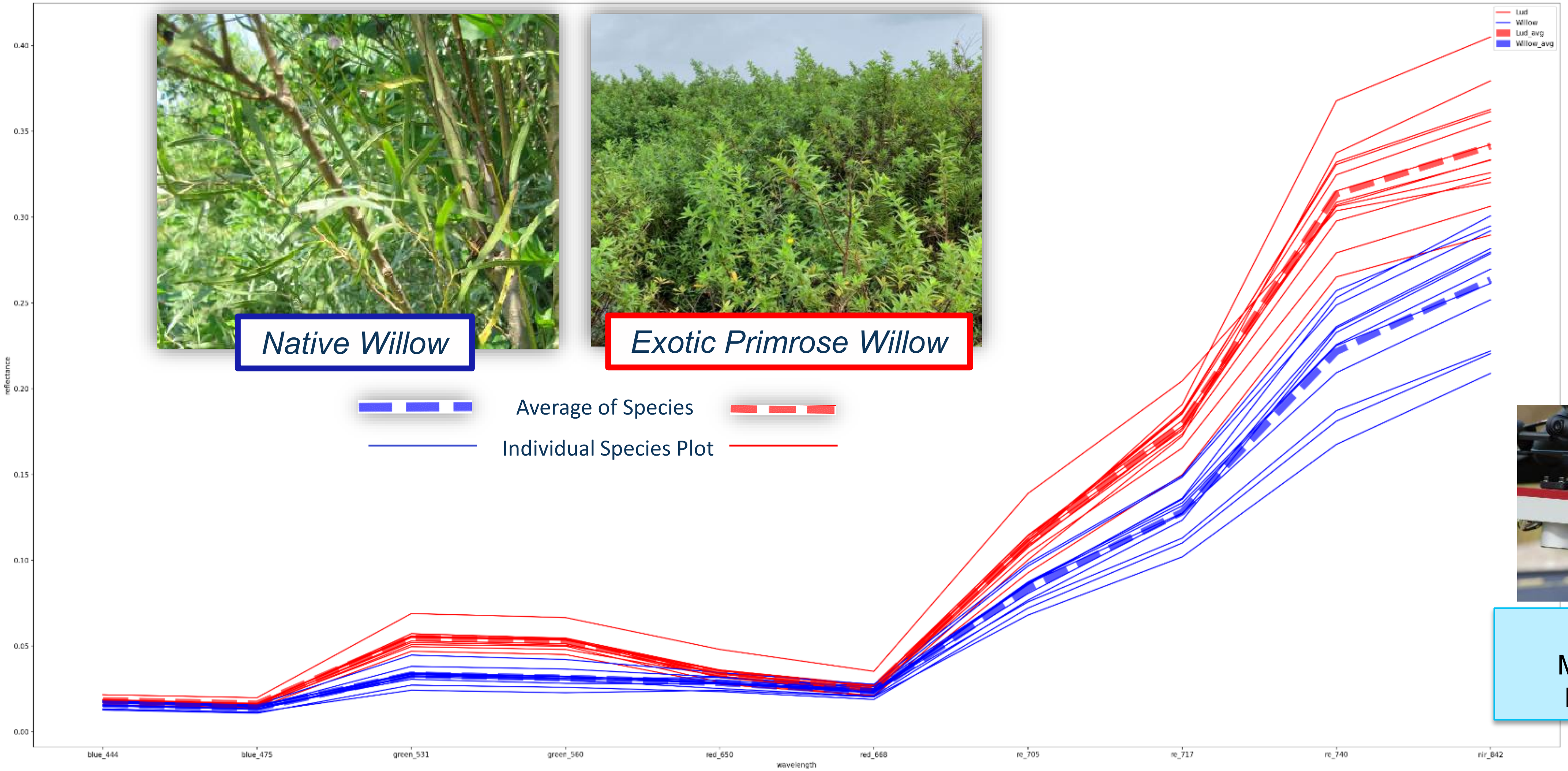
How do we identify invasive species and assess the effectiveness of treatments to remove them?



Traditional approach for invasive species mapping is labor-intensive.

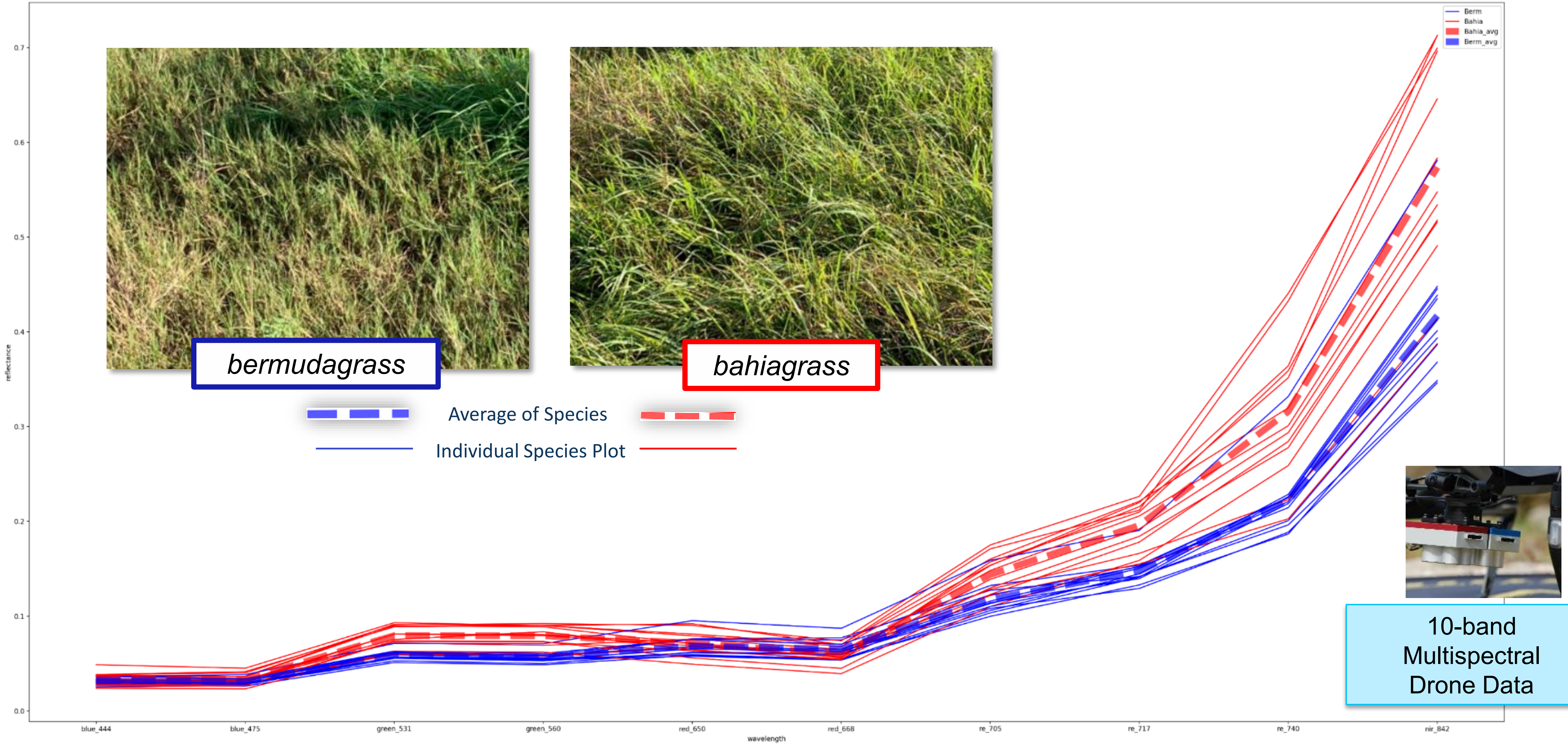
CDM Smith developed patent-pending data collection methods to increase efficiency and improve model accuracy.

Machine learning can use spectral patterns to identify species.



10-band Multispectral Drone Data

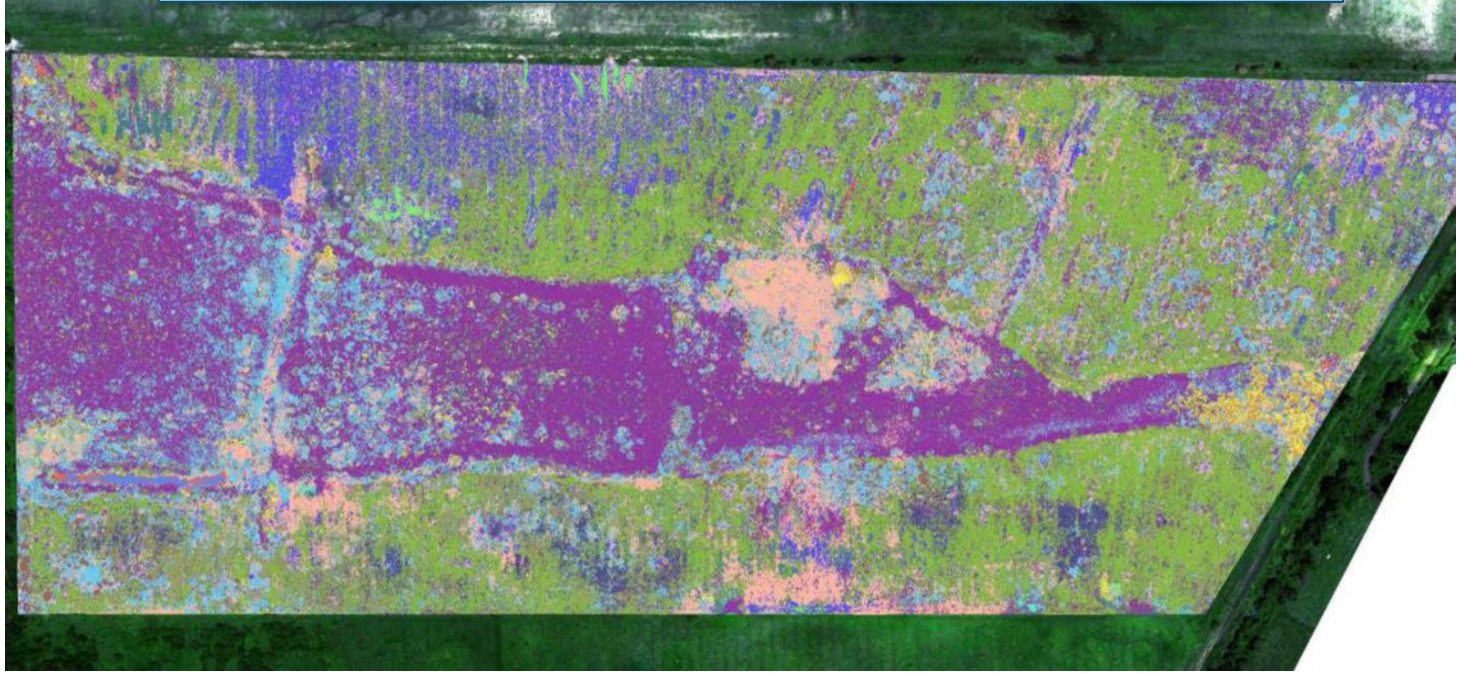
Species identification is possible between similar species.



10-band Multispectral Drone Data

CDM Smith developed a high accuracy map of native and invasive species using machine learning.

Overall machine learning model accuracy: > 80%

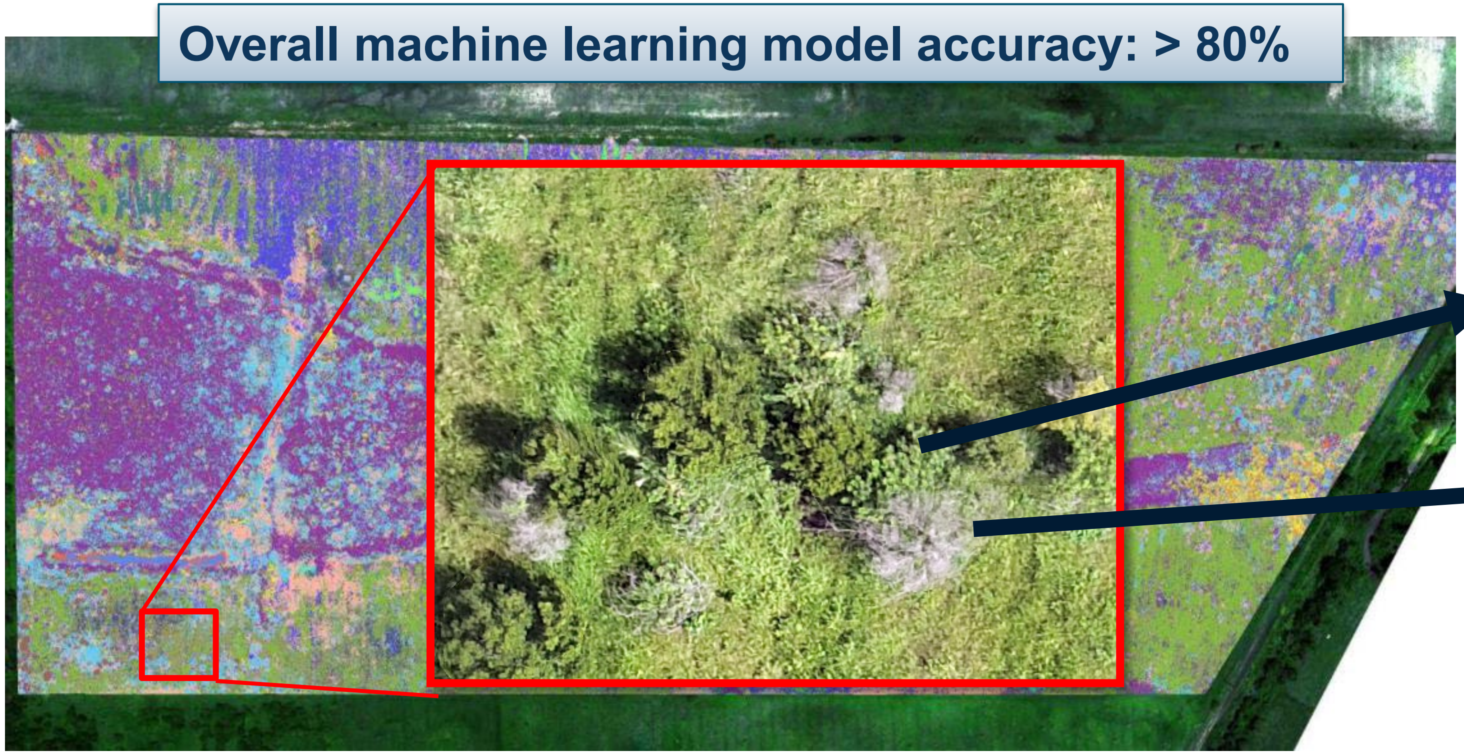


Species or land cover type

- bahiagrass ★
- bare
- brazilian pepper ★
- cabbage palm
- cogongrass ★
- dead shrub
- dogfennel
- hairy indigo ★
- primrose willow ★
- oak
- pine
- red maple
- submerged aquatic
- smutgrass ★
- water
- wax myrtle
- willow

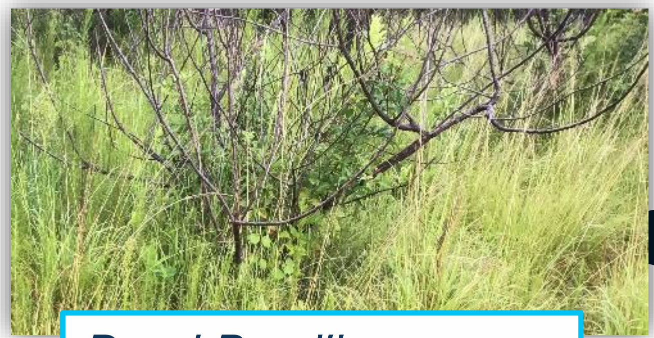
★ **Invasive Species**

The machine learning model can identify and quantify living and dead Brazilian pepper.



The machine learning model can identify and quantify dead Brazilian pepper.

Brazilian pepper



Dead Brazilian pepper

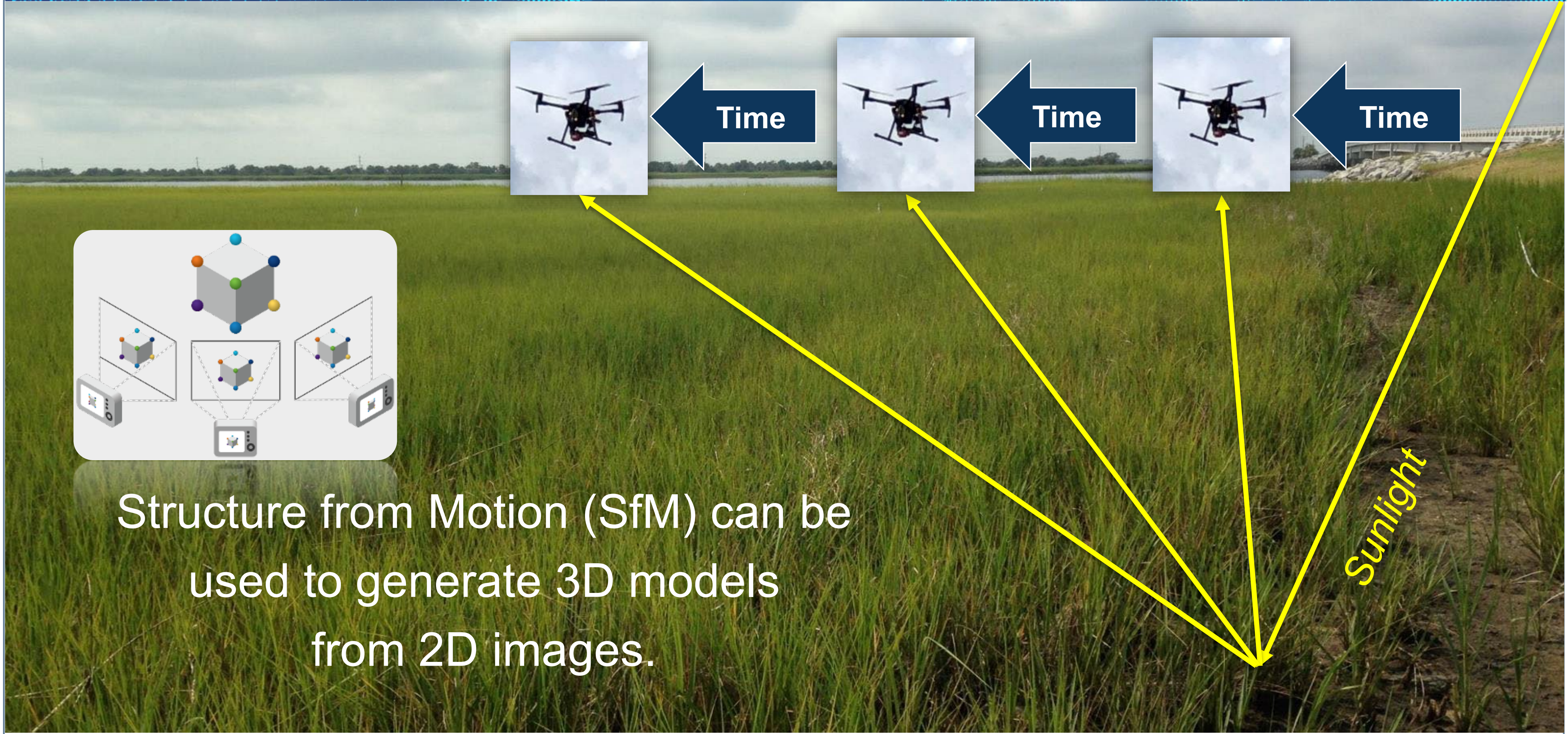
Restoration and resiliency: Tidal marsh assessment

- How do we assess restoration success and resiliency in the face of climate change?

Ft. Pulaski National Monument
Savannah, GA

Restoration and resiliency: Tidal marsh assessment

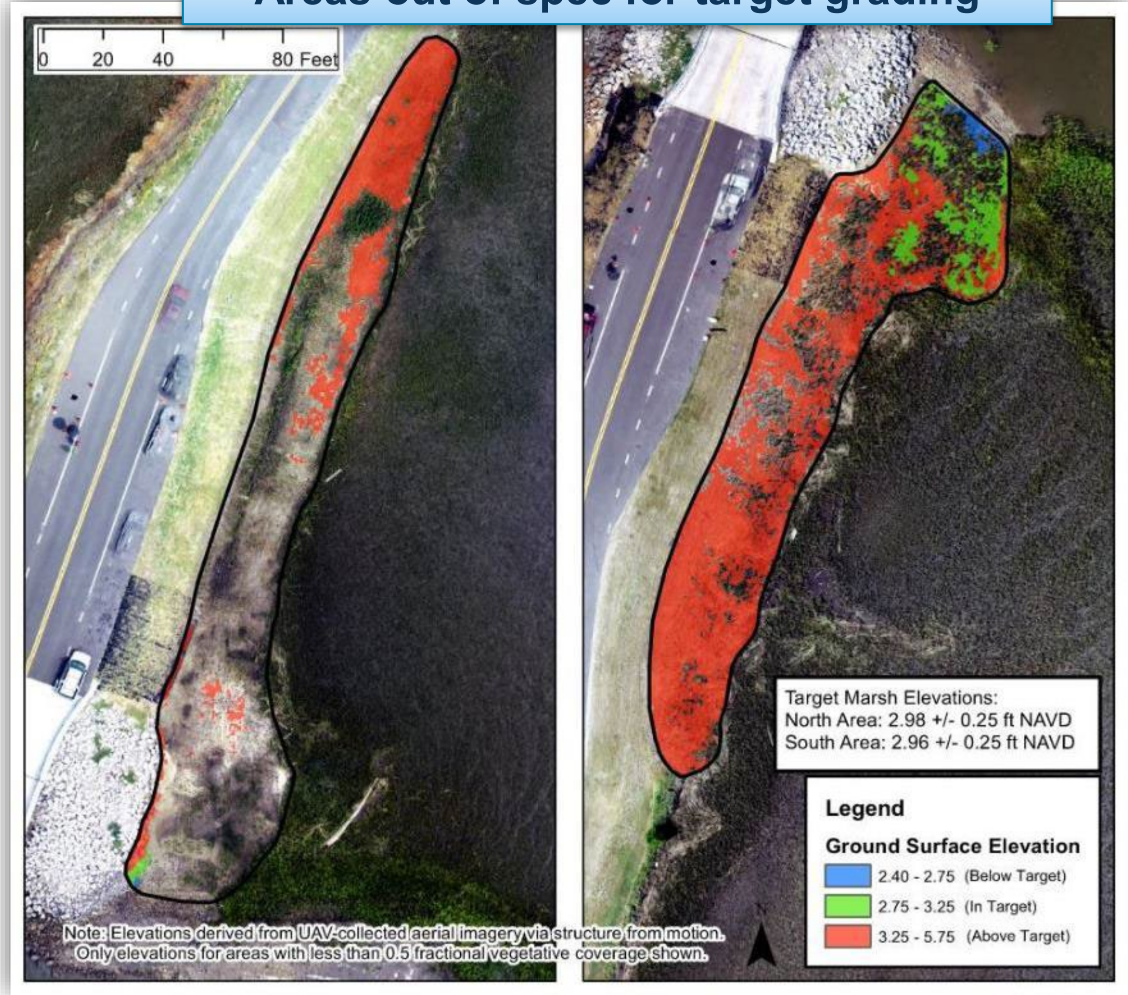
Marsh Restoration



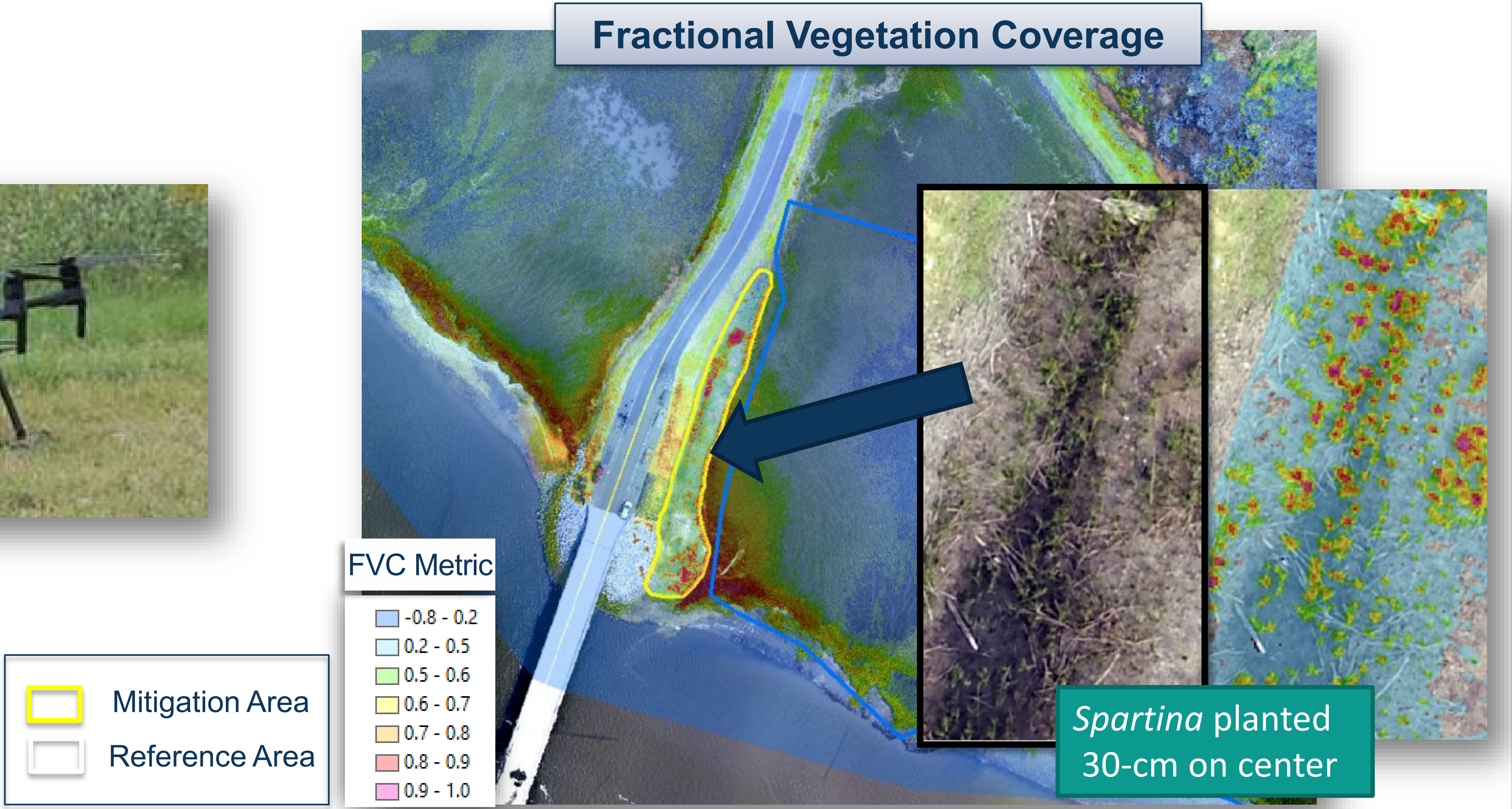
Structure from Motion (SfM) can be used to generate 3D models from 2D images.

Drone data revealed that the contractor graded too high.

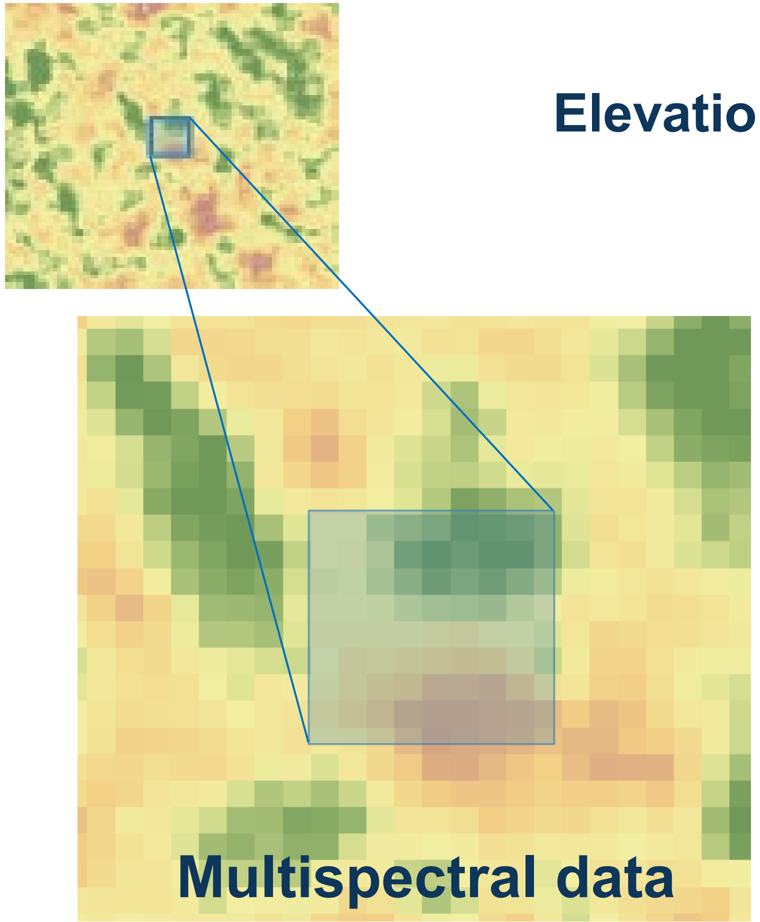
Areas out of spec for target grading

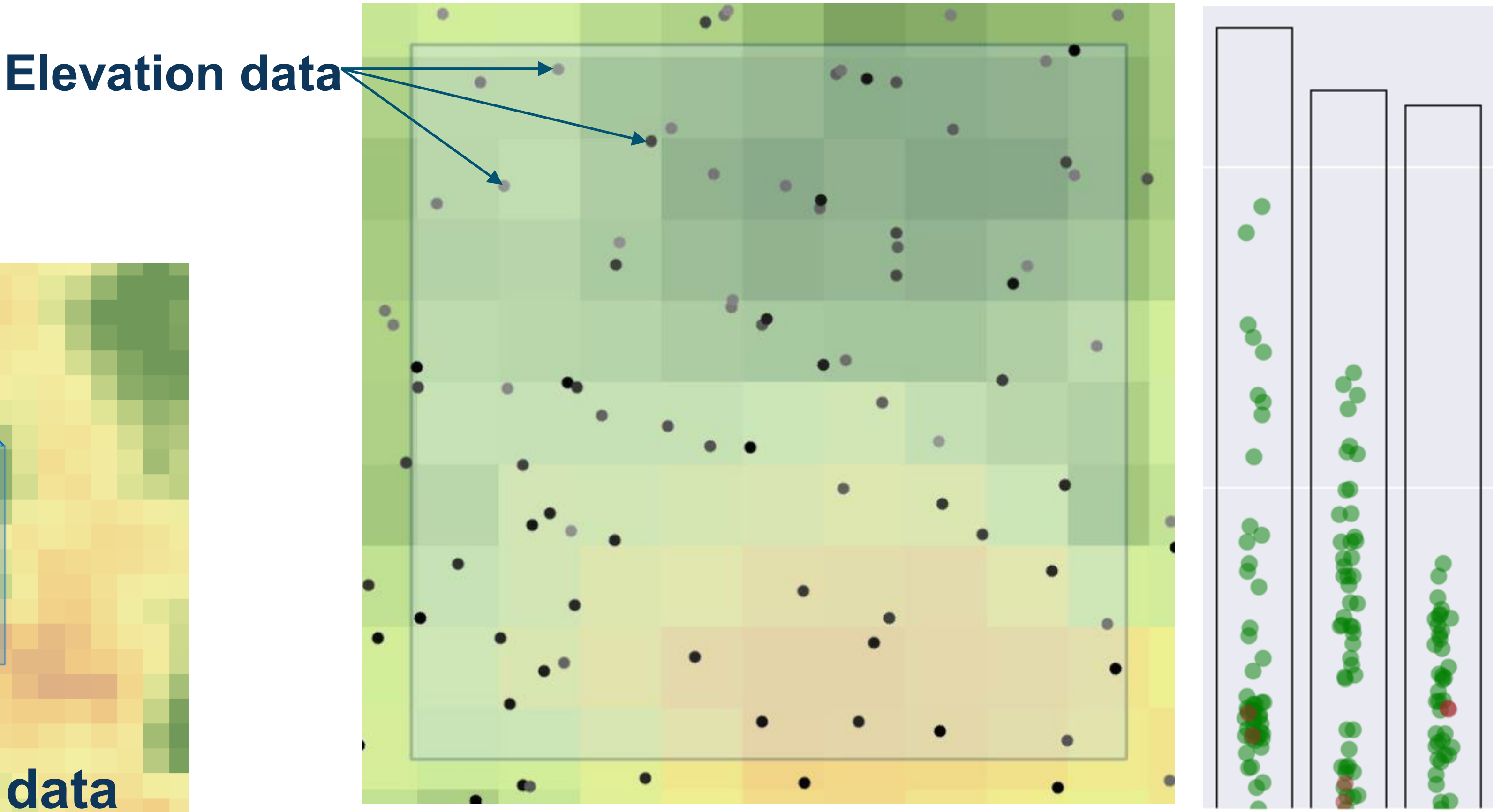


High resolutions pixels identify individual *Spartina* plugs.

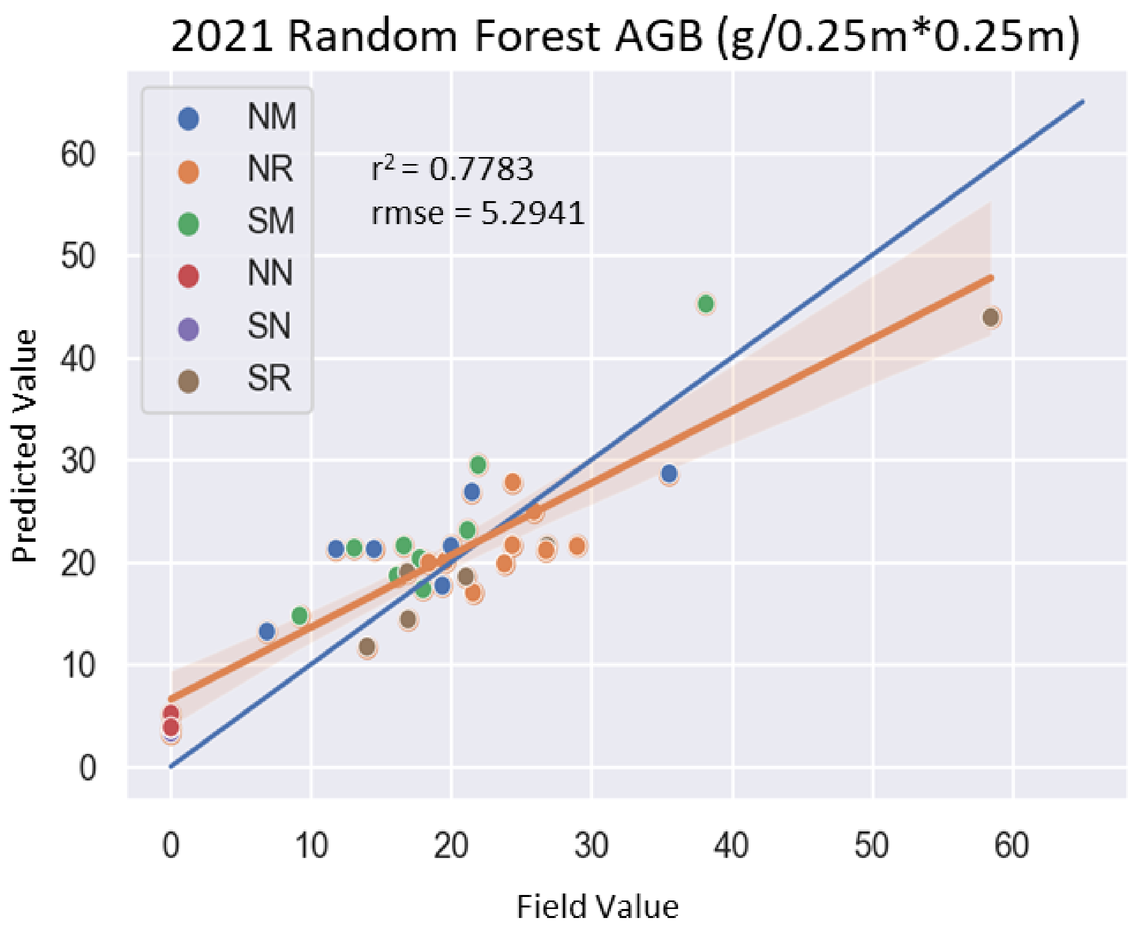


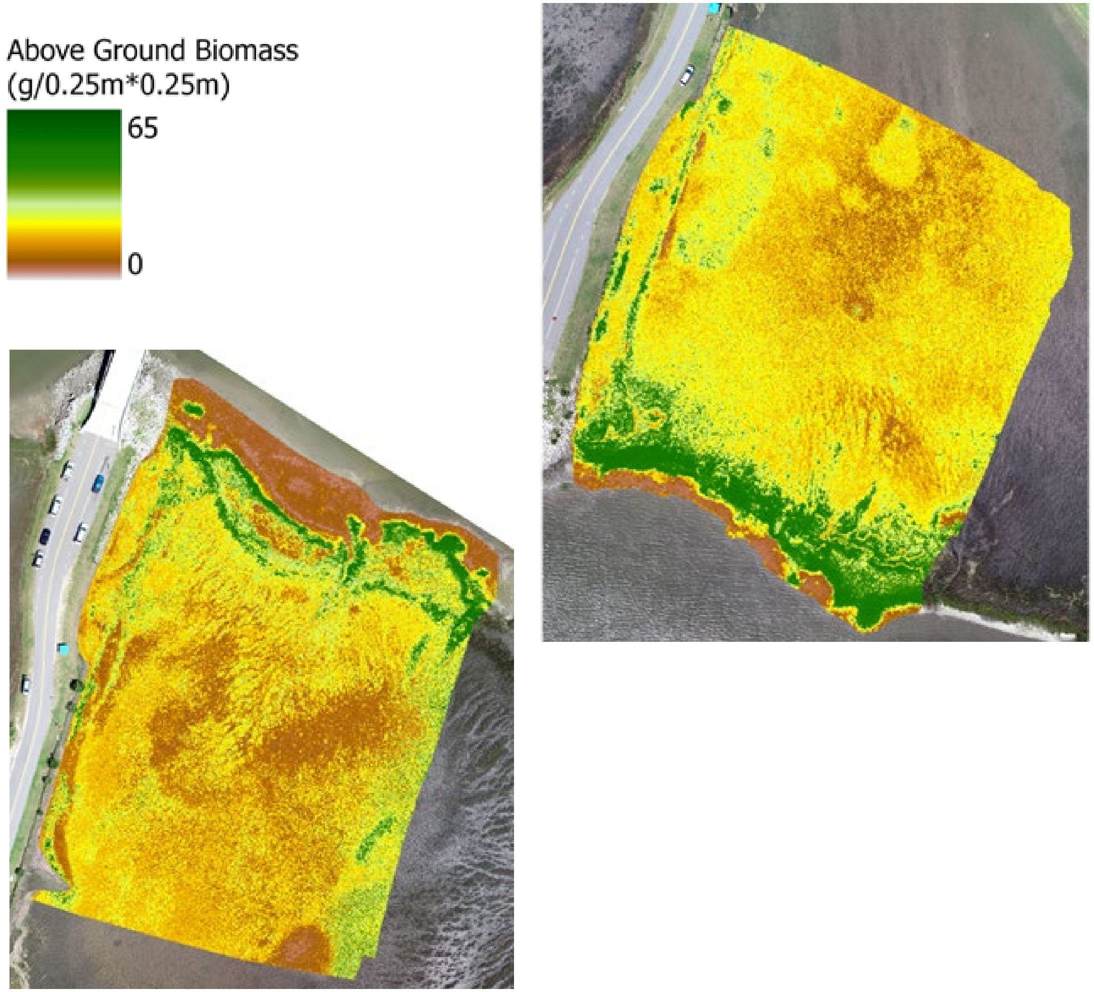
CDM Smith combined field data, 3D drone data, and multispectral data in a machine learning model to quantify site-wide biomass.



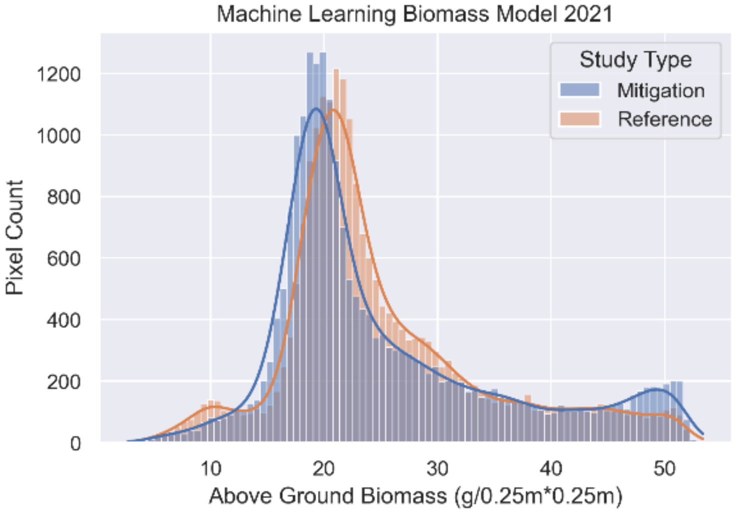


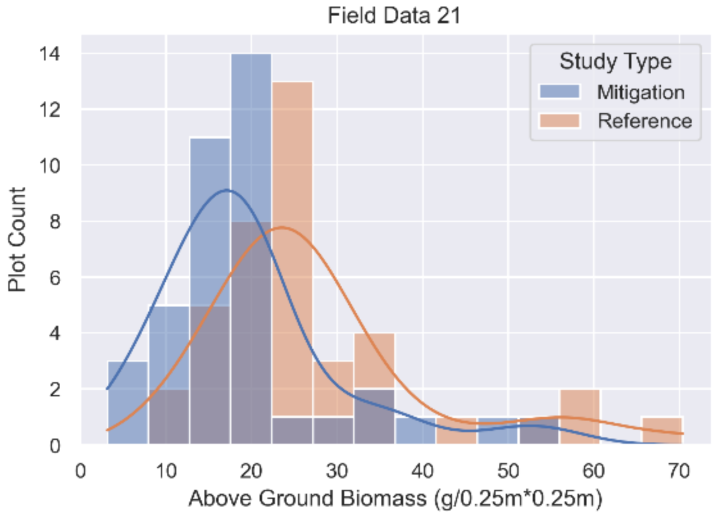
The machine learned model accurately predicted biomass.

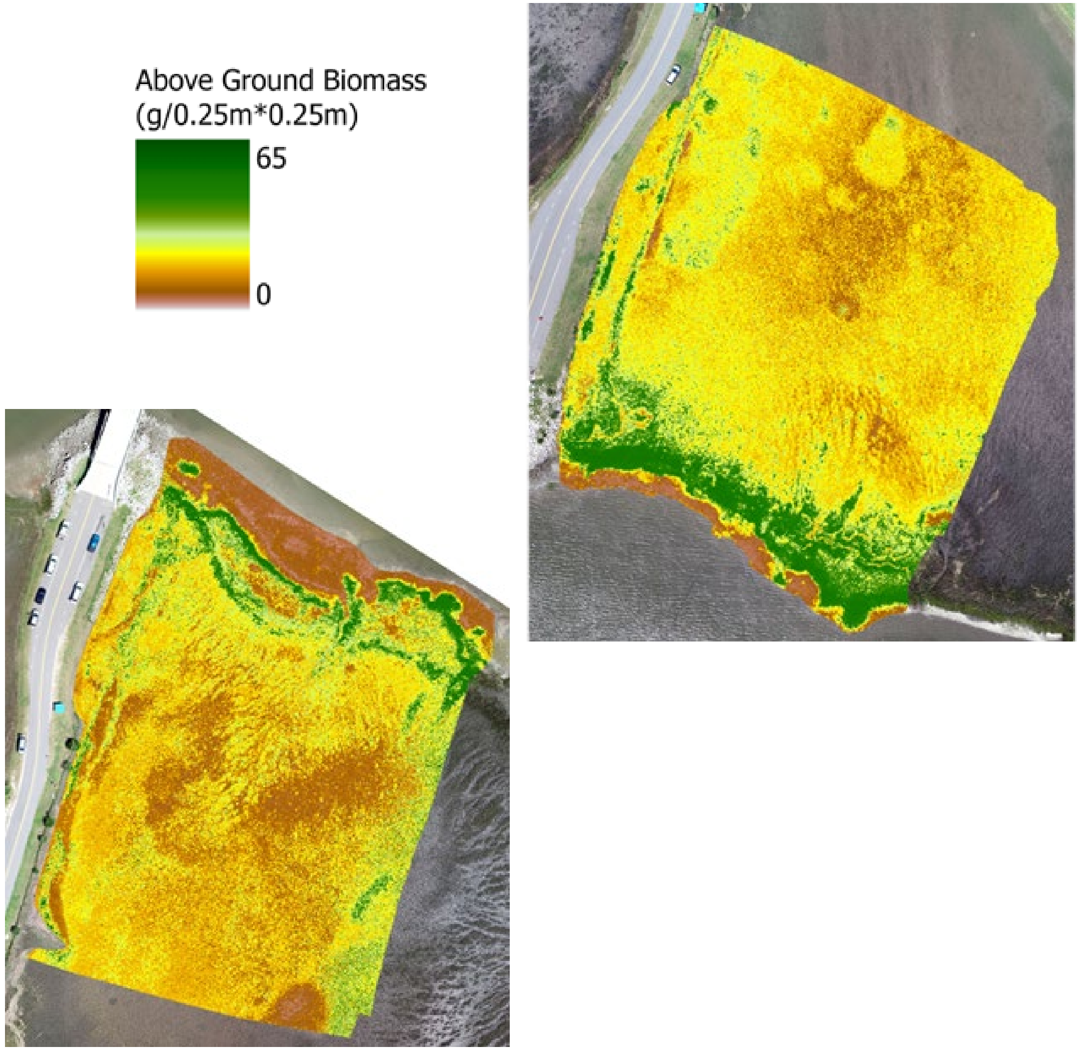




Model results were similar to field results.







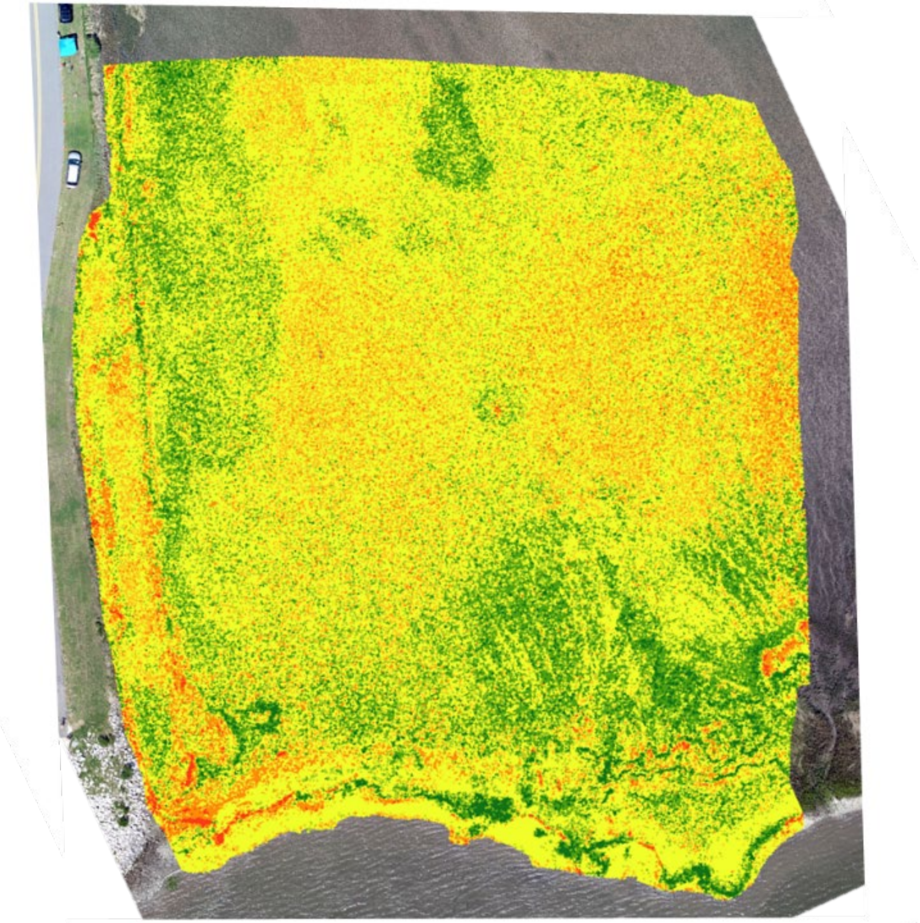
Machine learning model results allow for easy identification of biomass loss and gain over time.

2022 - 2021

Biomass Loss

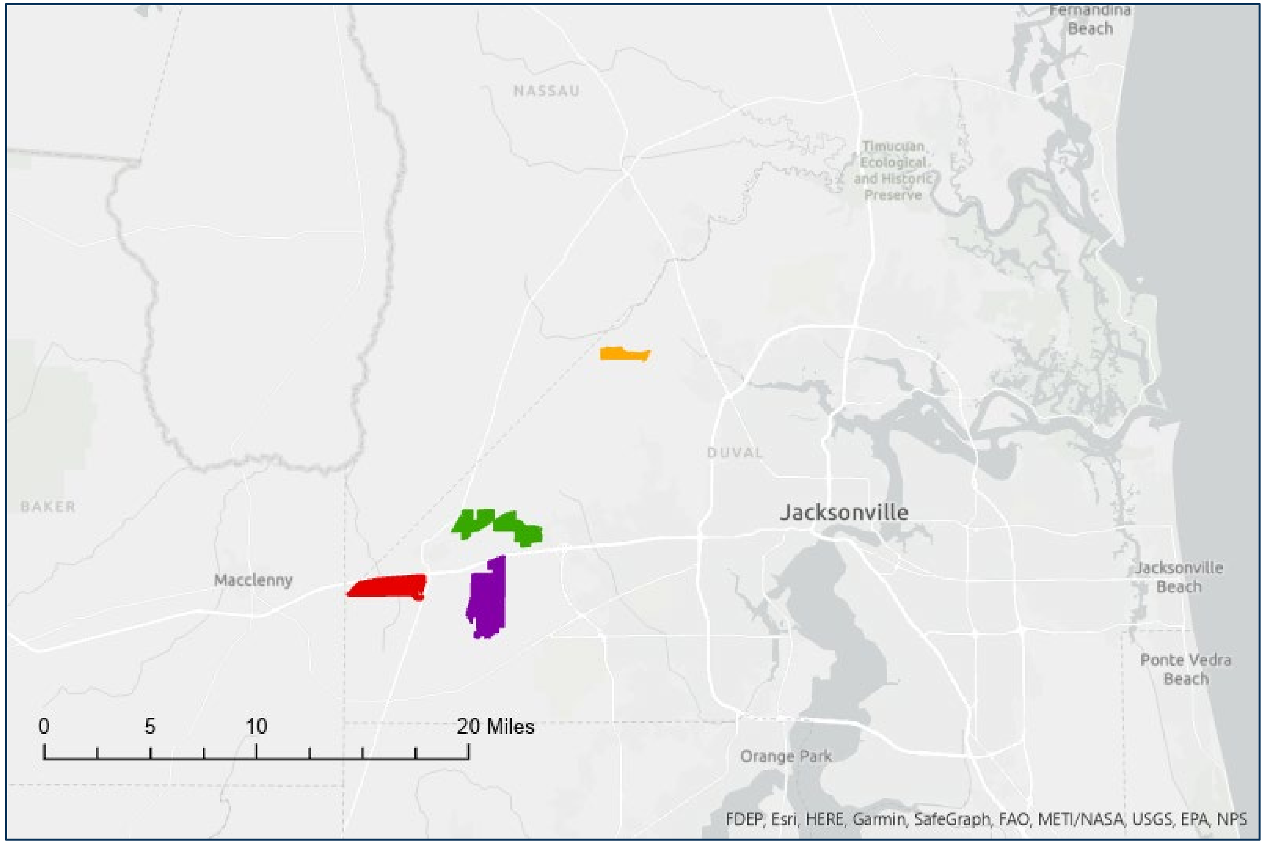
Biomass Stable

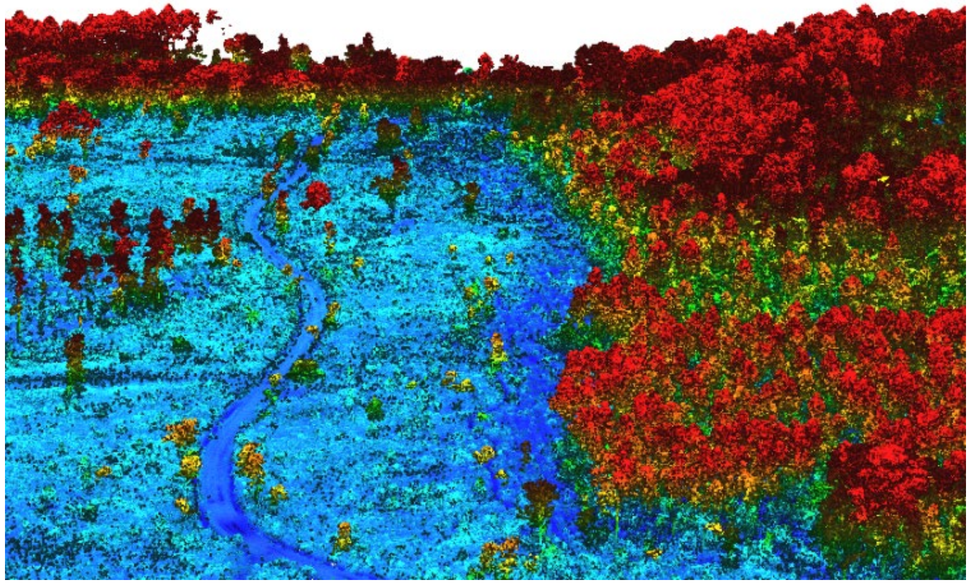
Biomass Gain



Site Feasibility: Wetland Delineation

How do we locate wetlands to quantify how much land is available for development?





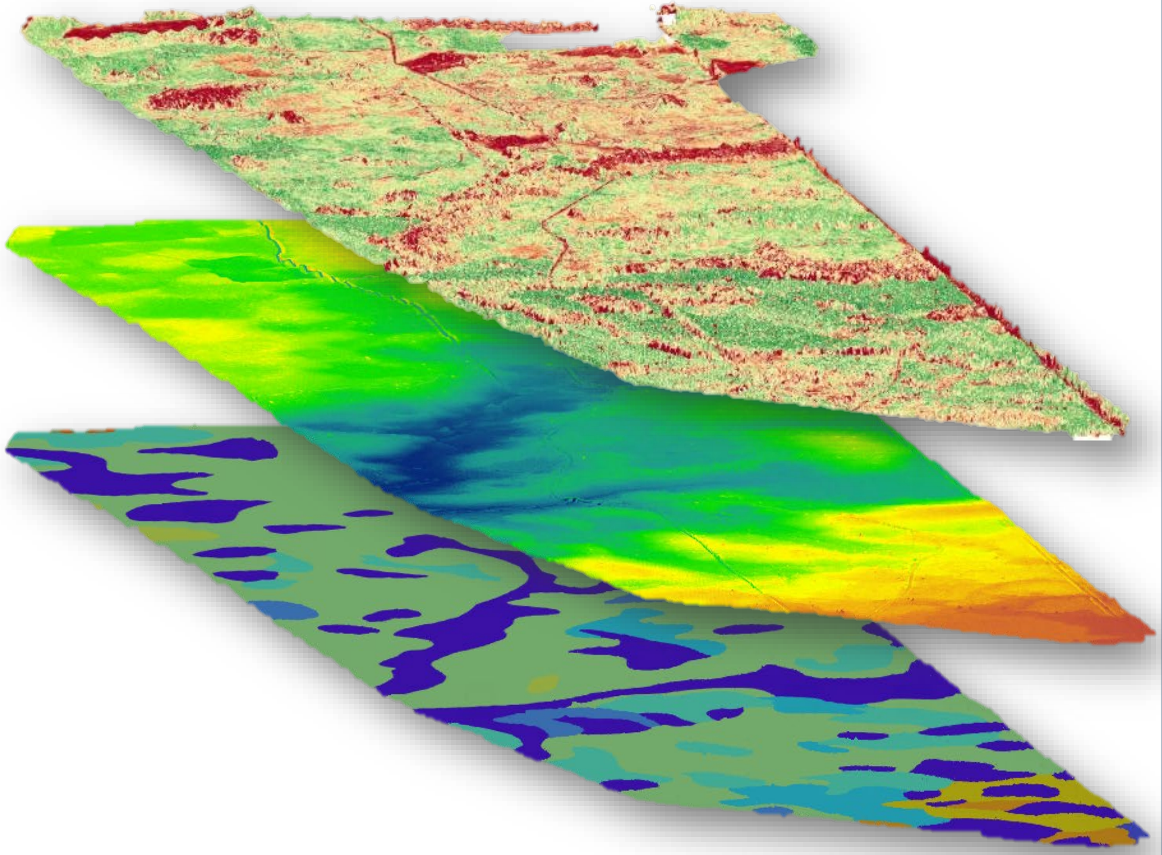
Traditional approach for delineating wetlands.

What defines a wetland and how can we predict their location?

NDVI from NAIP

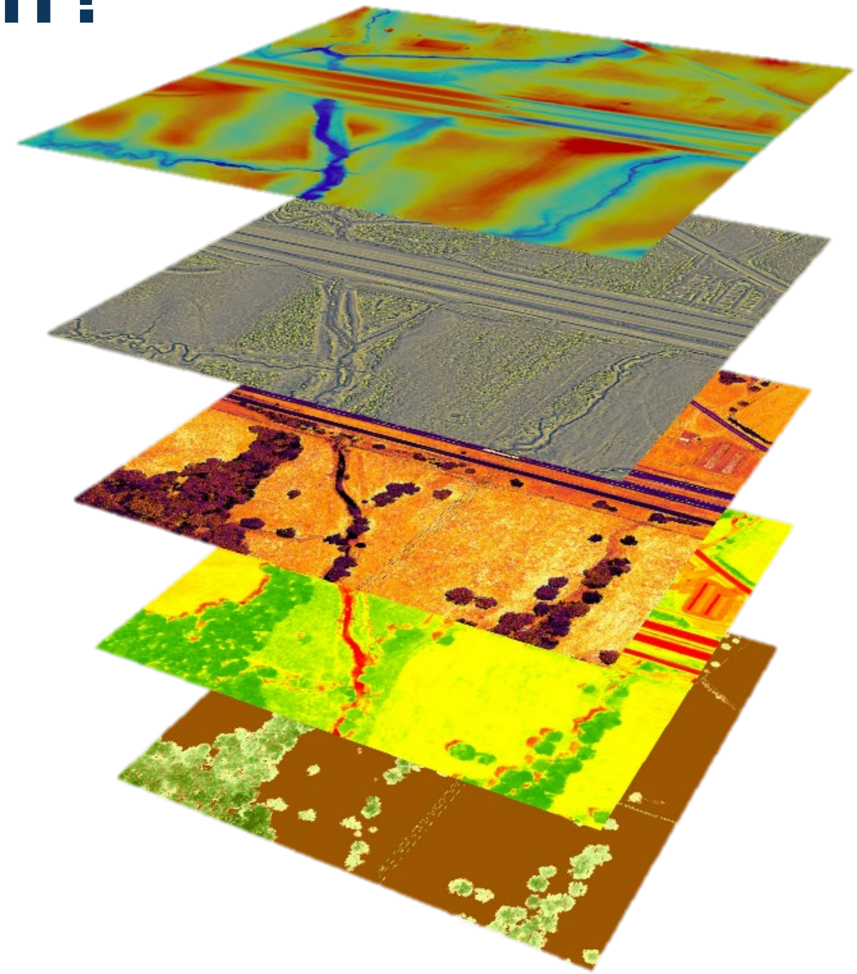
LiDAR Products

SSURGO Soils Data



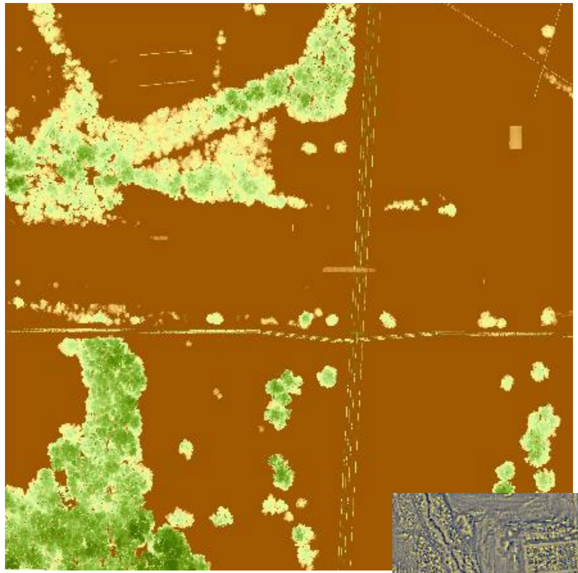
What defines a wetland and how can we predict their location?

- **NDVI from NAIP**
- LiDAR Products
  - **CHM**
  - Bare earth DEM
    - **Deviation from mean**
  - **Intensity**
- SSURGO Soils Data

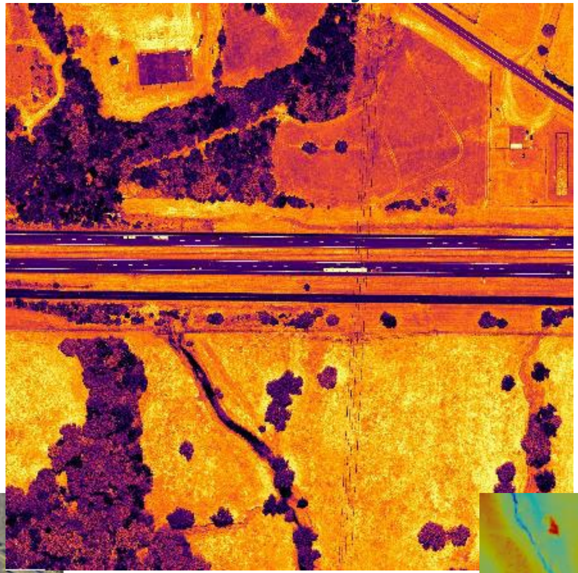


Remote Sensing Features

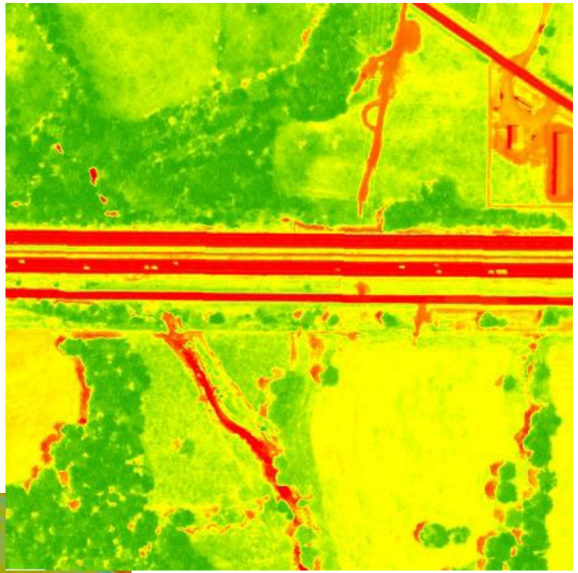
CHM

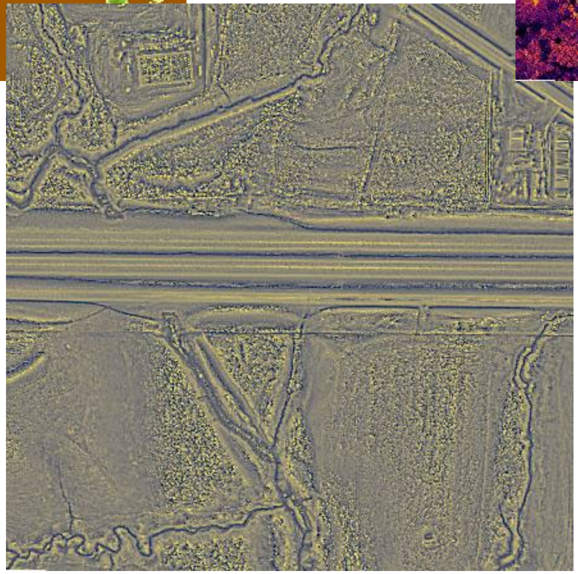


Intensity

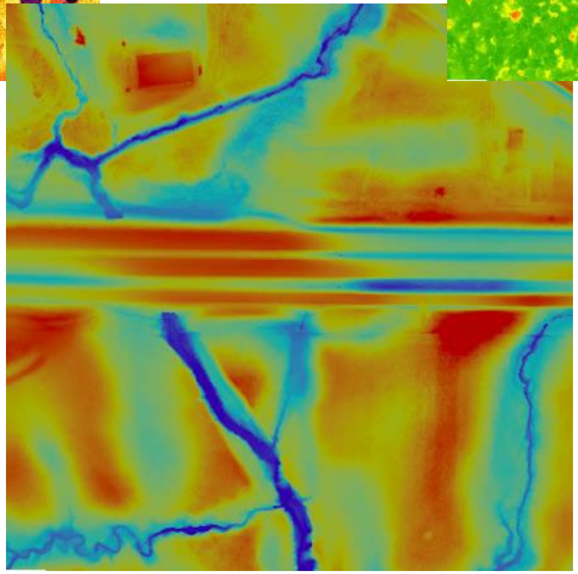


NDVI



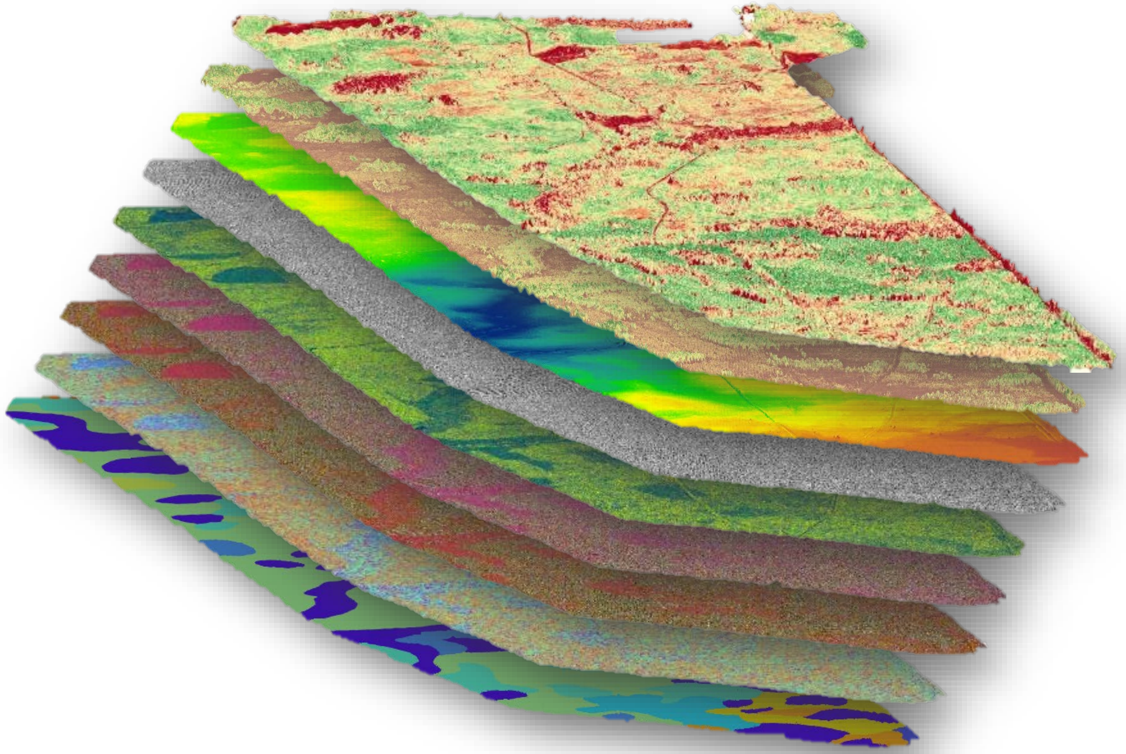


Deviation from mean (small area)



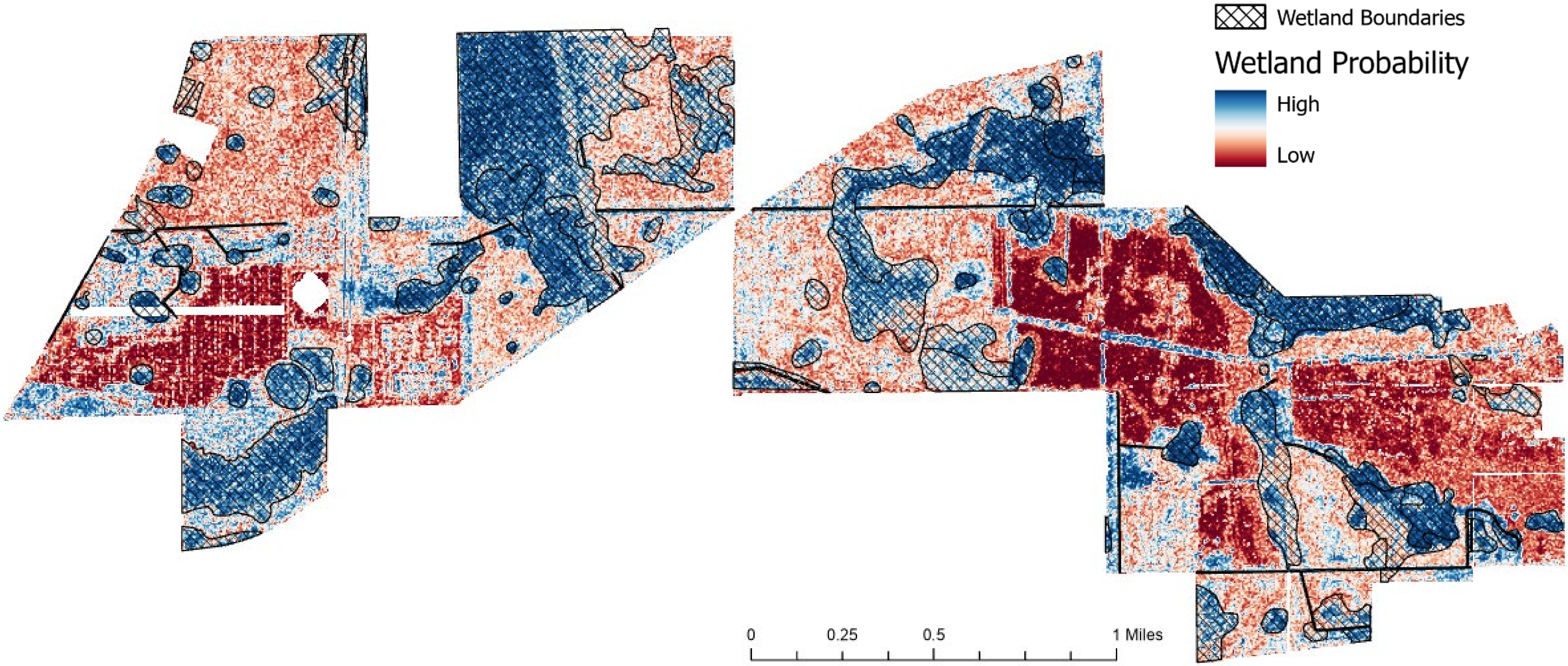
Deviation from mean (large area)

Tabular/Pixel Based Machine Learning

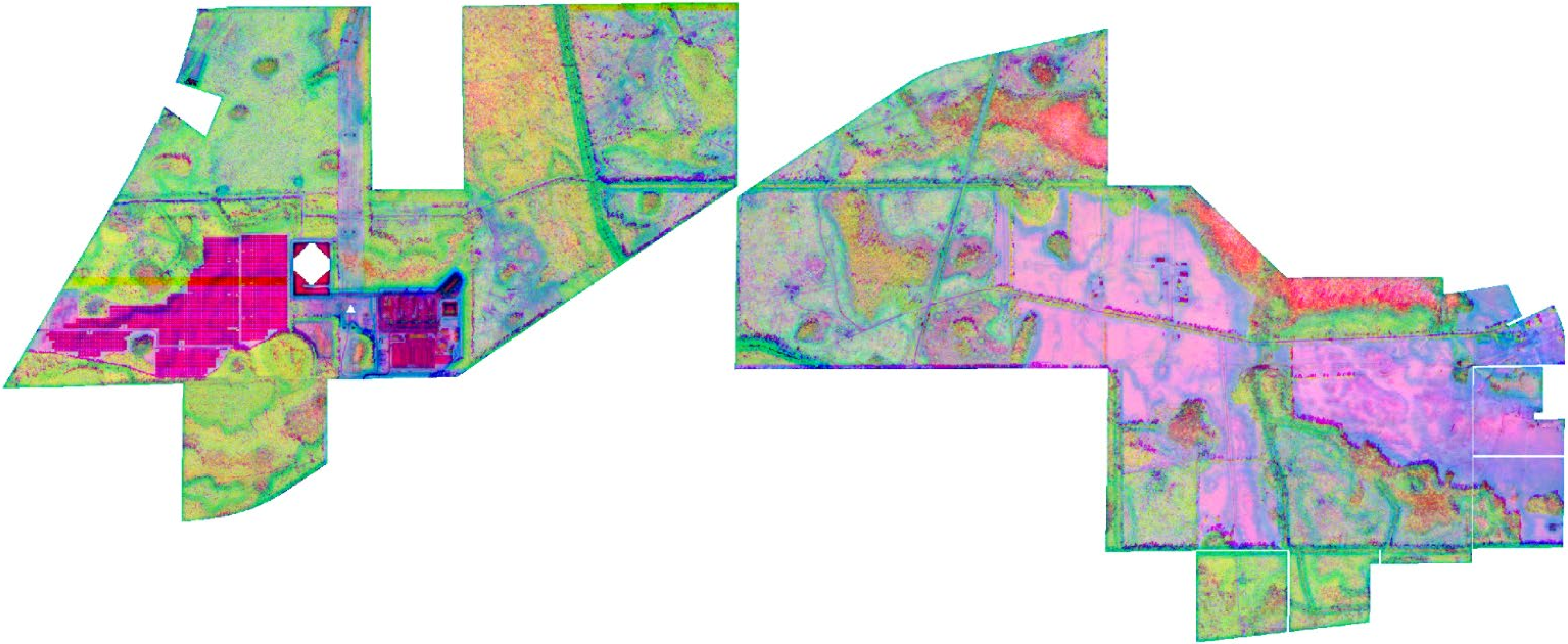


	grnd	bcon	chm	grad	plan	prof	twi	ndvi	soil
0	0.848292	1.168940	4.480000	0.155842	0.280000	0.039993	3.049424	0.349663	96.0
1	1.097692	0.433987	0.490000	0.087569	0.026195	-0.073811	2.948446	0.189539	5.0
2	-1.546986	1.550257	0.190000	0.162854	0.018937	0.058930	2.267665	0.194915	41.0
3	1.151135	1.346371	11.780000	0.045512	-0.032000	0.088011	3.089783	0.183789	5.0
4	0.525409	0.794799	0.620000	0.108565	-0.077797	0.002205	2.220407	0.148438	5.0
5	-1.654614	0.842667	1.070000	0.214368	-0.220559	0.299447	2.107459	0.170622	96.0
6	-1.059320	0.816192	0.040000	0.123974	0.399878	-0.060131	3.647214	0.160622	41.0
7	0.137206	2.055617	4.010000	0.013117	0.013995	-0.025983	4.333852	0.168724	3.0
8	-1.591522	1.809911	1.050000	0.145349	-0.031793	-0.071787	2.383315	0.324561	41.0
9	0.469739	0.000077	0.590000	0.050373	0.105280	-0.134711	6.356588	0.130081	5.0
10	0.472708	0.663679	23.139999	0.096262	-0.137603	0.142397	2.340686	0.279412	5.0
11	-1.060805	0.923987	1.160000	0.162201	0.119405	-0.060596	4.151978	0.188679	41.0
12	-1.365874	0.706800	14.959999	0.086919	-0.058871	-0.038875	3.184917	0.097893	100.0
13	-1.616017	1.505951	0.010000	0.017339	-0.181535	0.118461	4.054793	0.151515	41.0
14	0.814891	1.617866	17.760000	0.074437	-0.020164	-0.060157	2.597808	0.235669	5.0
15	-1.735521	1.540530	3.070000	0.136662	-0.044501	-0.404495	2.627947	0.178325	41.0
16	0.614480	0.916568	65.909996	0.115491	0.066427	-0.133555	3.257171	0.432836	5.0
17	-0.211657	3.033164	0.570000	0.051313	-0.314218	0.185753	2.969817	0.126984	3.0
18	0.965570	1.091349	19.504999	0.357448	-0.077501	0.082503	1.721911	0.358025	5.0
19	-1.080104	1.074648	12.910000	0.056568	-0.010010	0.029999	3.565446	0.254902	3.0

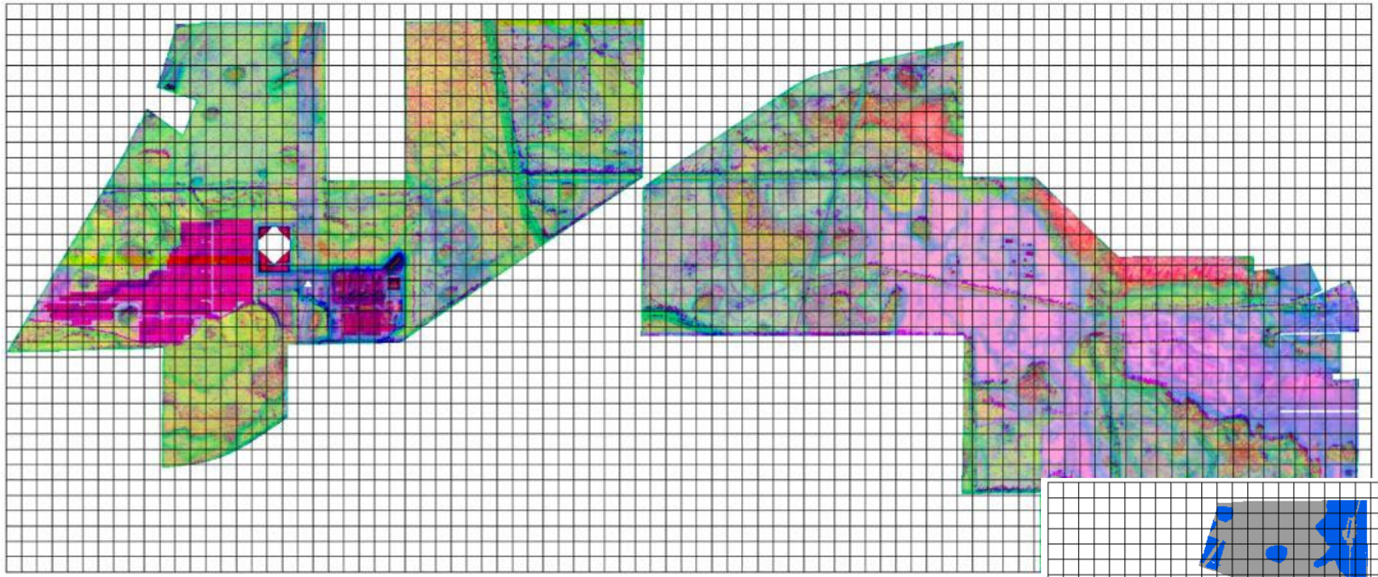
Tabular/Pixel Based Machine Learning

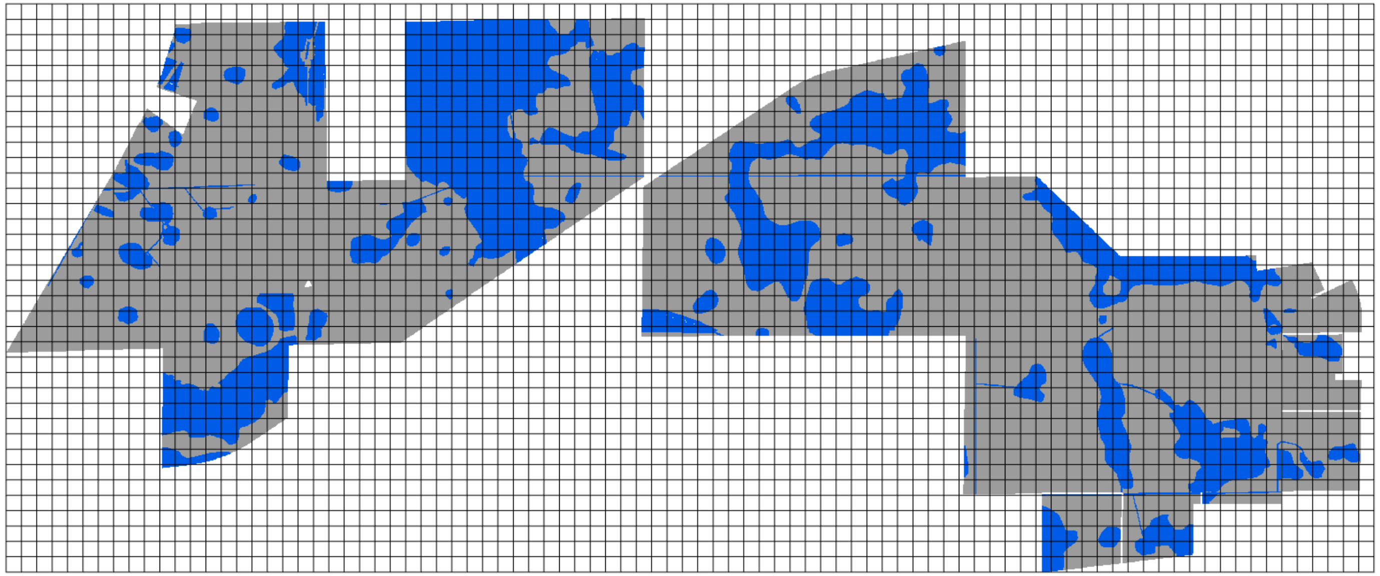


Deep Learning

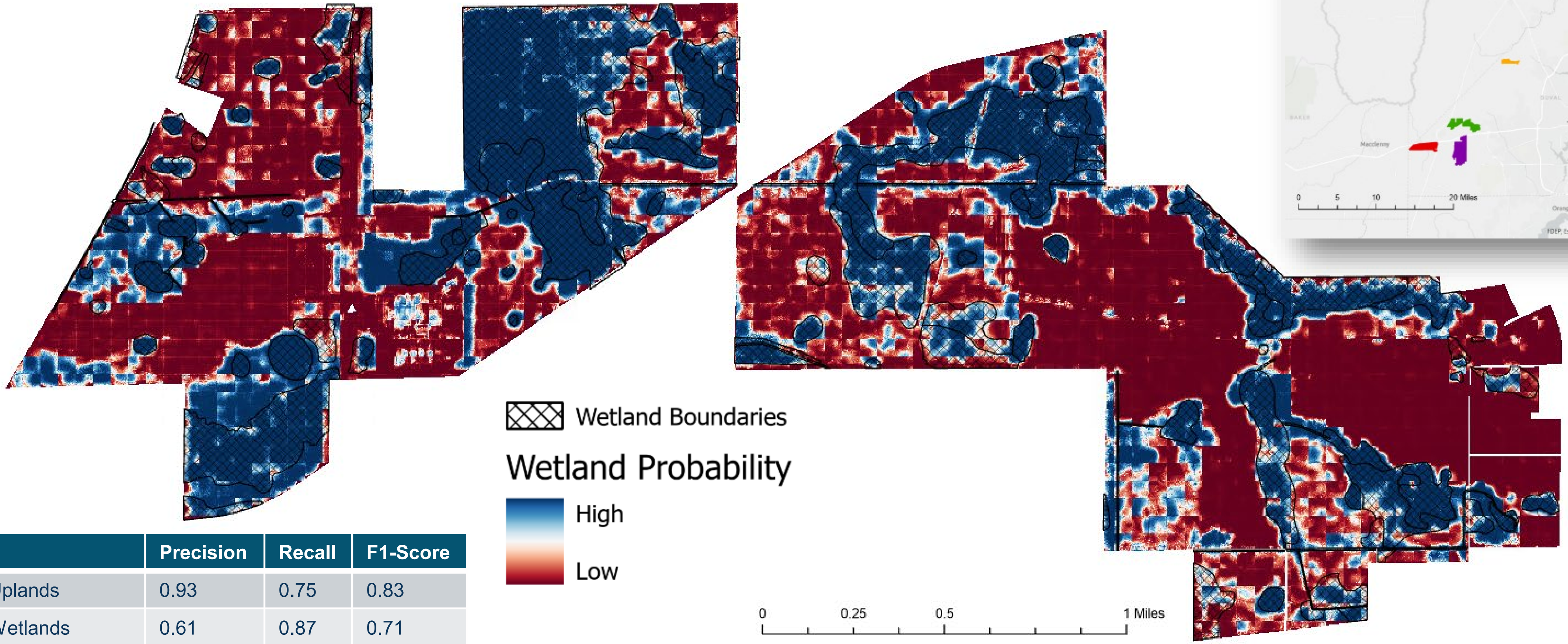


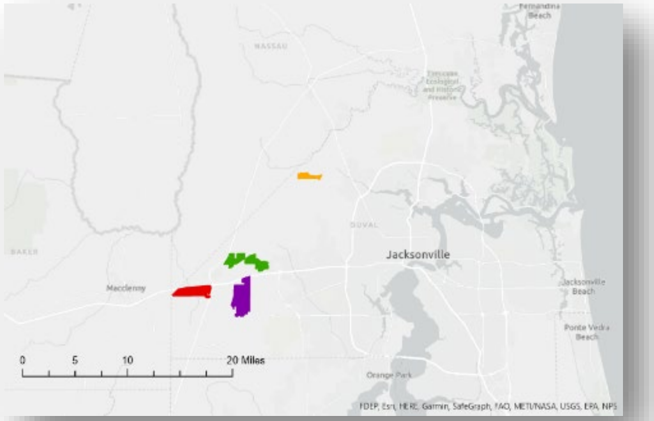
Deep Learning





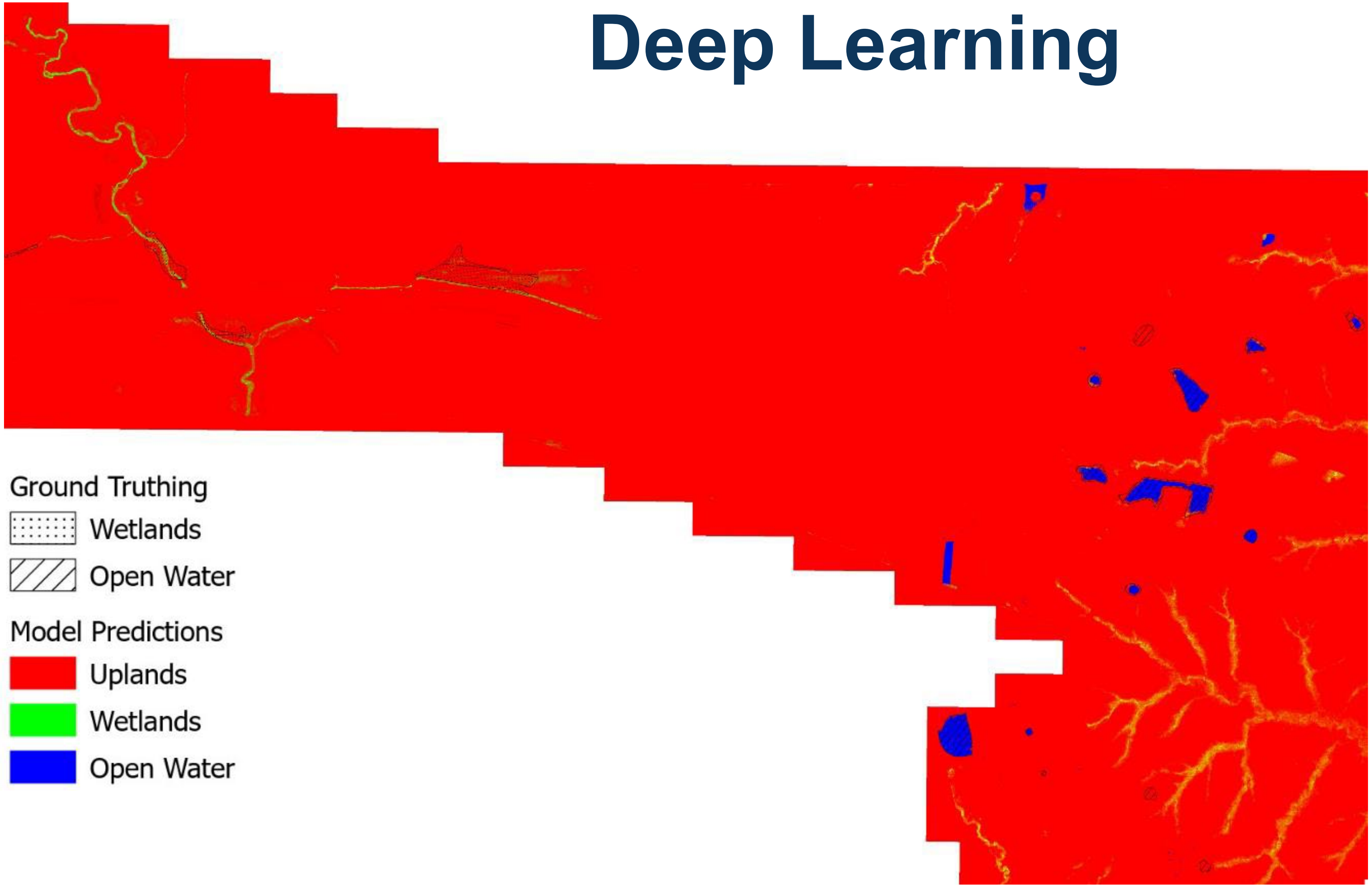
Deep Learning





	Precision	Recall	F1-Score
Uplands	0.93	0.75	0.83
Wetlands	0.61	0.87	0.71
Accuracy			0.79
Macro Avg	0.77	0.81	0.77
Weighted Avg	0.83	0.79	0.79

Deep Learning

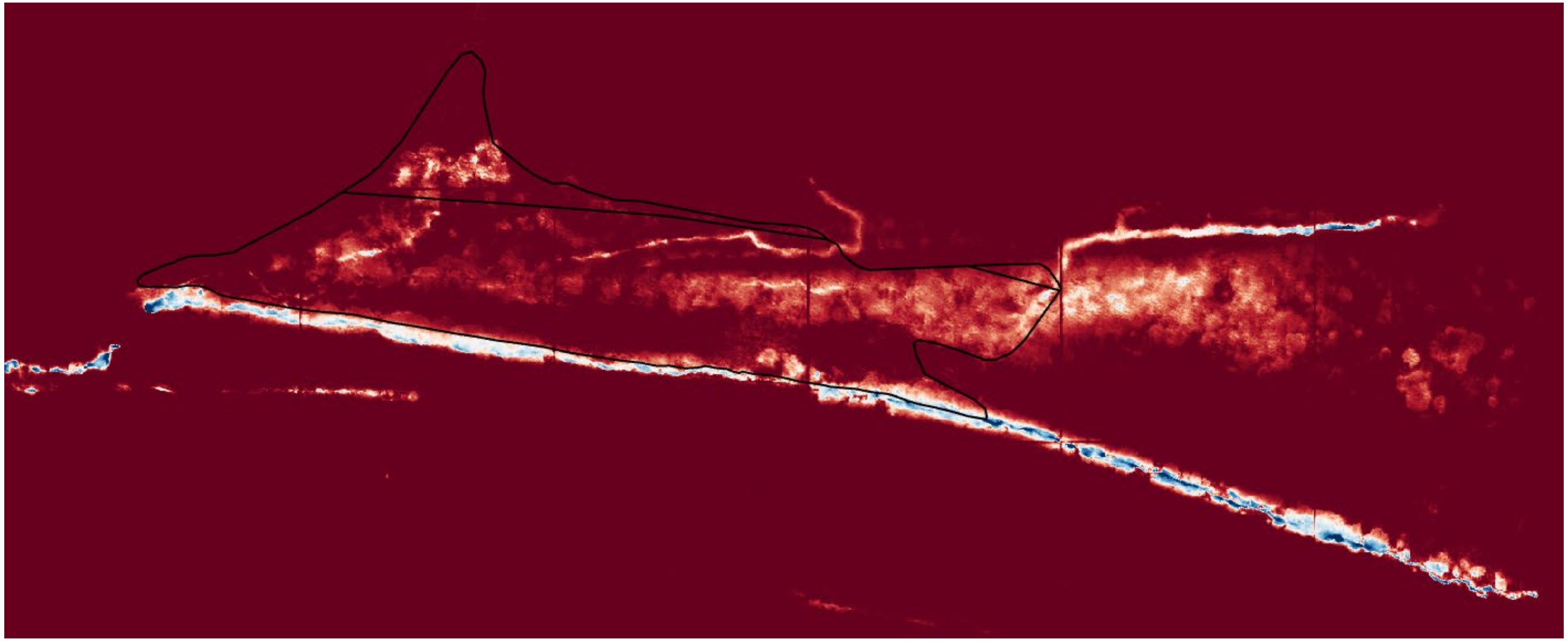


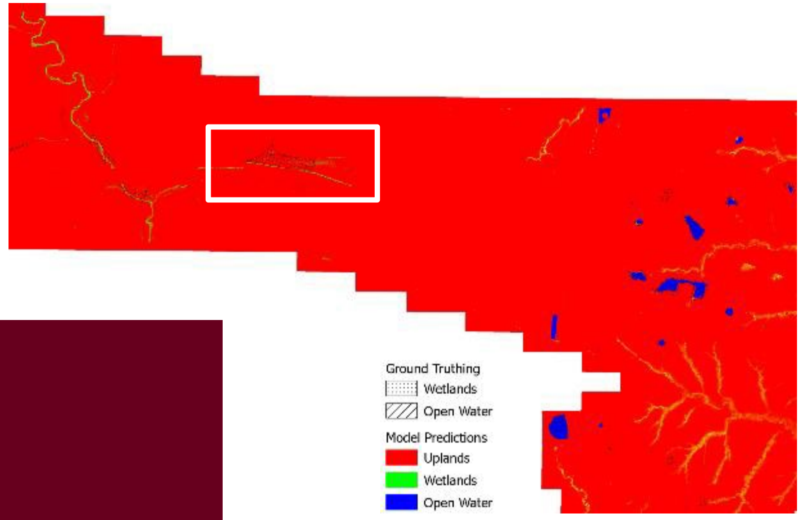
Deep Learning

Wetland Probability

High

Low





Resiliency: New urban development

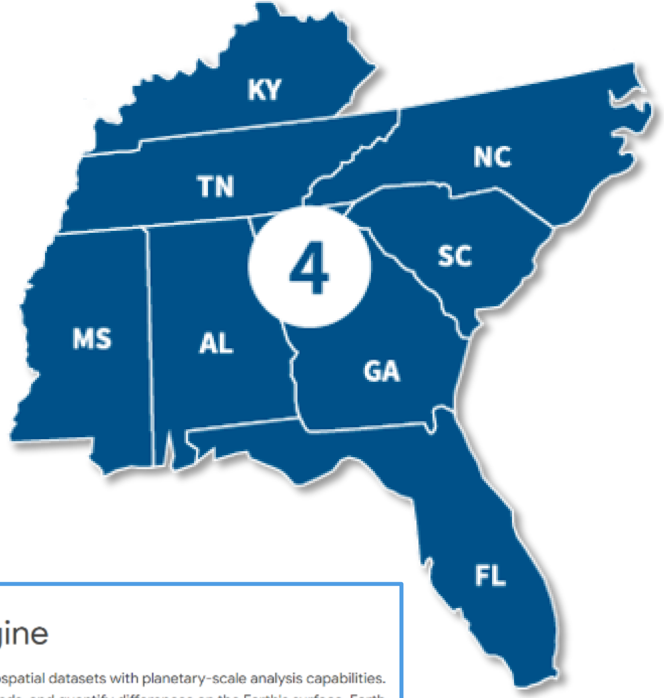
How do we identify newly built structures to assess building code effectiveness?

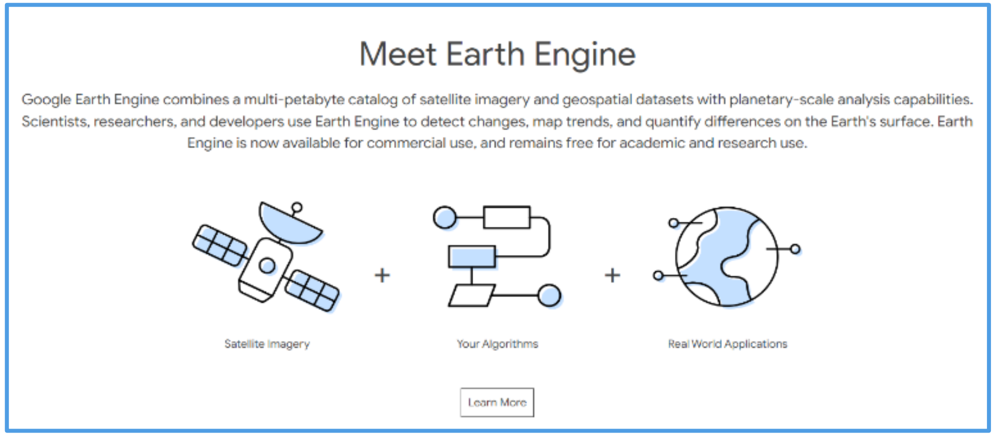
Traditional approach for identifying new urban development

- Parcel and permit data
  - Availability limitations
  - Temporal differences
- Imagery
  - Manual comparison of historical imagery

Identifying New Urban Development

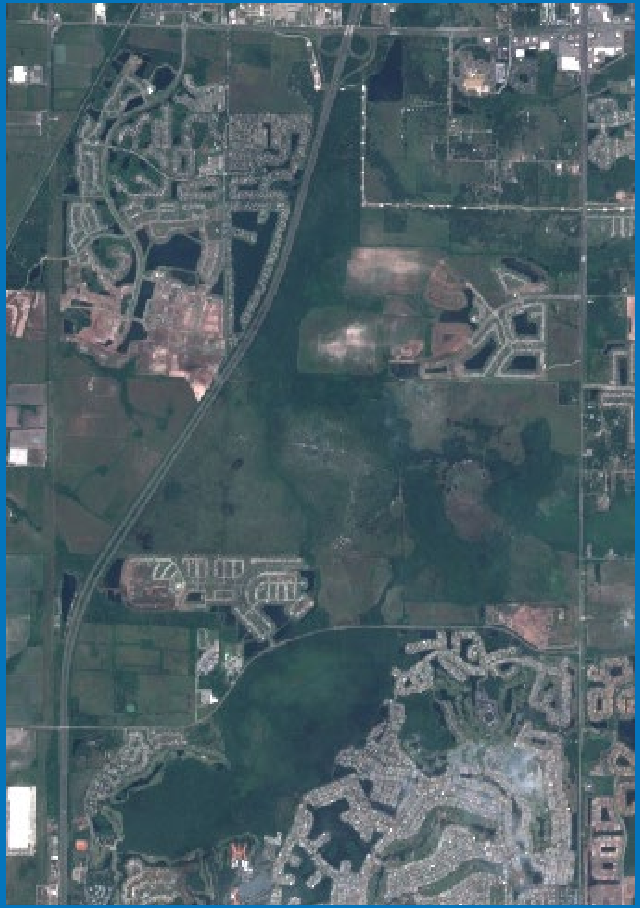
- Southeastern U.S. - FEMA Region IV
- Publicly available data
  - Sentinel
- Quick computation
  - Google Earth Engine
- Leveraging existing LULC model
  - Dynamic World



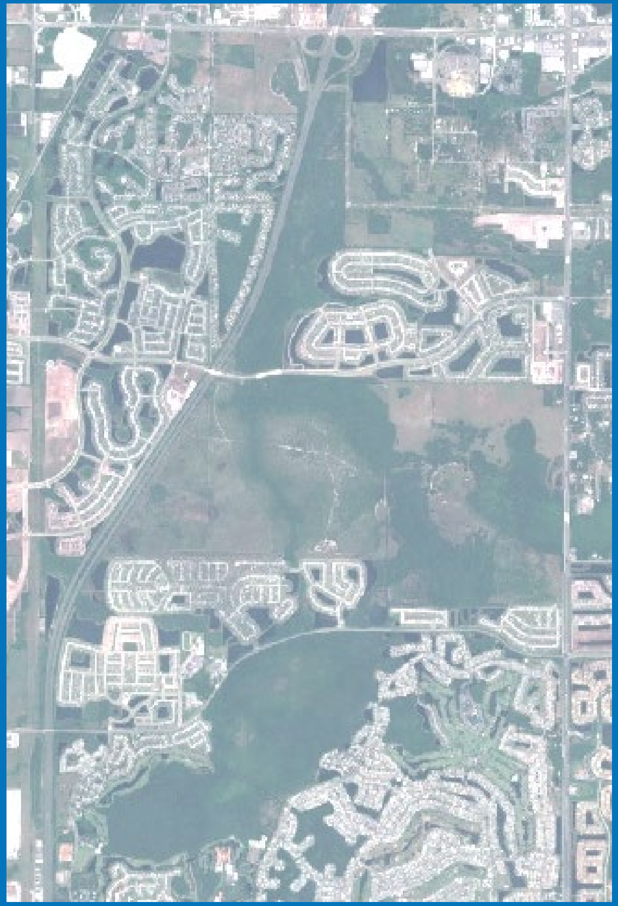


Identifying New Urban Development

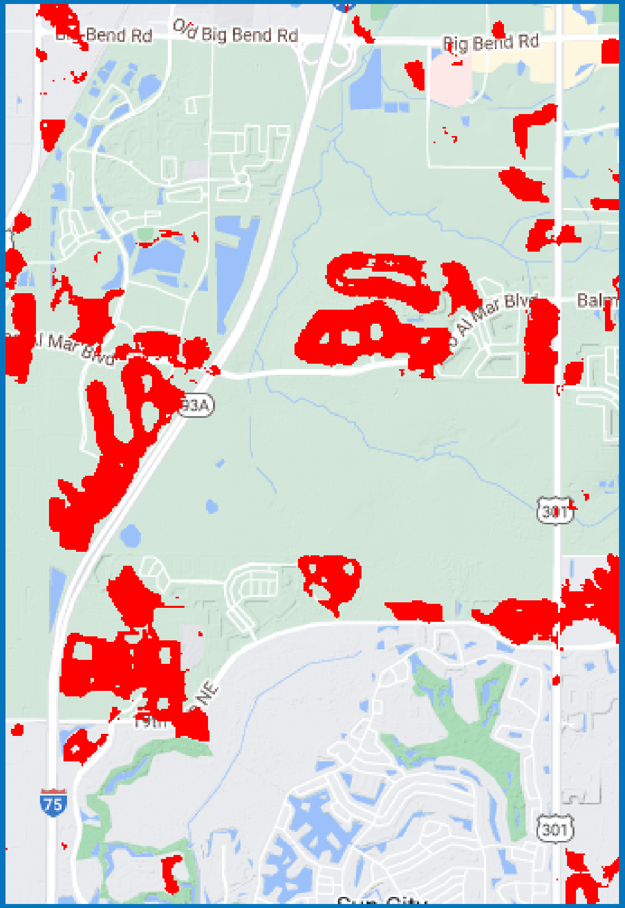
2017



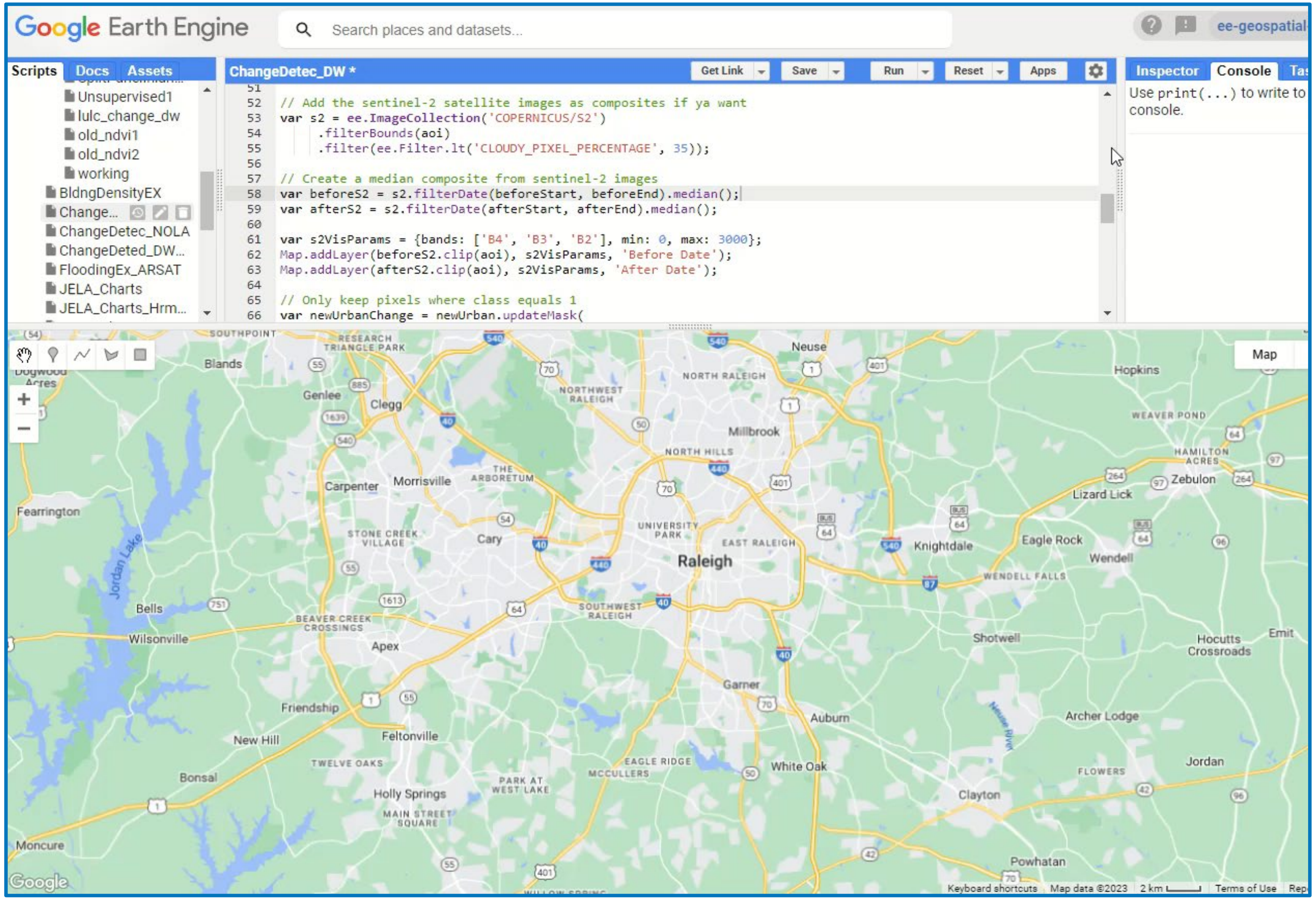
2022



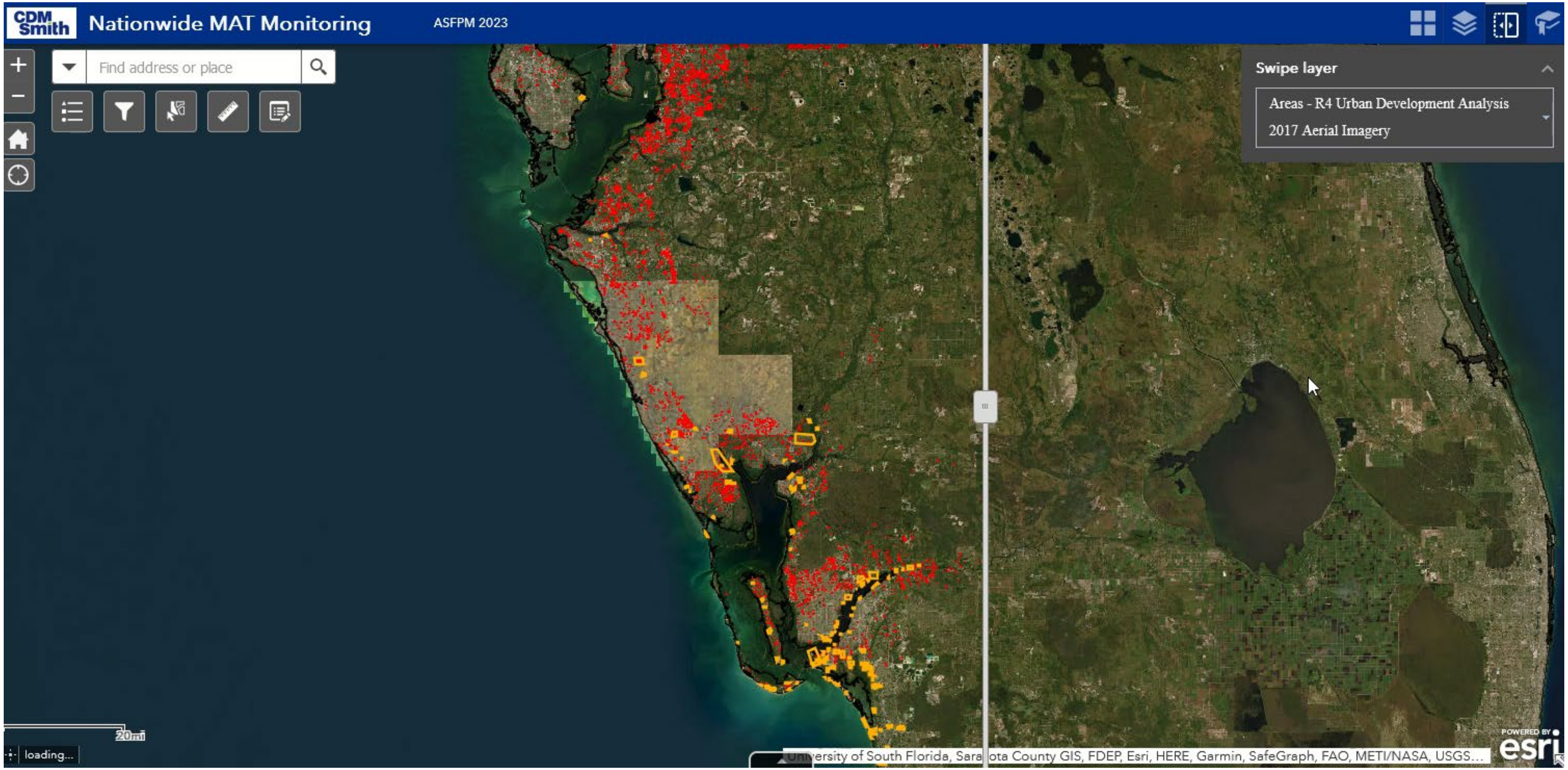
Results



Identifying New Urban Development



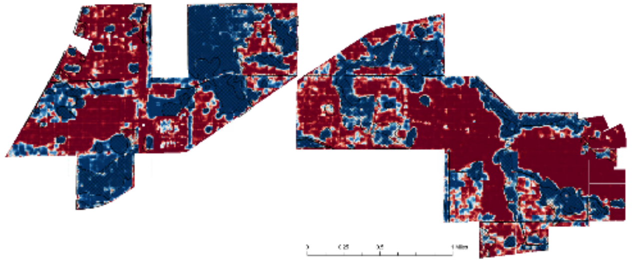
Integration to Collector App



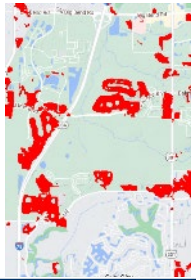
Advanced remote sensing and machine learning can benefit environmental projects.

Invasive and Native Species Mapping

Restoration Monitoring



Wetland Mapping/ Permitting



Urban Development

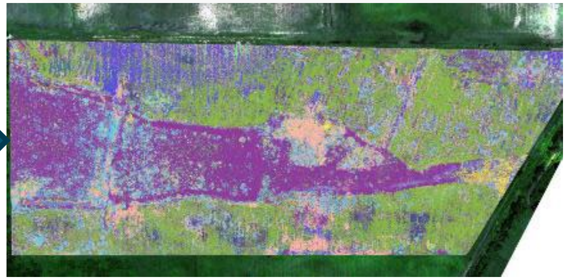
There are multiple advantages of using these technologies.

Save time/shorten schedule
Reduce field labor
Increase human safety

There are multiple advantages of using these technologies.

Save time/shorten schedule
Reduce field labor
Increase human safety

Higher quality data
Digital record
Data consistency
Data repeatability
Track change over time
100% site coverage



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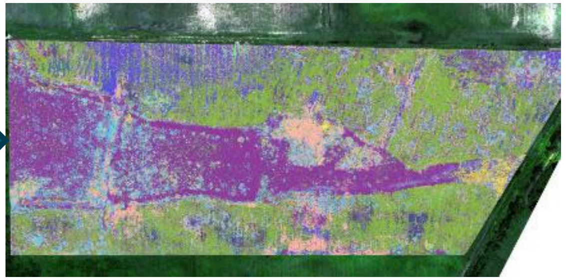


These technologies can improve the efficiency, scale, and accuracy of environmental evaluations conducted on federal lands:

- Threatened and endangered species habitat
- Native plant communities
- Biodiversity
- Biomass/carbon sequestration
- Invasive and exotic species
- Wildland fire activities
- Resilience
- Track affects of climate change

Land managers have an important role to play in leveraging these technologies at their sites.

Target of Interest

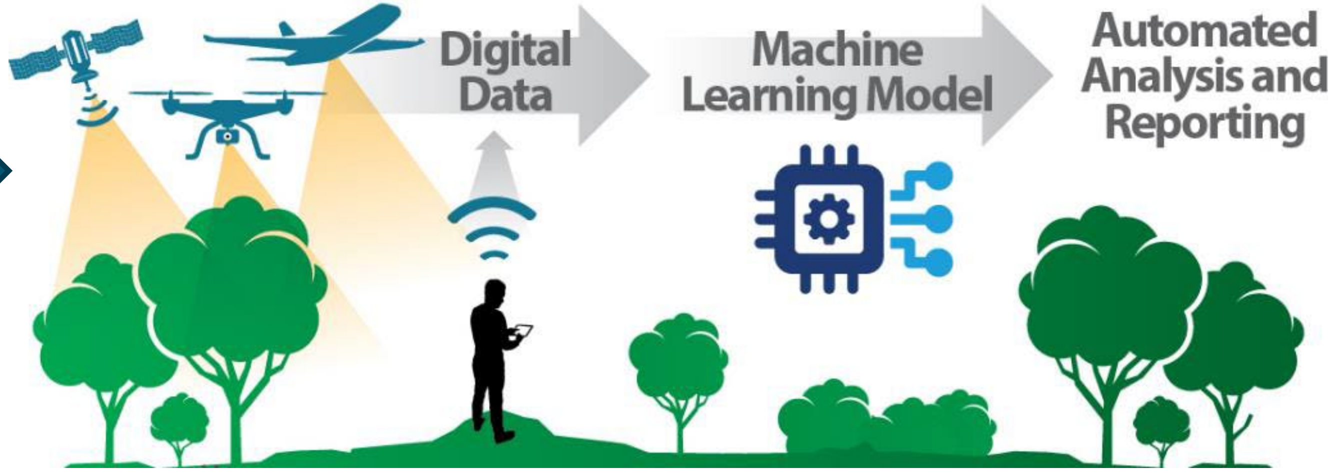
Temporal Resolution

Spatial Resolution

Field Data

Abundance/Frequency

Better understanding the goals and objectives facilitates selection of the right resolution, sensors, and models.



The right questions can help determine the scale, sensors, models, and outputs to optimize data collection and analysis.

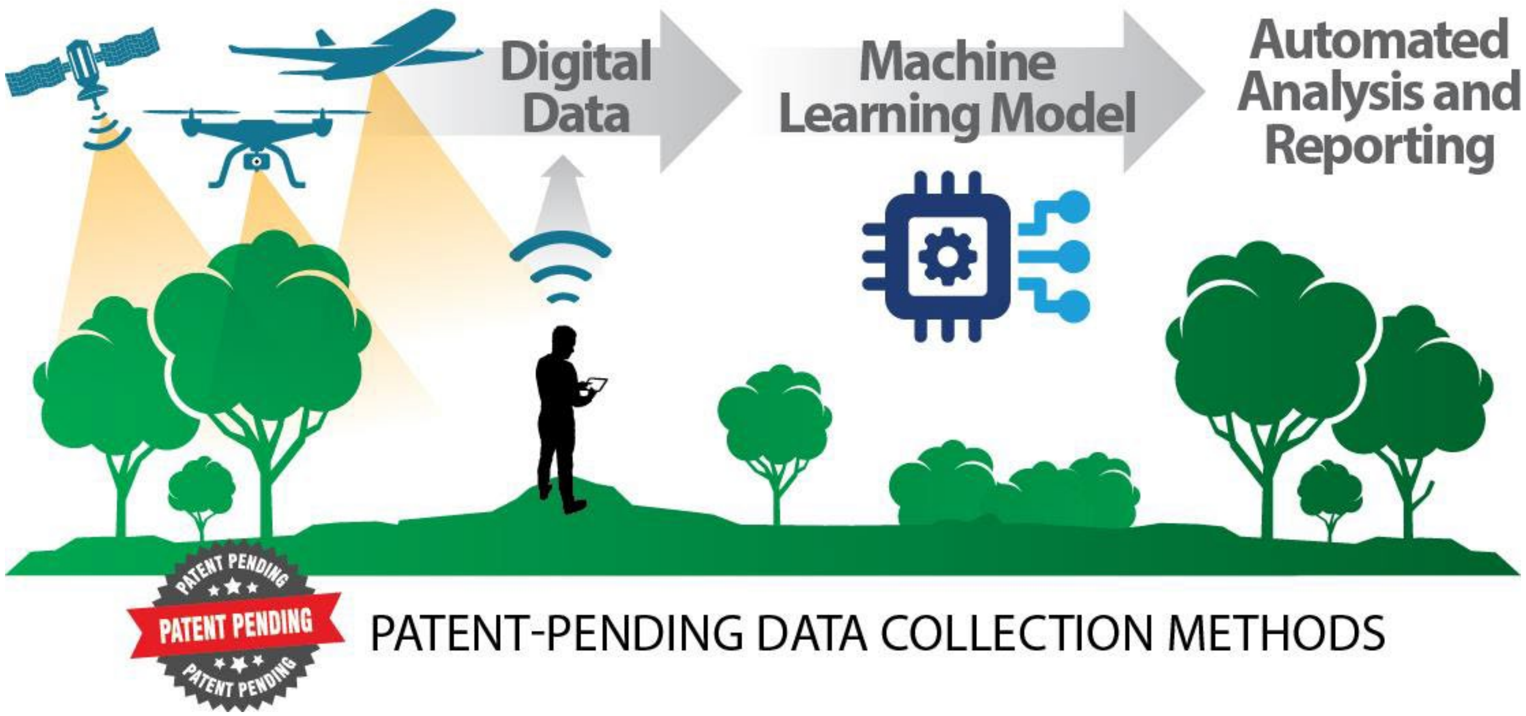
- What do I want to identify or know about my land?
- Why do I want to know this (regulatory, restoration, risk mitigation)?
- How frequently do I need to assess change or the target of interest?
- What is the size of the problem?
- How common is the target of interest on the landscape?
- How big of an area of interest is there?
- How might I use this information?
- What field data do I already have or collect regularly?
- What baseline data do I have?
- Are there site constraints or access issues?

Sky Wave combines machine learning and advance remote sensing to drive data to decisions.

sky wave™

Contact us:
skywave@cdmsmith.com

Find out more:
cdmsmith.com/skywave



THANK YOU

Please take a few minutes to complete a short survey about this session. Your feedback will help us improve future programming for JETC.

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