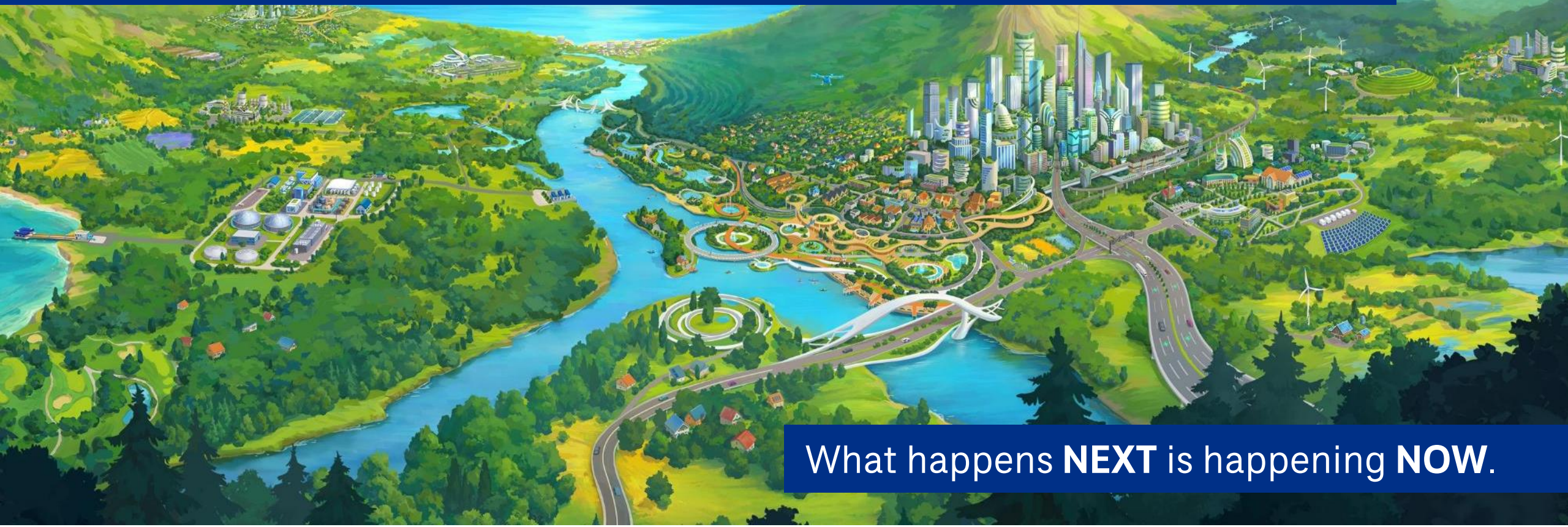
Drones and AI



Brendan Brown, PWS

November 2025

sky wave® at CDM Smith

There is a 400,000 to 800,000 position deficit each year in our industry.

The US Needs More Engineers. What's the Solution?

By Abhi Kodey, Julie Bedard, Jonathan Nipper, Nancy Post, Sibley Lovett, and Adriann Negreros

BCG

ARTICLE DECEMBER 13, 2023 15 MIN READ

https://www.bcg.com/publications/2023/addressing-the-engineering-talent-shortage

There are multiple ways to leverage AI in our industry.

Administrative AI

LLMs progress has reached a performance plateau.

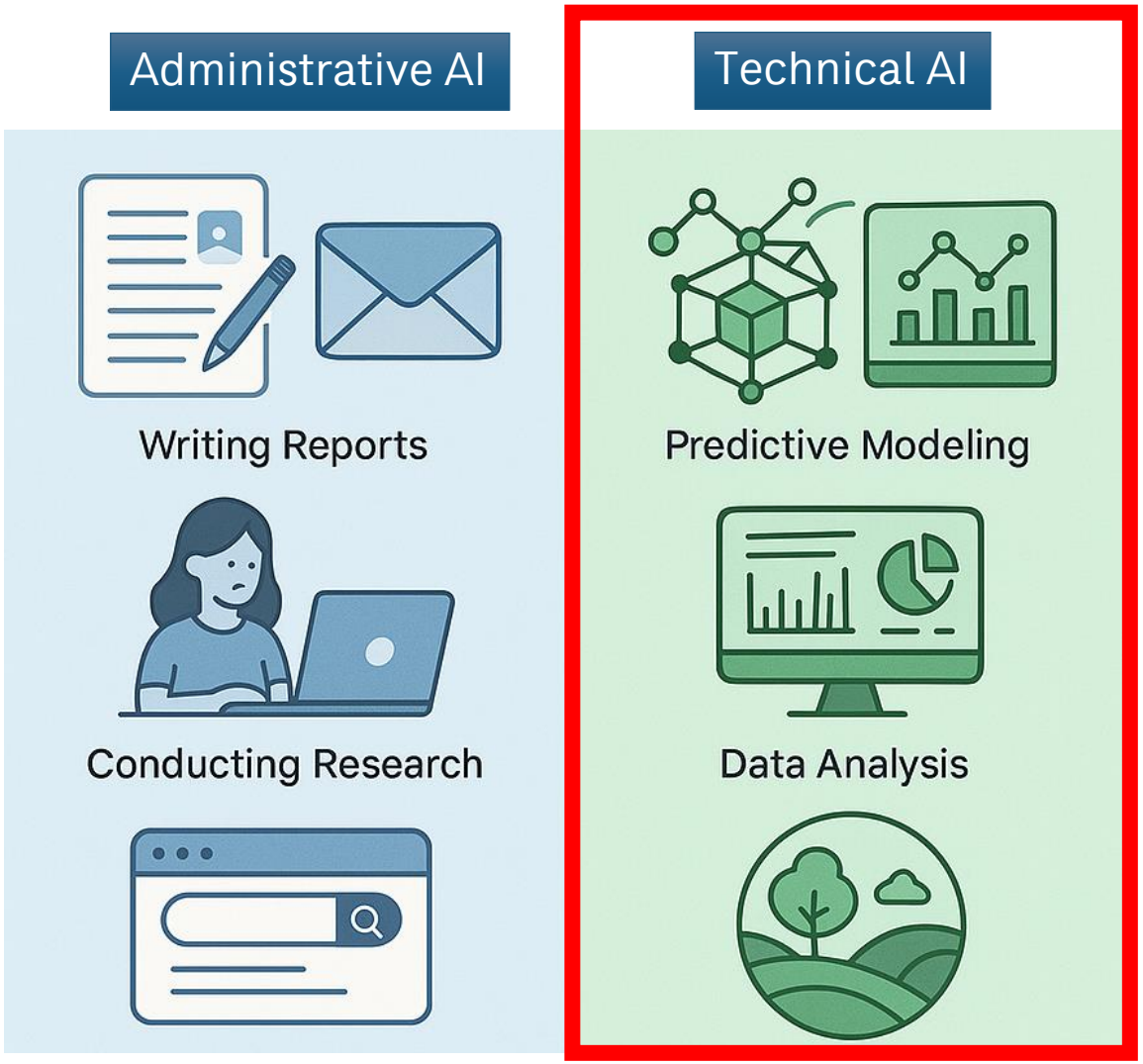
perplexity

Microsoft Copilot

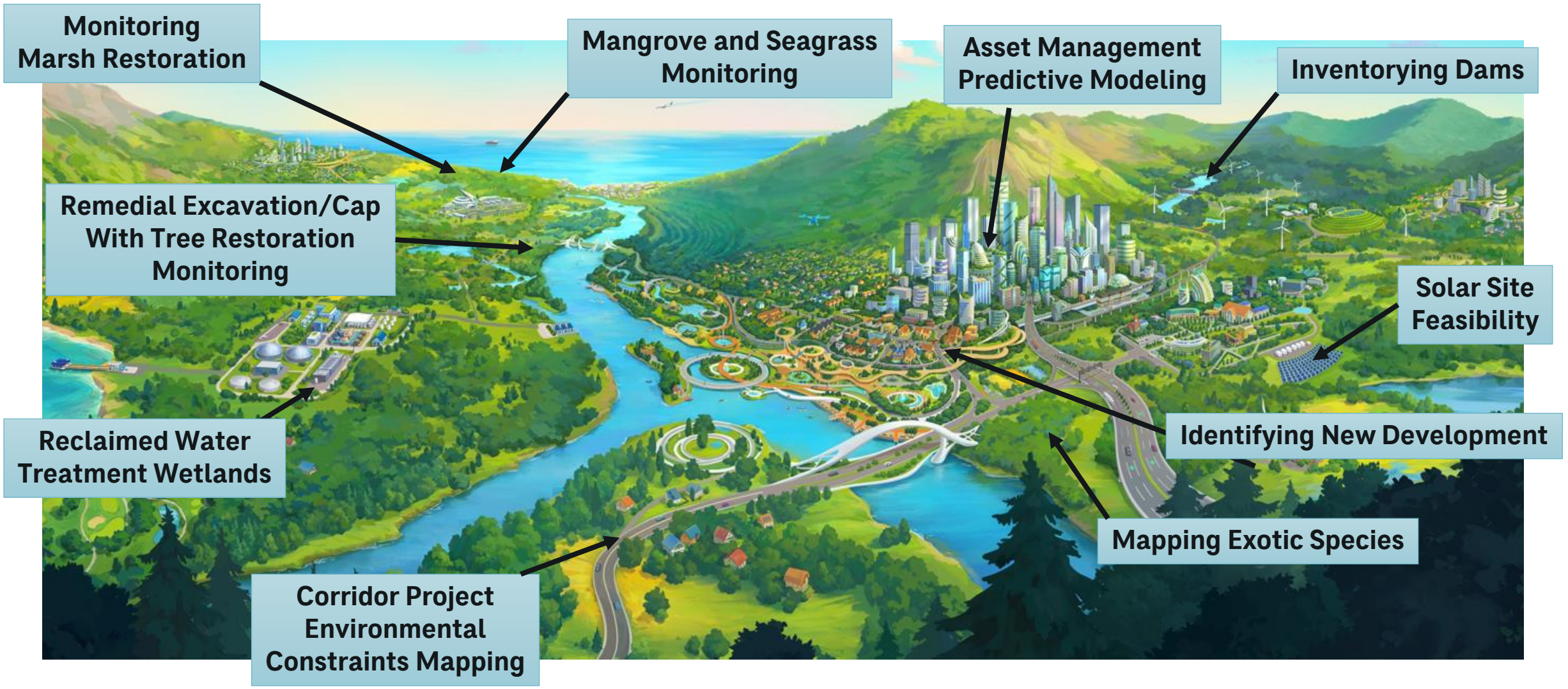
Gemini

Administrative AI

Technical AI will transform the industry; there is room for unprecedented growth.

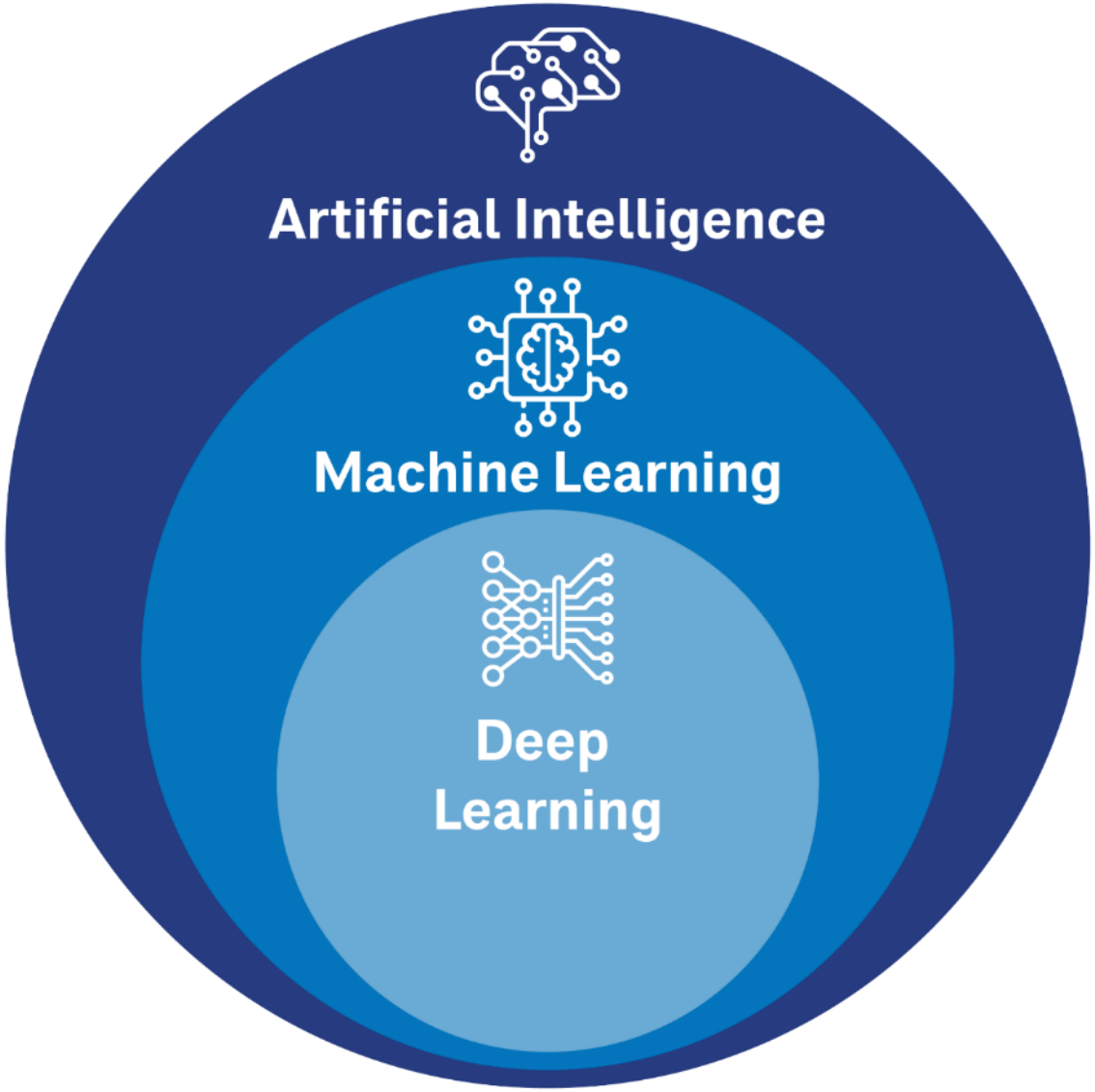


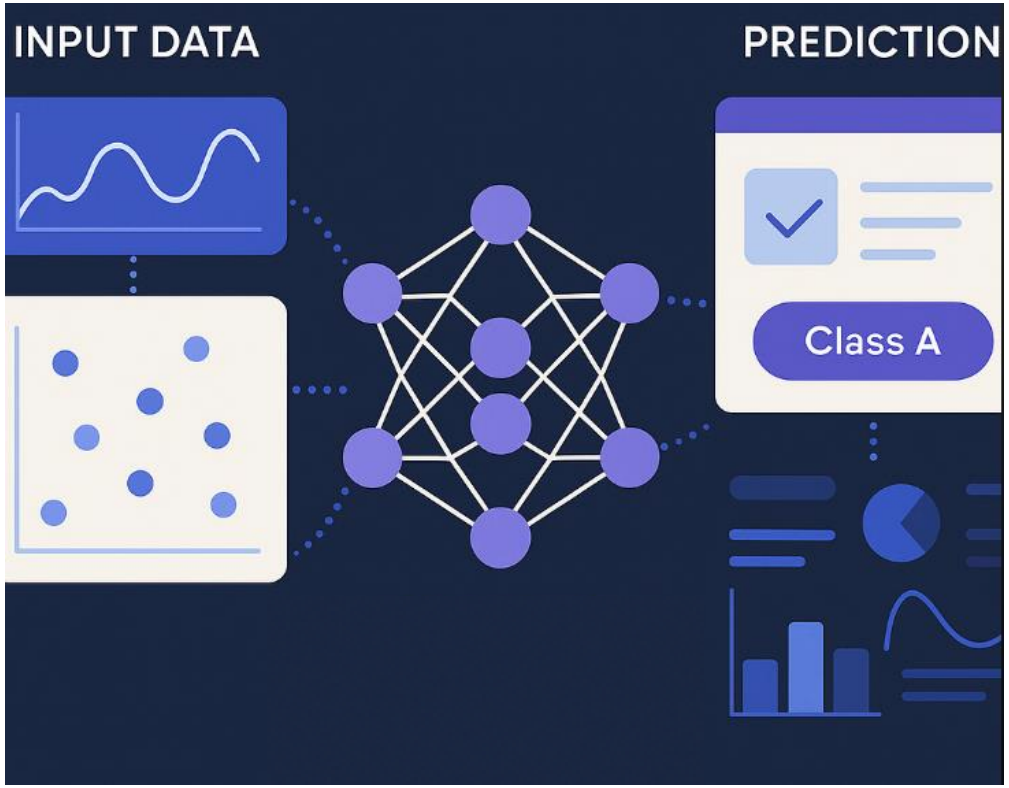
CDM Smith is leveraging AI to drive data to decisions.



CDM Smith is leveraging AI to drive data to decisions.

AI models are used to make predictions based on input data.





Modern-day computer processing power has opened the door to widespread use of AI.

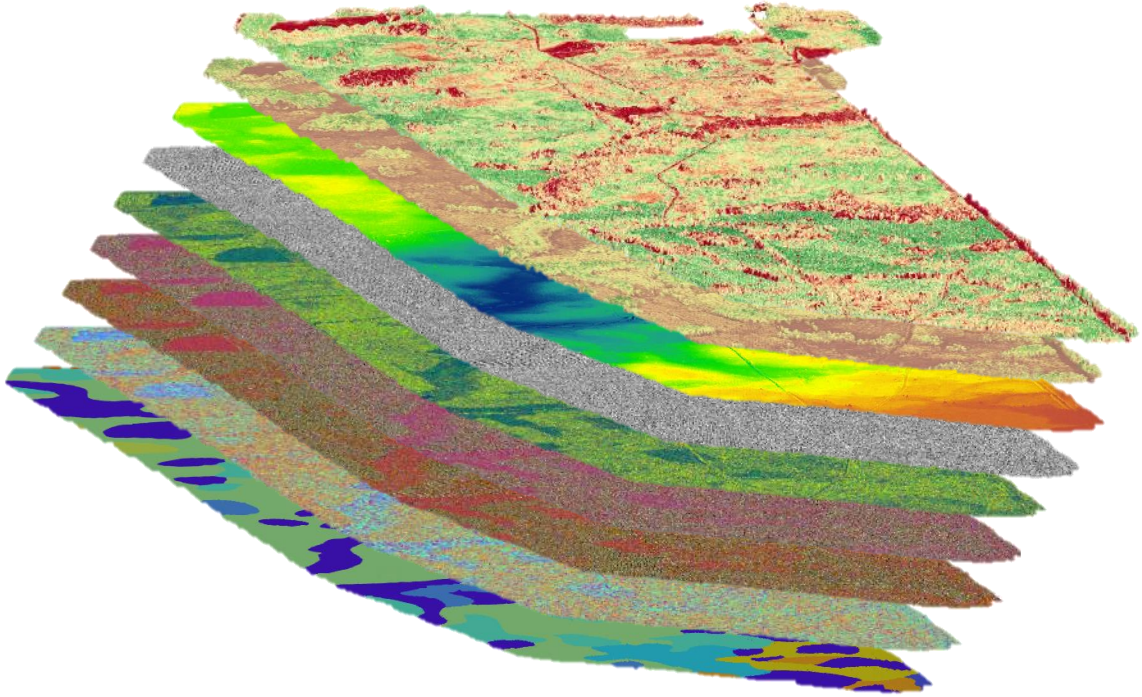
1985

2025

Modern-day computer processing power has opened the door to widespread use of AI.

Machine learning models are used to predict values or variables of interest based on input data.

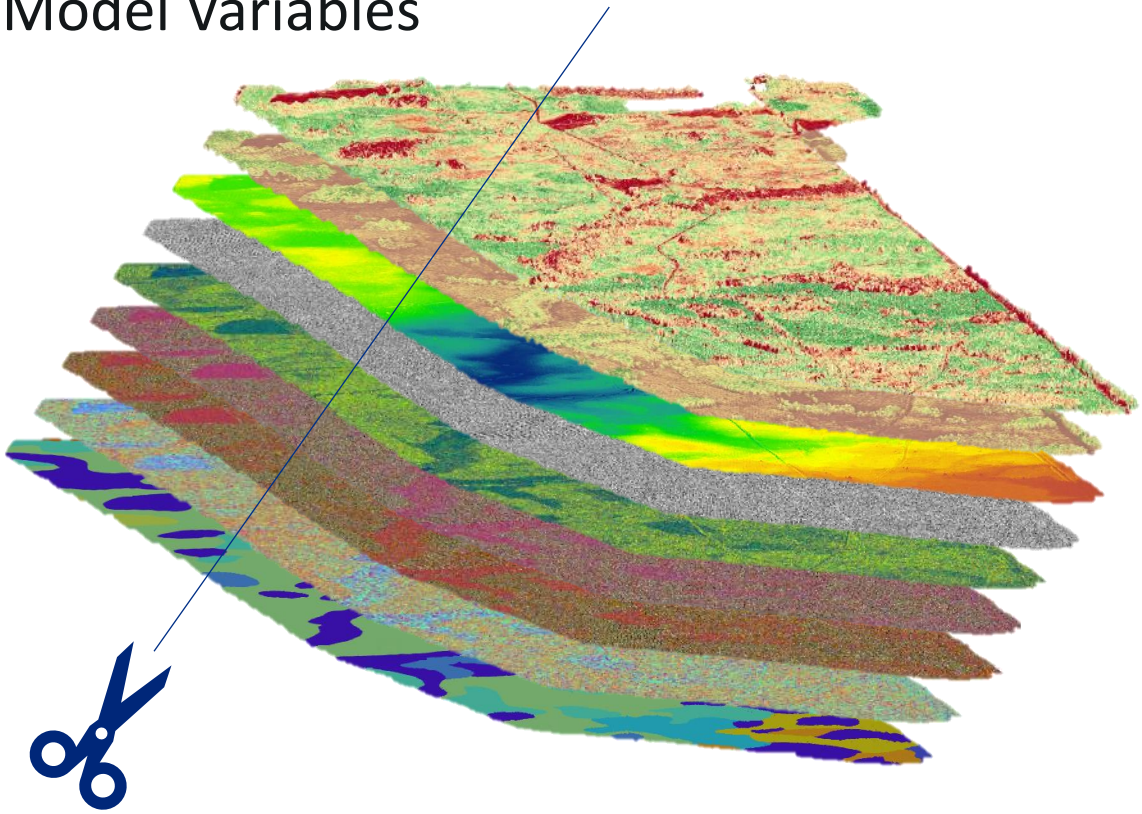
Model Variables



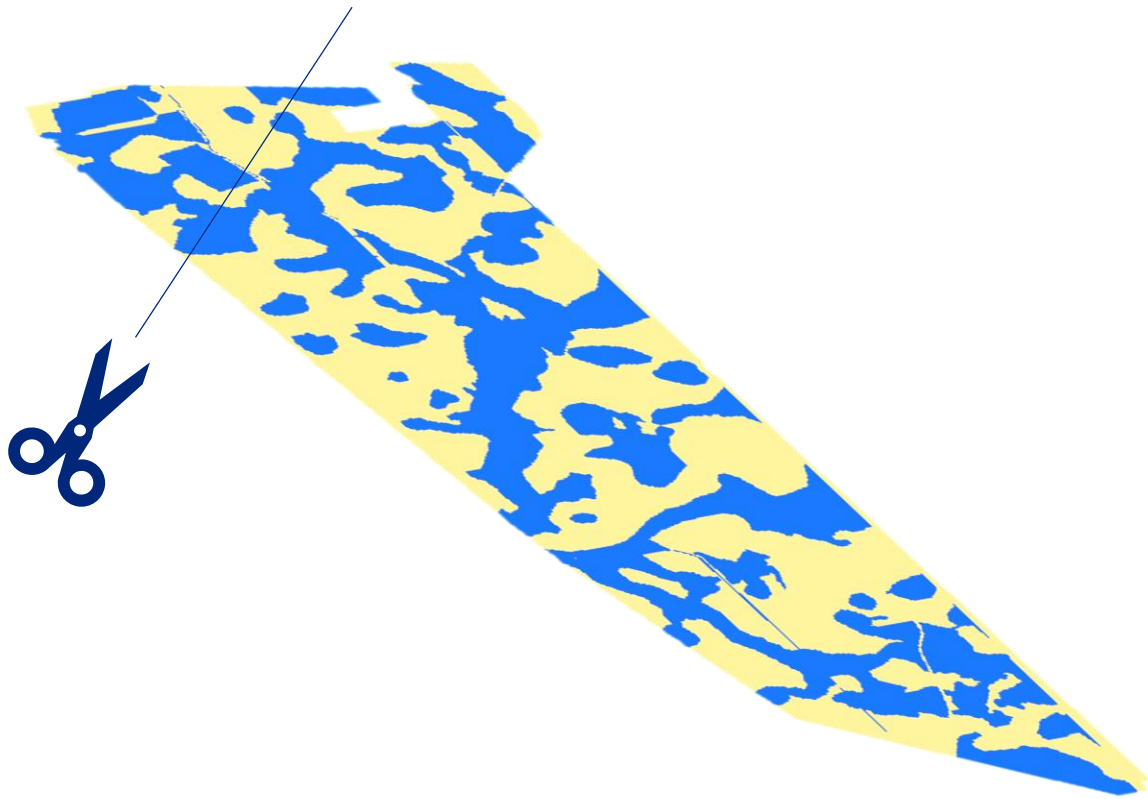
Target Variable

Machine learning models are used to predict values or variables of interest based on input data.

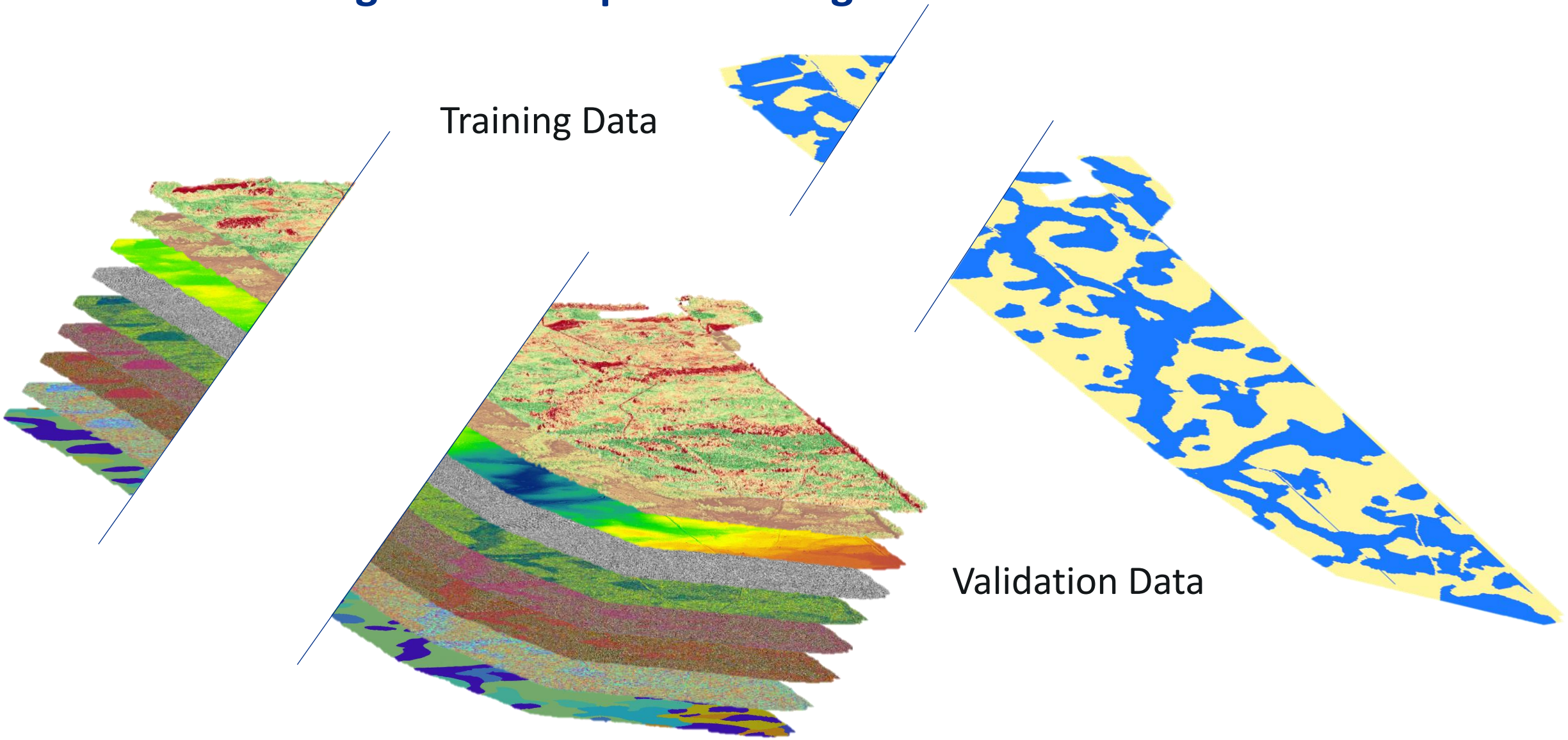
Model Variables



Target Variable

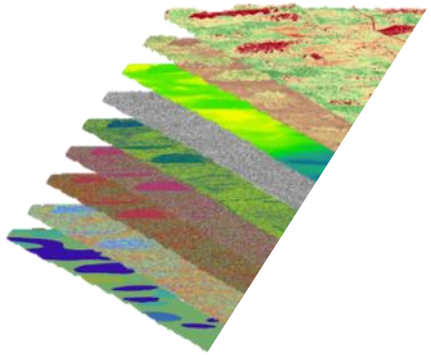


Machine learning models require training data and validation data.



Training data is then used to train the machine learning model.

DATA INPUTS

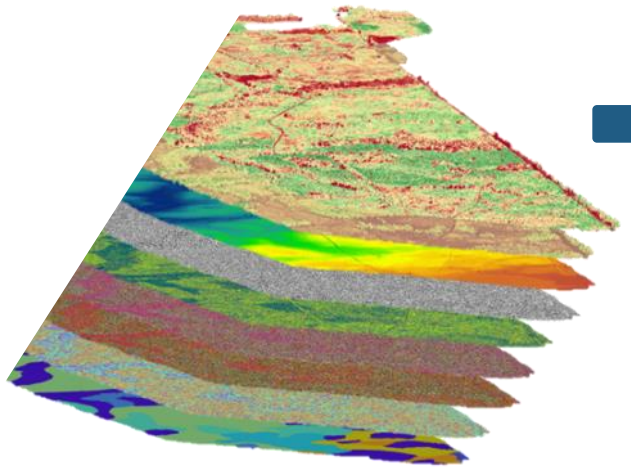


GROUND TRUTHING

MACHINE LEARNING MODEL

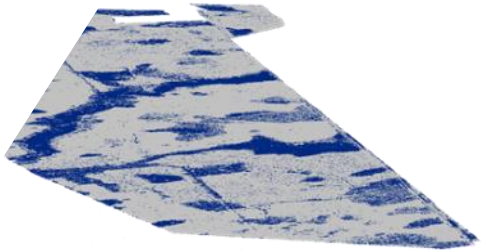
Model predictions are then compared to data of known values to determine model accuracy.

DATA INPUTS



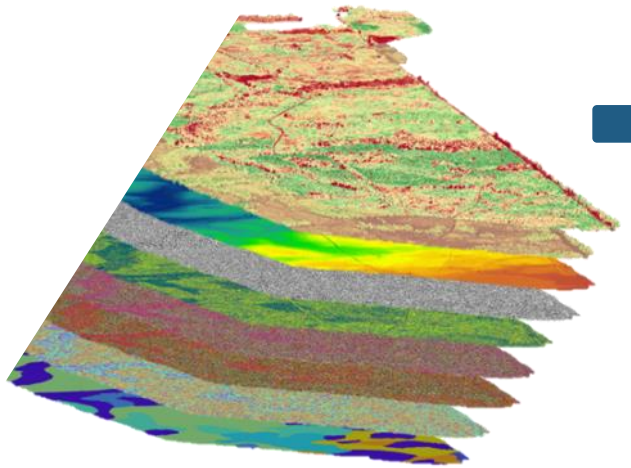
MACHINE LEARNING MODEL

MODEL PREDICTIONS



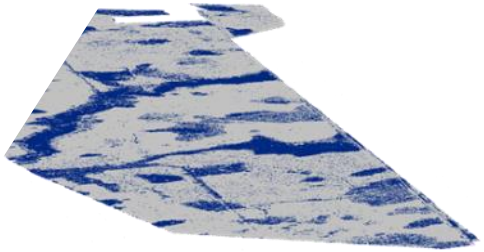
Model predictions are then compared to data of known values to determine model accuracy.

DATA INPUTS

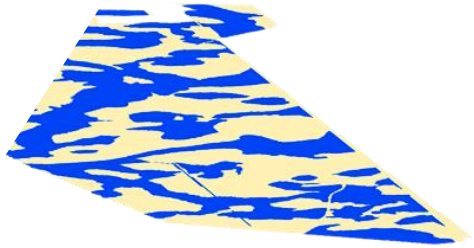


MACHINE LEARNING MODEL

MODEL PREDICTIONS

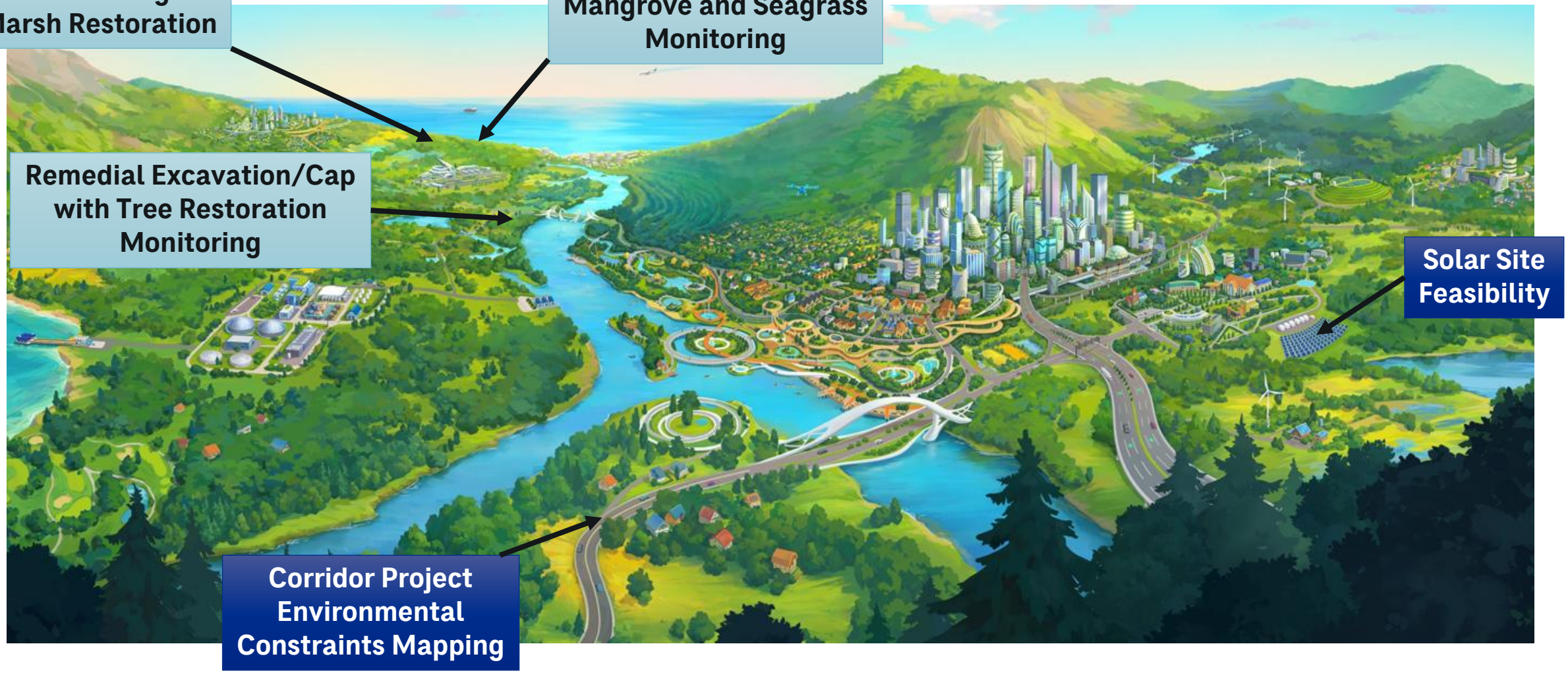


MEASURED AGAINST

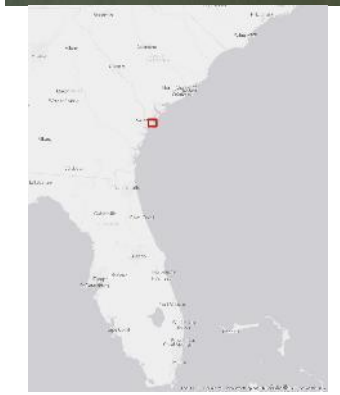


GROUND TRUTHING

Lets start our adventure!

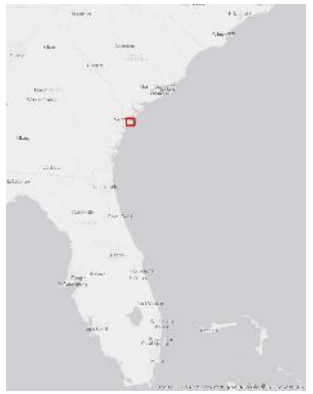


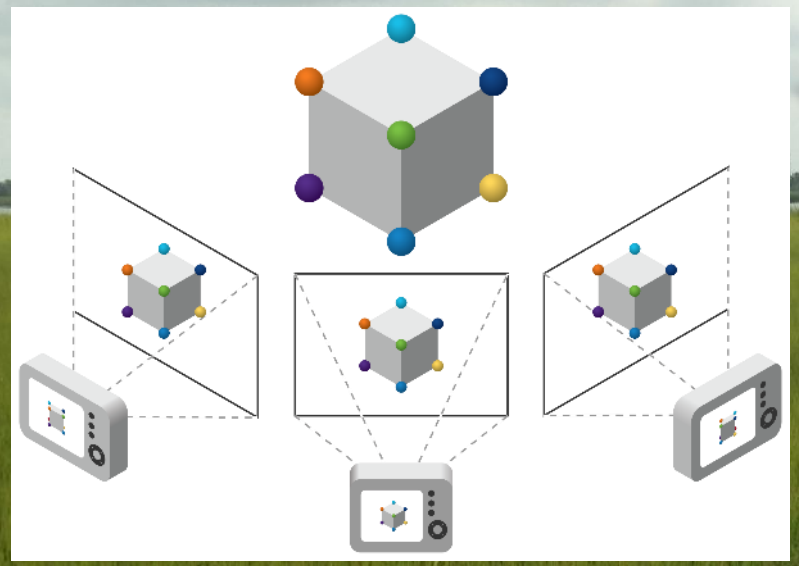
CDM Smith monitored a nature-based solution project at the mouth of the Savannah River.



CDM Smith monitored a nature-based solution project at the mouth of the Savannah River.

Marsh Restoration





Time

Time

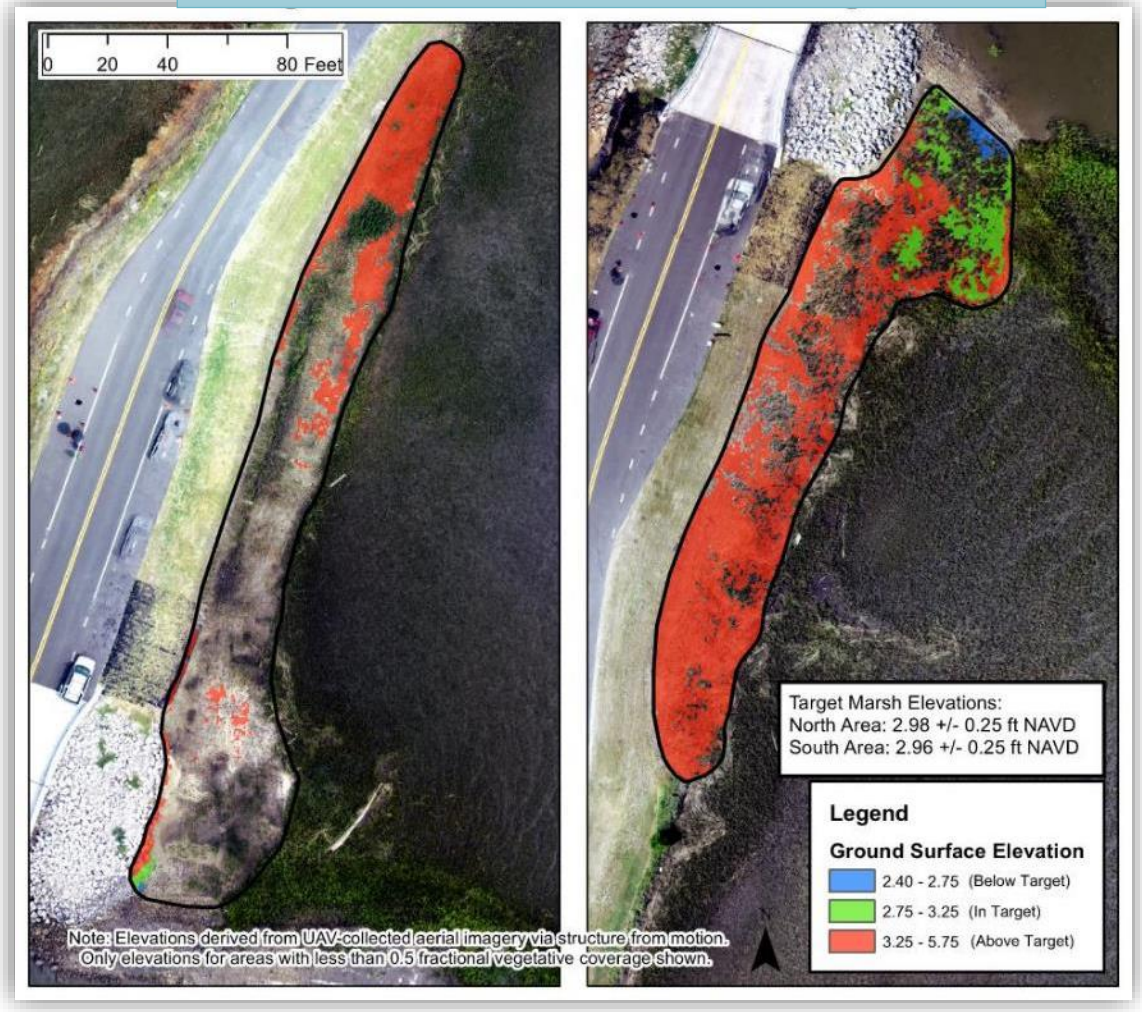
Time

Sunlight

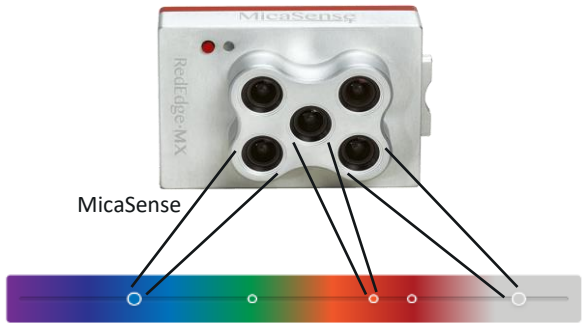
Structure from Motion (SfM) can be used to generate 3D models from 2D images.

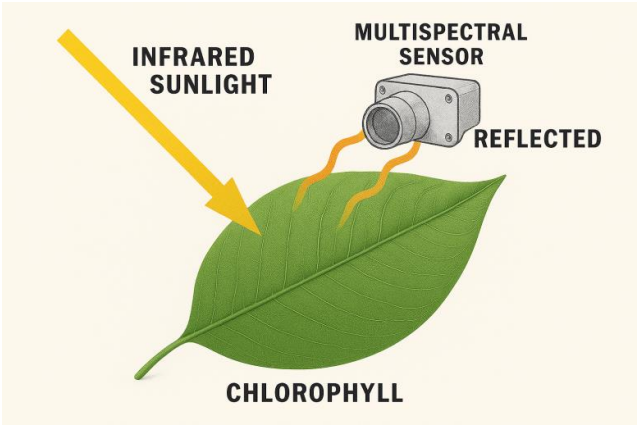
Drone data revealed that the contractor graded too high.

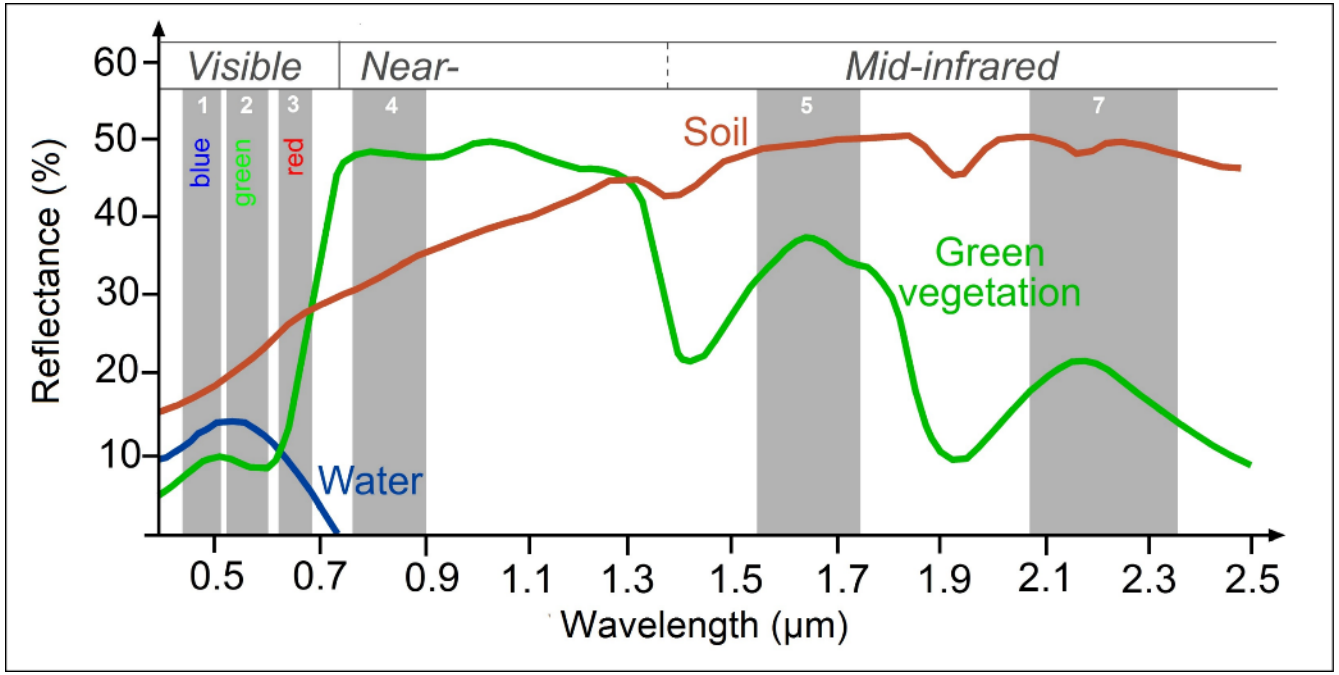
Areas out of spec for target grading



Multispectral data provides information vegatative cover and health.





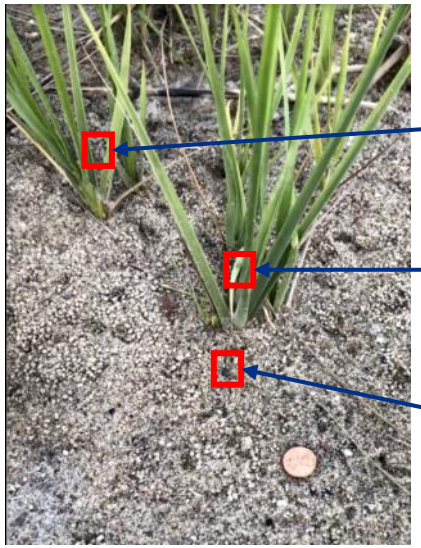


Source: NASA

High resolution pixels identify individual *Spartina* plugs.

Fractional Vegetation Coverage (FVC)

$$\frac{NDVI - NDVI_{soil}}{NDVI_{veg} - NDVI_{soil}}$$



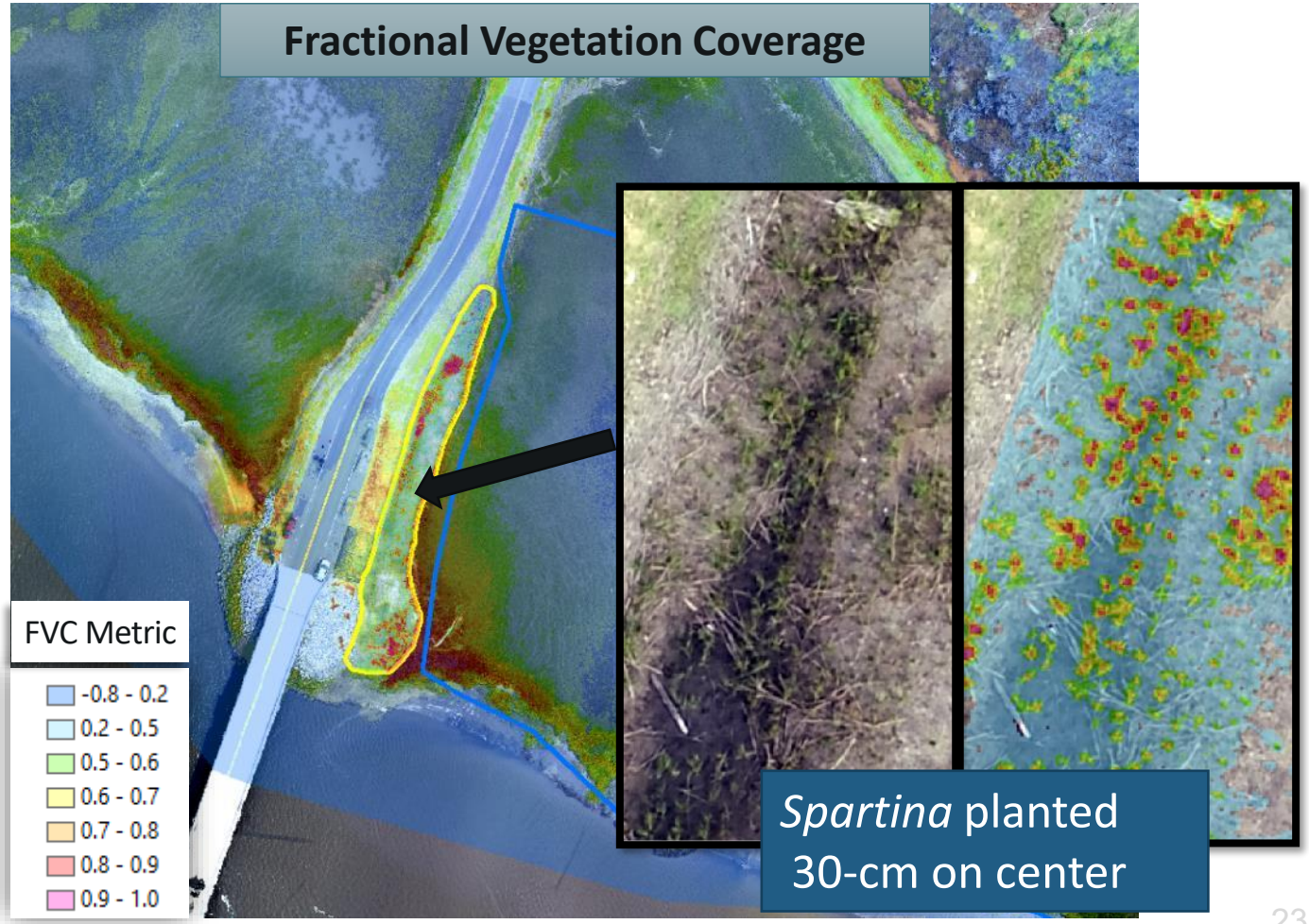
NDVI of Target

$NDVI_{veg}$ (100%)

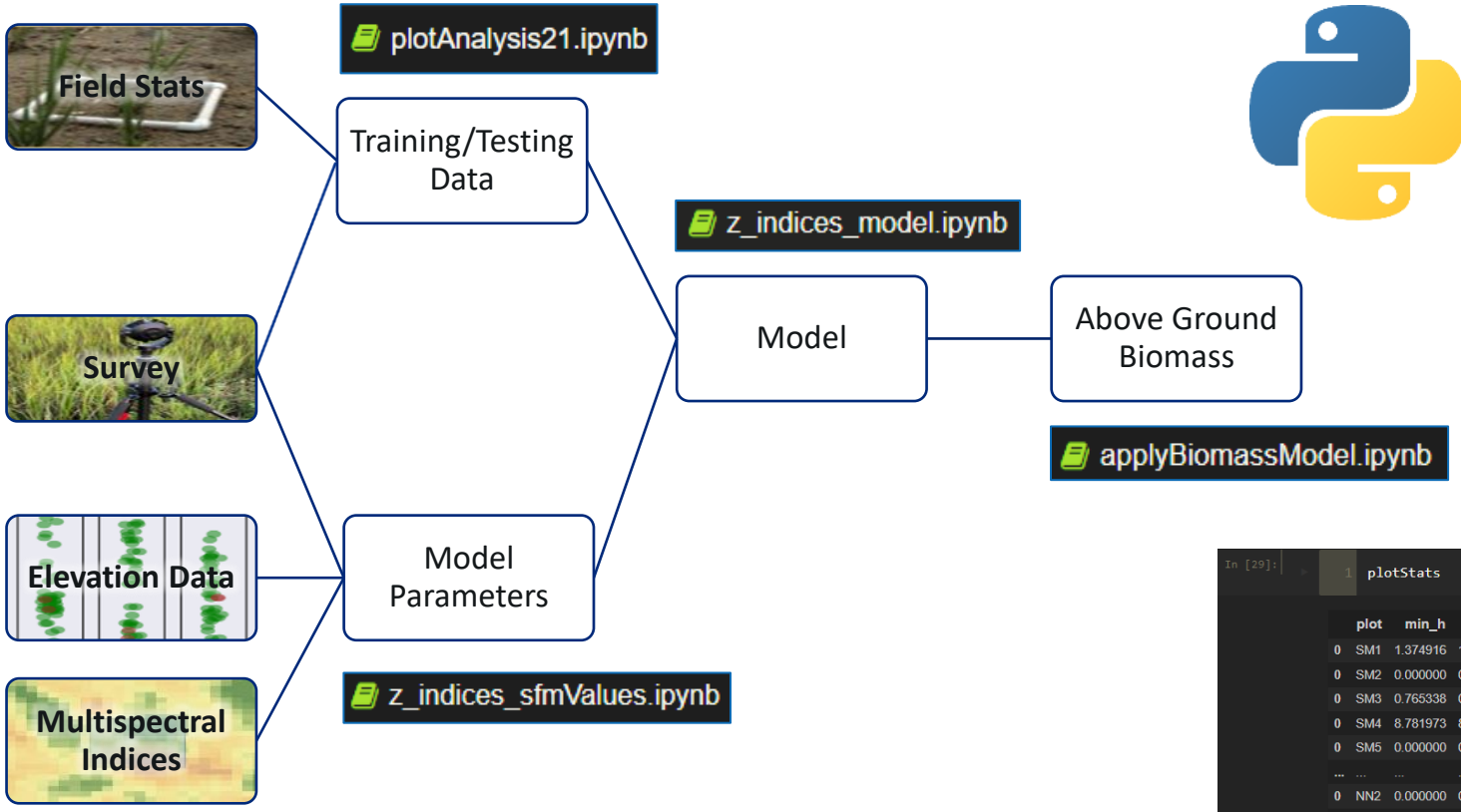
$NDVI_{soil}$ (100%)

Mitigation Area

Reference Area



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




```
In [27]:
def objectSzCnt(fvcArray):
    global fvcStats
    vals=fvcArray.reshape((fvcArray.shape[1], fvcArray.shape[2]))#array of points
    idxs=[]
    for idx, val in np.ndenumerate(vals):
        if val==1:
            idxs.append(idx)
    fvcStats=[]
    while len(idxs)>0:
        objP=[idxs[0]]
        count=0
        while count<len(vals):
            for cell in idxs:
                for obj in objP:
                    if (cell[0]==obj[0] and (abs(cell[1]-obj[1])==1)) or (cell[1]==obj[1] and (abs
                        if cell not in objP:
                            objP.append(cell)
            count+=1
        fvcStats.append(len(objP))
        for i in objP:
```

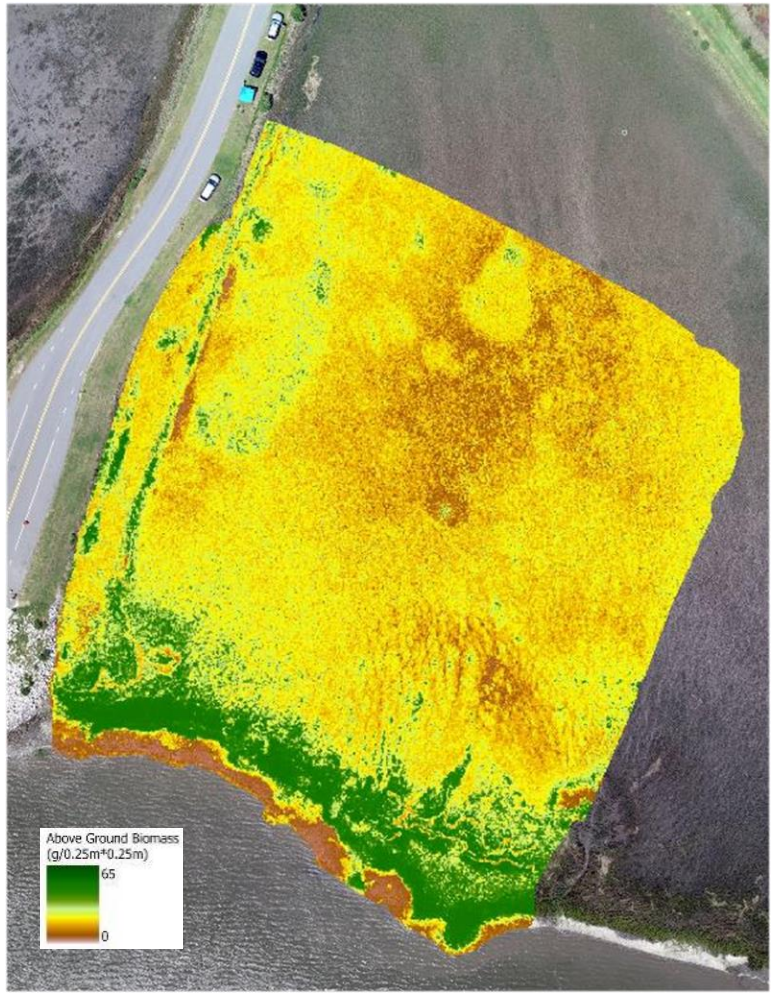
```
In [29]:
plotStats
```

	plot	min_h	p5_h	p25_h	p50_h	p75_h	p90_h	max_h	mean_h	std_h	...	ndvi_std	ndviPV
0	SM1	1.374916	1.441972	1.710196	2.045476	2.243596	2.362468	2.441716	1.954036	0.440293	...	0.031970	12.0
0	SM2	0.000000	0.000000	0.978388	4.090376	11.999936	16.660328	21.433496	7.354360	7.499678	...	0.024759	16.0
0	SM3	0.765338	0.853730	1.207298	1.649258	2.091218	2.356394	2.533178	1.649258	0.883920	...	0.033537	9.0
0	SM4	8.781973	8.832265	9.033433	9.803053	10.984153	11.875693	12.470053	10.214533	1.450765	...	0.043940	16.0
0	SM5	0.000000	0.137490	1.509493	7.605493	12.246073	13.015693	14.112973	7.084212	5.344436	...	0.034234	16.0
...	...	...	...	...	...	...	...	...	...	...	...	...	...
0	NN2	0.000000	0.000000	0.000000	0.000000	2.771751	12.610695	19.169991	4.388349	7.468375	...	0.019852	0.0
0	NN3	0.000000	1.197049	3.419342	7.899902	13.233902	16.275806	16.739102	8.522429	5.627527	...	0.020292	0.0
0	SN1	3.710798	3.791570	4.114658	4.518518	4.922378	5.164694	5.326238	4.518518	0.807720	...	0.015117	0.0
0	SN2	0.476578	1.112086	3.654118	5.261938	5.848678	5.917258	5.962978	4.240858	2.226136	...	0.020728	0.0
0	SN3	0.000000	0.000000	0.000000	0.000000	0.778743	1.245988	1.557485	0.519162	0.734206	...	0.009841	0.0

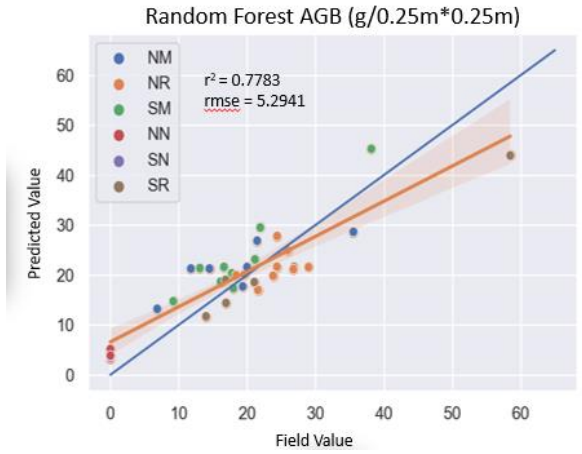
86 rows × 43 columns

The machine learning model can output site wide biomass.

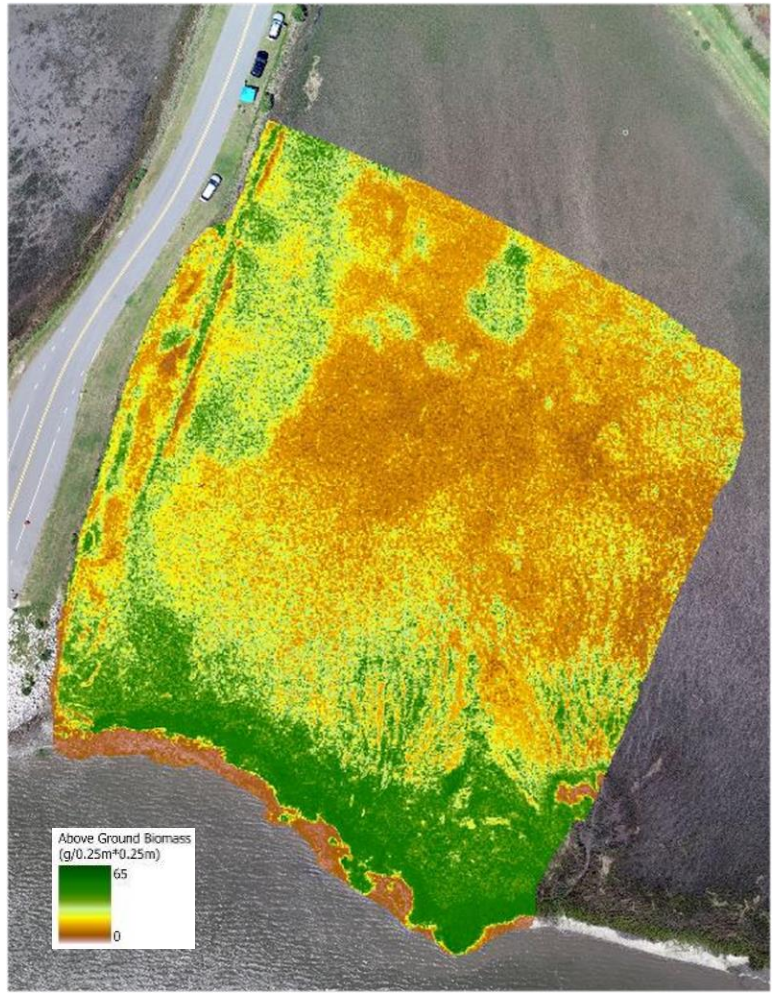
2021



Above Ground Biomass
(g/0.25m*0.25m)
65
0

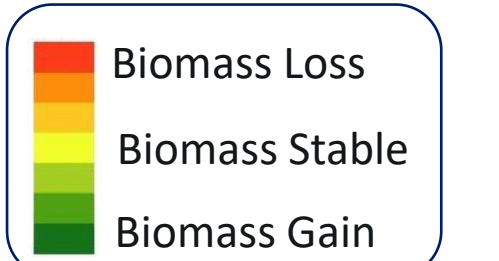


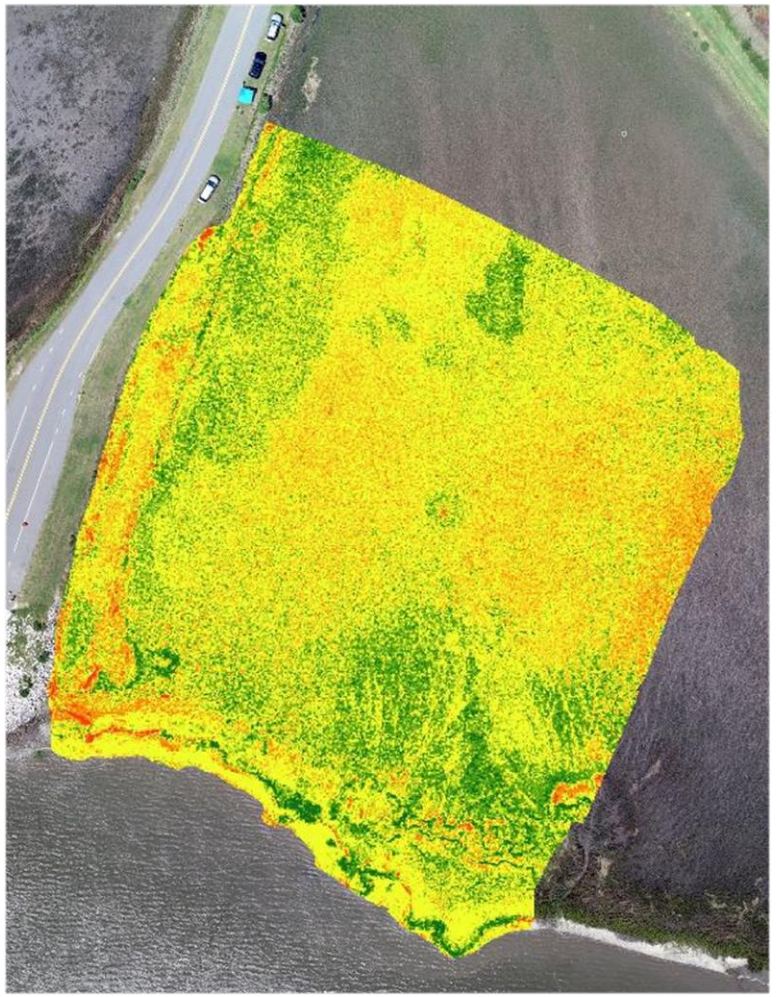
2022



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

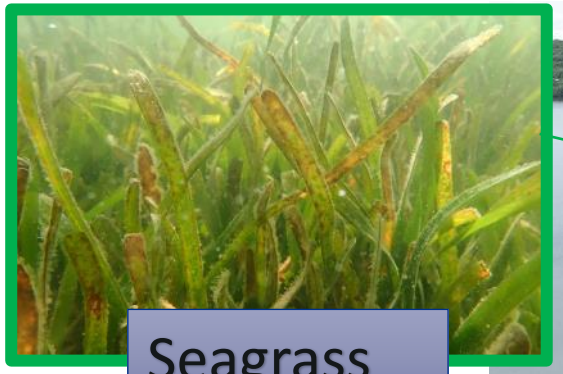
Change from 2021 to 2022



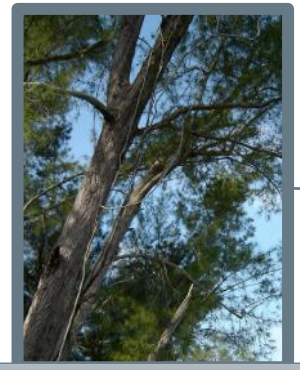


CDM Smith used drone data and machine learning used to monitor multiple ecosystems in Vero Beach, Florida.

Red Mangrove



Seagrass



Australian Pine (invasive)

CDM Smith used 10-band multispectral sensors to map the site.

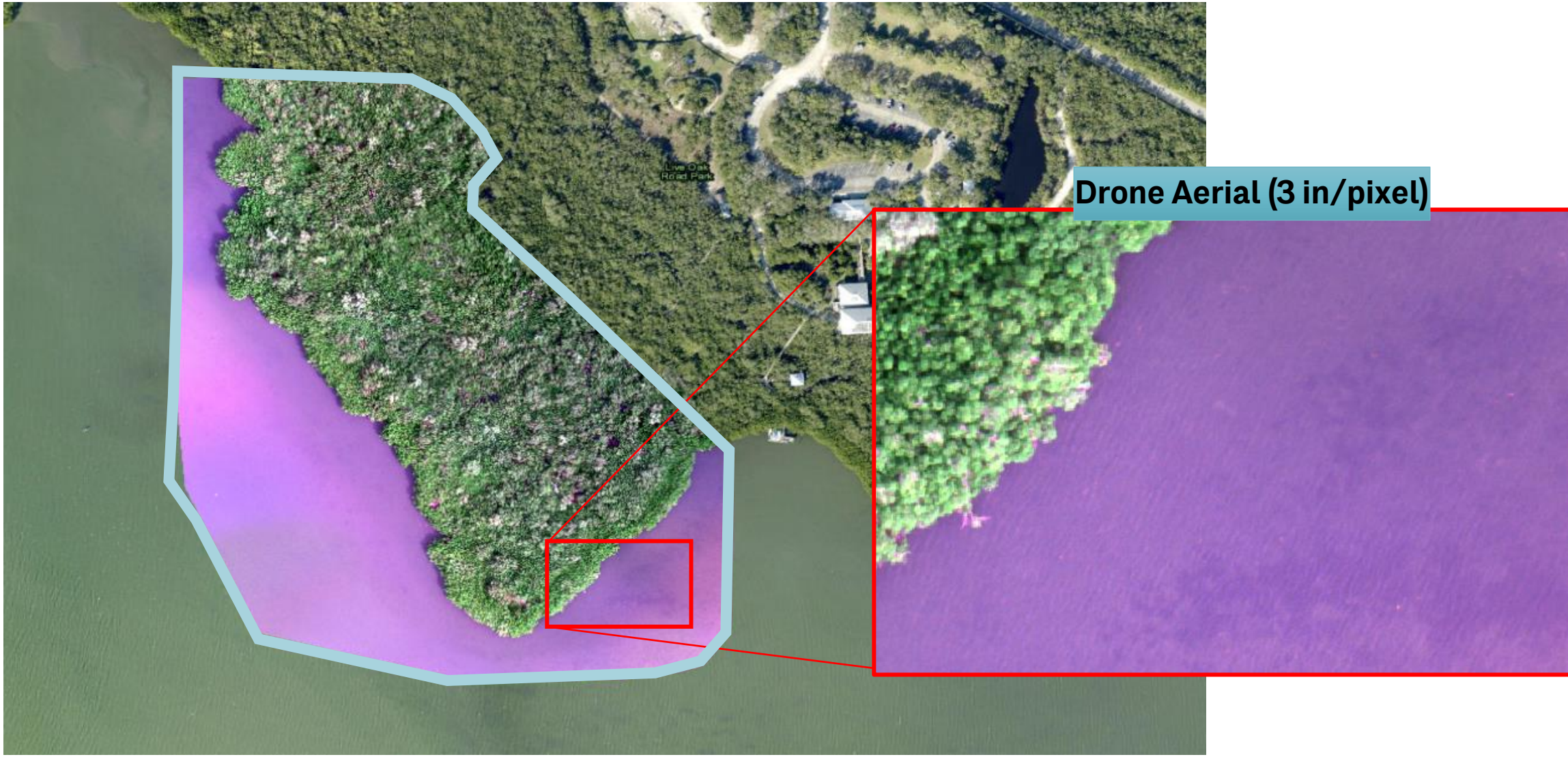
Inspire 2 Drone

Flight Path

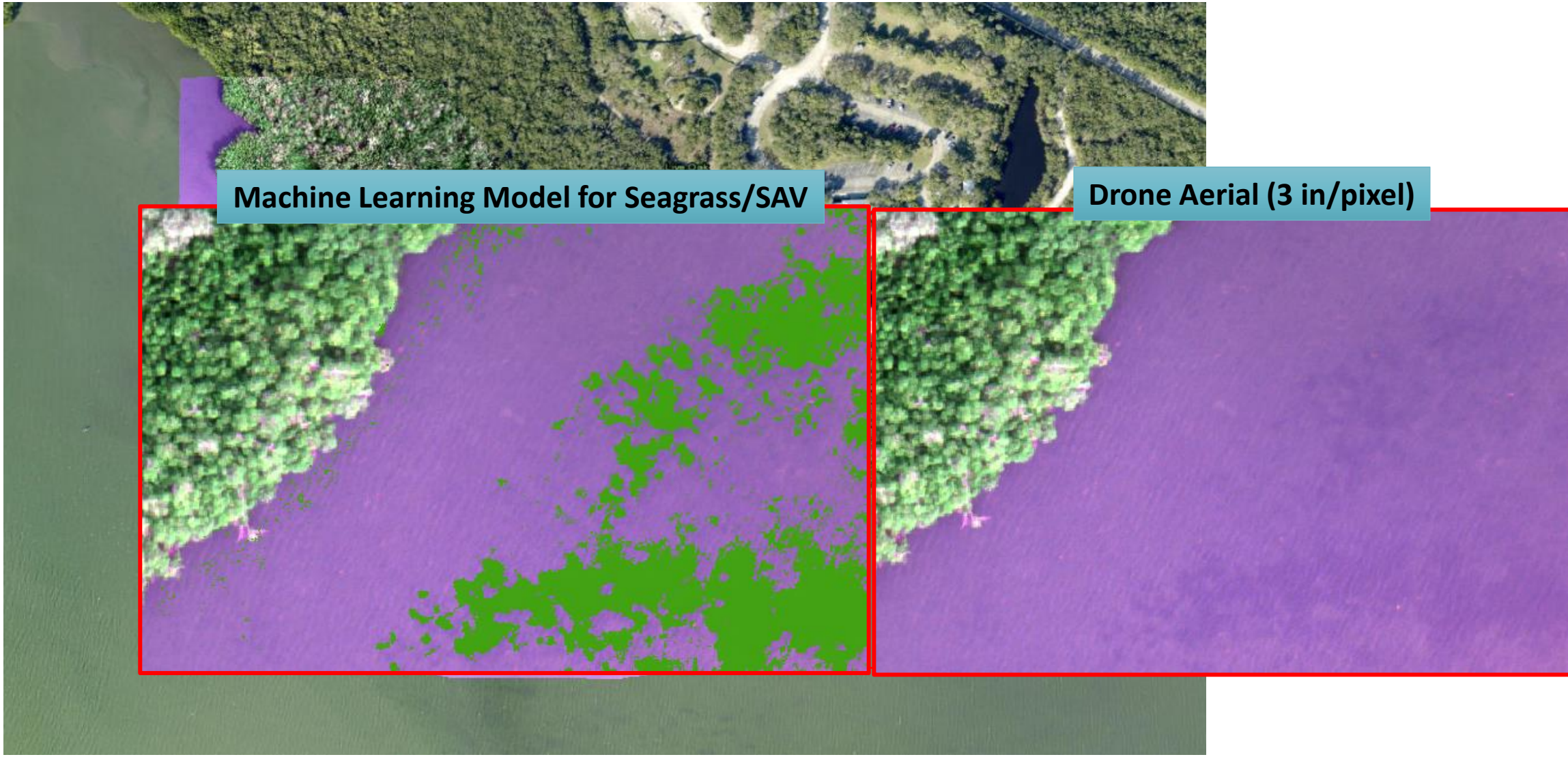
Drone-derived Aerial

10-band Dual Camera

Multispectral drones can monitor 100s of acres of seagrass at high resolution.

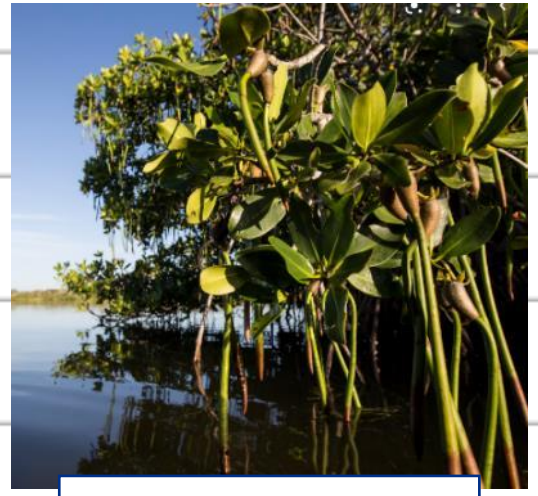


CDM Smith developed learning models to map seagrass/SAV versus sandy substrate.



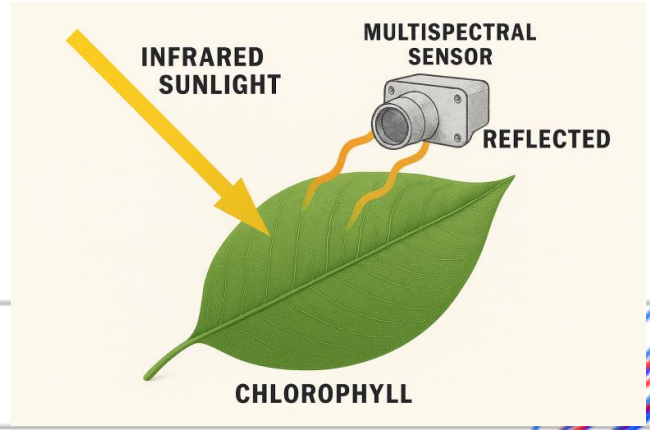
Red mangroves have a different spectral signature than Australian pine which allows for machine learning-based mapping and monitoring.

Australian Pine

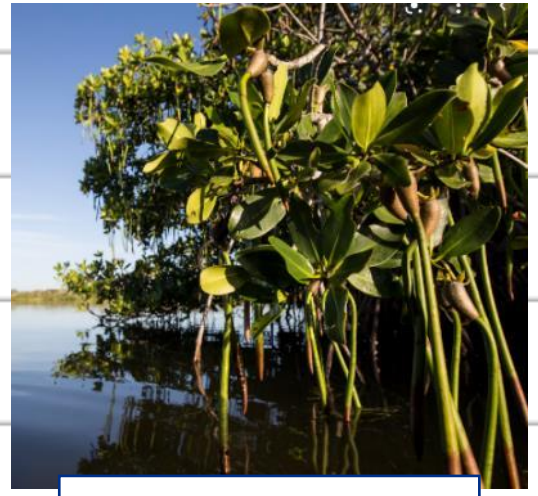


Red Mangrove

10-band multispectral



Australian Pine



Red Mangrove

Reflectance (%)

0.4
0.35
0.3
0.25
0.2
0.15
0.1
0.05

Not visable to human eye

Blue-1 Blue-2 Green-1 Green-2 Red-1 Red-2 Rededge-1 Rededge-2 Rededge-3 Near Infrared

Wavelength

CDM Smith developed a machine learning model with over 95% accuracy to identify the invasive species Australian pine.

Drones and machine learning can fill the gap between field transects and plane-based mapping.

Plane-based Mapping

Image: Courtesy of SurvTech

High-resolution/Efficient Collection

Time-consuming Field Transects

CDM Smith used machine learning to map exotic and native species and help Hillsborough County evaluate fire risk.

The wildland urban interface presents land management challenges.

Advanced remote sensing and AI provides better data to decisions makers.

- Exotic Species
- Biodiversity
- Vegetative Cover
- Vegetative Health

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

CDM Smith created high-resolution 10-band orthophotographs.

False Color Composite Aerial with Near-infrared

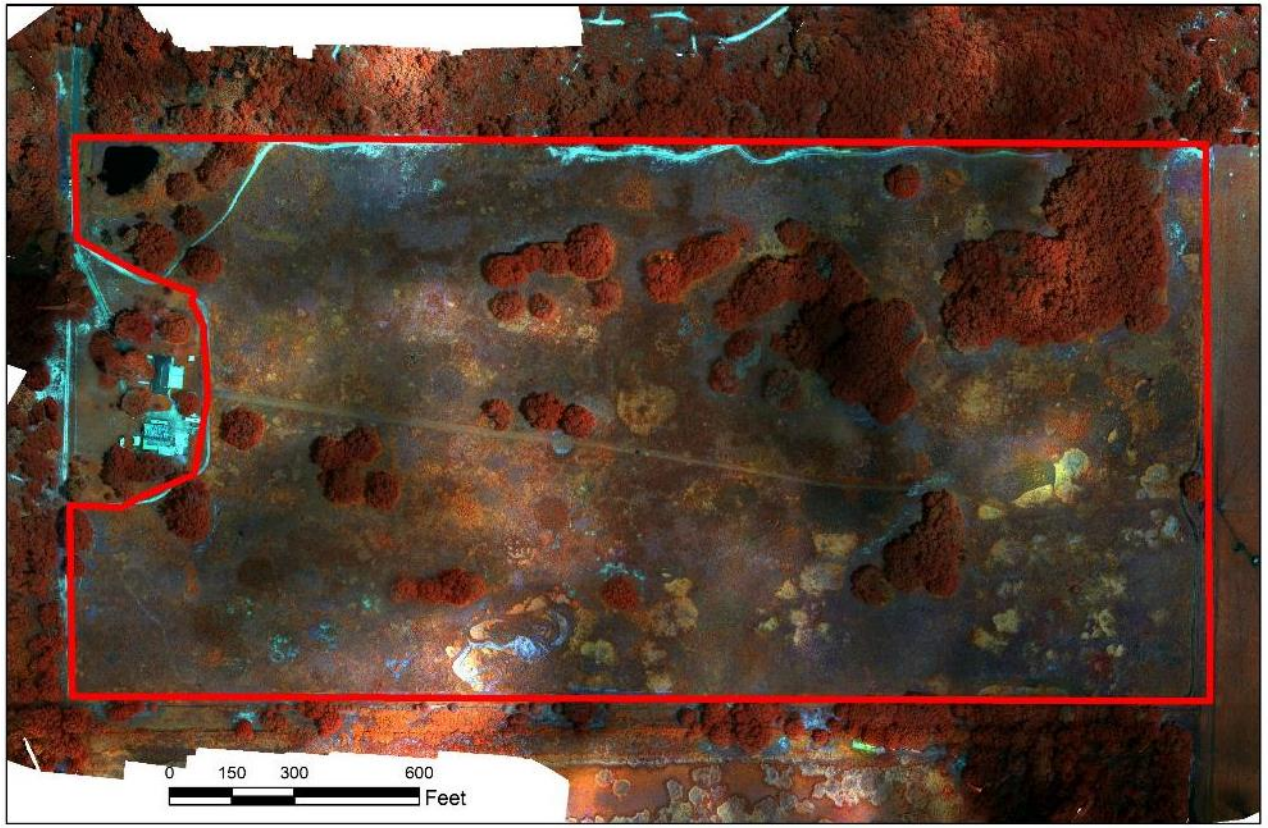


Image Resolution
3-in per pixel

Machine learning can use spectral patterns to identify species.

Cogongrass

Bahiagrass

Average of Species

Individual Species Plot

Reflectance (%)

0.00 0.05 0.10 15 20 0.25 0.30 0.35

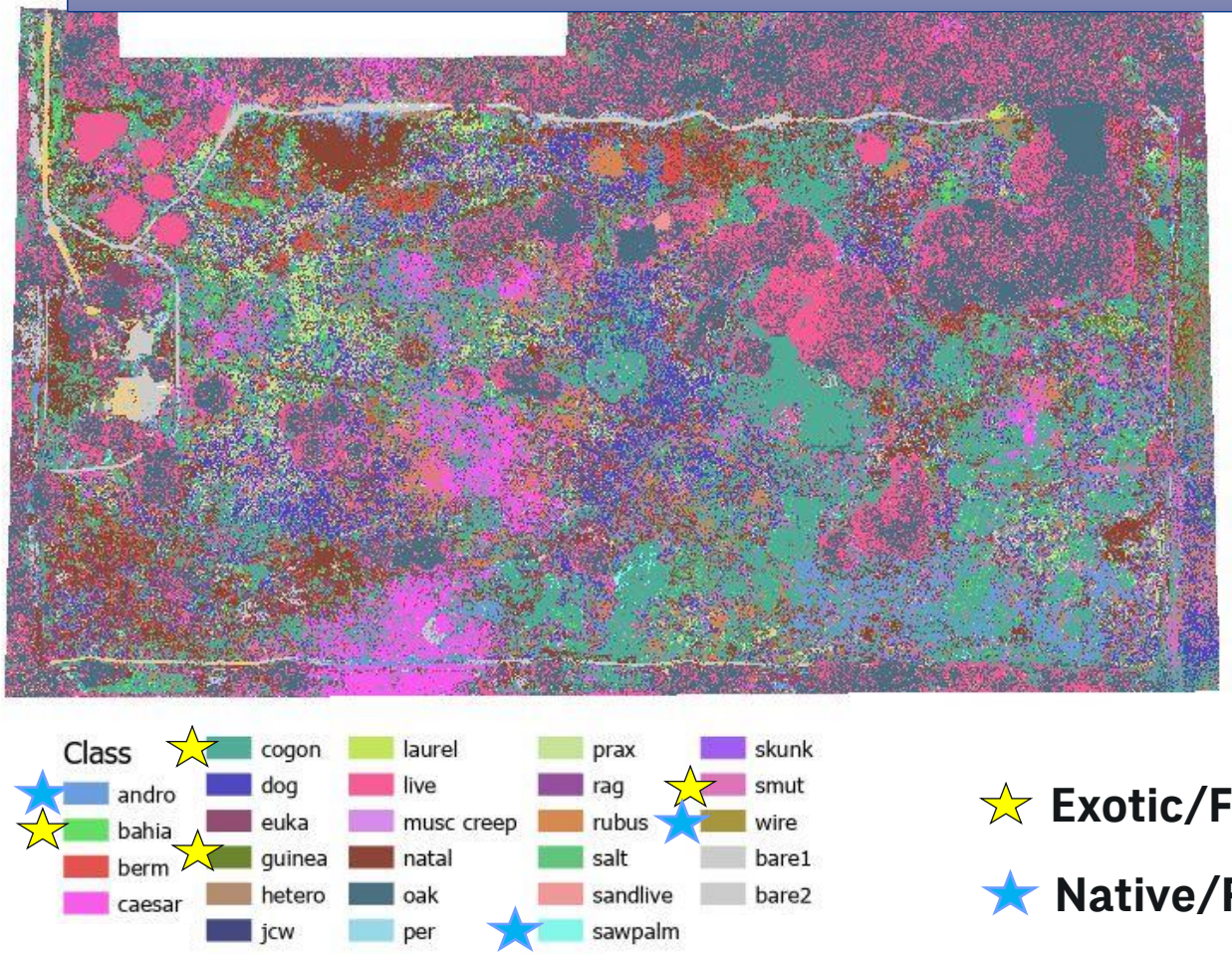
Blue-1 Blue-2 Green-1 Green-2 Red-1 Red-2 Rededge-1 Rededge-2 Rededge-3 Near Infrared

Wavelength

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

Pixel size = 3 inches

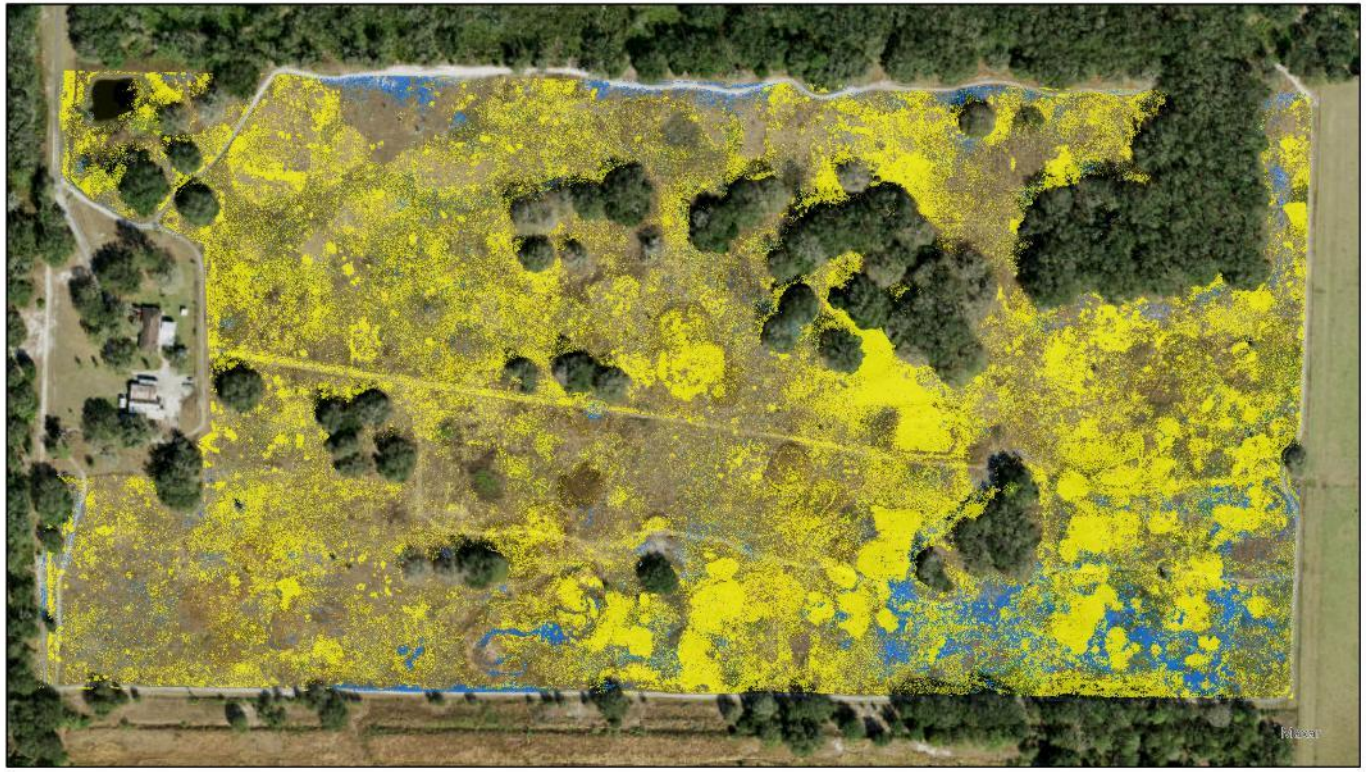
Overall machine learning model accuracy: > 80%



Exotic/Fire Species

Native/Fire Species

Machine learning model results can be used to pinpoint locations of exotic and native fire species.



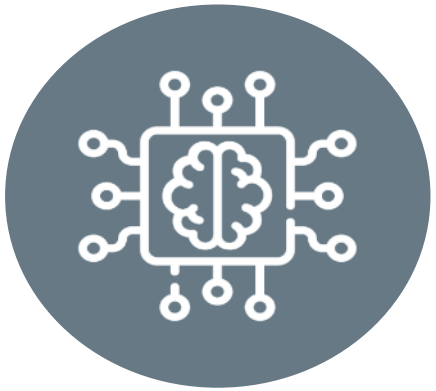
Exotic/Fire Species

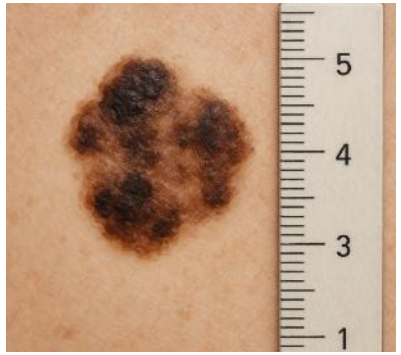
Native/Fire Species

N

0 200 400 US Feet

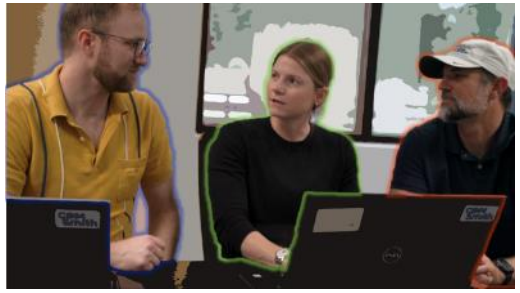
Subject matter experts play a vital role in AI model development and accurate interpretation of predictions.

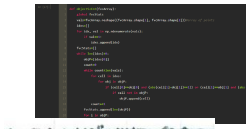


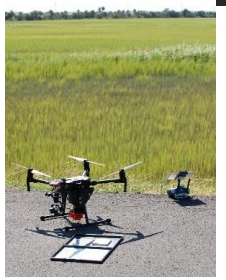


Subject matter experts play a vital role in AI model development and accurate interpretation of predictions.

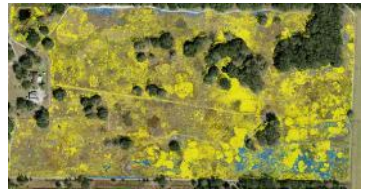
Wetlands



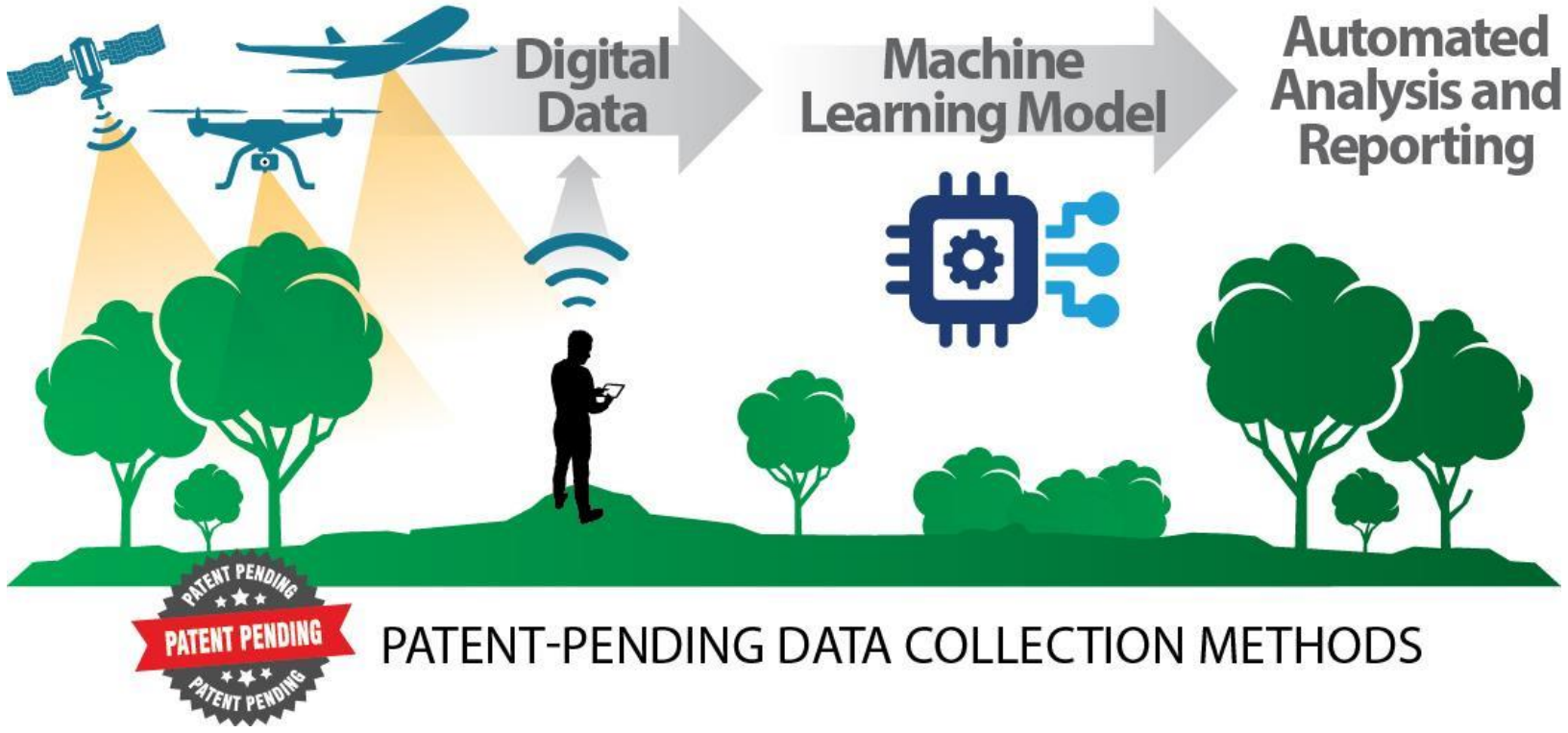




Exotic Species



Sky Wave at CDM Smith leverages advanced remote sensing, automation, and AI to develop environmental solutions.



Contact:
skywave@cdmsmith.com

sky wave® at CDM Smith

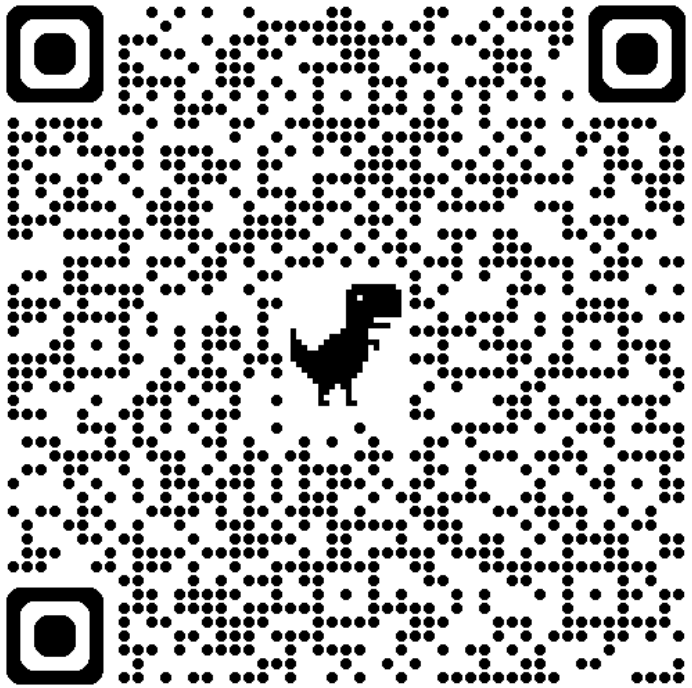
IDEAS

The Age of De-Skilling

Will AI stretch our minds—or stunt them?

By Kwame Anthony Appiah

Scan for more information



sky wave® at CDM Smith

Case Study: Remedial Excavation and Capping Jacksonville, FL

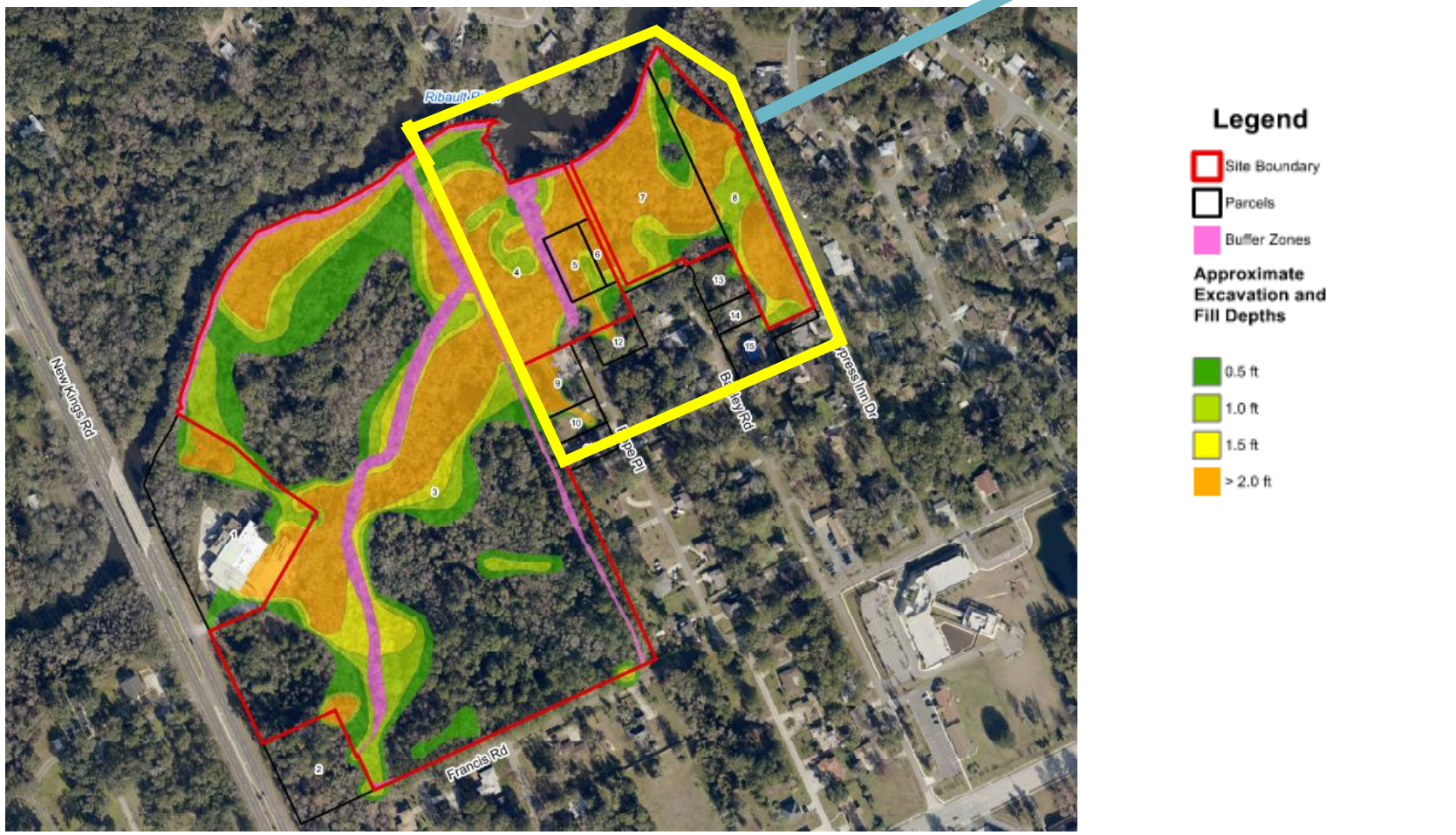
CDM Smith used automation and machine learning to monitor excavation and verify cap placement at a remediation site.

- Objectives
  - Track contractor performance
  - Earth volume measurement
  - Compliance
- Location
  - Ribault River, Jacksonville, FL

- Size
  - 50 acres
- Sensors

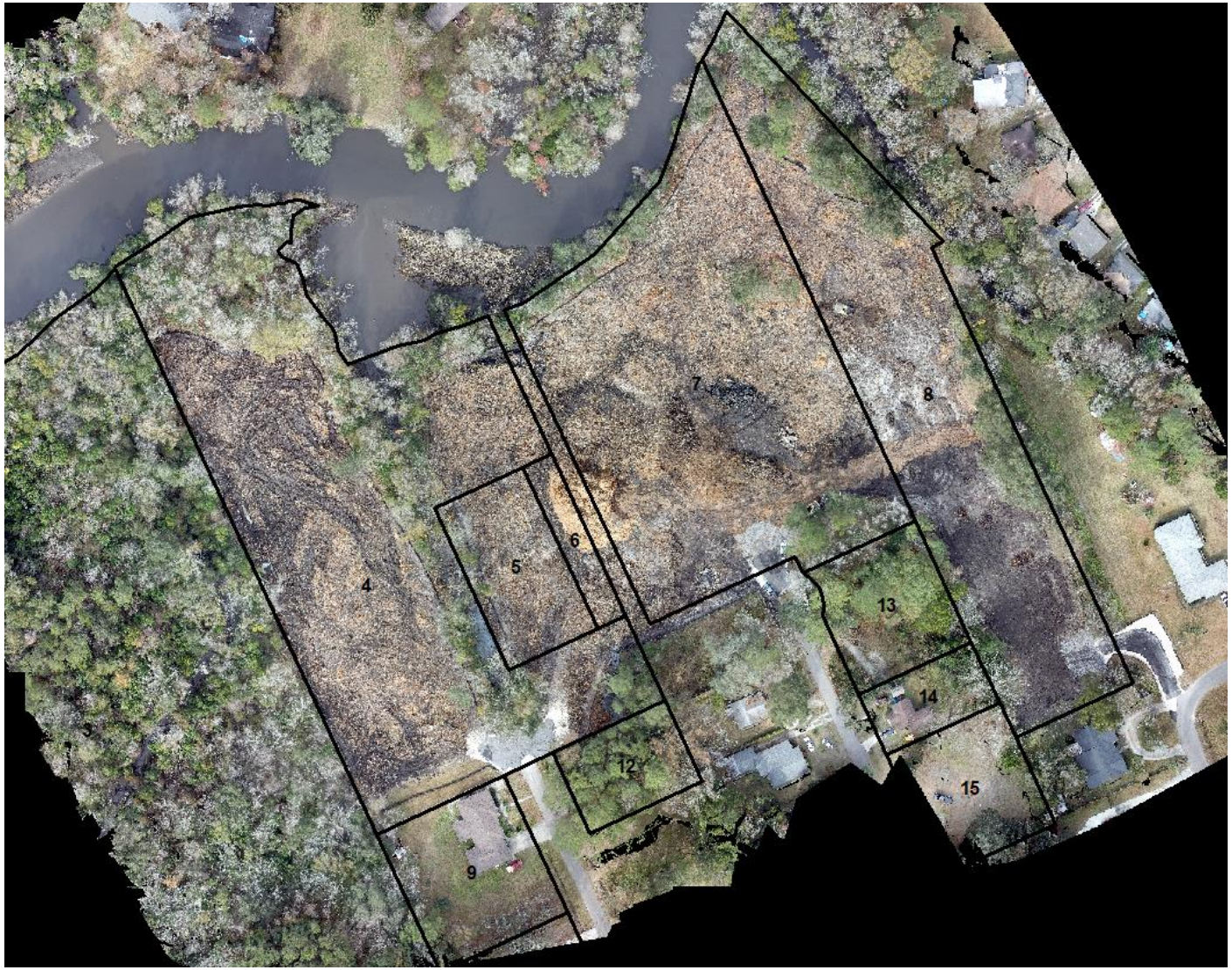
Phase I of the remediation included excavation of 2 feet and capping with clean fill.

Remedial Action Plan

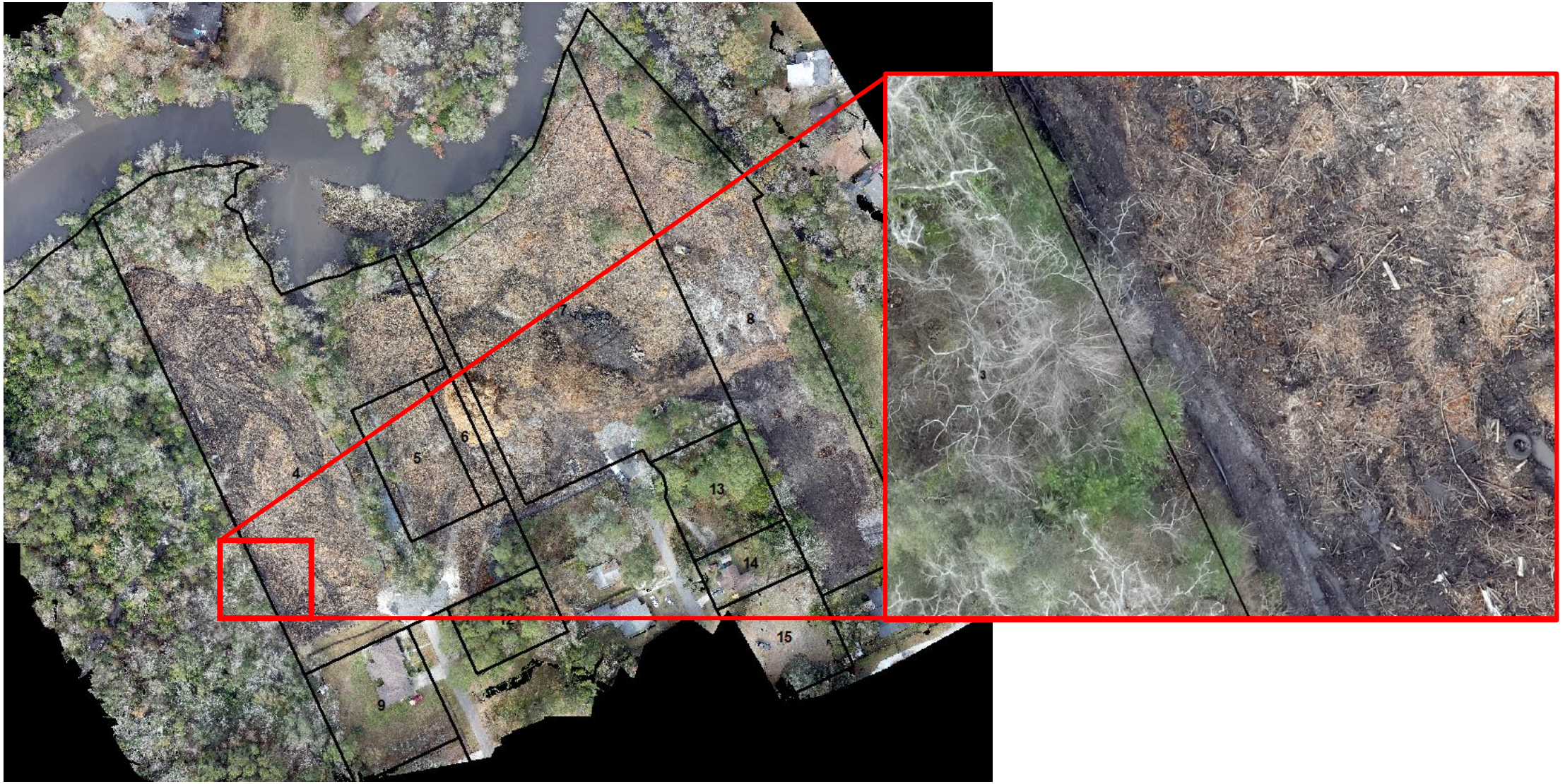


High resolution cameras are used to collect digital imagery of the site monthly.

High resolution aerial imagery documents site conditions.



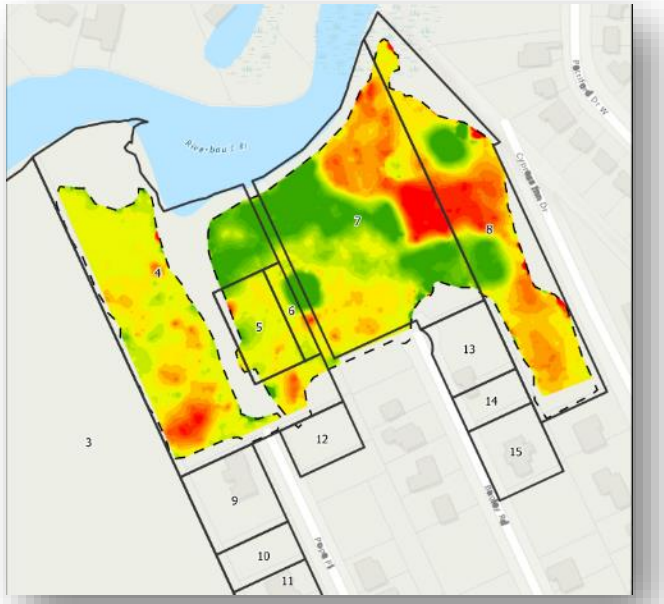
Imagery can be used to assess contractor performance.



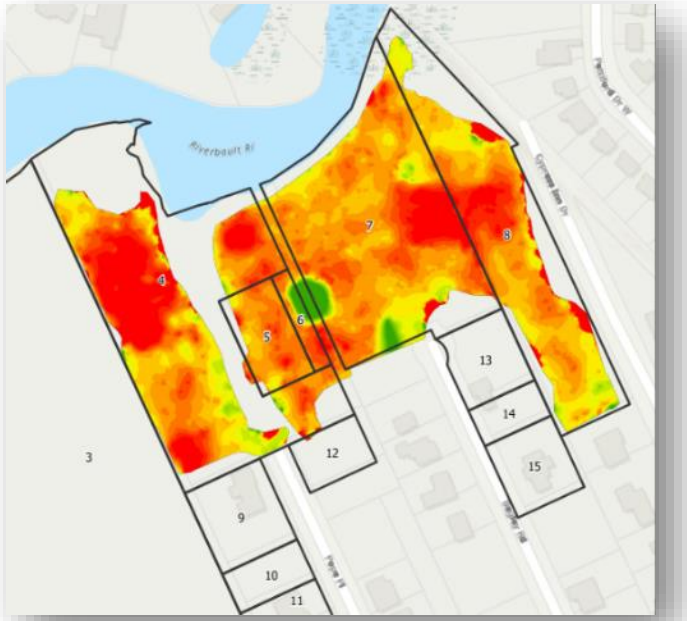
A 3D model is created for the site from each monthly drone flight.

CDM Smith uses automation to track topographic changes over time.

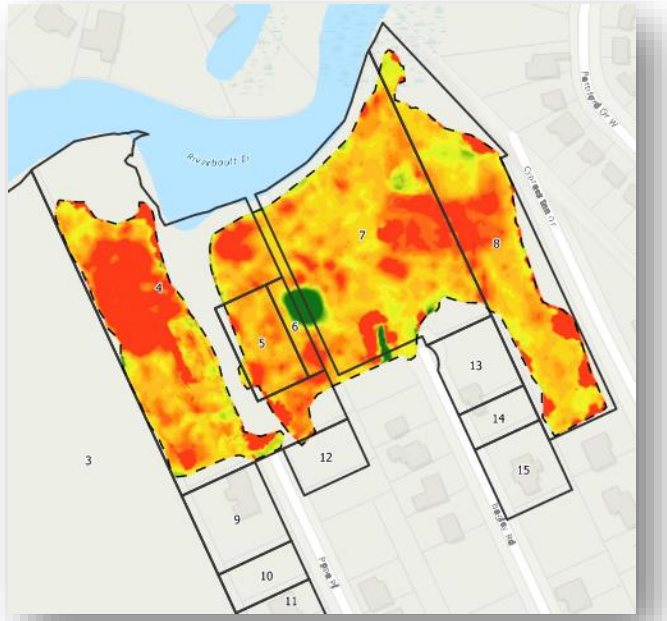
February

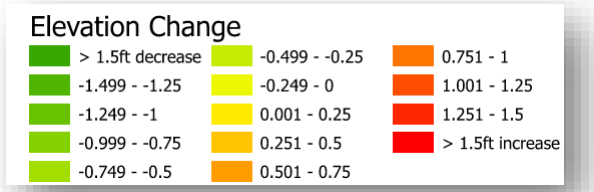


March

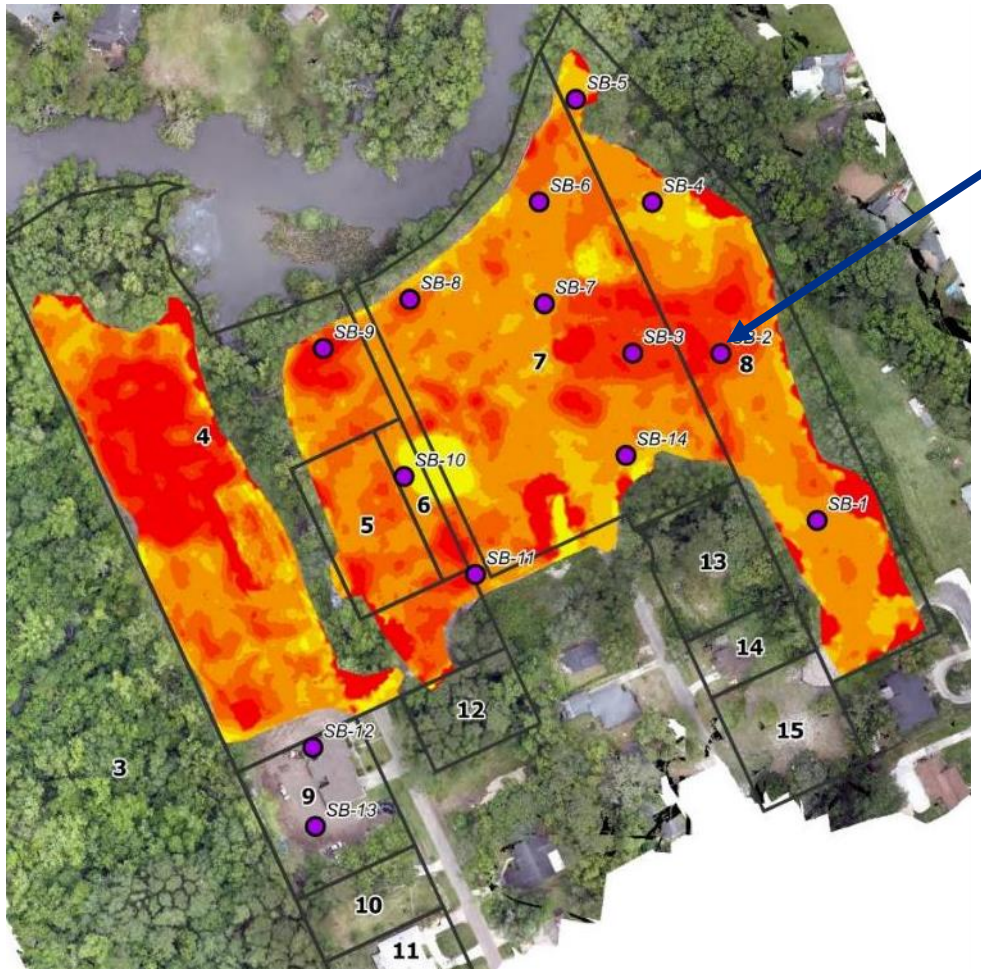


April

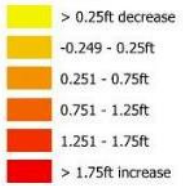




The drone data is used to guide field efforts and verification sampling.



Random samples apportioned by elevation change



Drone data can be used to assess BMPs.

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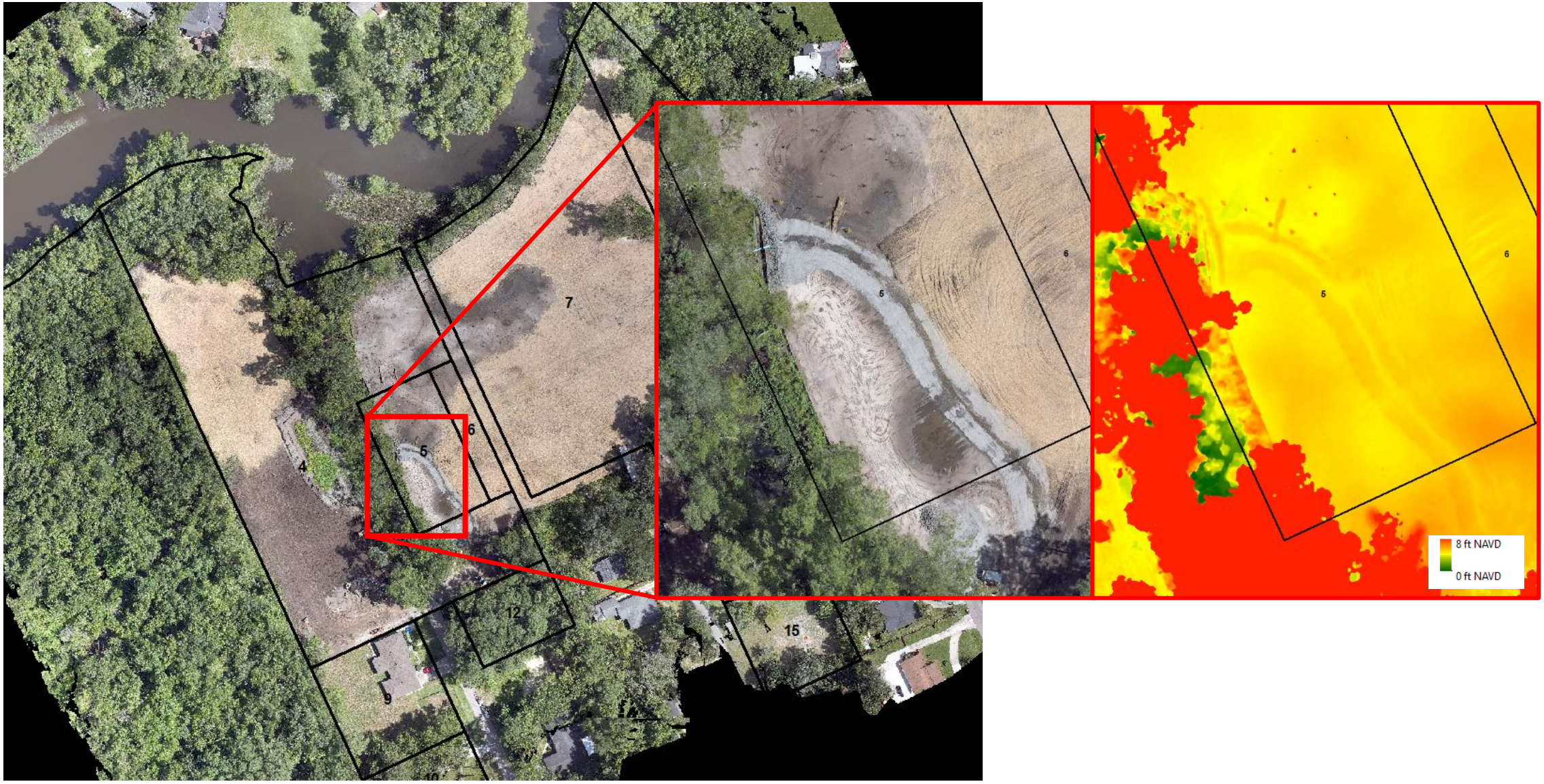

After capping wetland trees were planted in a portion of the site to comply with state and federal permit requirements.

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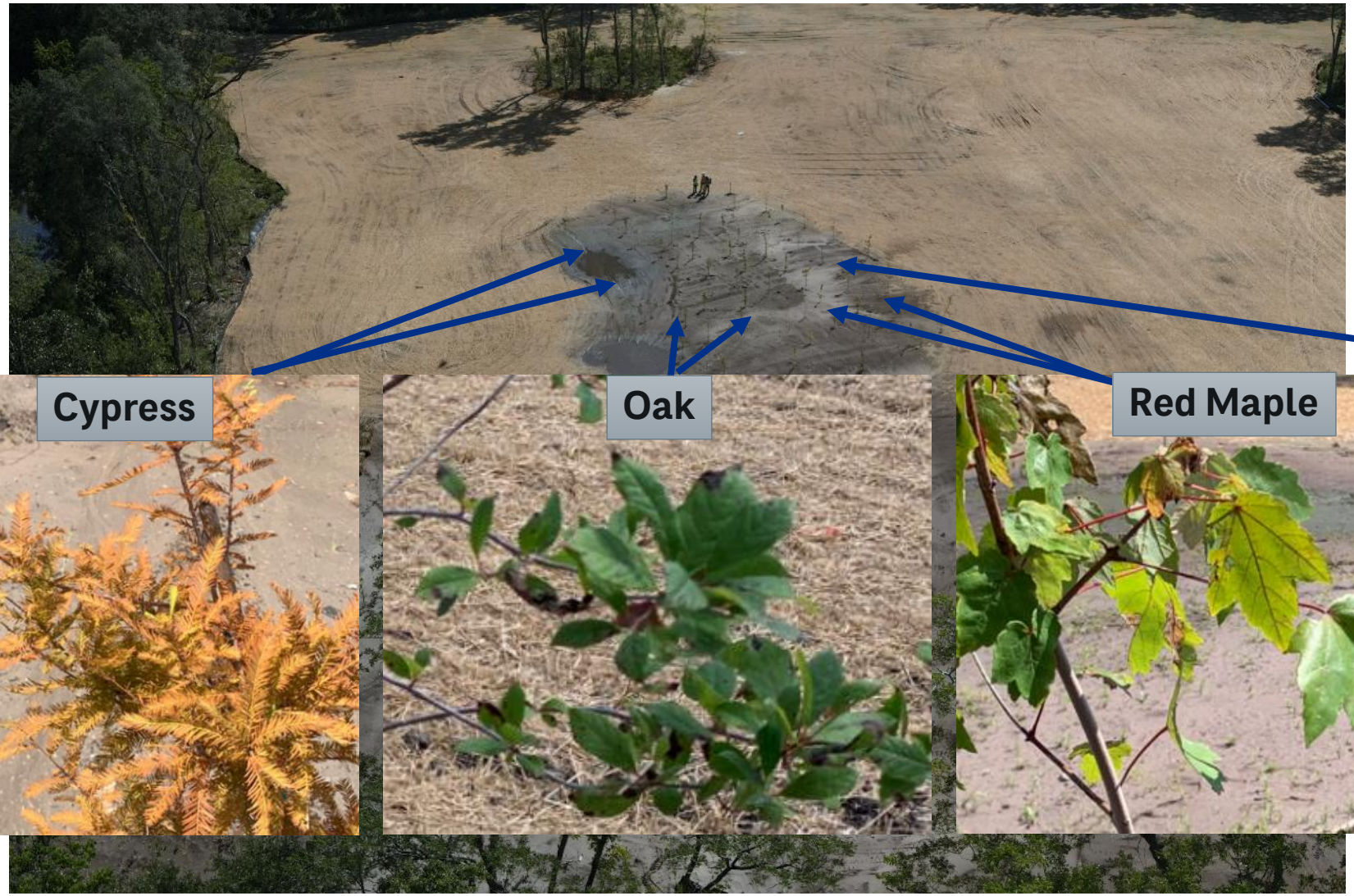
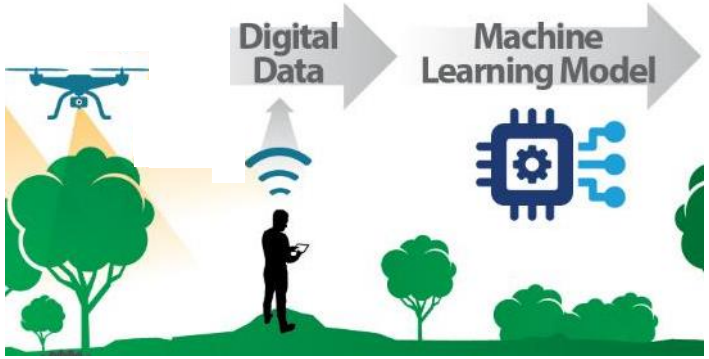
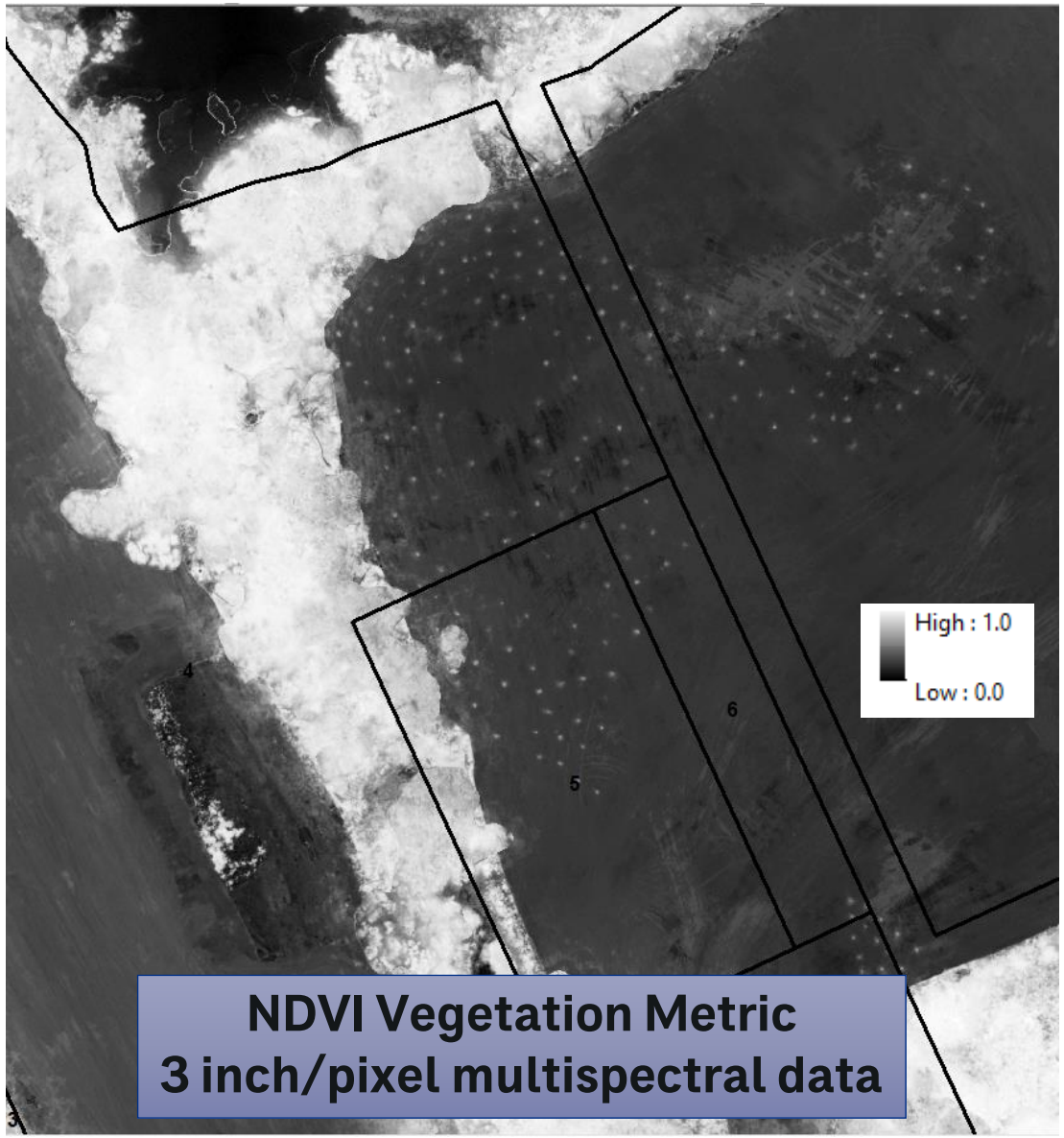


Phase I	=	470 trees
Phase II	=	1,370 trees
Total	=	1,840 trees

Ground truthing data was collected for use in a machine learning model.

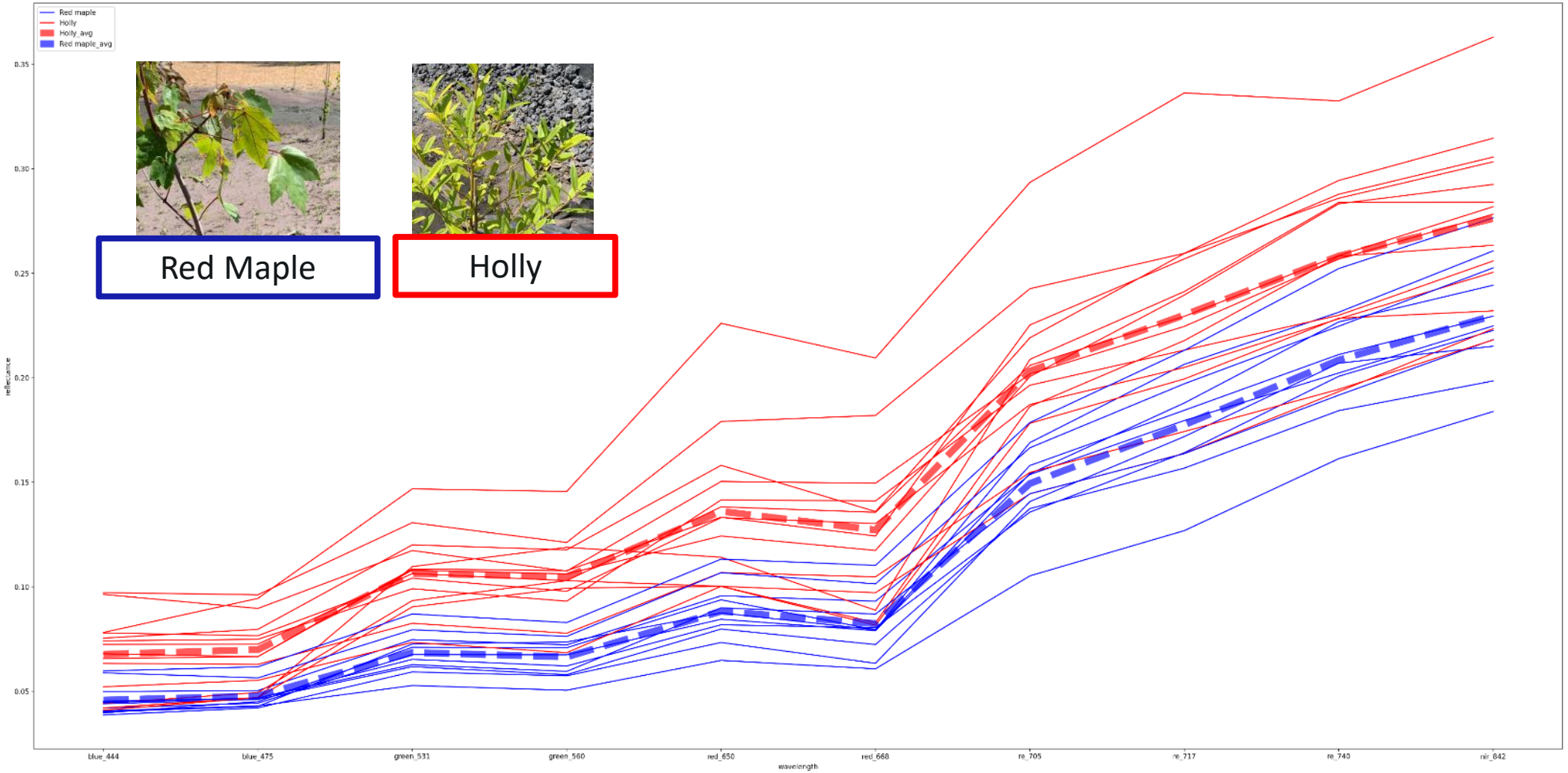


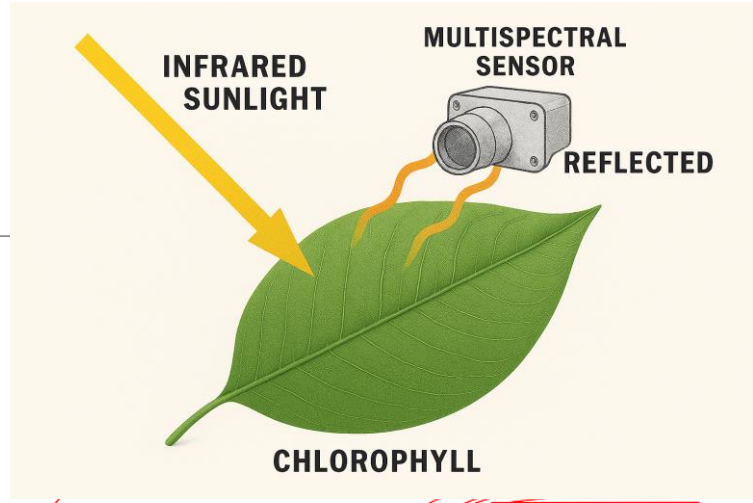
Multispectral sensor collects near-infrared and provides data on vegetation.



10-band
Multispectral
Drone Data

The spectral signatures are often different between species.



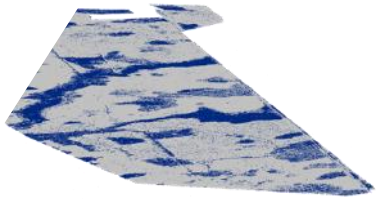

INFRARED
SUNLIGHT
MULTISPECTRAL
SENSOR
REFLECTED
CHLOROPHYLL

Red maple
Holly
Holly_avg
Red maple_avg
Red Maple
Holly
Not visable to human eye
Reflectance (%)
Wavelength

CDM Smith used a machine learning model to identify tree species in the restoration area.

MACHINE LEARNING MODEL

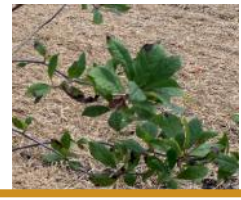
MODEL PREDICTIONS



Holly

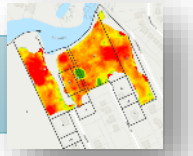
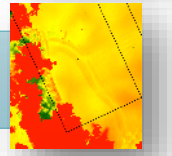
Cypress

Red Maple



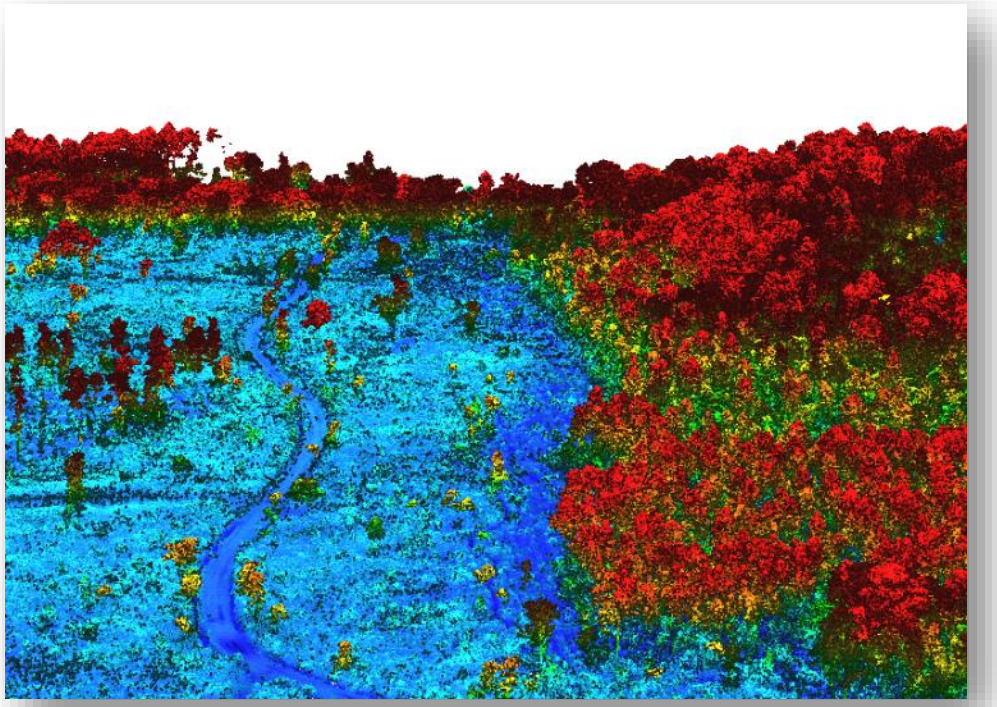
Oak

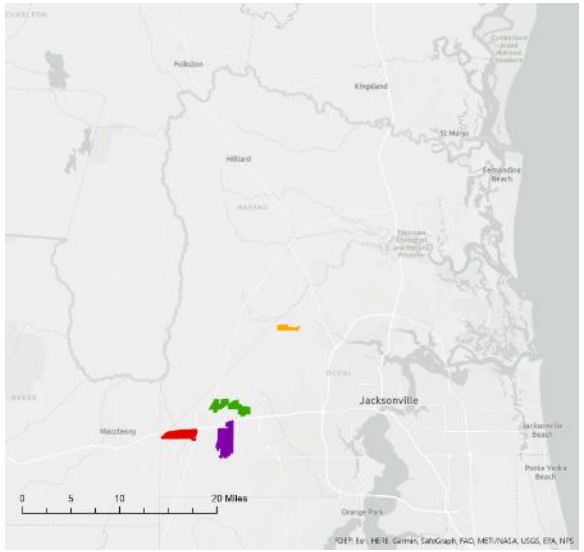
Digital data, automation, and machine learning provide multiple project benefits.

- Contractor Performance 
- Site Documentation 
- Permit Compliance 
- Restoration Monitoring 

Case Study: Solar Site Feasibility and Wetland Mapping

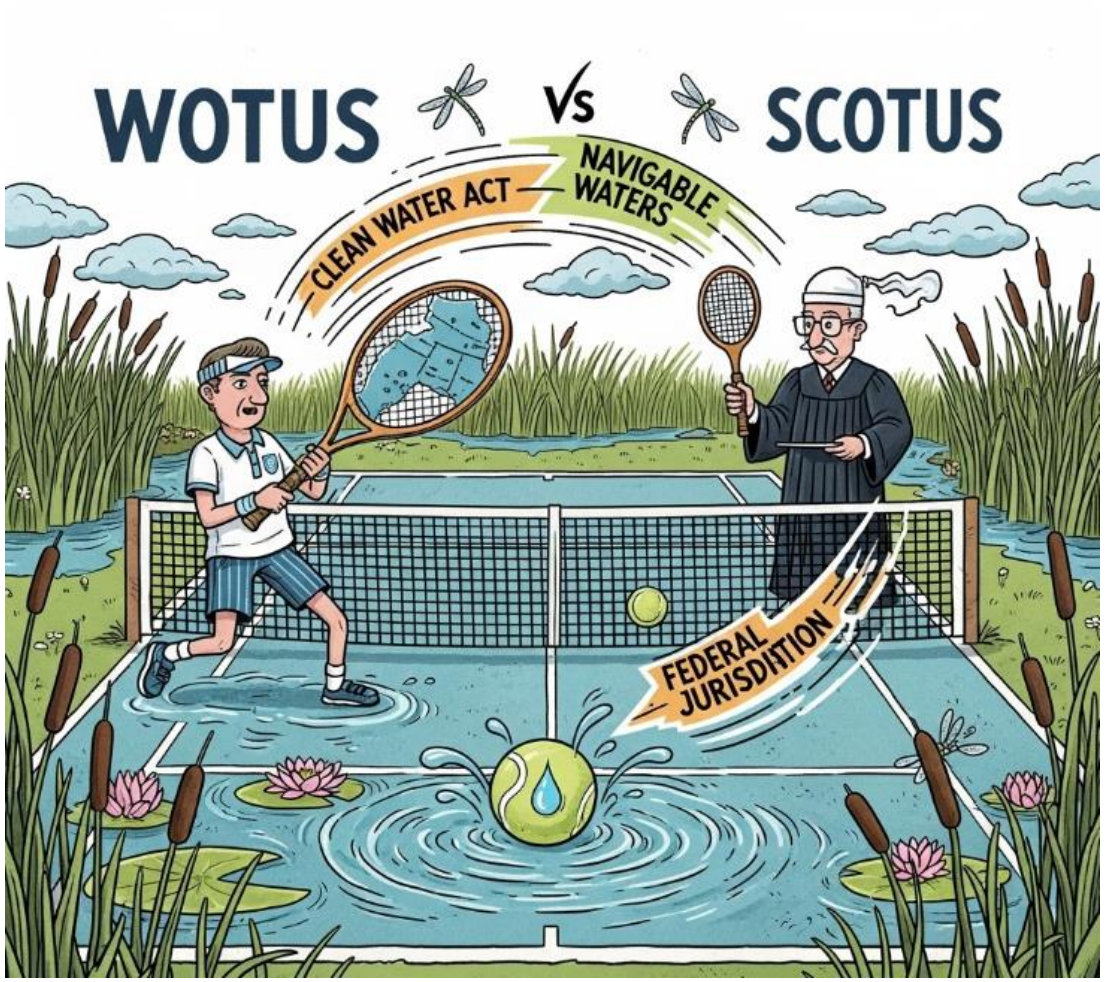
CDM Smith used deep learning to evaluate the extent of uplands and wetlands in support of solar site feasibility.





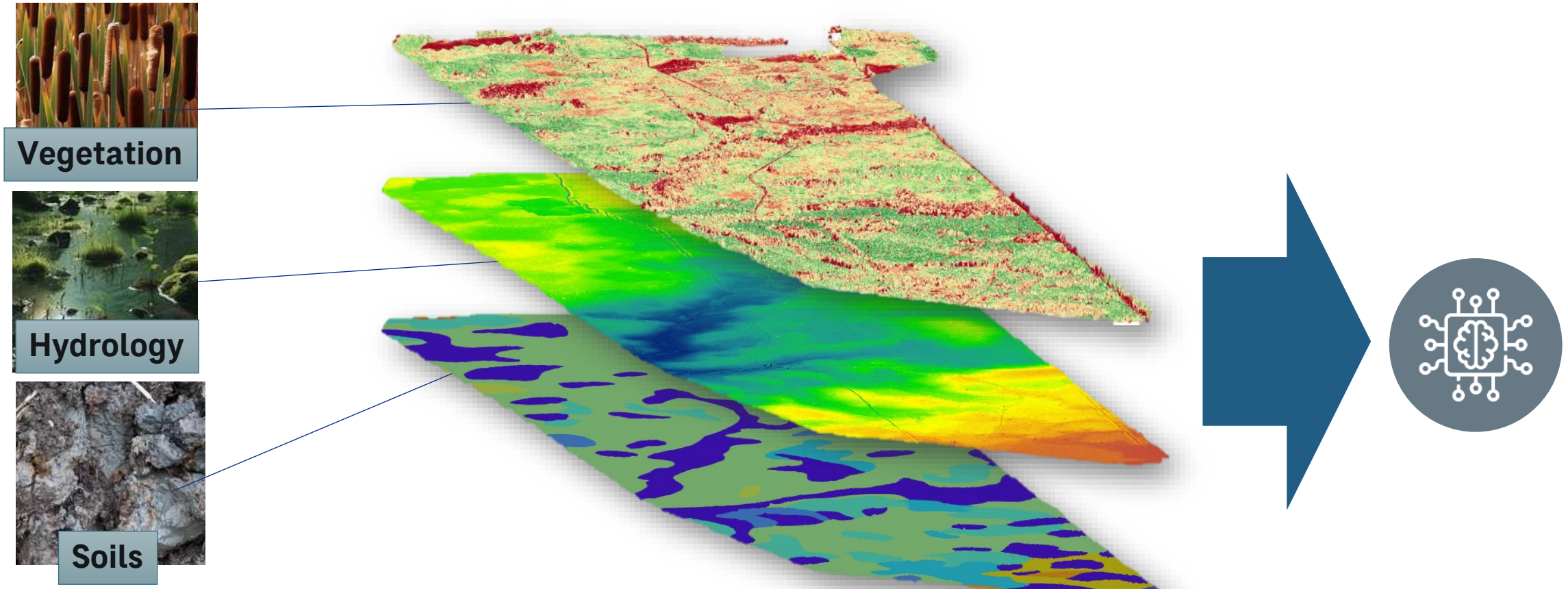
- Size
  - 4 sites
  - Total of 7,000 acres
- Sensors

Wetlands and other Waters of the US regulations are in constant flux.



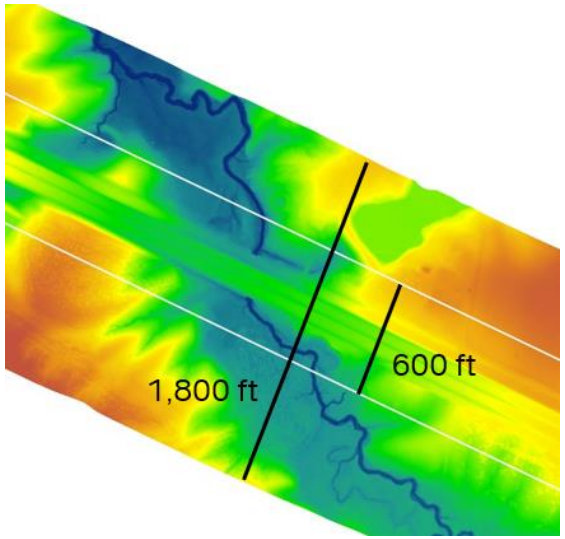
Field work crucial, but limiting, time-consuming, and hazardous.

Remote sensing data provides information that can be used to predict wetland presence with AI models.

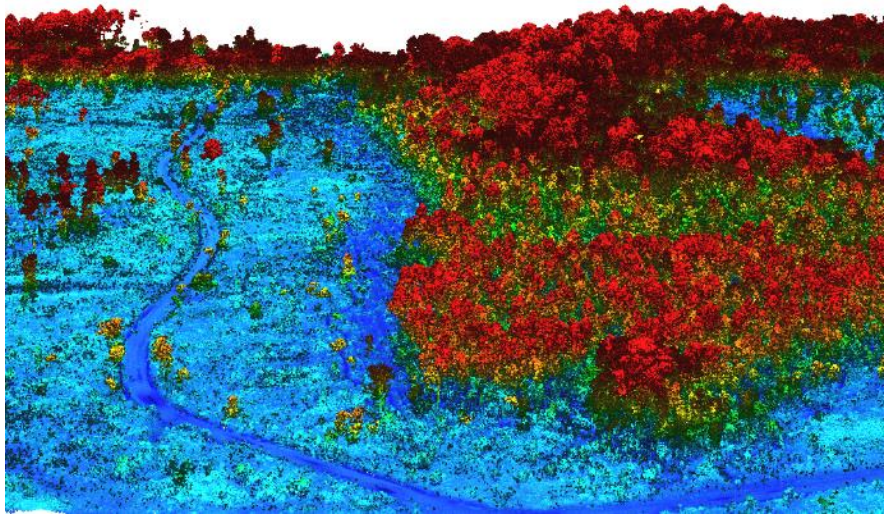


There are multiple advantages of using lidar data.

Extra data

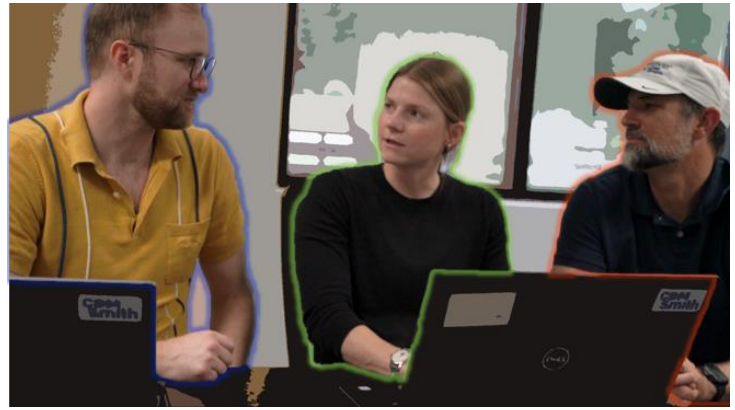


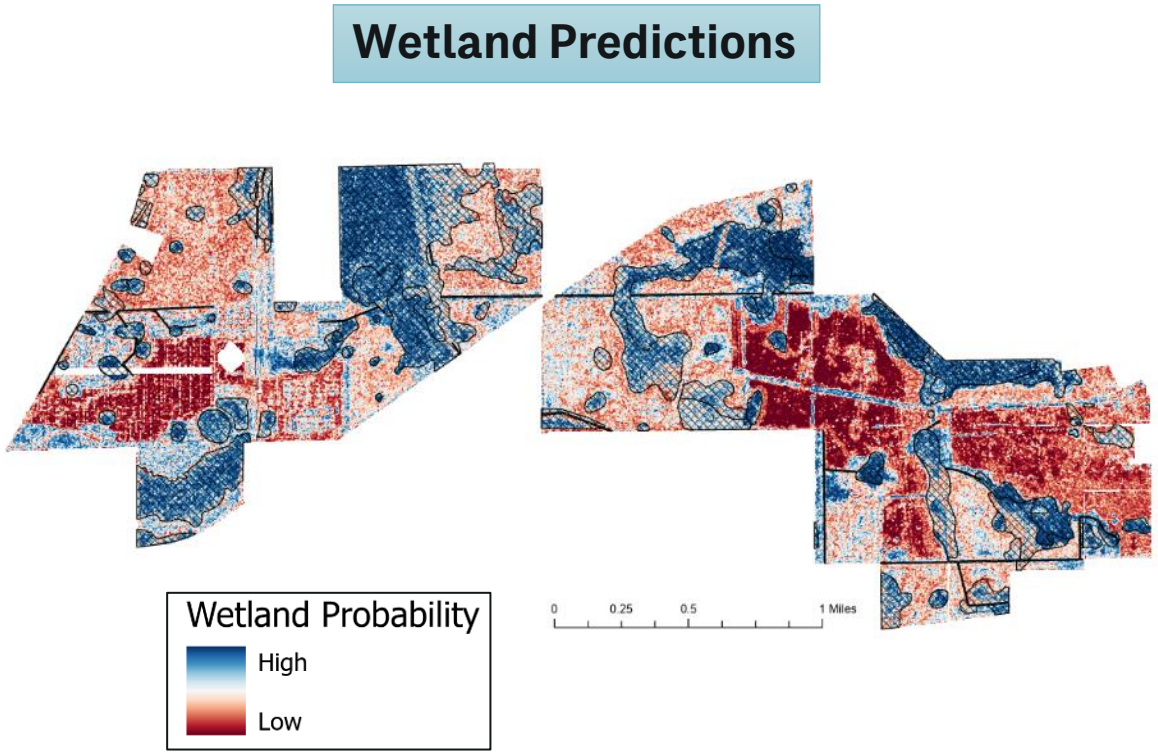
Details on Vegetation

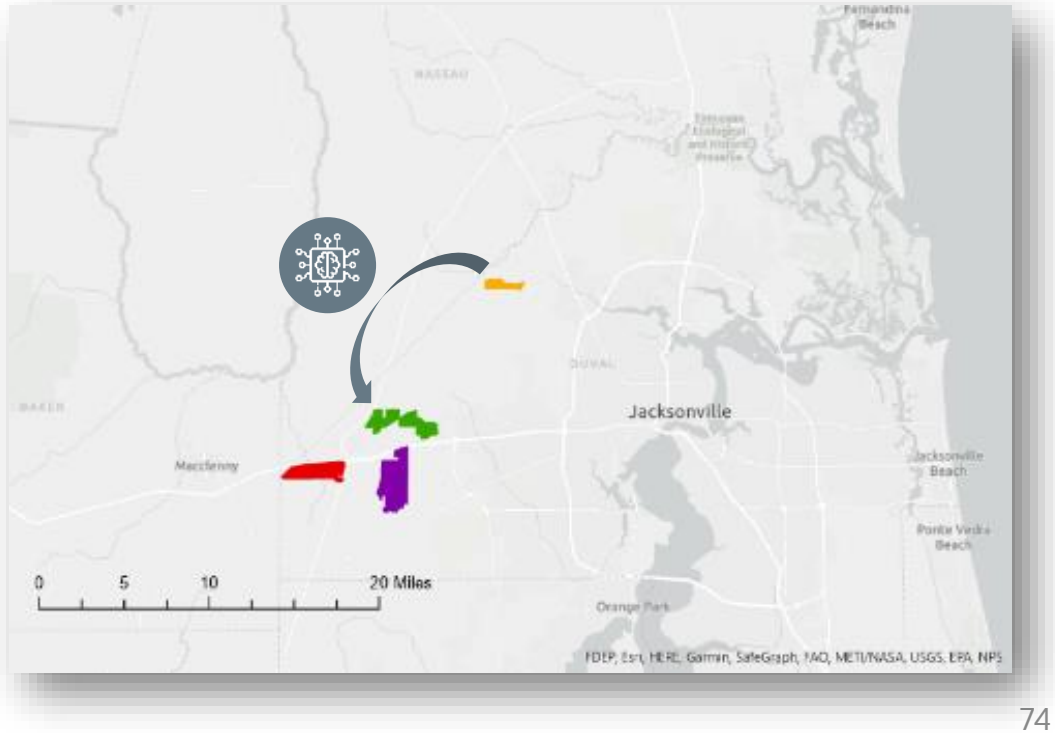


Site Access Not Required

CDM Smith developed a machine learning model to map streams and wetlands.

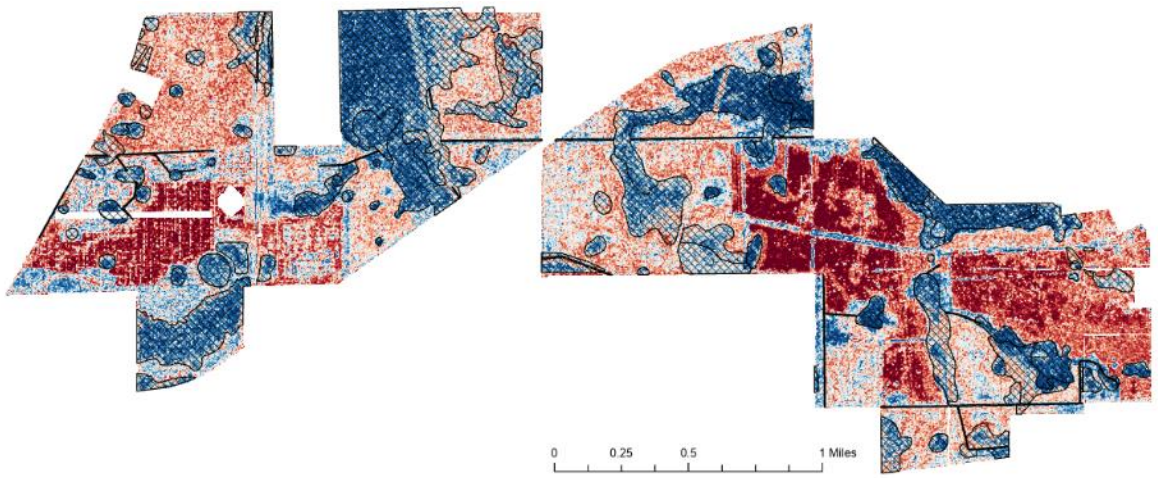




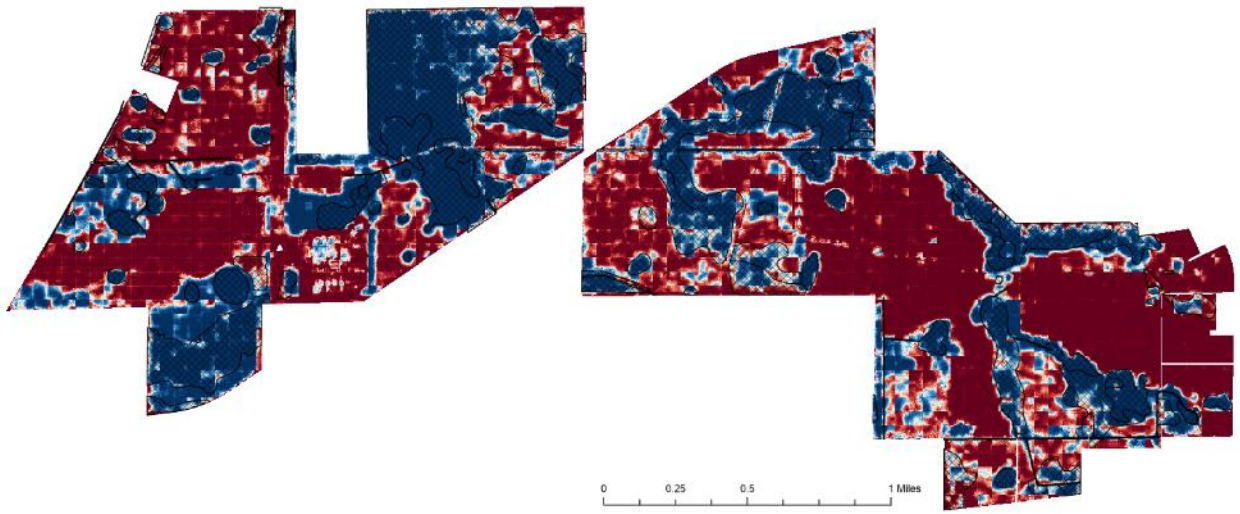


CDM Smith's deep learning model increased accuracy and ability to transfer the model to new sites.

Machine Learning Model



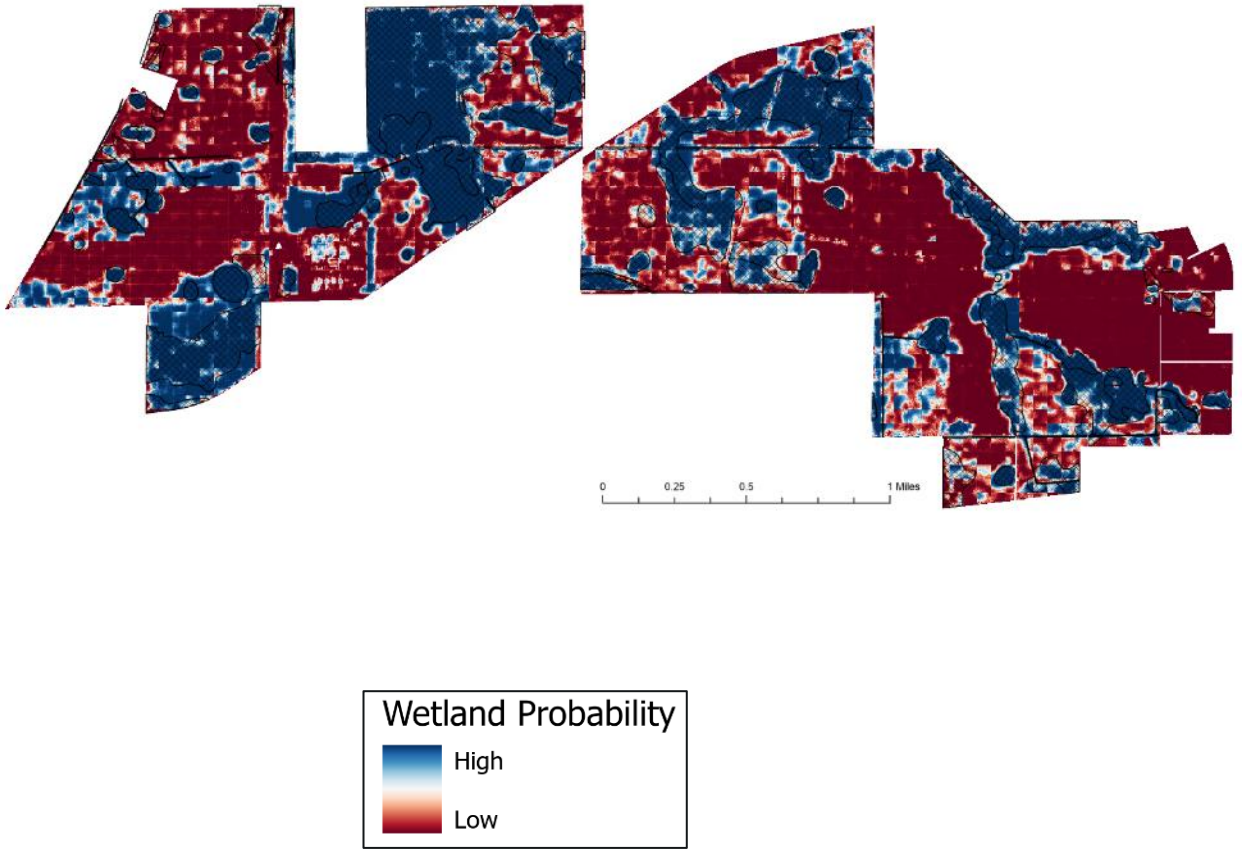
Deep Learning Model



Wetland Probability
High
Low

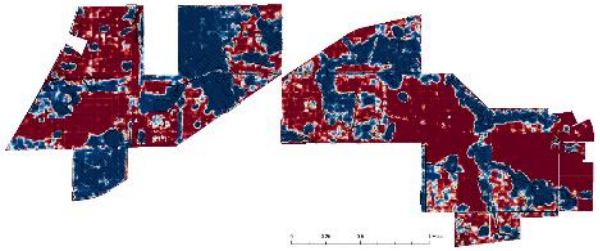
CDM Smith's deep learning model increased accuracy and ability to transfer the model to new sites.

Deep Learning Model



The model results drastically reduce field time for delineations and provide high accuracy results for planning projects.

Deep Learning Model



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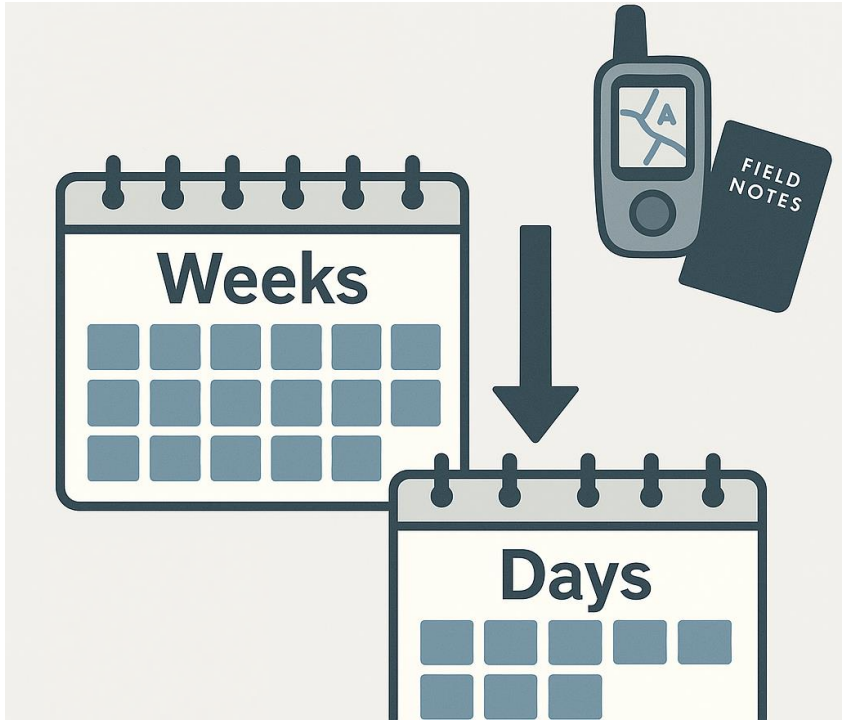
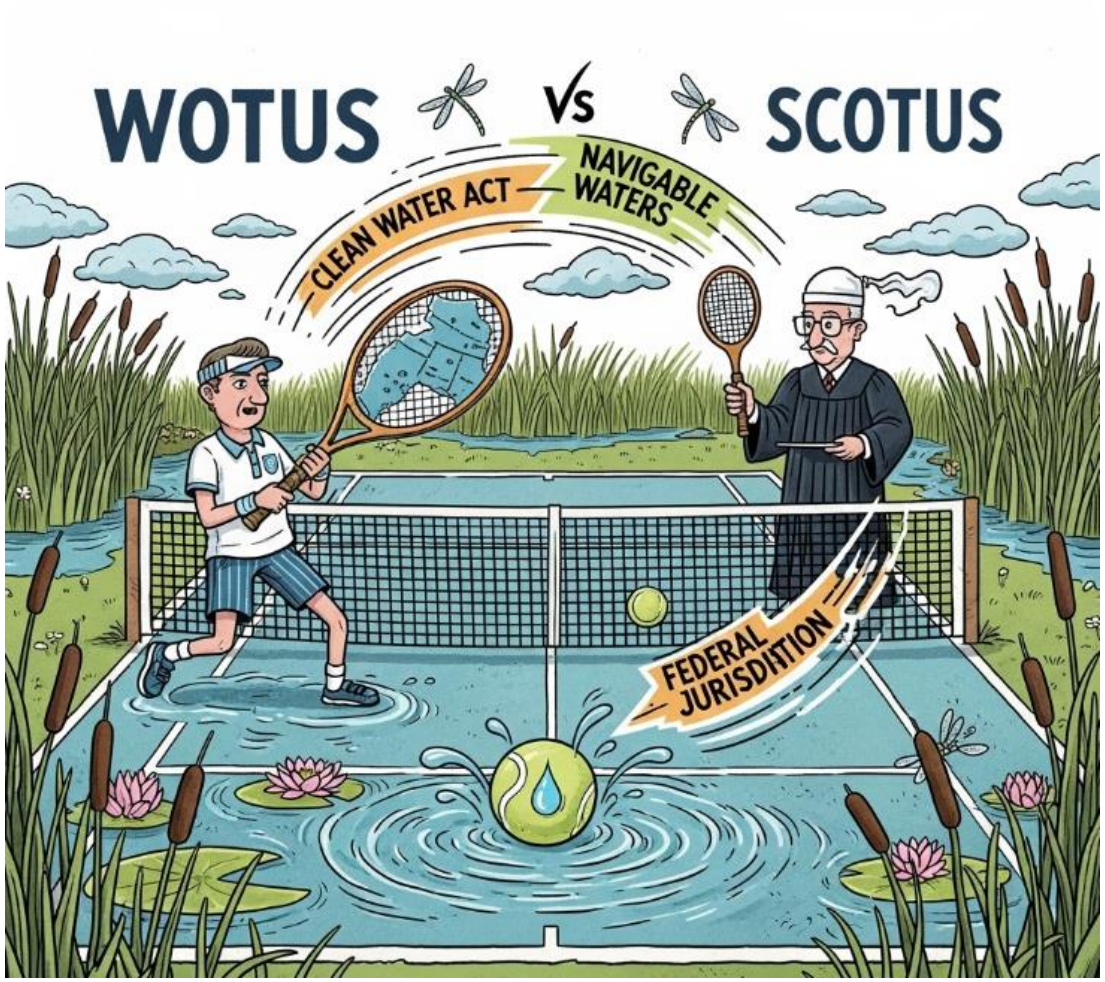


Case Study: MoDOT I-70 Expansion Corridor Project Wetland and Stream Delineation

13 miles

Wetlands and other Waters of the US regulations are in constant flux.



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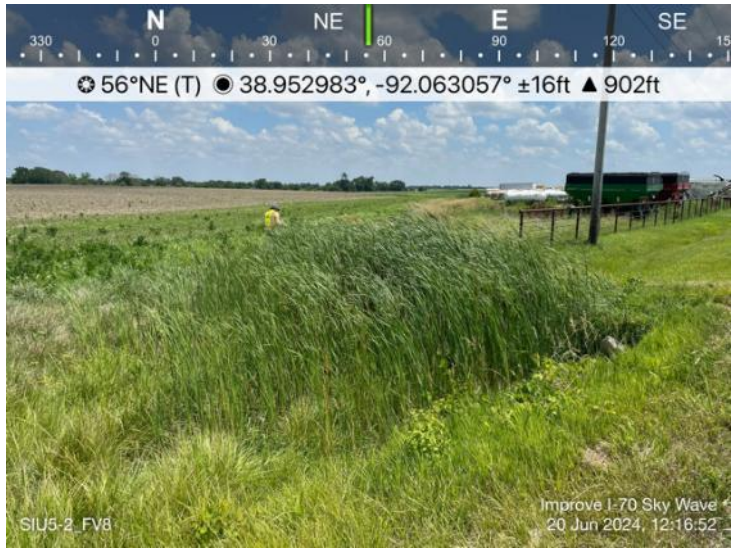
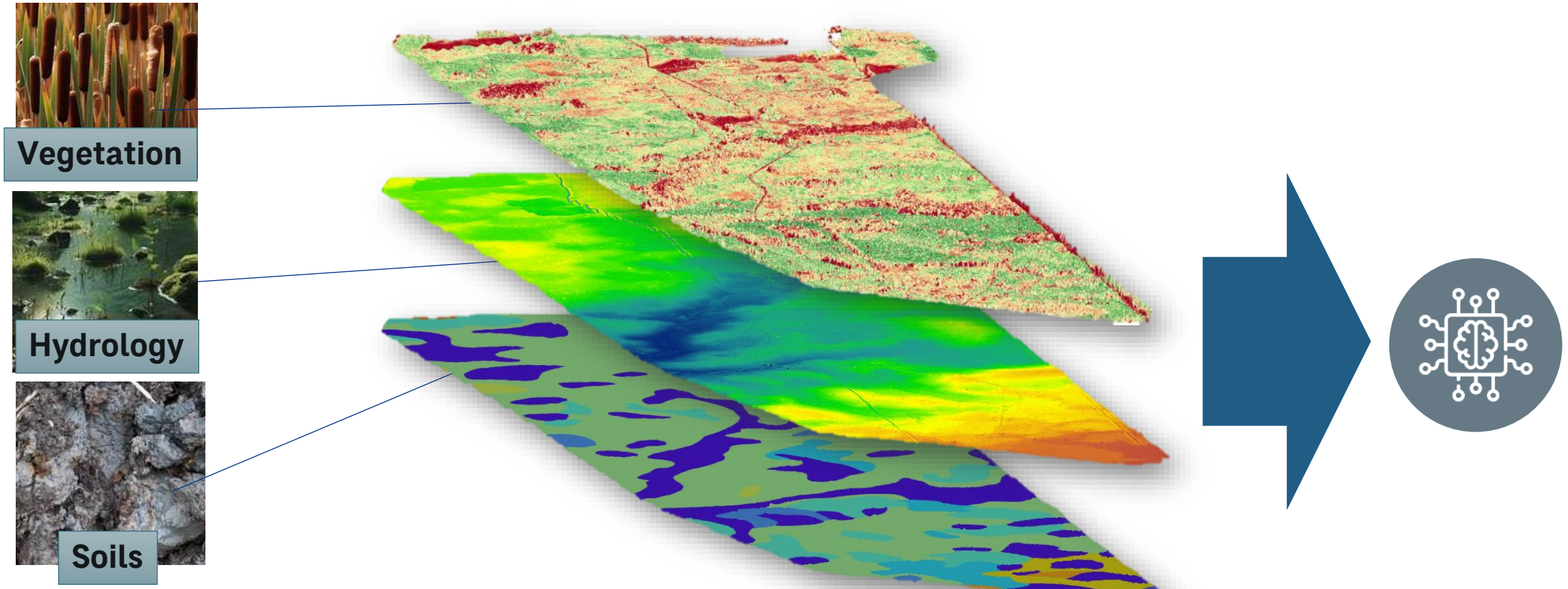


Remote sensing data provides information that can be used to predict wetland presence with AI models.



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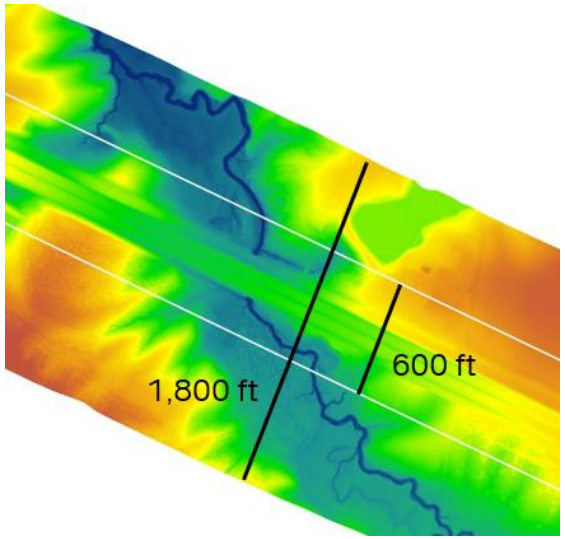
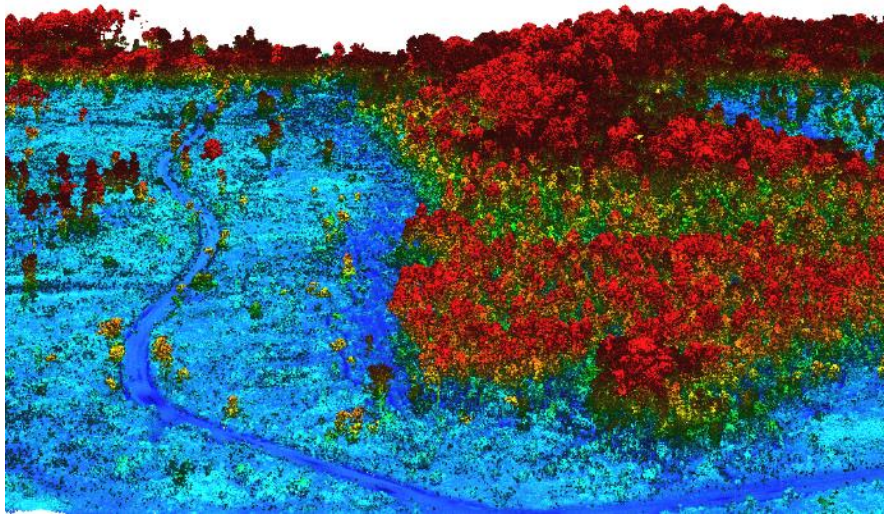
Extra data



Details on Vegetation



Site Access Not Required

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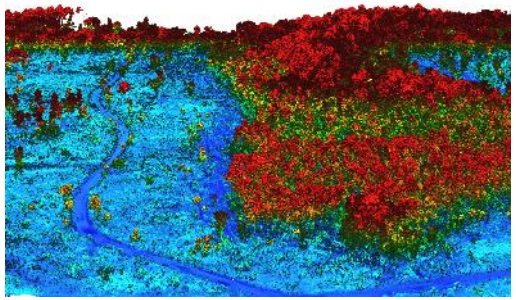
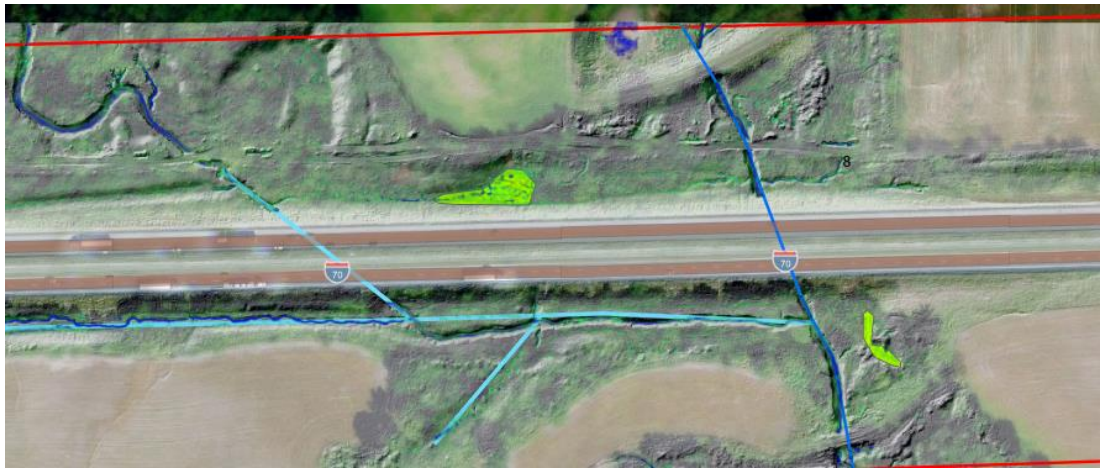


Wetland and Stream Predictions



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Deep Learning Model Results

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