

Navigating the Digital Expanse:

Empowering Environmental Decisions
with Machine Learning and Remote
Sensing

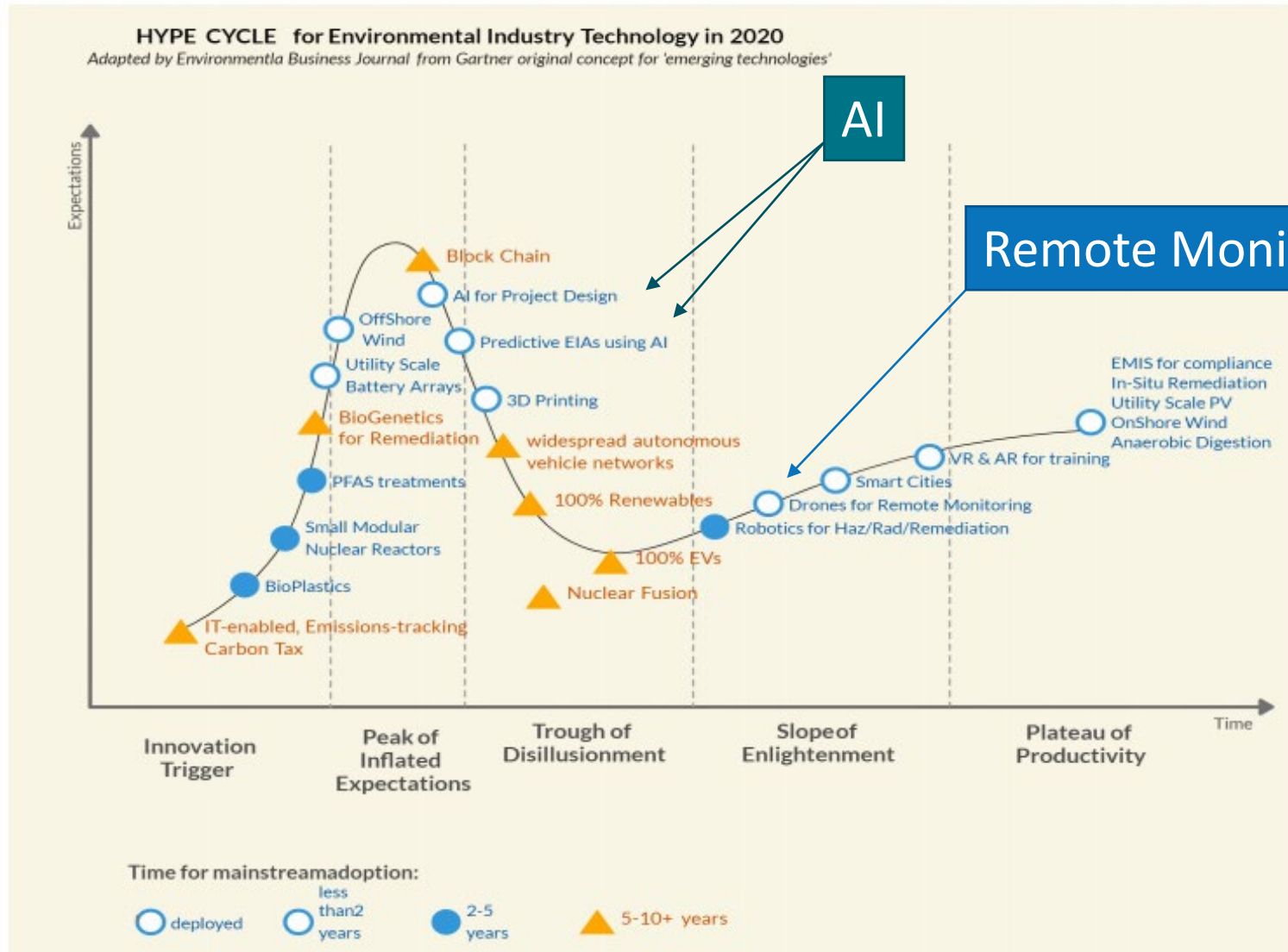


Devin Wilson, PWS

May 2024



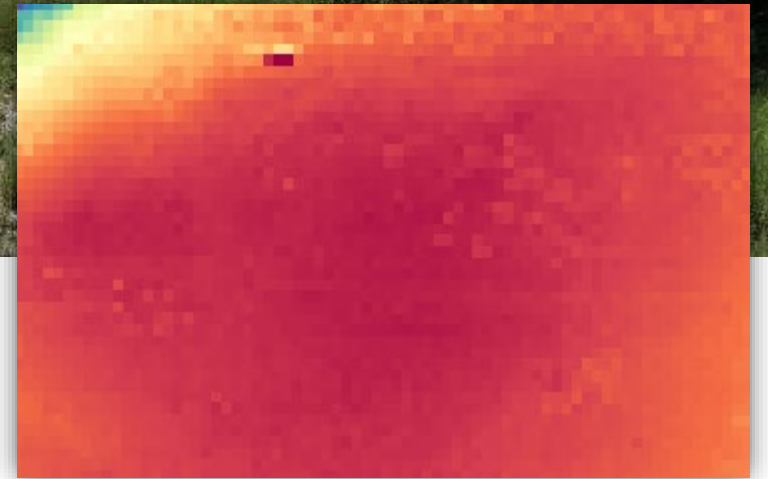
AI and remote sensing will be vital to the environmental industry.



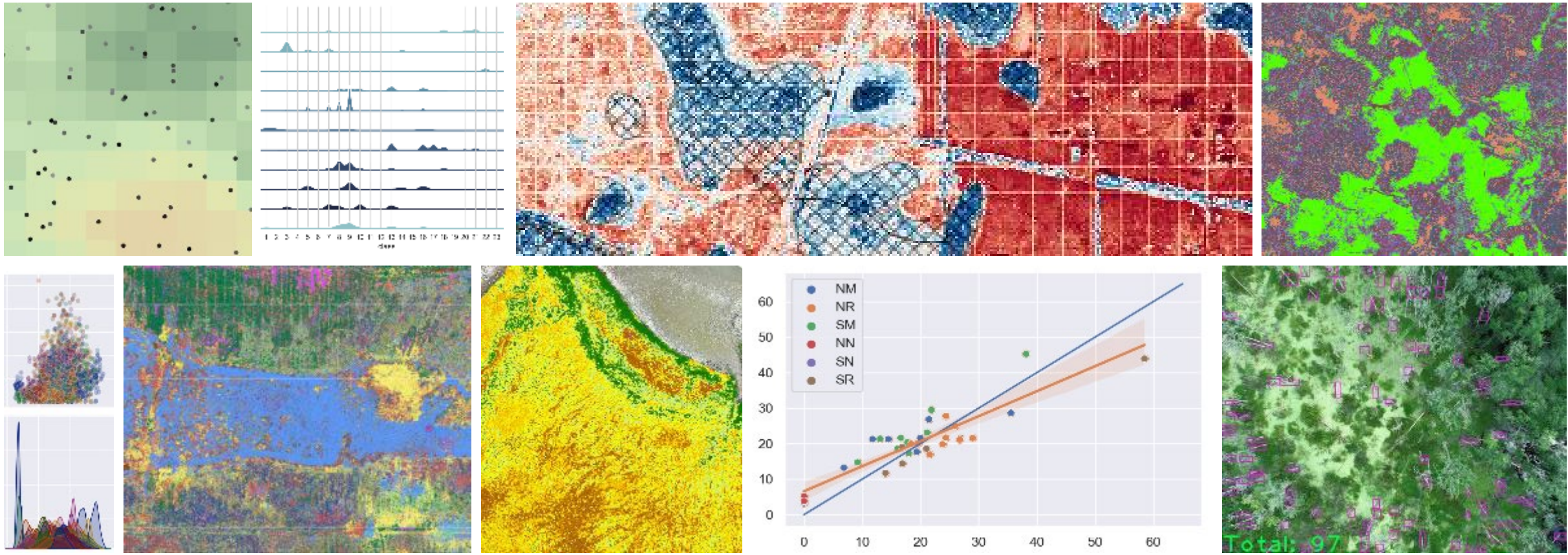
Field work is an invaluable but limiting factor.



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



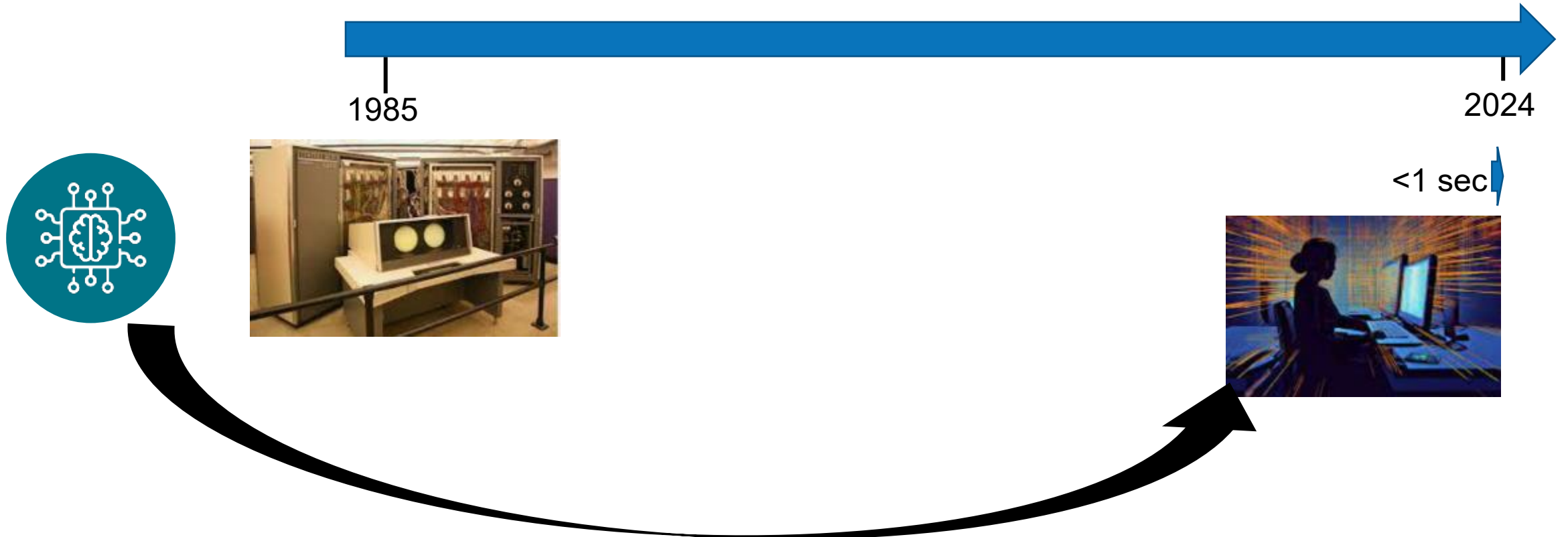
We are finally seeing the promise of machine learning being delivered, but environmental applications are lagging.



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

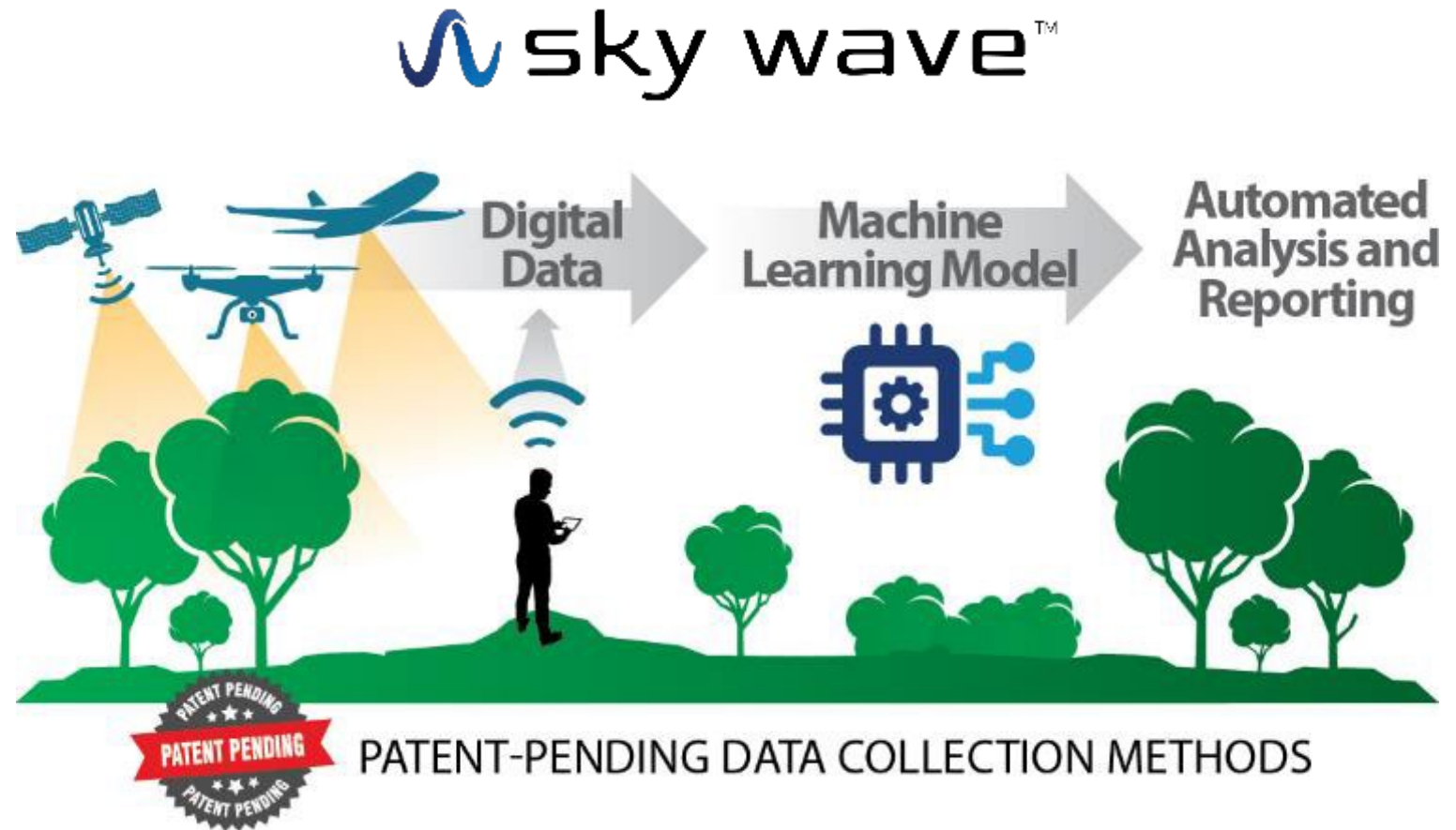


Modern day computer processing power has opened the door to widespread use of AI.



An expert-centered digital pipeline empowers better decisions.

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



Agenda

Remote Sensing Basics

Machine Learning Basics

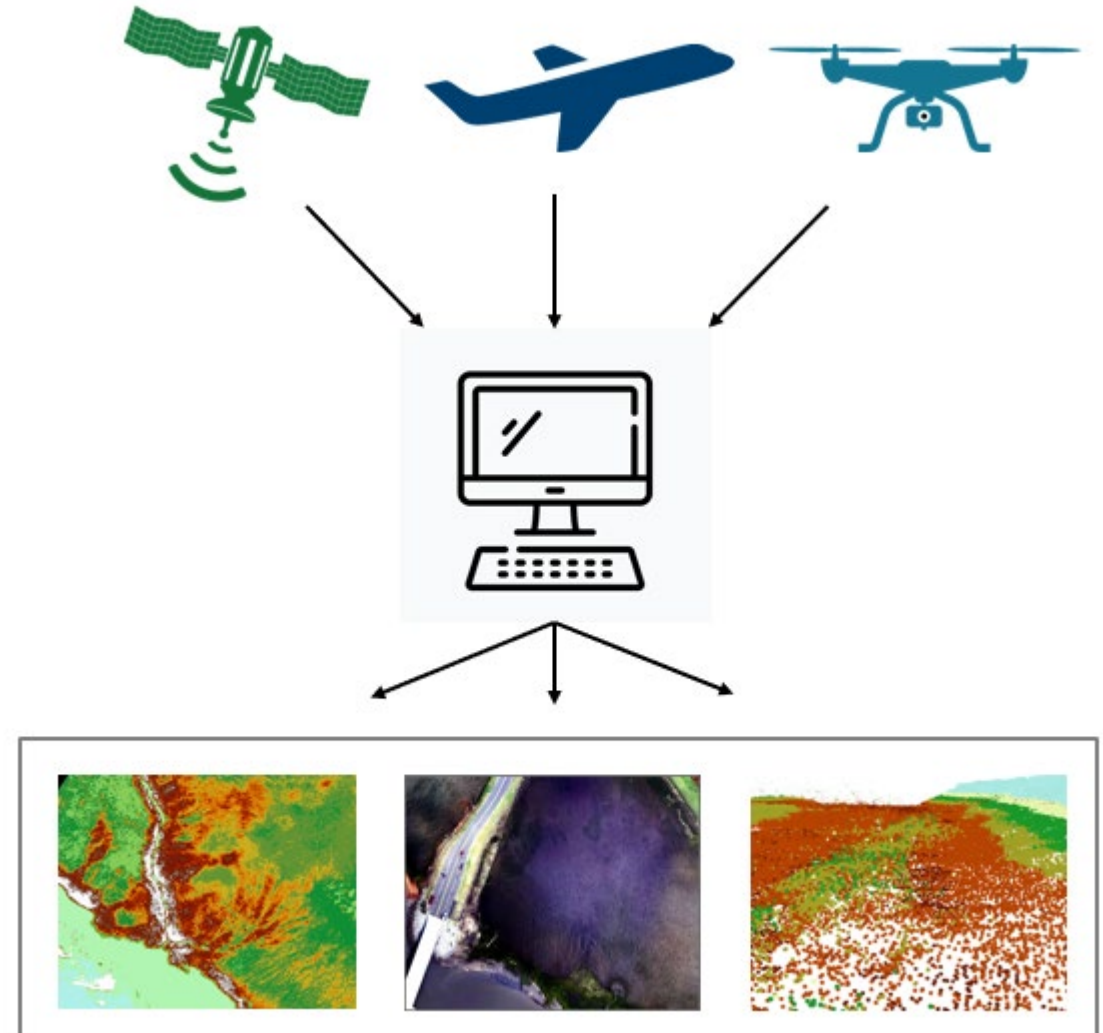
Site Feasibility: Wetland delineation

Land Management: Invasive species identification

Remediation: Excavation and Capping/
Tree Monitoring

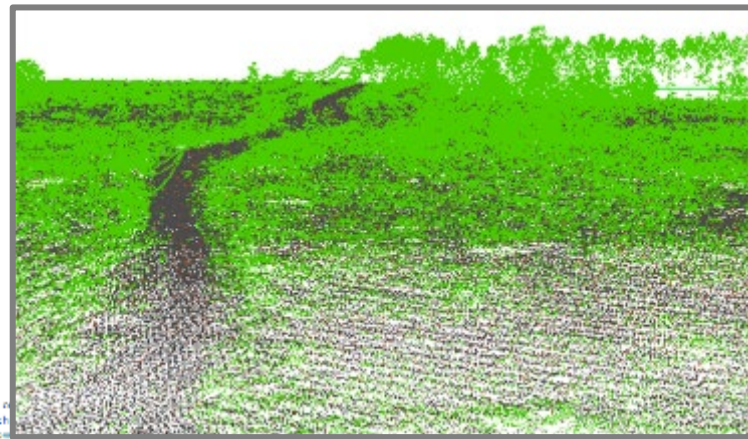
Remote Sensing

- 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

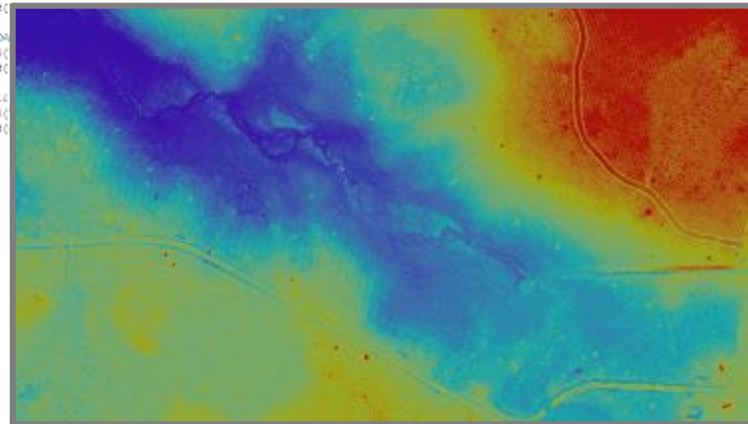
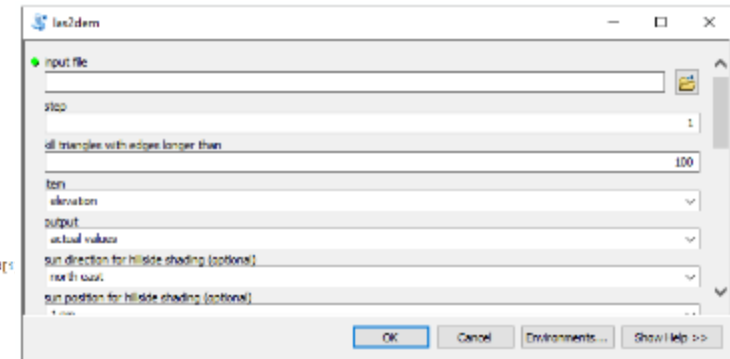


Automation

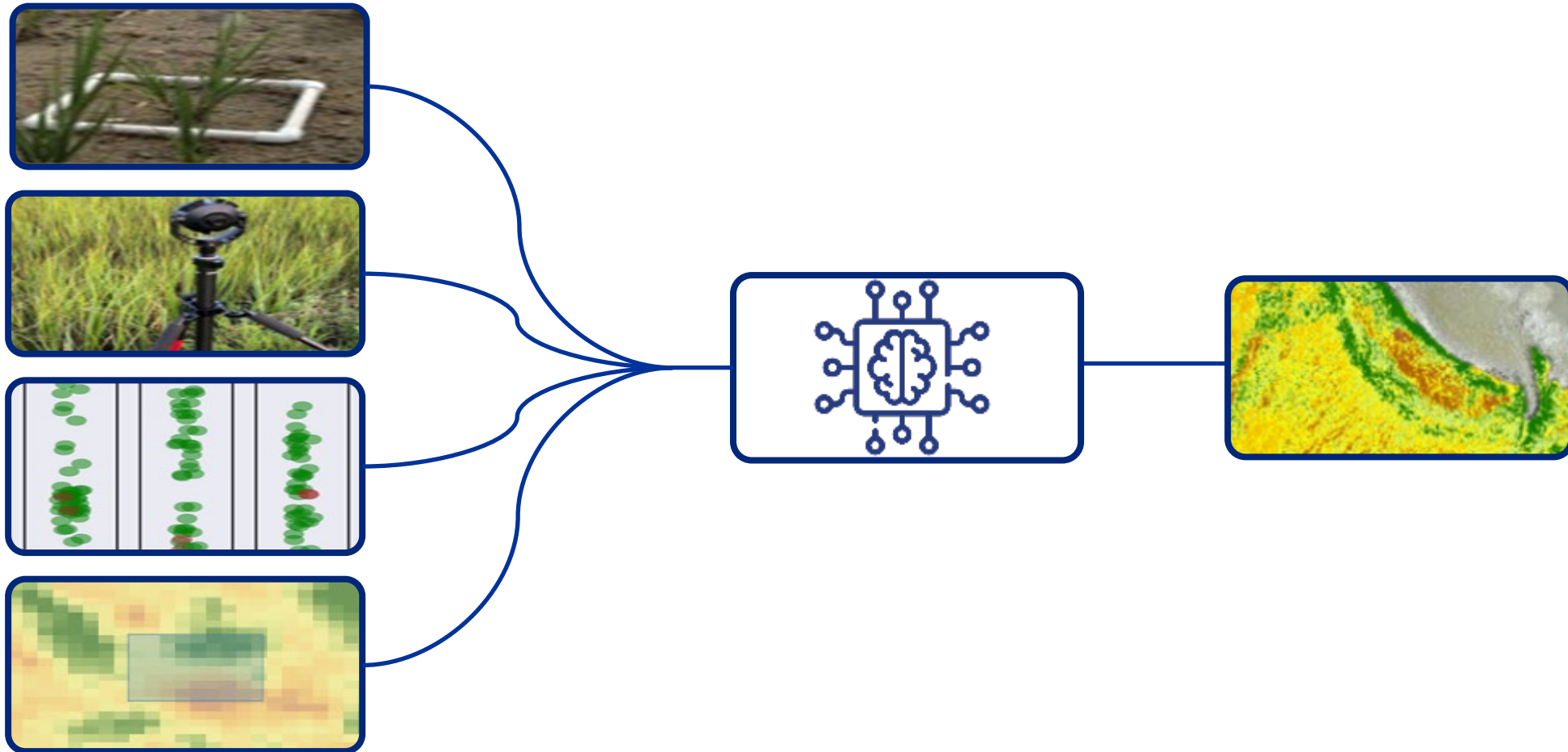
- Automation \neq machine learning
- Automation is a pivotal part of the process
- How can we make things easier?
 - Automate it!



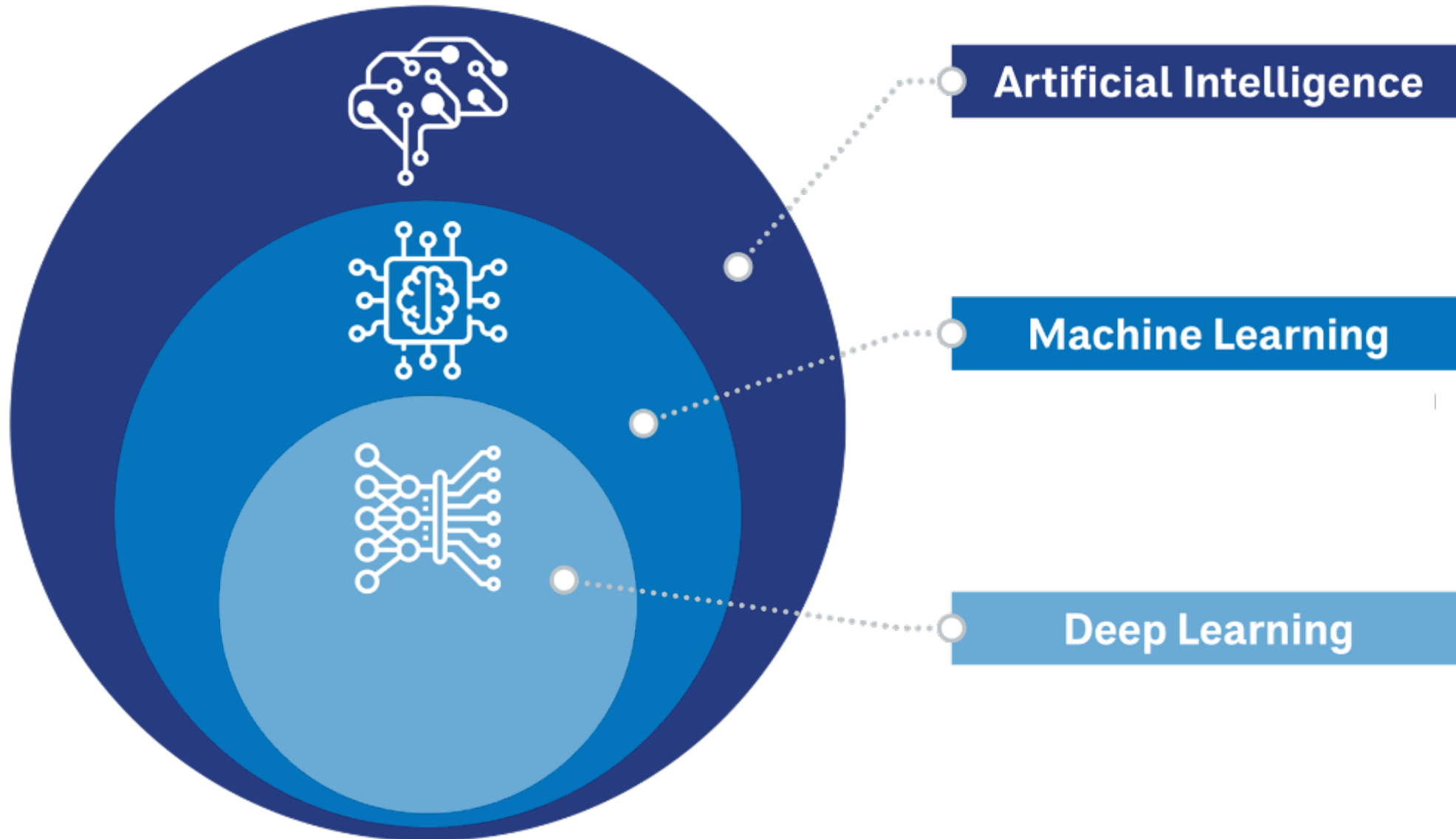
```
200 #@EOL@crp044@
201 def las2img(las, out, out7, lasTools_path, tileSize, buffSize):
202     lasTools_path = os.path.join(lasTools_path, 'las2img.exe')
203     #create the command string for las2img.exe
204     command = ["%s" % lasTools_path]
205
206     #use verbose, default is not verbose
207     command.append("-v")
208
209     #add input file
210     command.append("-i")
211     command.append("%s" % las)
212
213     #add output folder
214     command.append("-o")
215     command.append("%s" % out)
216
217     #additional command-line options
218     #see man print -help
219     command.append("-tileSize")
220     command.append(str(tileSize))
221
222     #report command string
223     command_string = " ".join(command)
224     command_string = str(command_string)
225     command[0] = command[0].rstrip("\n")
226     for i in range(1, command_length):
227         command_string = command_string + " " + str(command[i])
228         command[i] = command[i].rstrip("\n")
229
230     #run command
231     check_output(command_string)
232
233 #@EOL@crp044@
234 def las2img(las, out7, out8, lasTools_path, tileSize, buffSize):
235     lasTools_path = os.path.join(lasTools_path, 'las2img.exe')
236     #create the command string for las2img.exe
237     command = ["%s" % lasTools_path]
238
239     #use verbose, default is not verbose
240     command.append("-v")
241
242     #add input file
243     command.append("-i")
244     command.append("%s" % las)
245
246     #add output folder
247     command.append("-o")
248     command.append("%s" % out7)
249
250     #add output folder
251     command.append("-o")
252     command.append("%s" % out8)
253
254     #additional command-line options
255     #see man print -help
256     command.append("-tileSize")
257     command.append(str(tileSize))
258
259     #report command string
260     command_string = " ".join(command)
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267     #run command
268     check_output(command_string)
```



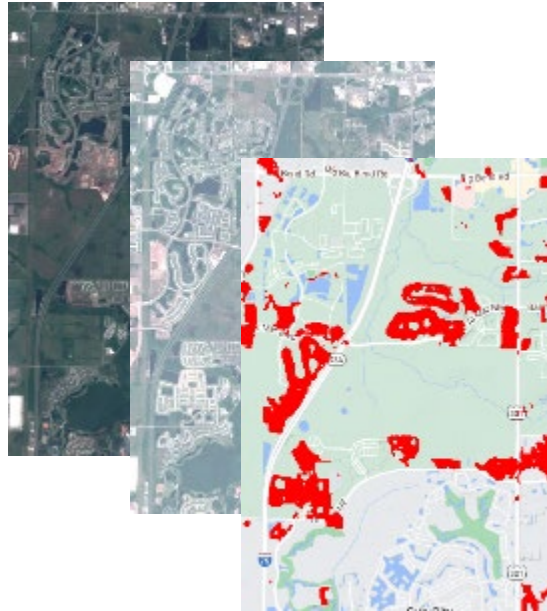
Automation's role in machine learning



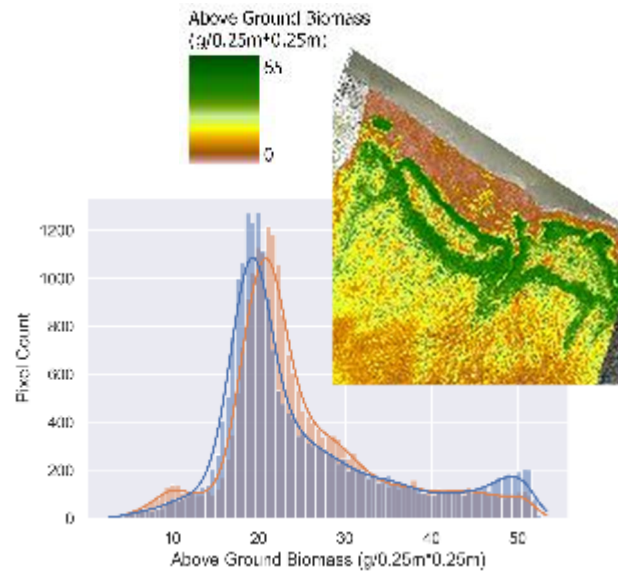
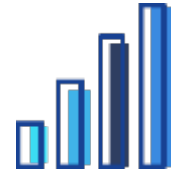
Machine Learning Basics



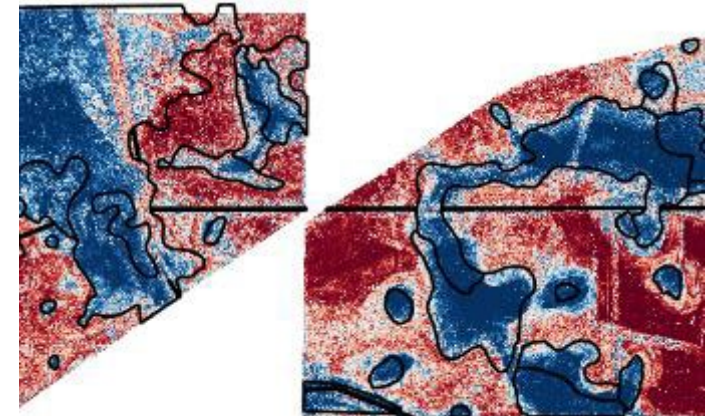
Classify/Locate



Quantify



Segment



Machine Learning Basics

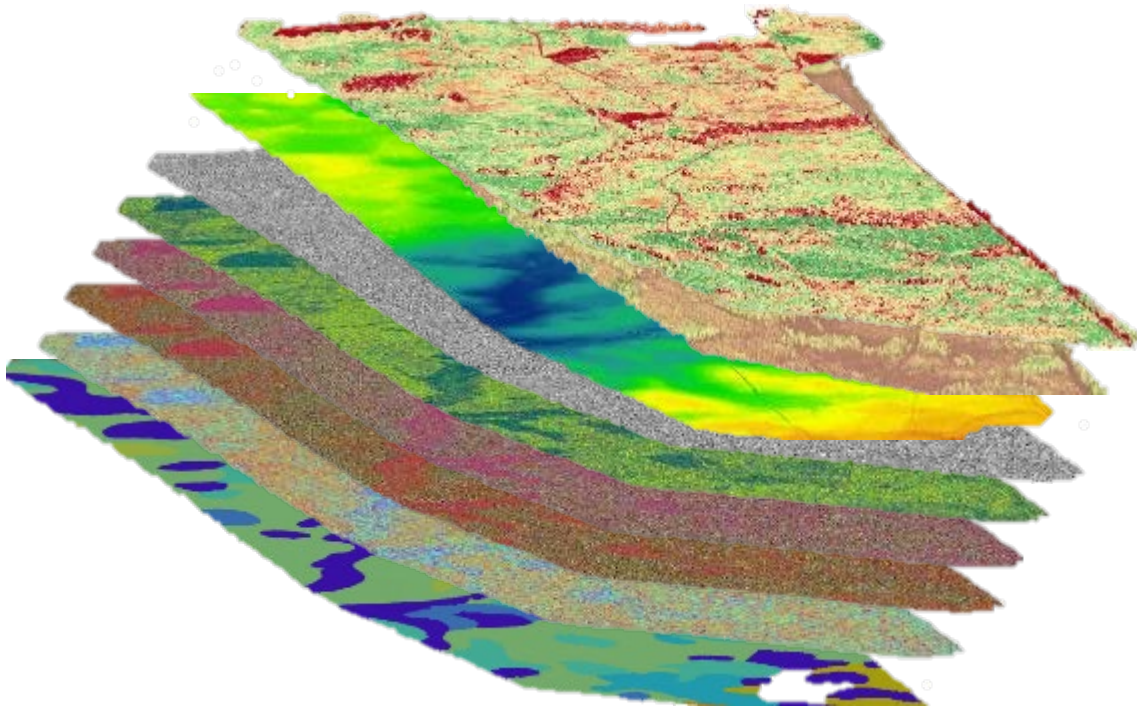
Multiple features

(easier/cheaper/faster to collect)



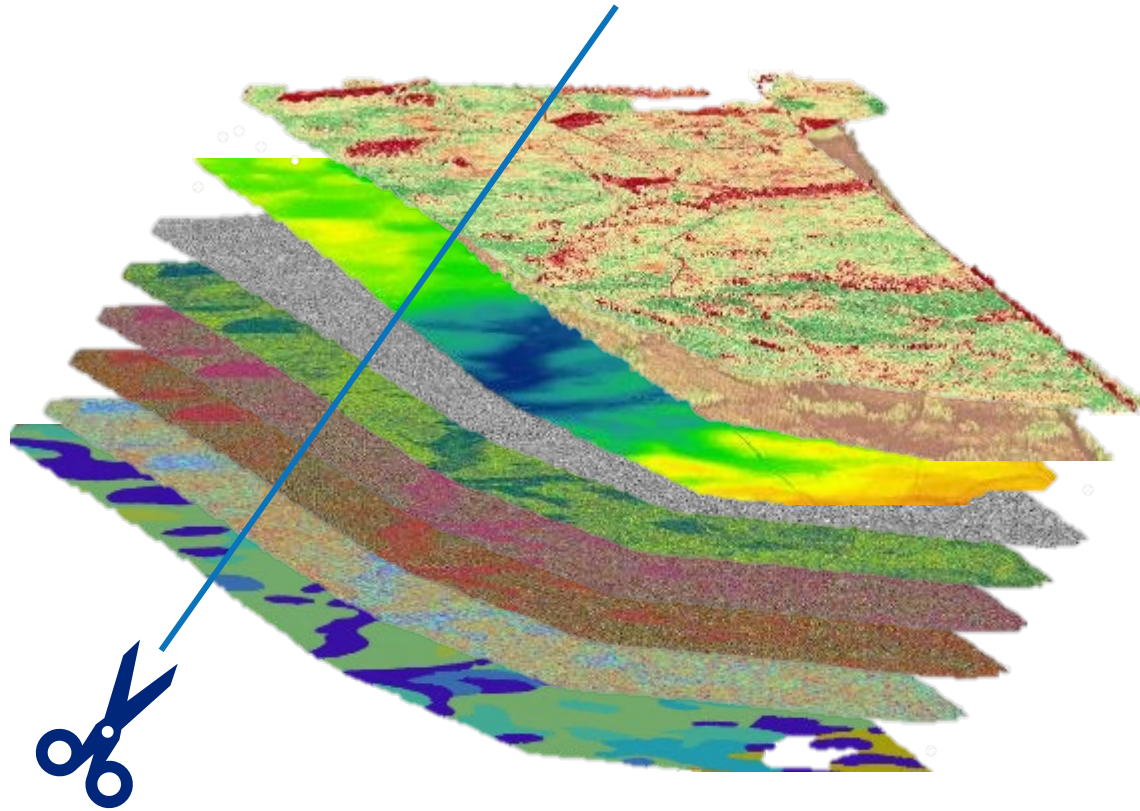
1 property to classify or quantify

(difficult /expensive/slower to collect)

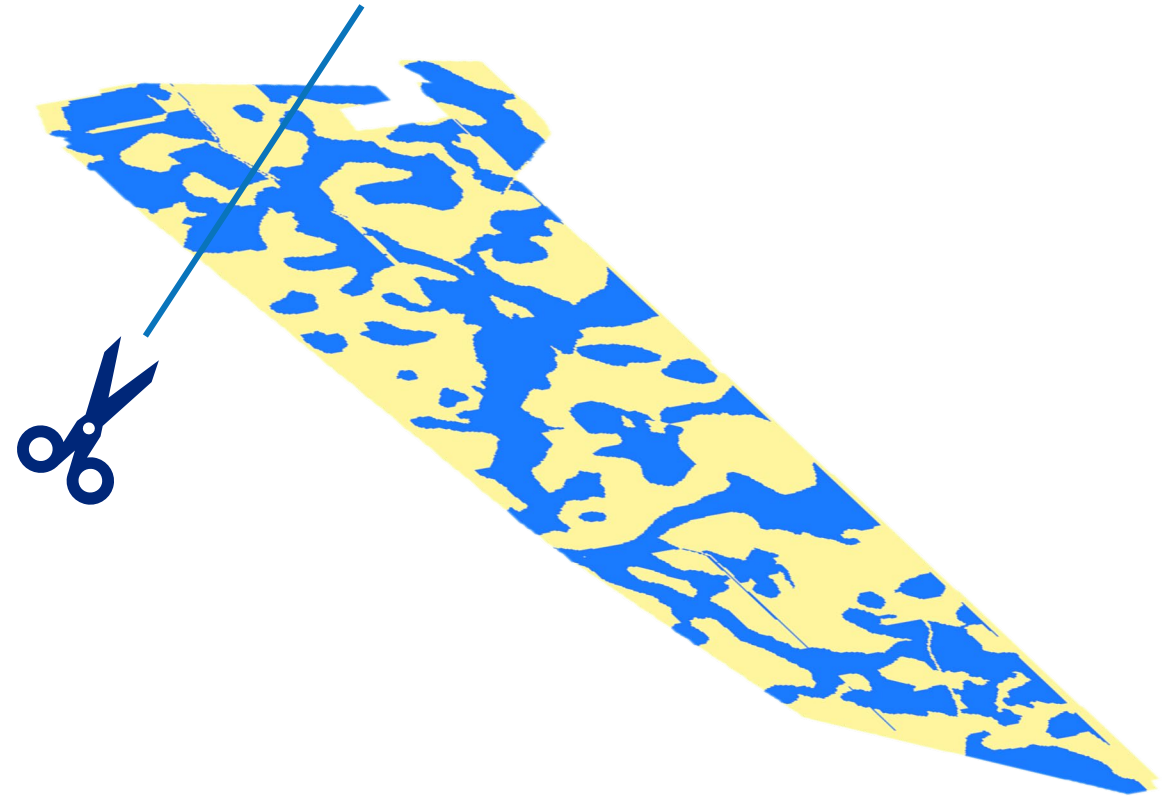


Machine Learning Basics

Model Variables



Target Class

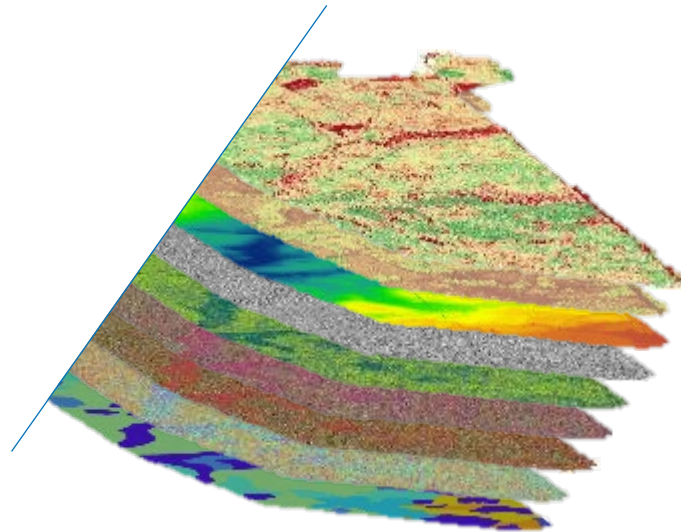
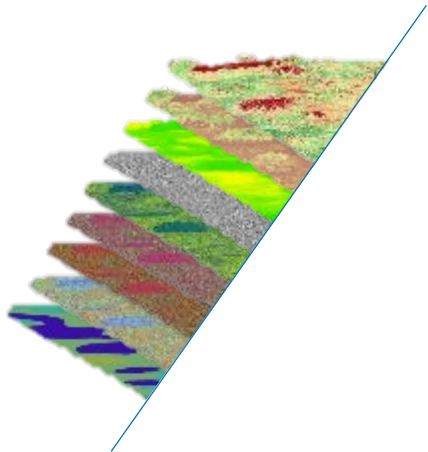


Machine Learning Basics

Training Data

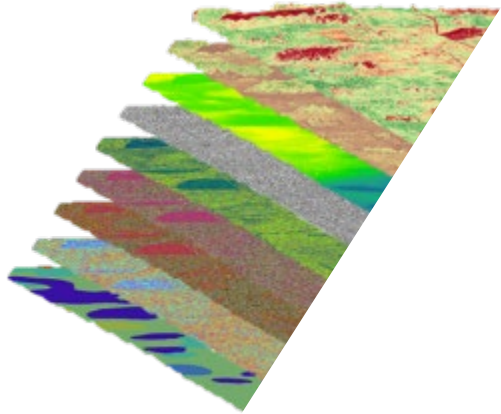


Validation Data



Train the Model

Data
Inputs



Ground
Truthing

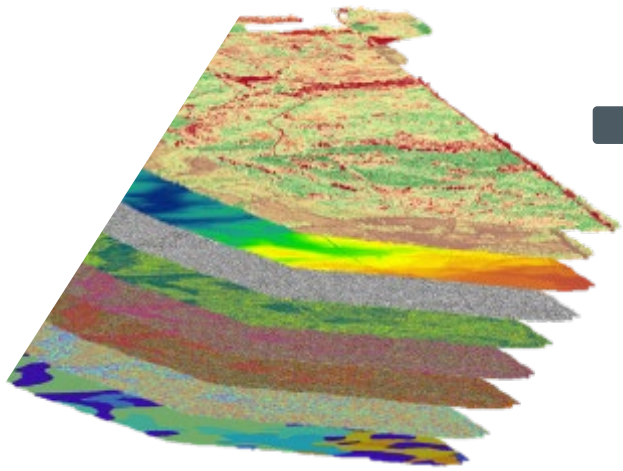


Machine
Learning

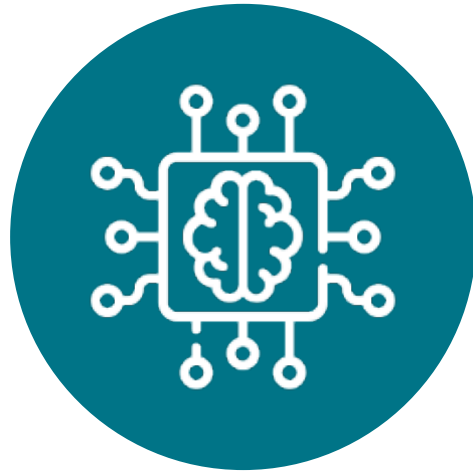


Model Accuracy

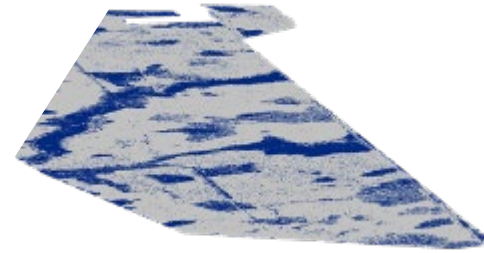
Data
Inputs



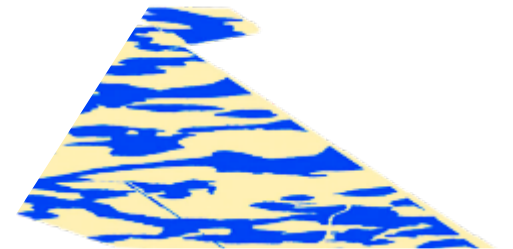
Machine
Learning Model



Model
Predictions



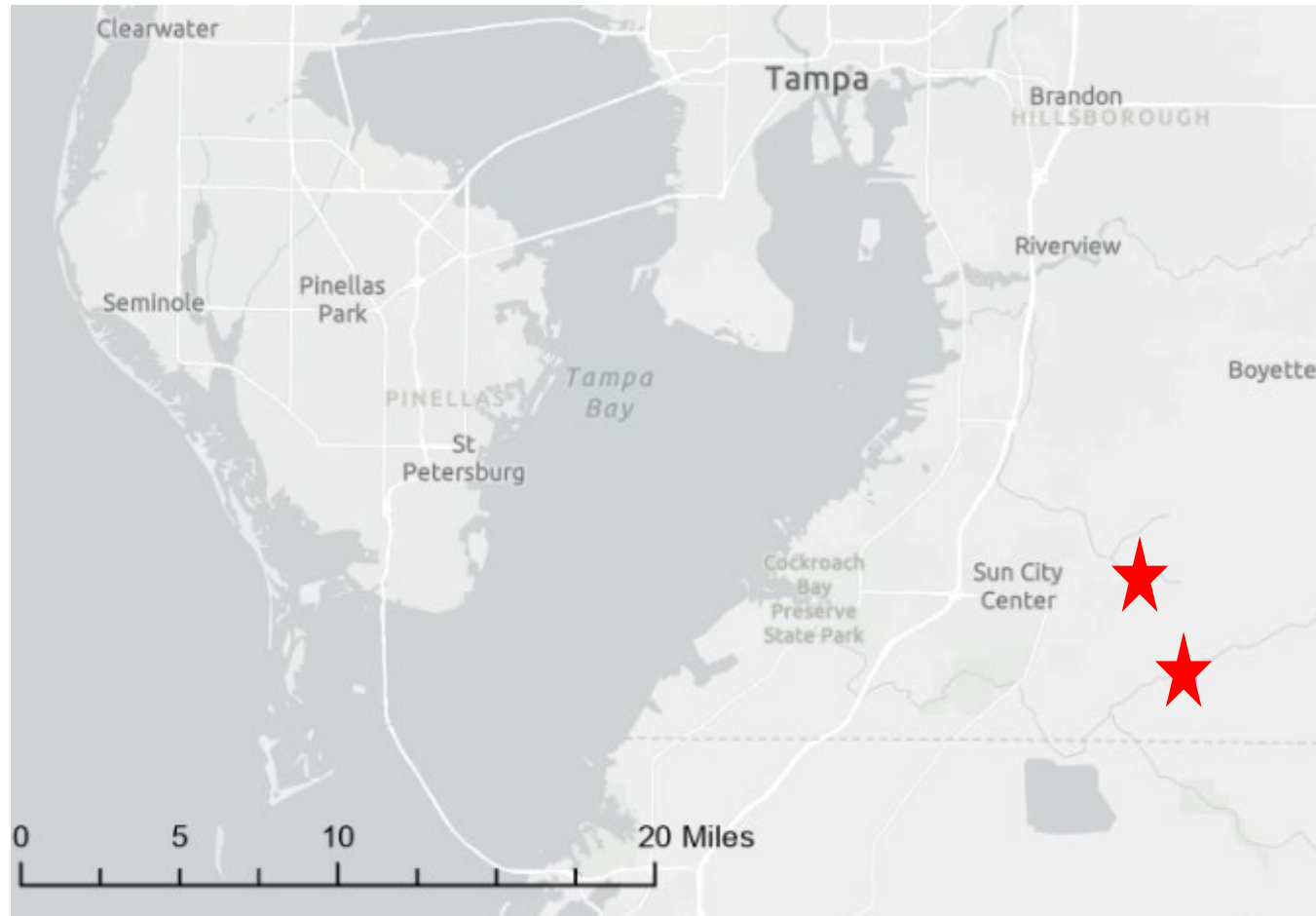
*Measured
Against*



Ground Truthing

Land Management: Invasive & Native species identification

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



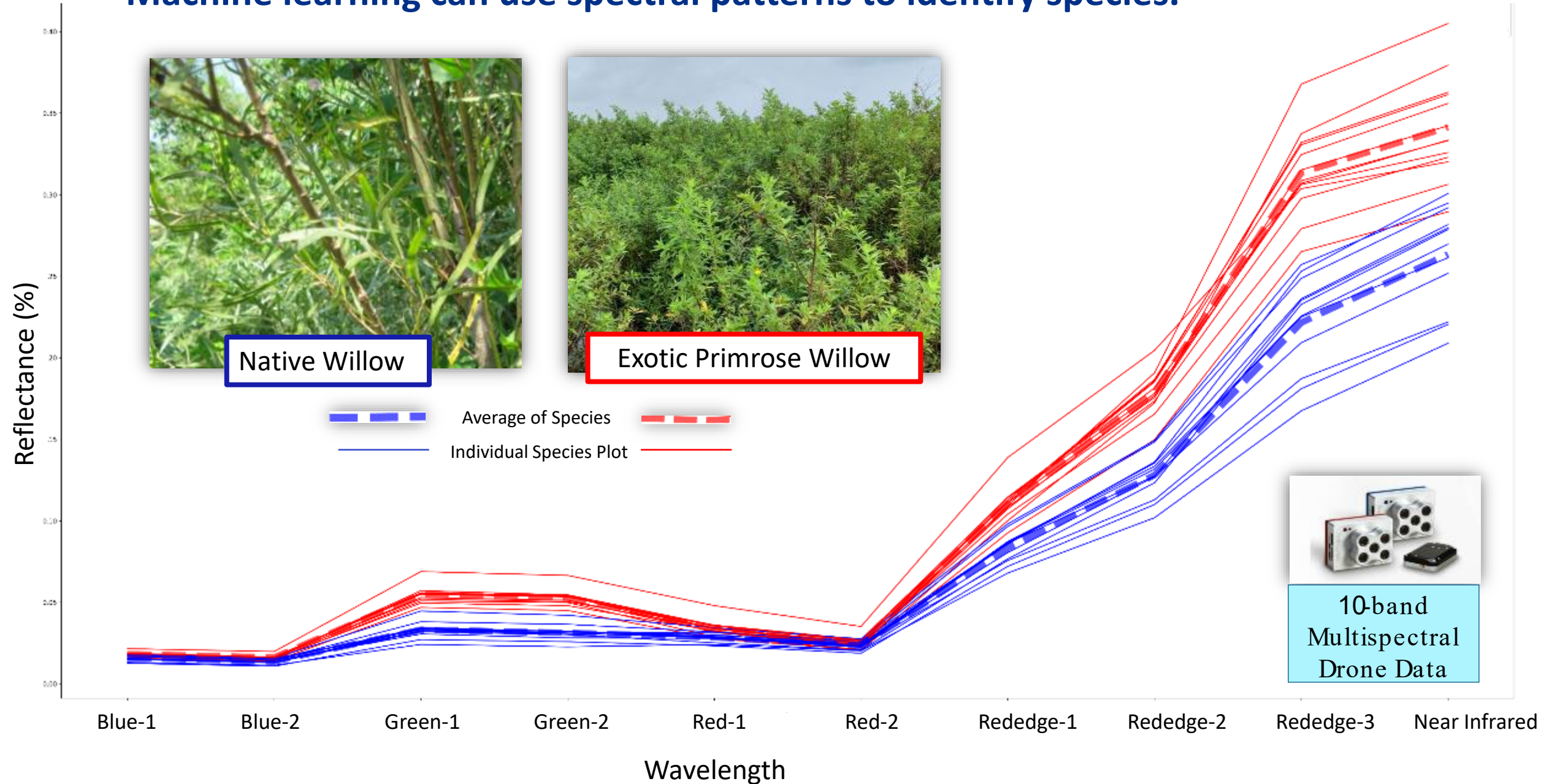
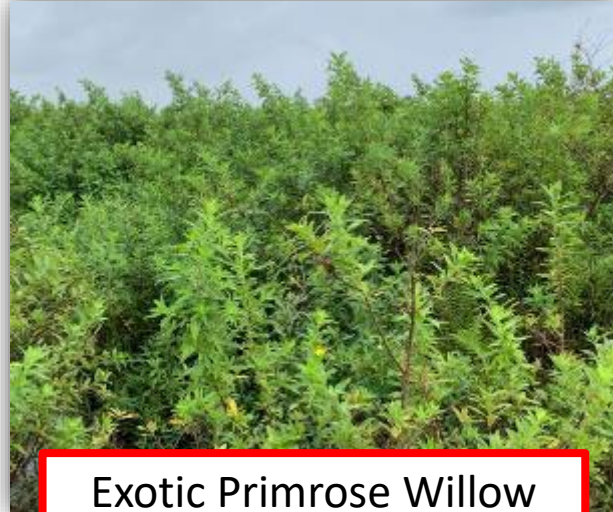
Traditional approach for invasive species mapping.



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

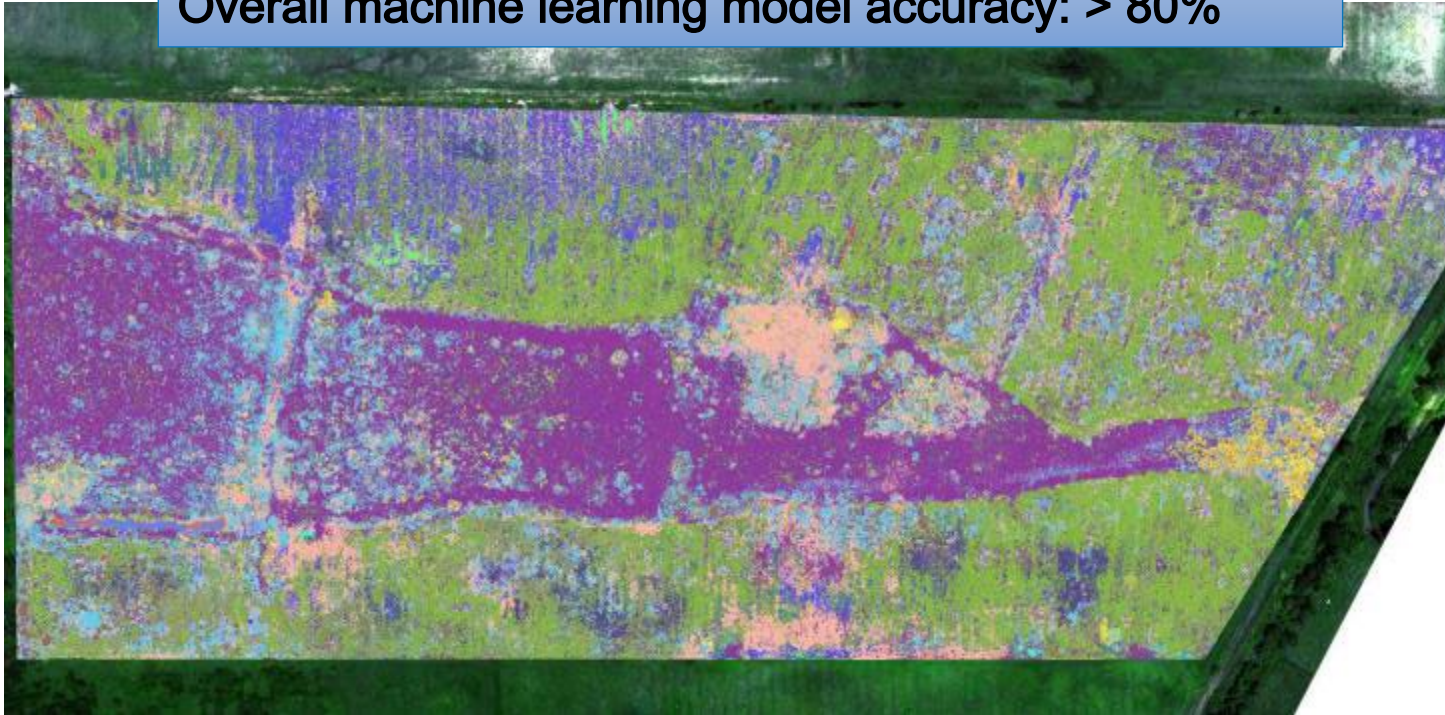


Machine learning can use spectral patterns to identify species.



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

Overall machine learning model accuracy: > 80%



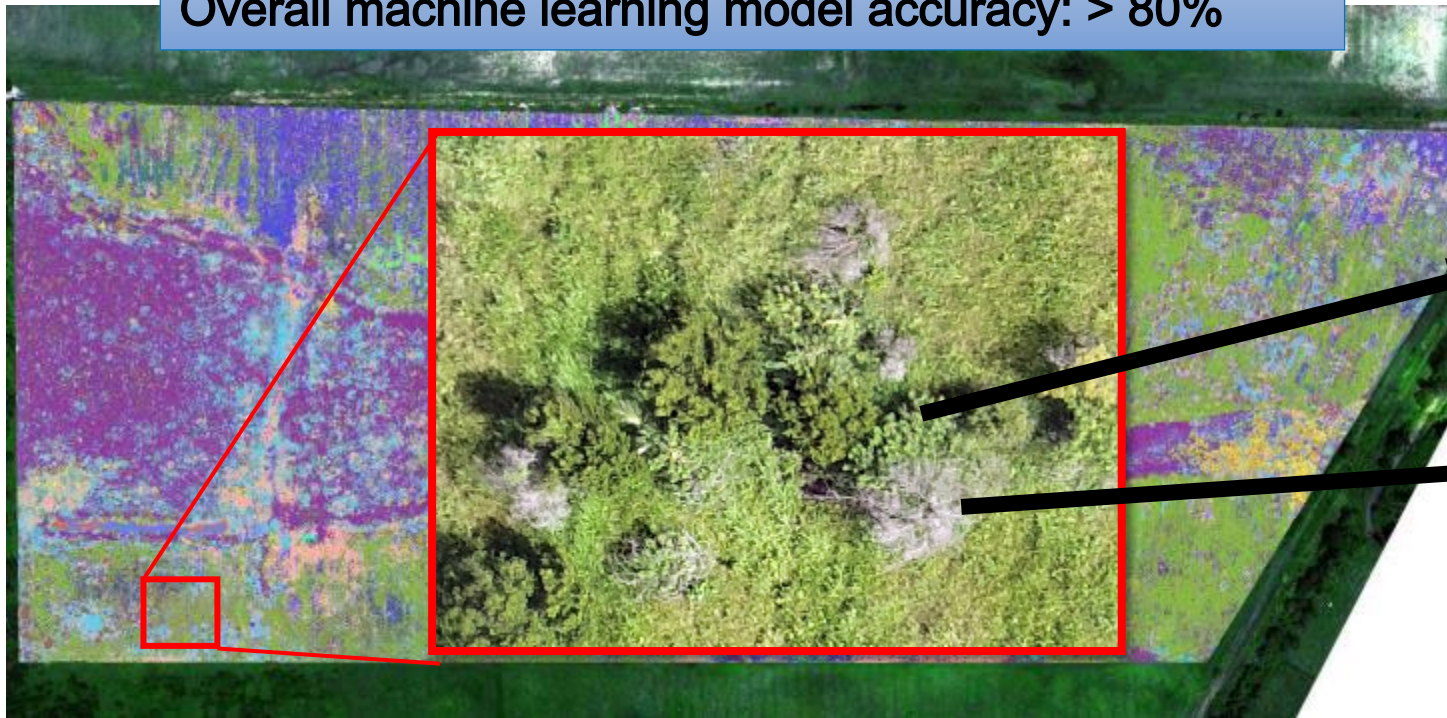
Species or land cover type

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

★ Invasive Species

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

Overall machine learning model accuracy: > 80%



Species or land cover type

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

★ Invasive Species

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



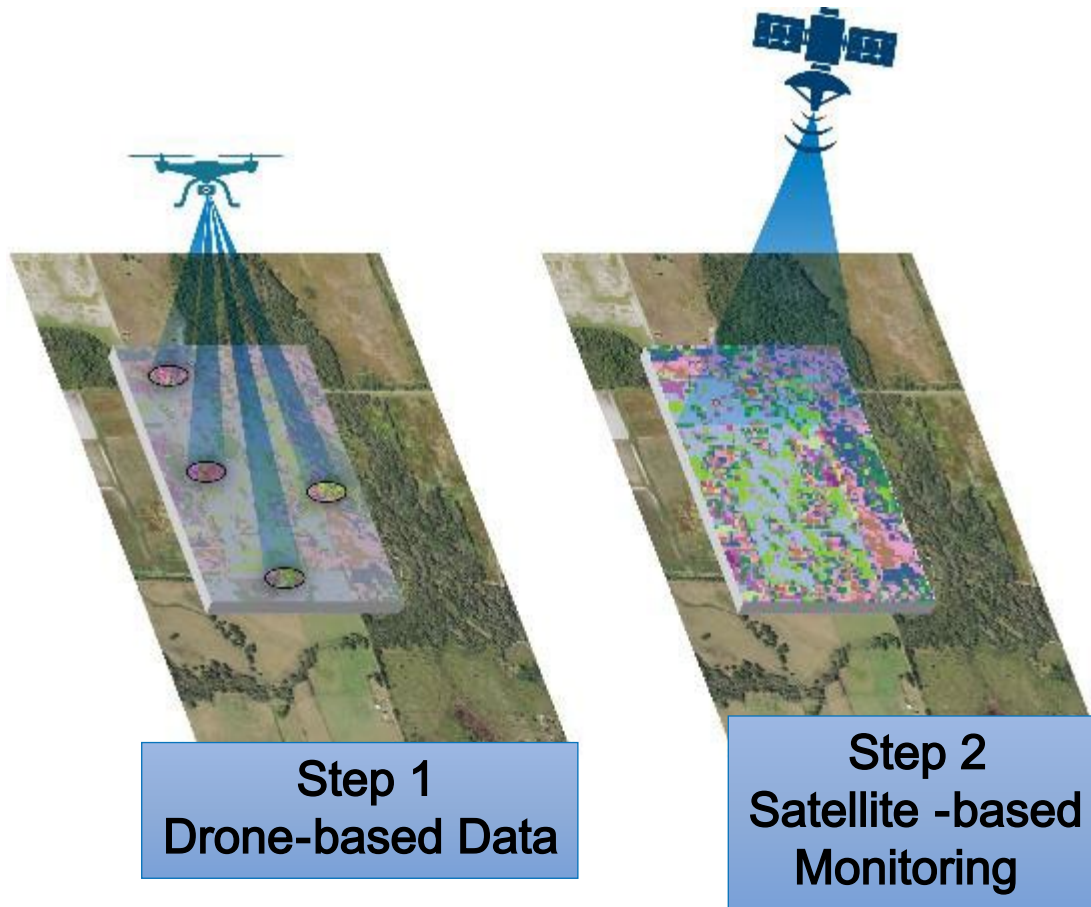
Brazilian pepper



Dead Brazilian pepper



Looking forward: machine learning models using high resolution satellite data increases spatial and temporal tracking of invasives and biodiversity.



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



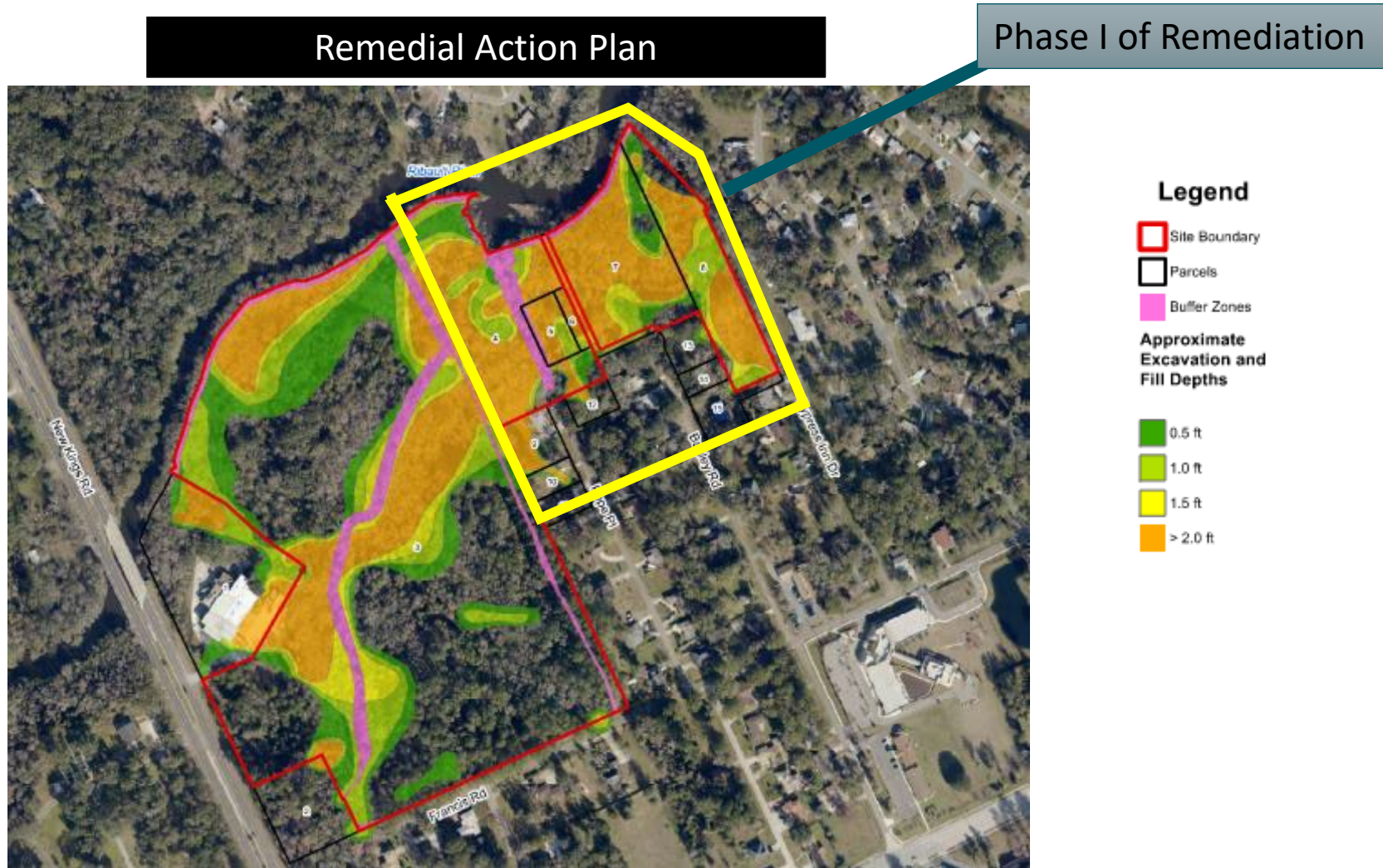
Size

- 50 acres

Sensors



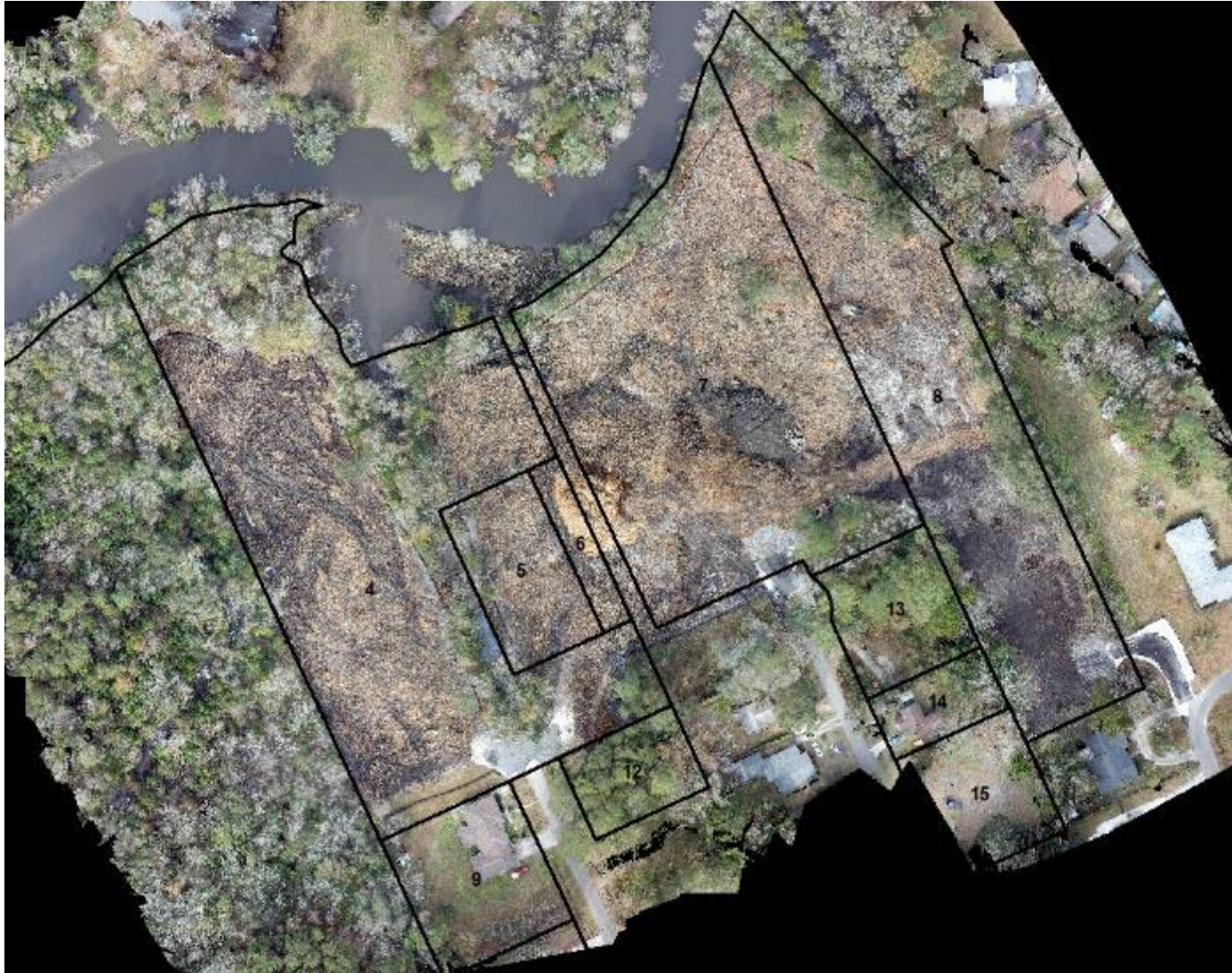
Phase I of the remediation included excavation of 2 feet and capping with clean fill.



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



High resolution aerial imagery documents site conditions.

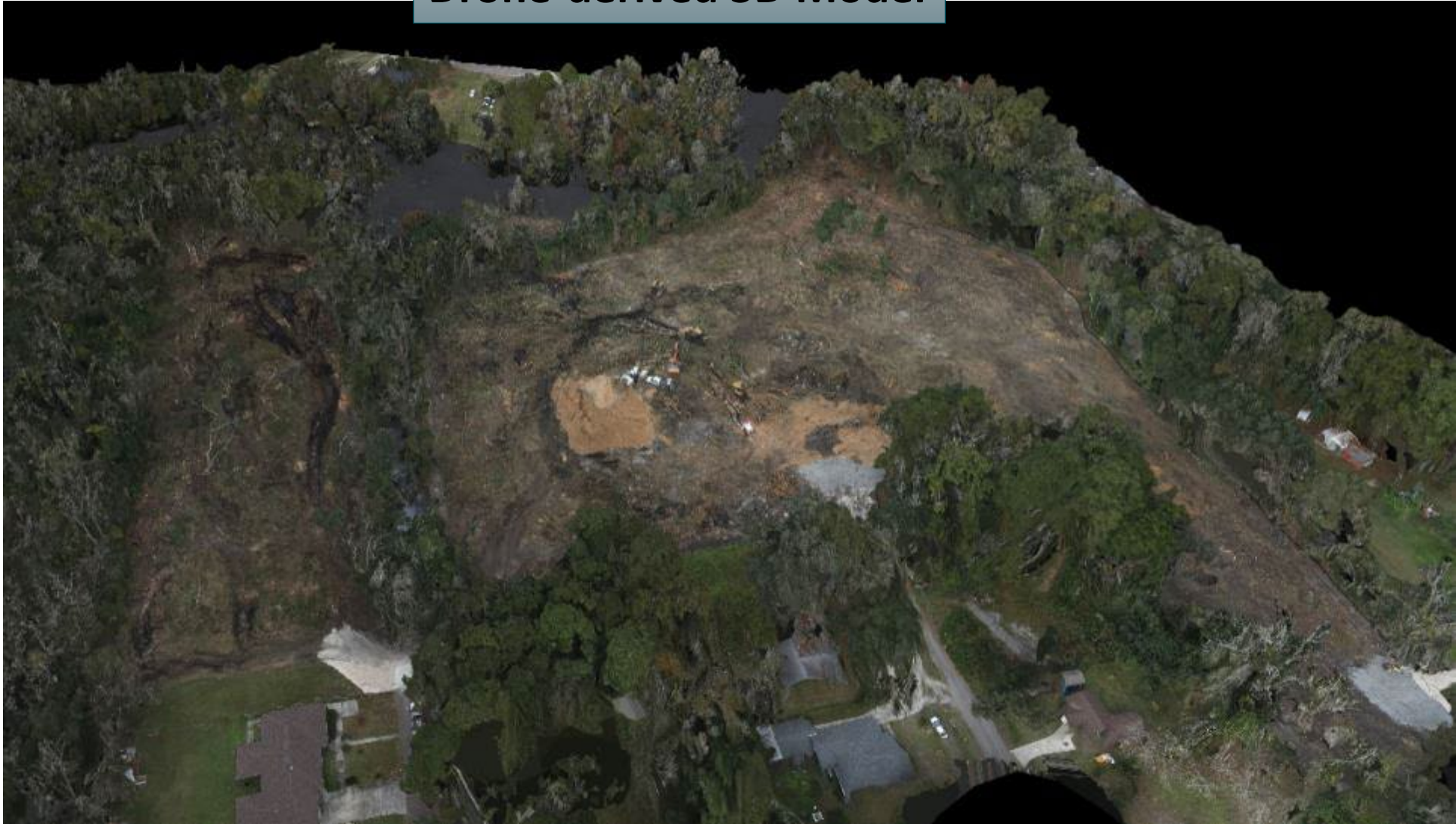


Imagery can be used to assess contractor performance.



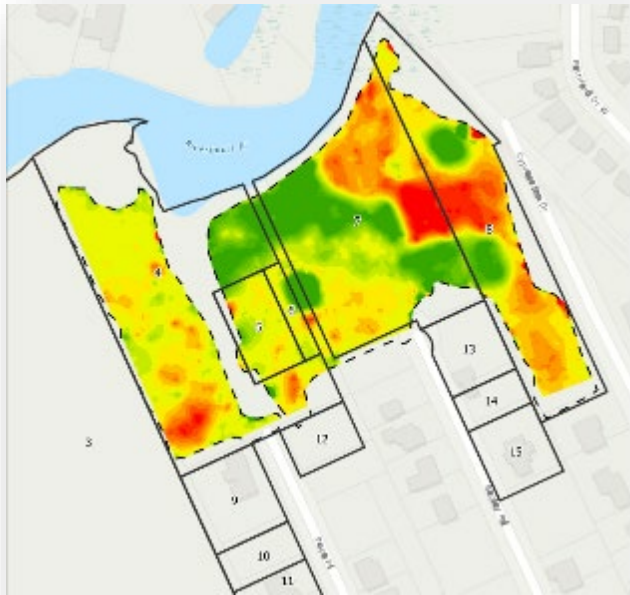
A 3D model is created for the site from each monthly drone flight.

Drone-derived 3D Model

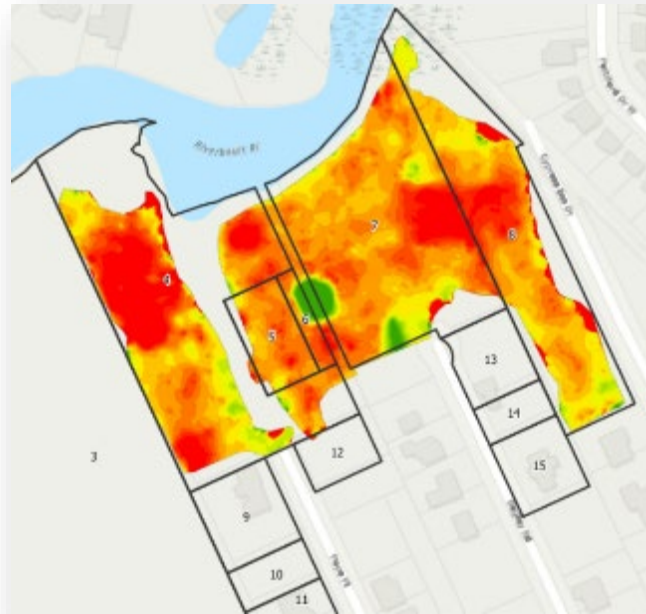


CDM Smith uses automation to track topographic changes over time.

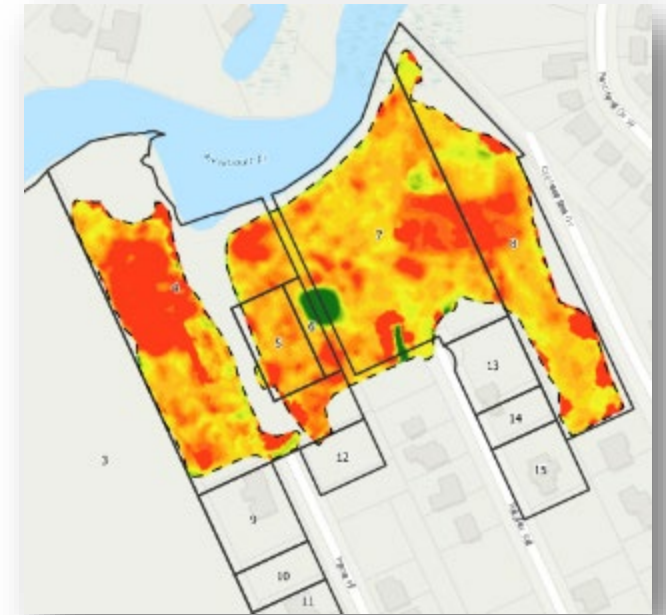
February



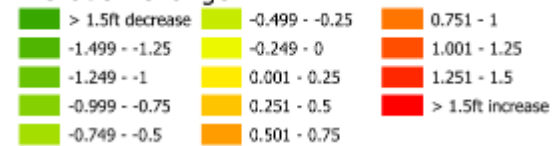
March



April



Elevation Change



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



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



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



Cypress



Oak



Red Maple

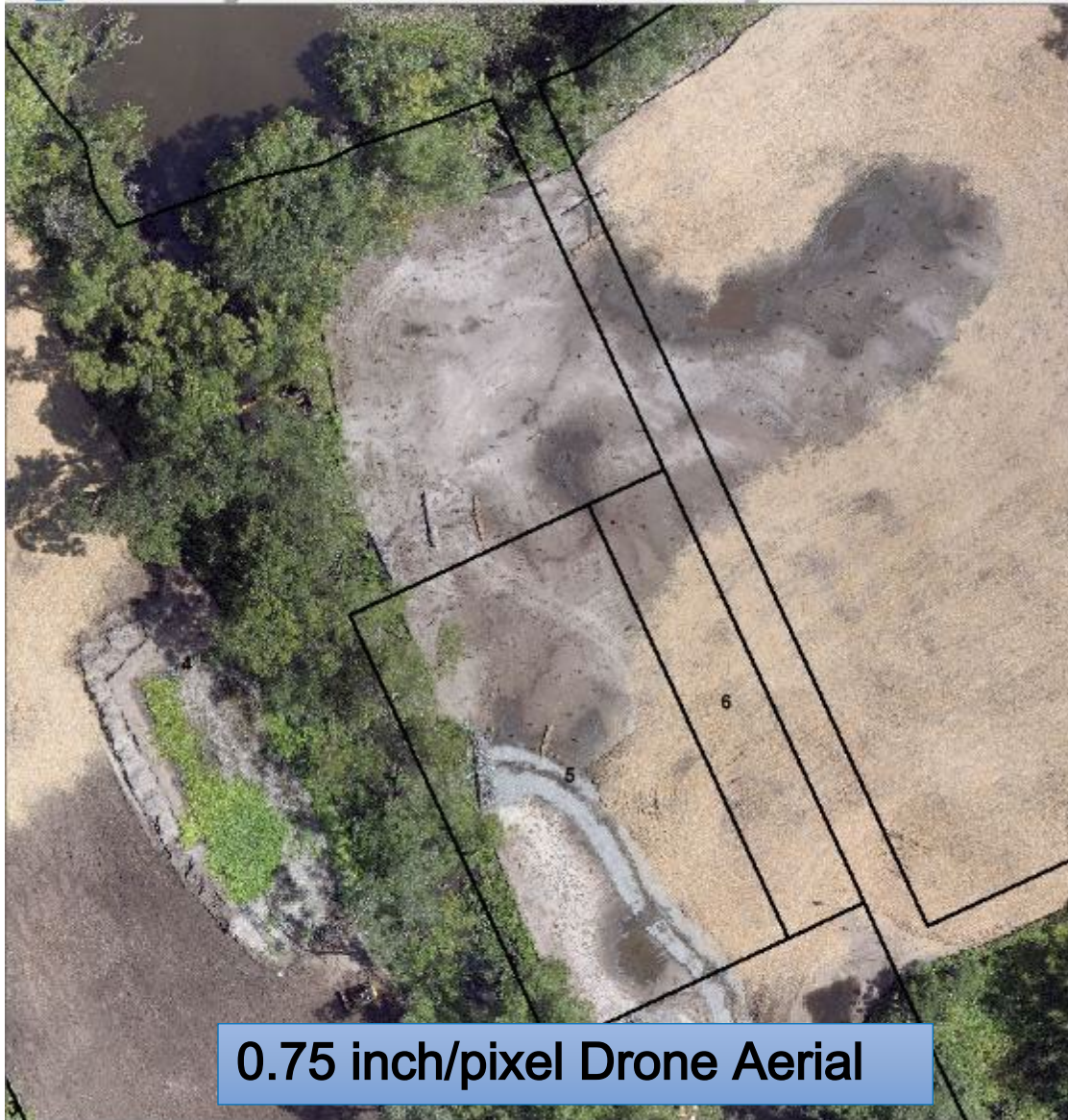


Holly

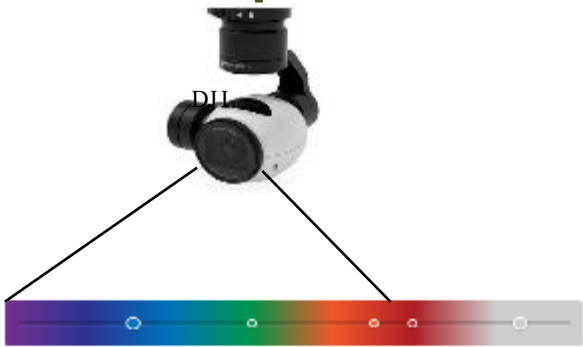
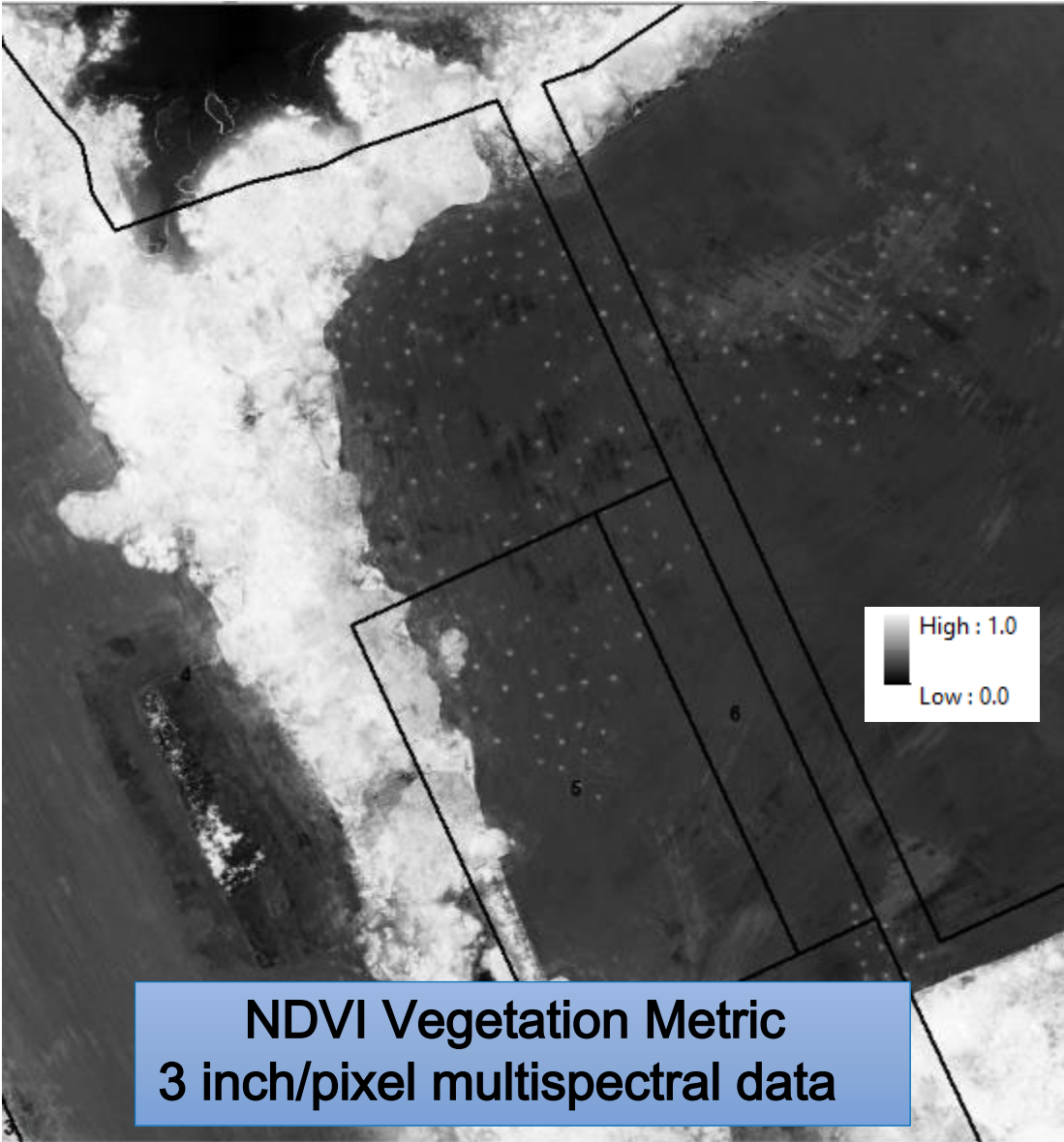
Ground truthing data was collected for use in a machine learning model.



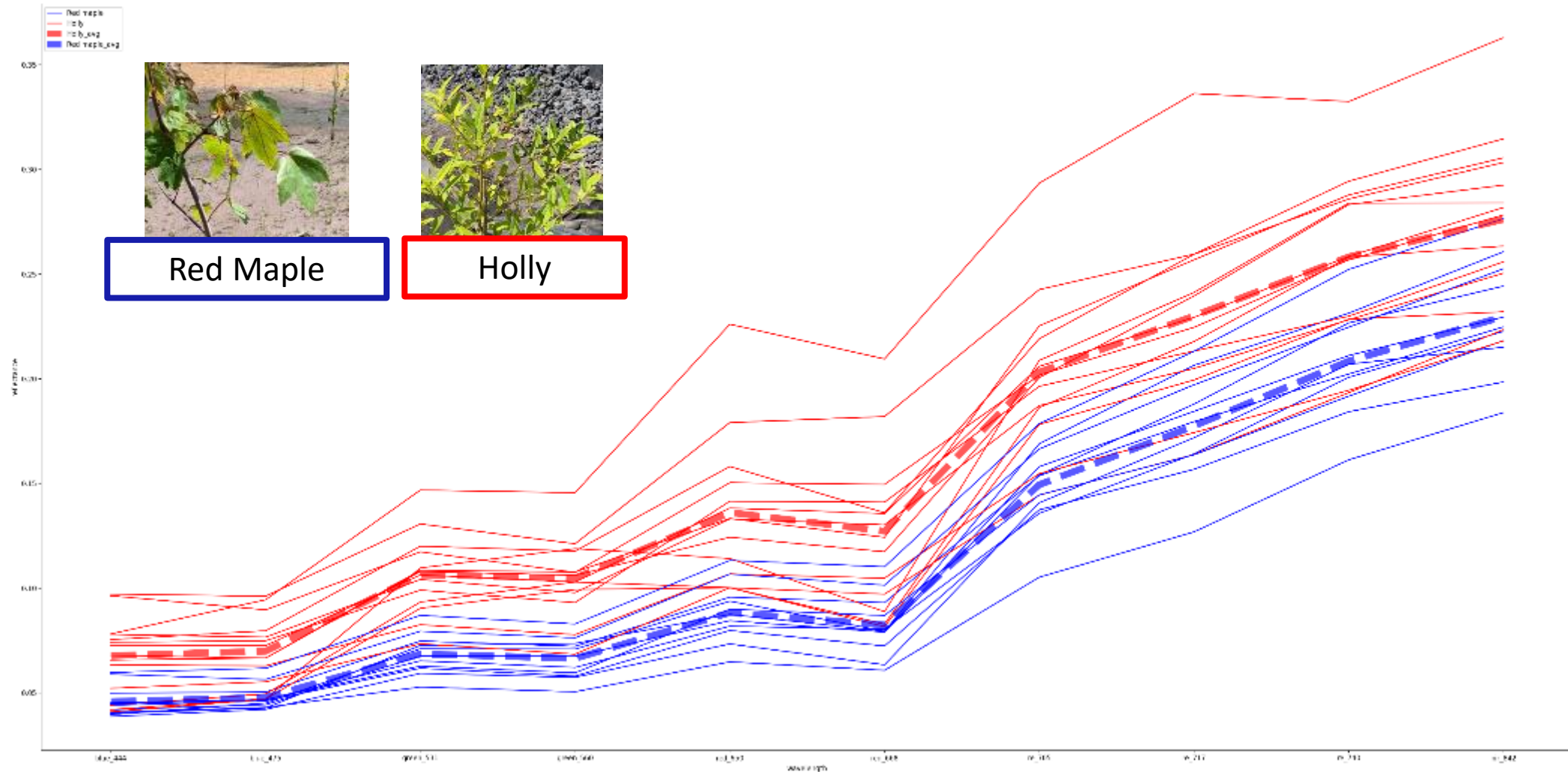
Regular digital camera and multispectral sensor were used to monitor the wetland restoration area.



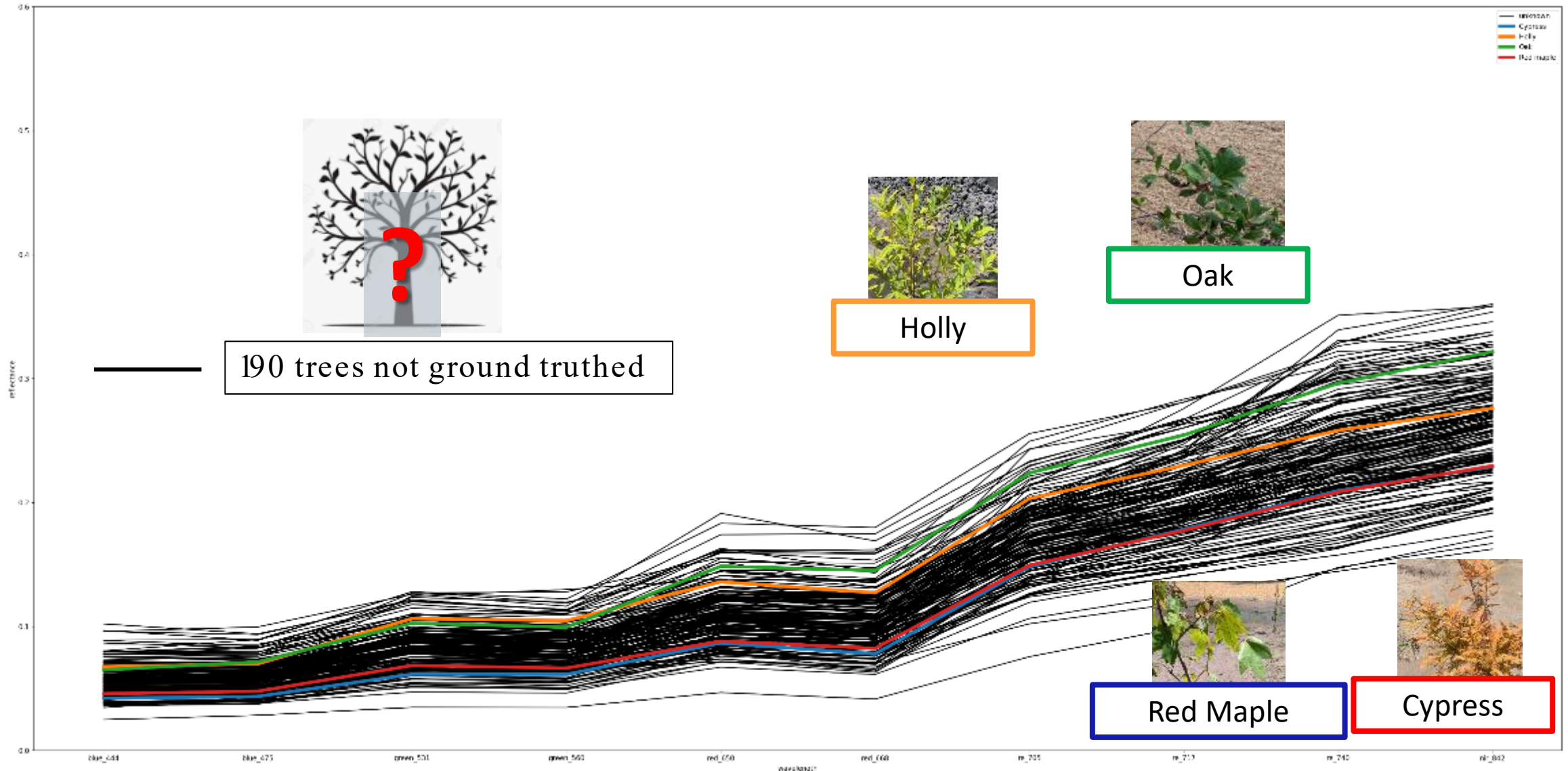
Multispectral sensor collects near-infrared and provides data on vegetation.



The spectral signatures are often different between species.



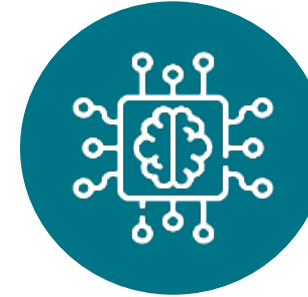
Machine learning is necessary to analyze the multifaceted high-volume dataset.



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



MACHINE LEARNING MODEL



MODEL PREDICTIONS



Holly



Cypress



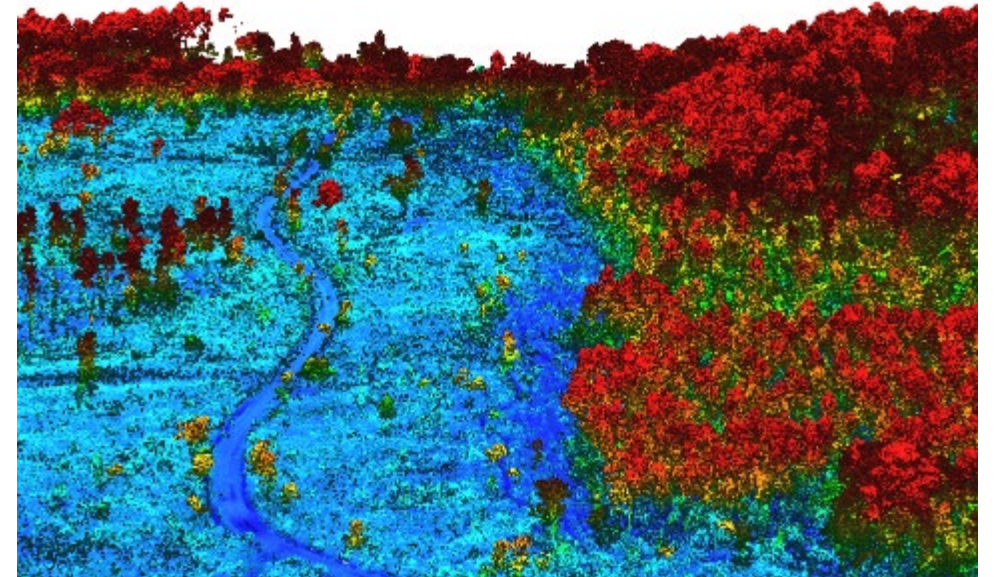
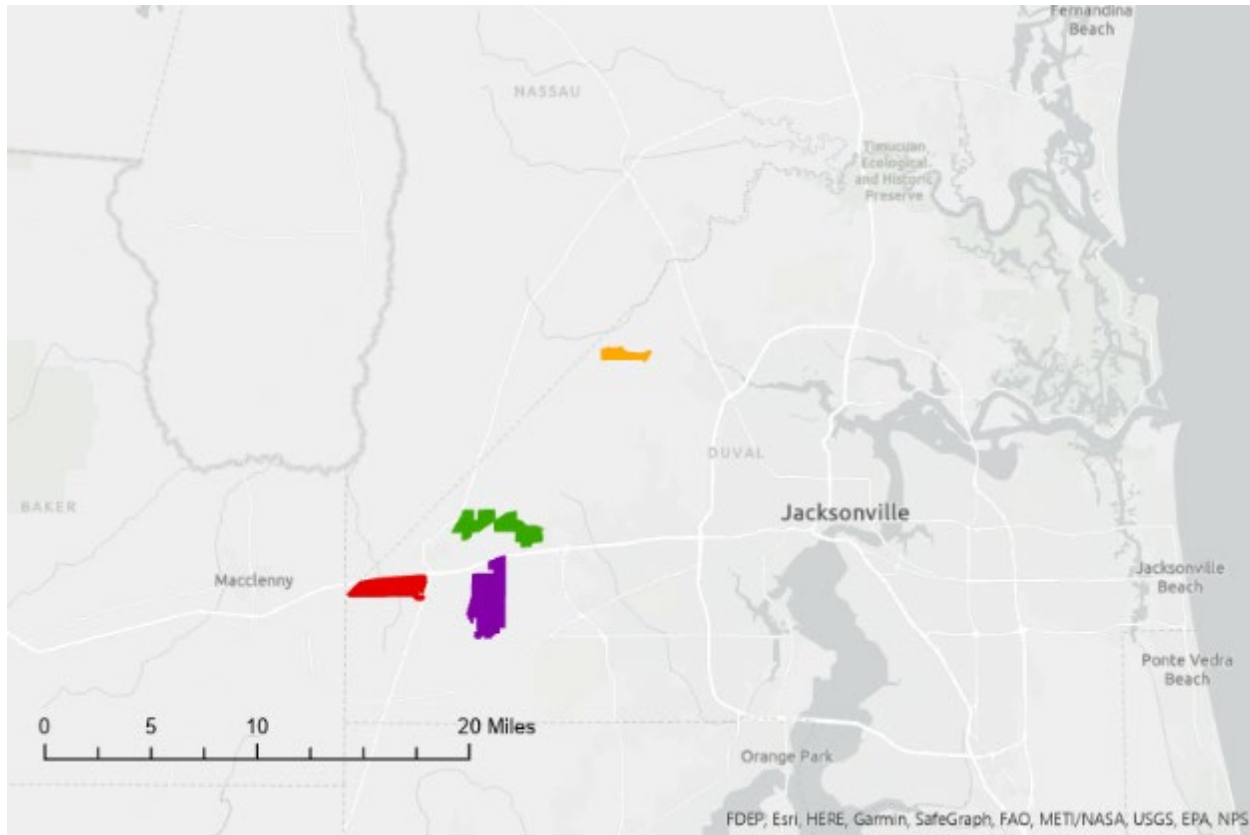
Red Maple



Oak

Site Feasibility: Wetland delineation

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



Traditional approach for delineating wetlands.



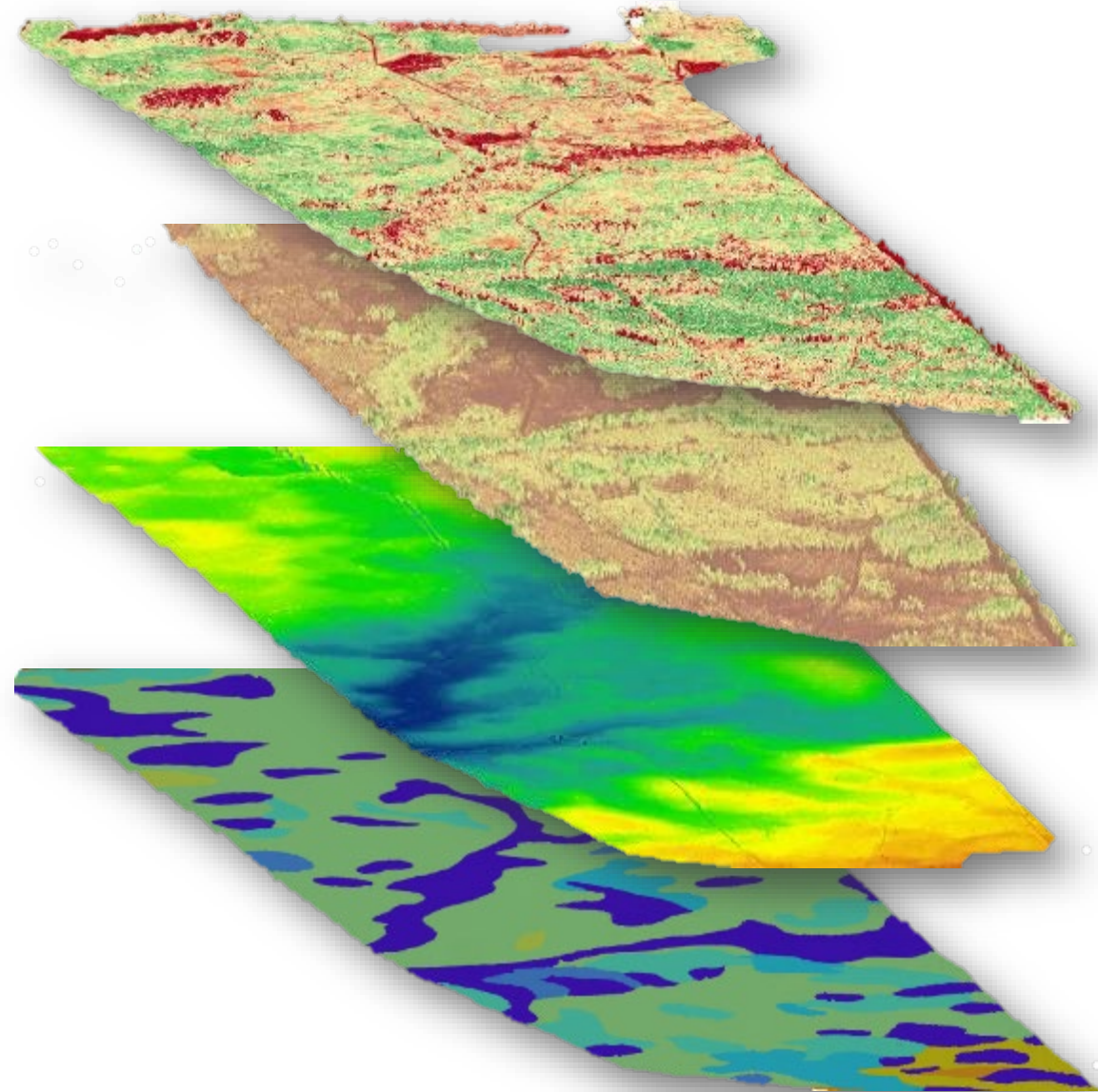
What defines a wetland and how can we predict their location?



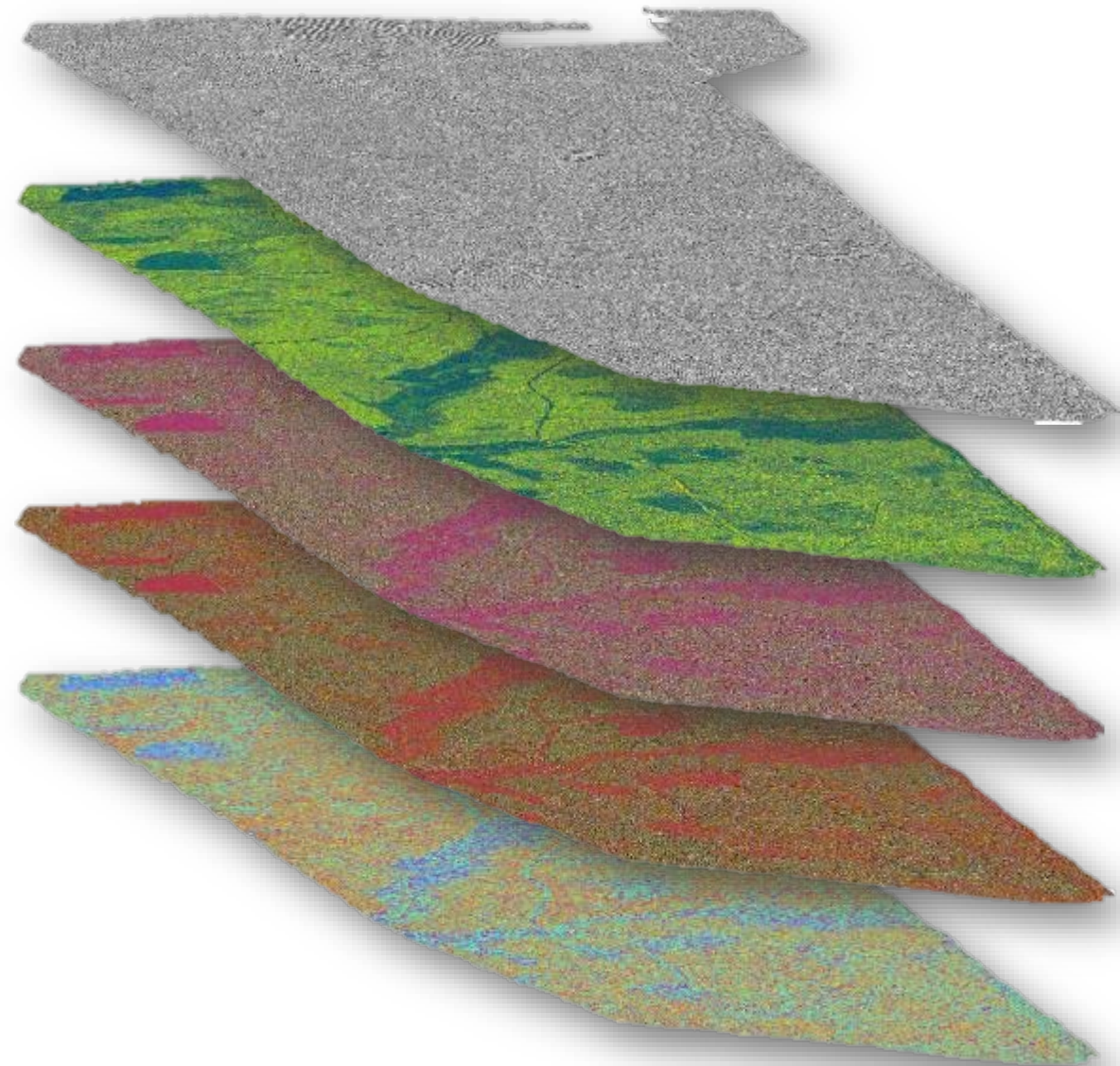
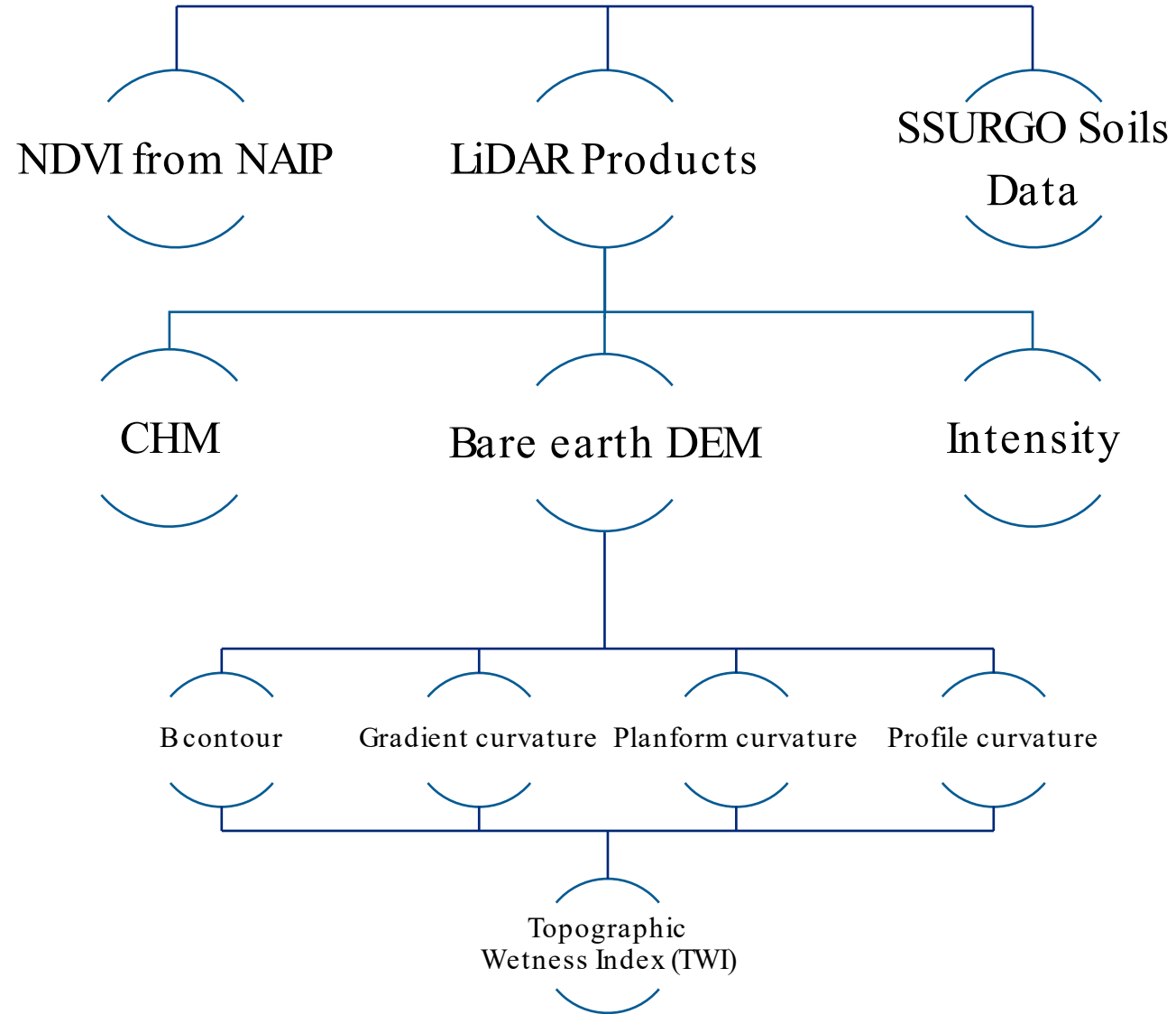
NDVI from NAIP

LiDAR Products

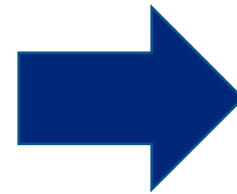
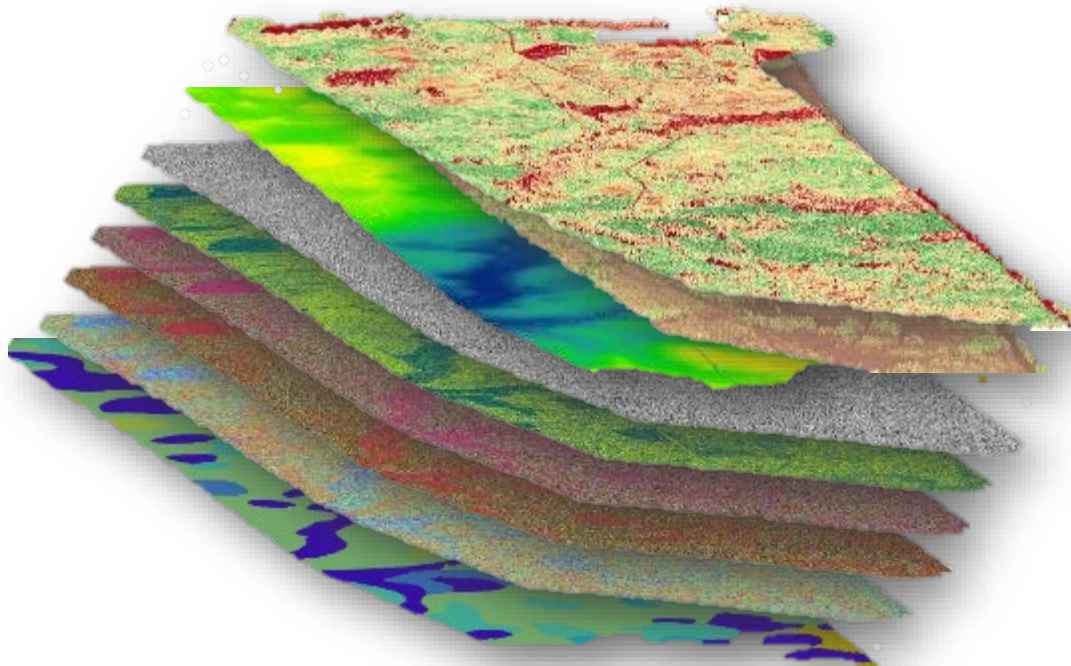
SSURGO Soils Data



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

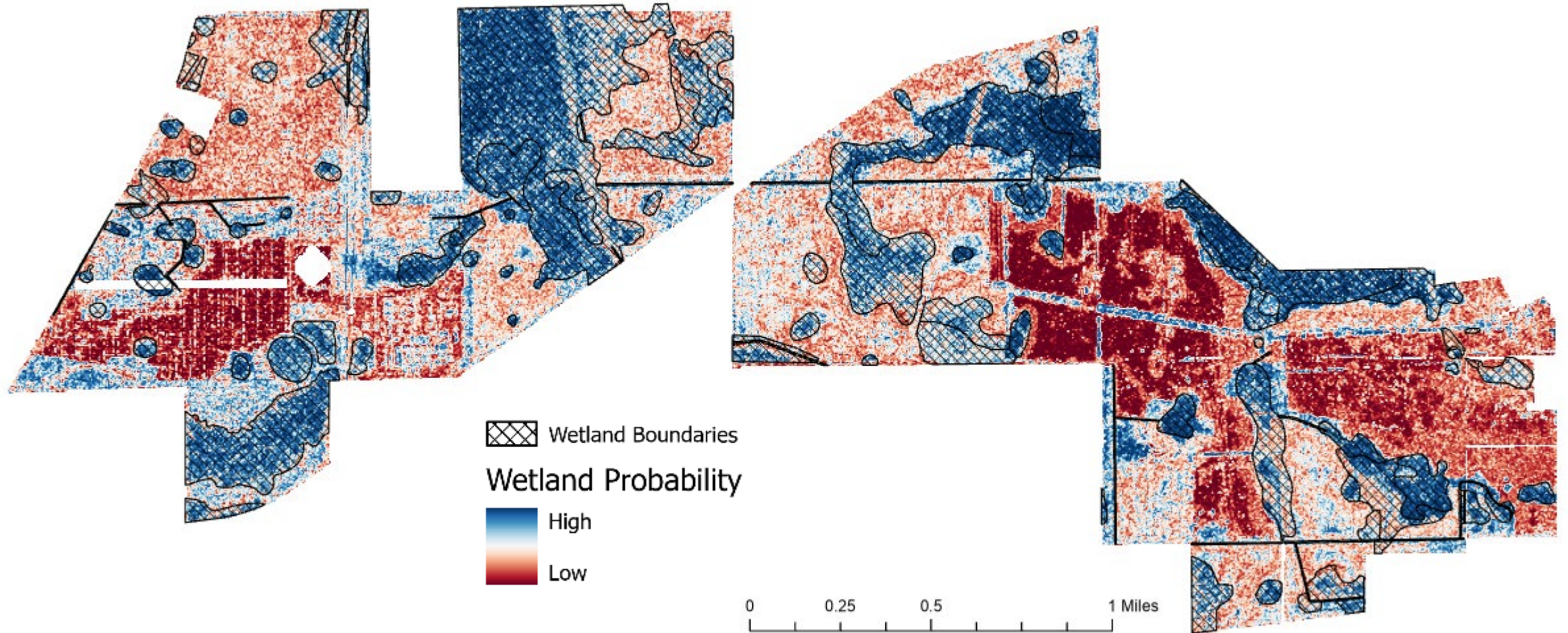


Machine learning models require data to be in certain formats.

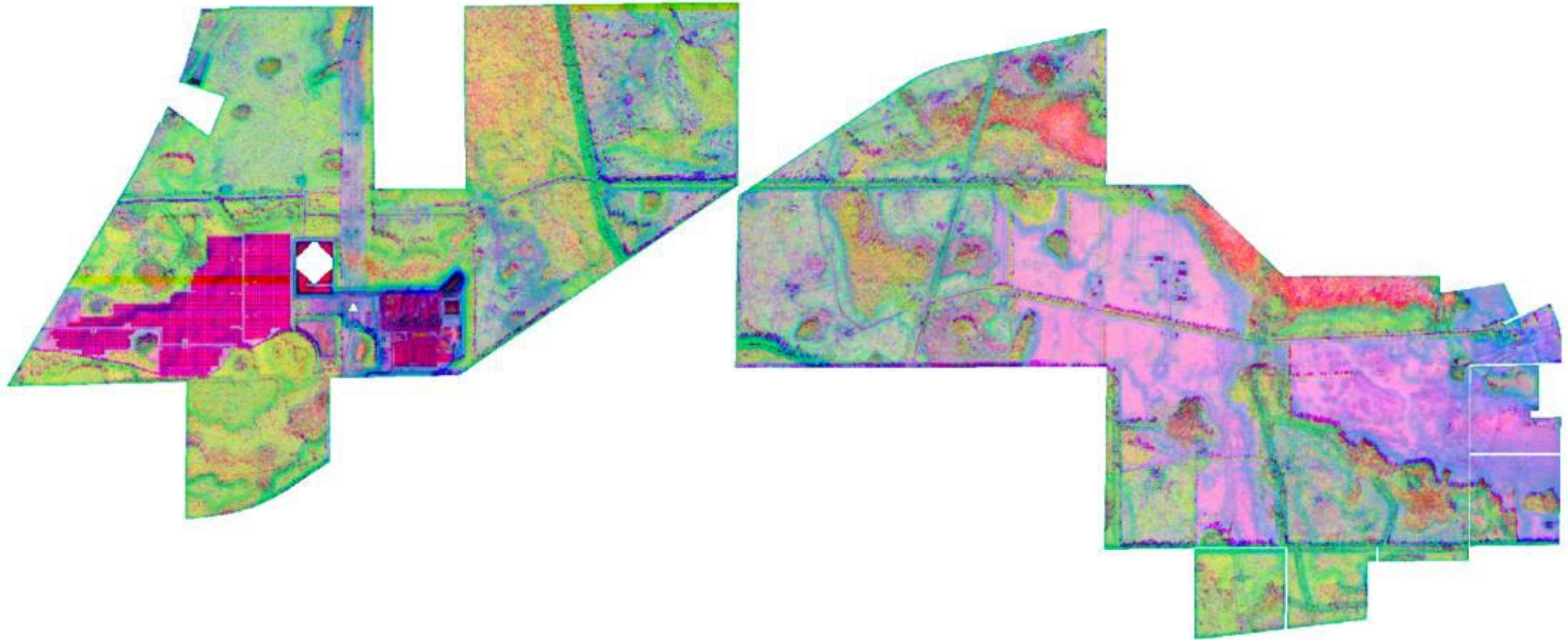


	grnd	bcon	chm	grad	plan	prof	twi	ndvi	soil
0	0.848292	1.168940	4.480000	0.155842	0.280000	0.039993	3.049424	0.349663	96.0
1	1.097692	0.433987	0.490000	0.007569	0.026195	-0.073811	2.948446	0.189539	5.0
2	-1.546986	1.550257	0.190000	0.162854	0.018937	0.058930	2.267665	0.194915	41.0
3	1.151135	1.346371	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	-1.060605	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

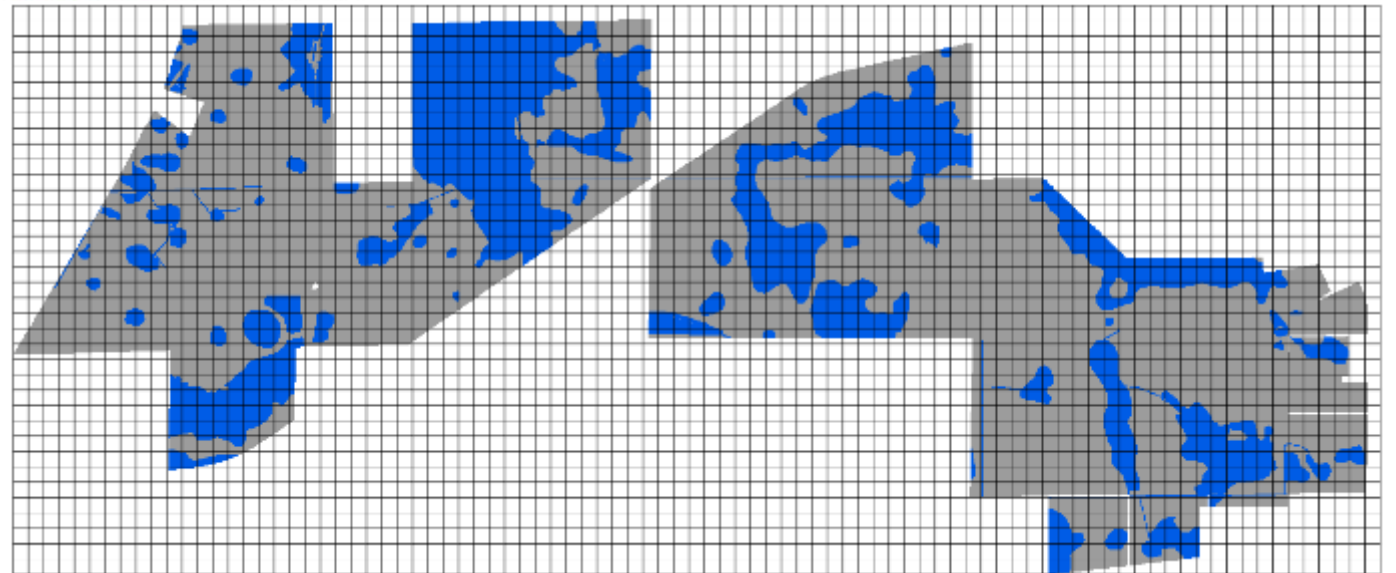
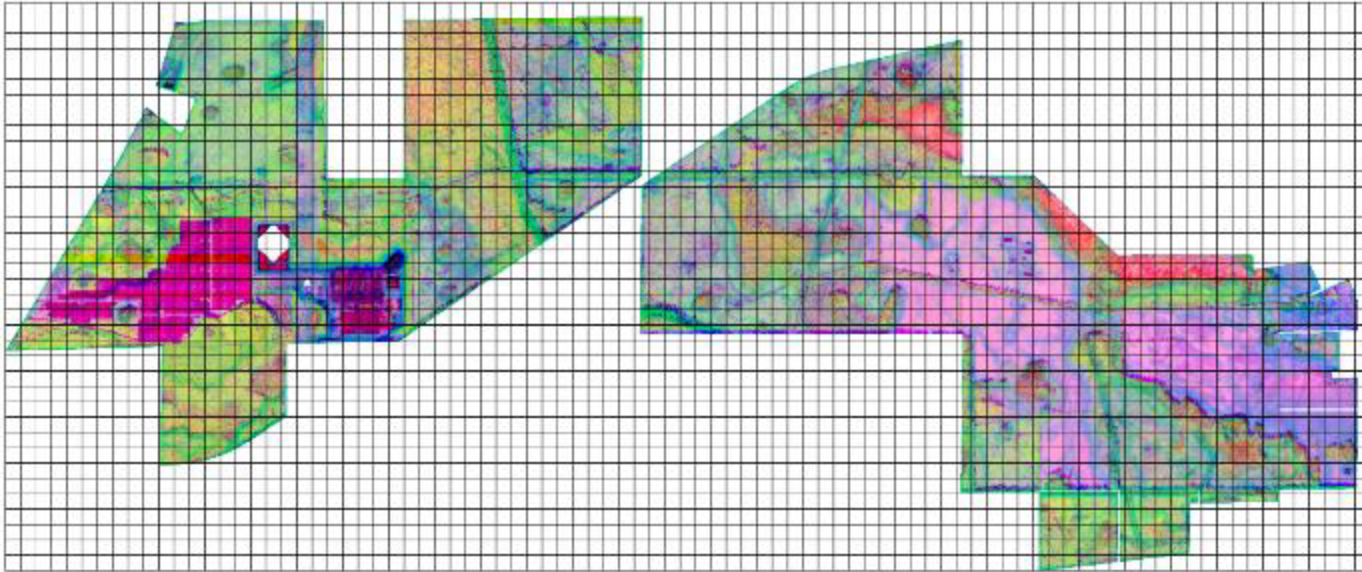
Machine learning models can provide nuanced evaluations of wetlands.



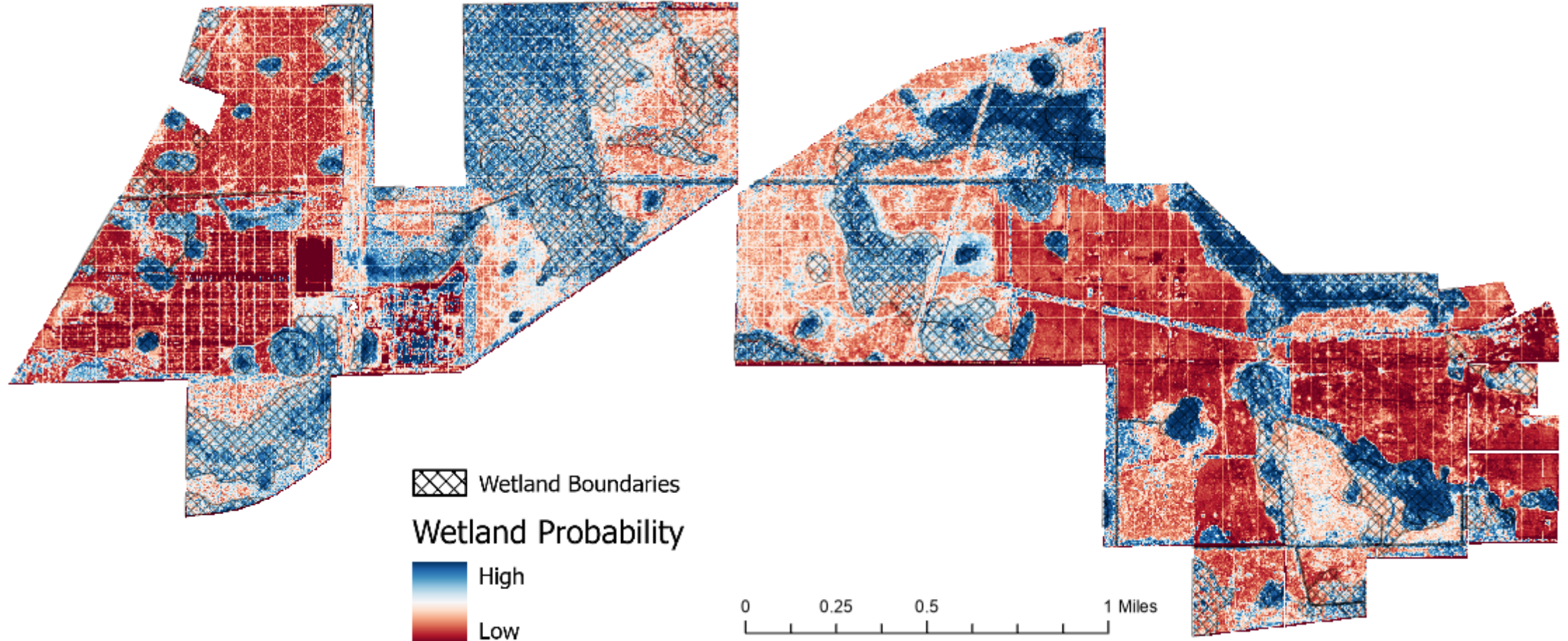
Complex environmental systems can require deep learning models.



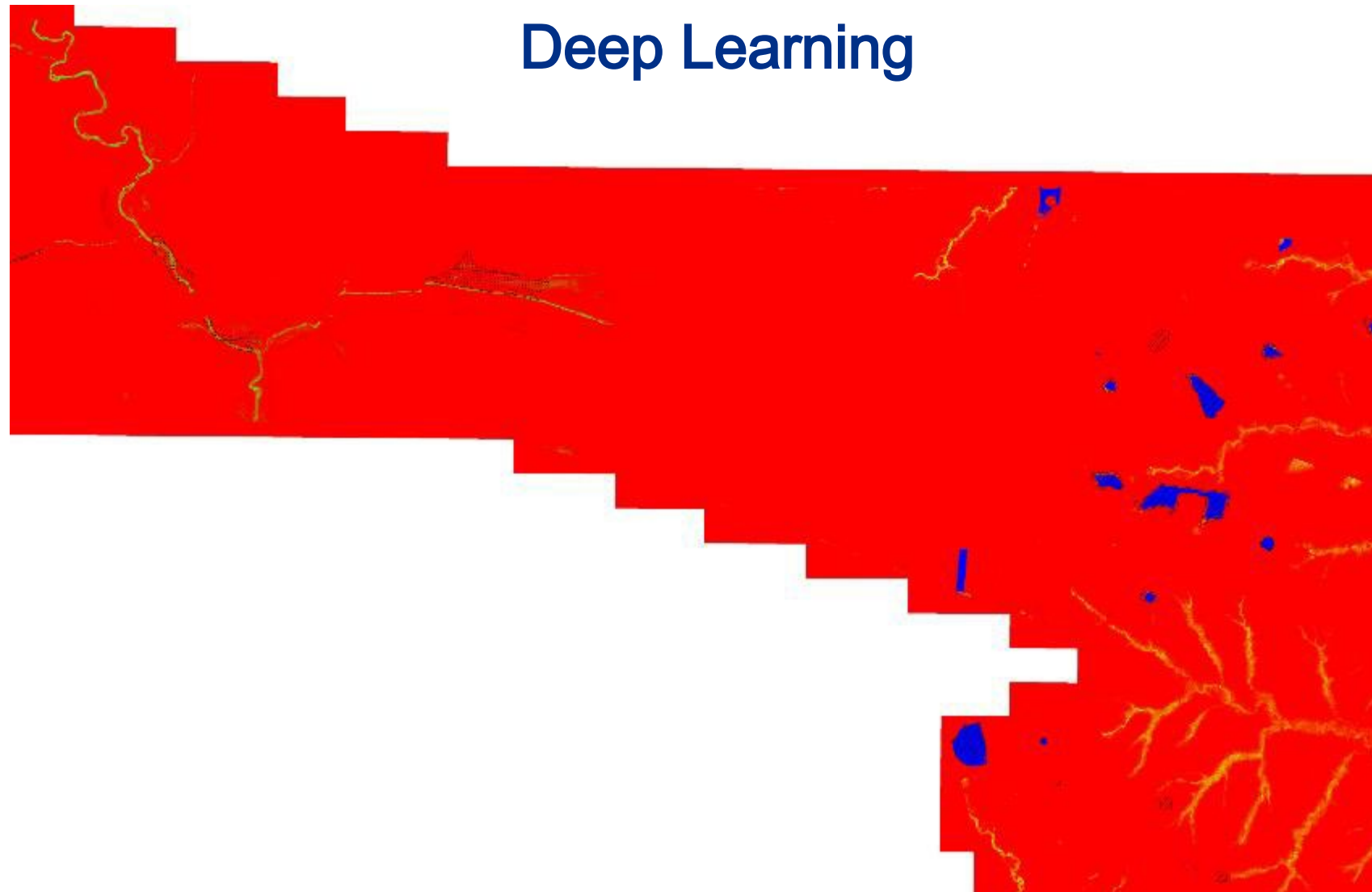
Deep Learning models often require data to be broken down.



The deep learning model was better at evaluating “blind” sites.

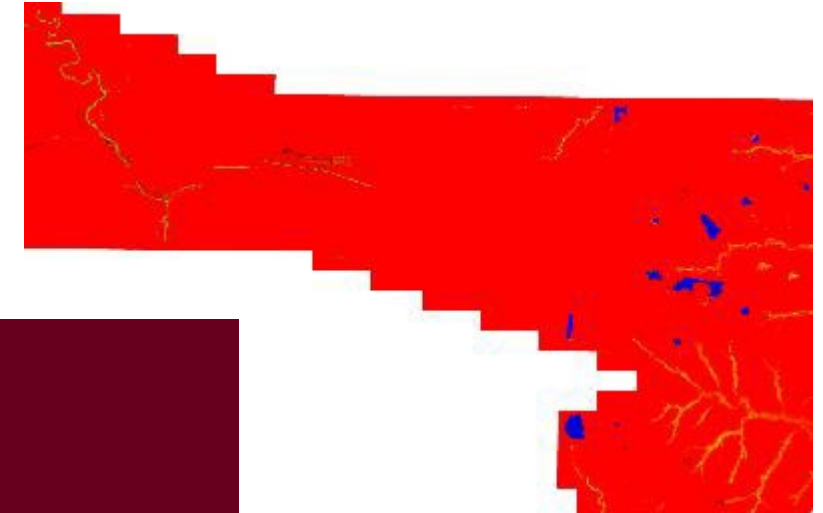
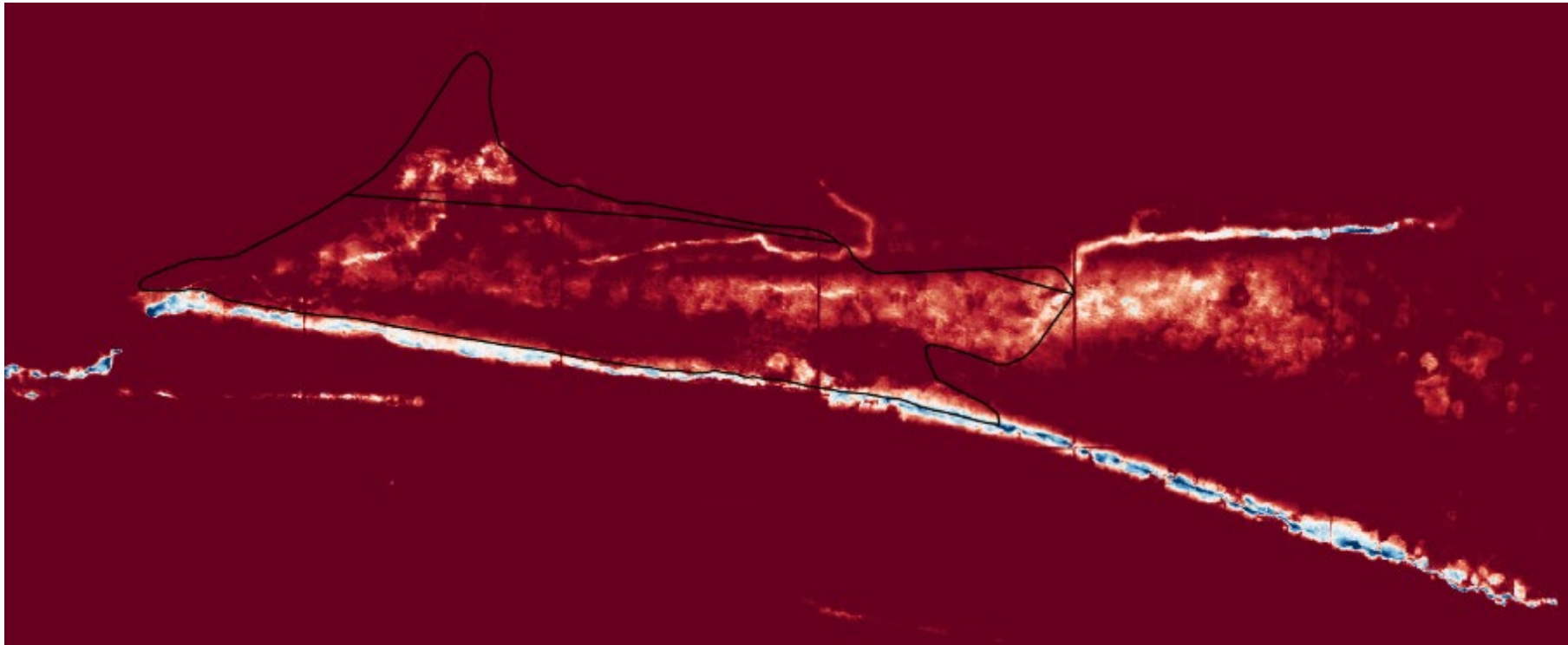


CDM Smith applied our deep learning model to a MoDOT corridor study.



CDM Smith applied our deep learning model to a MoDOT corridor study.

Wetland Probability

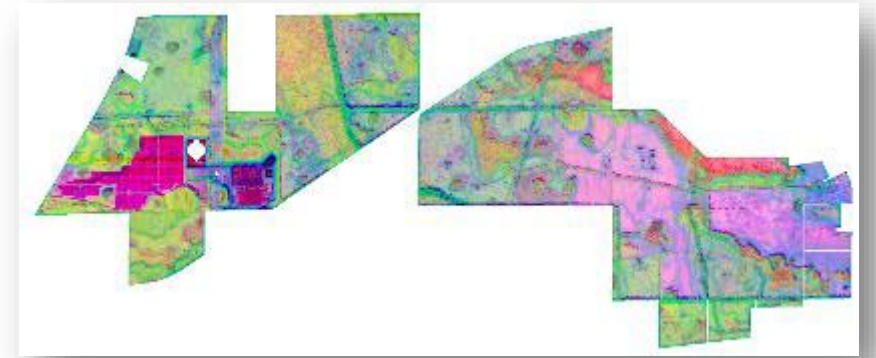


Looking forward: expanding capabilities for wetland delineation

- Drive strategic field collection/ verification design
- Support permitting
- Resiliency planning
- Access changes over time

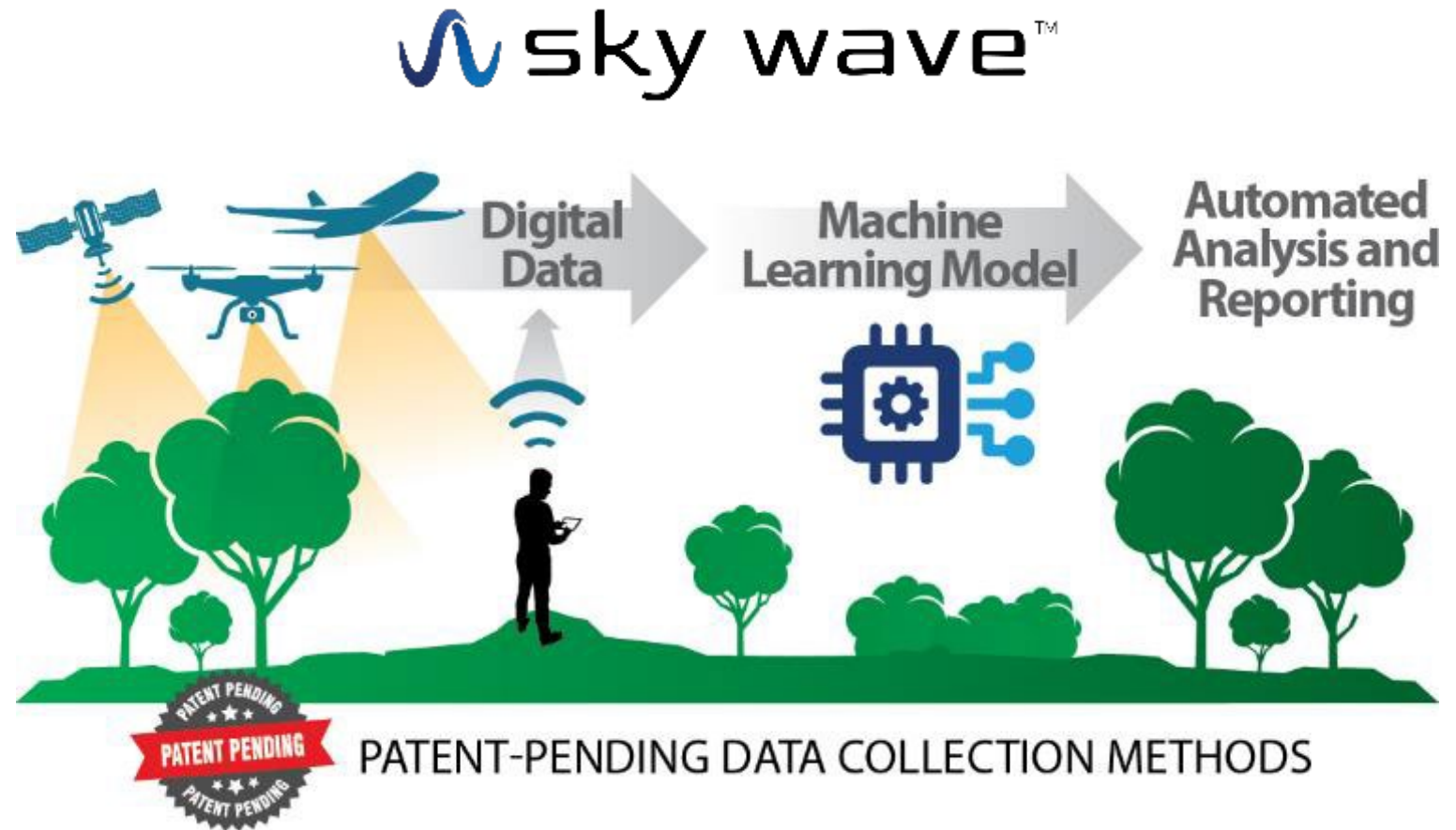


Machine learning and advanced remote sensing can help develop environmental solutions for the future.



Sky Wave provides multiple benefits to environmental projects.

- Lower Cost
- Improved Understanding
- Reduced Risk/Uncertainty



Contact us: skywave@cdsmith.com