Using Drones and Machine Learning for Mapping Mangroves and Assessing Salt Marsh Biomass

CHIMMP & MWG 2024

Brendan Brown, PWS

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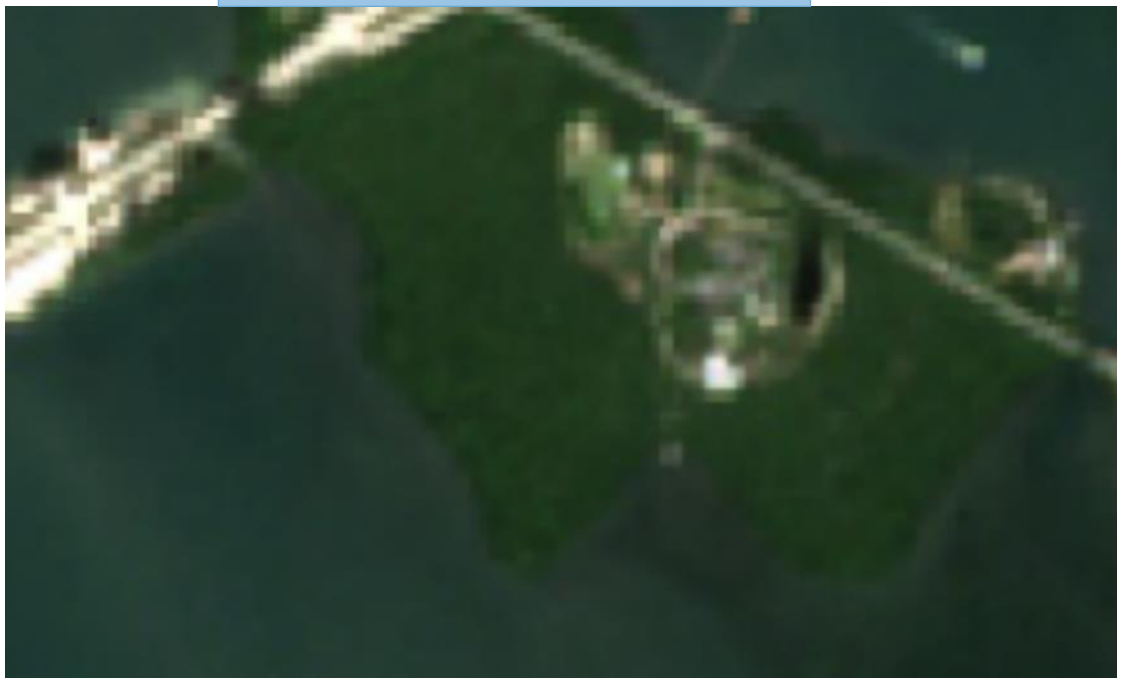
sky wave™ at CDM Smith

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

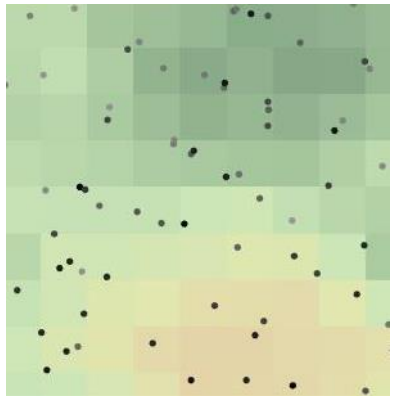
Sentinel

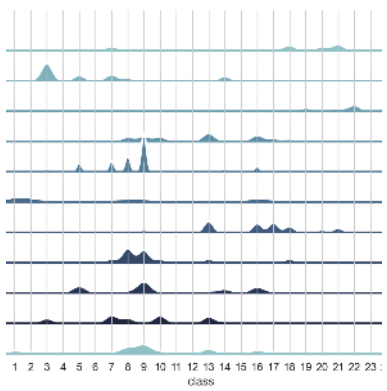


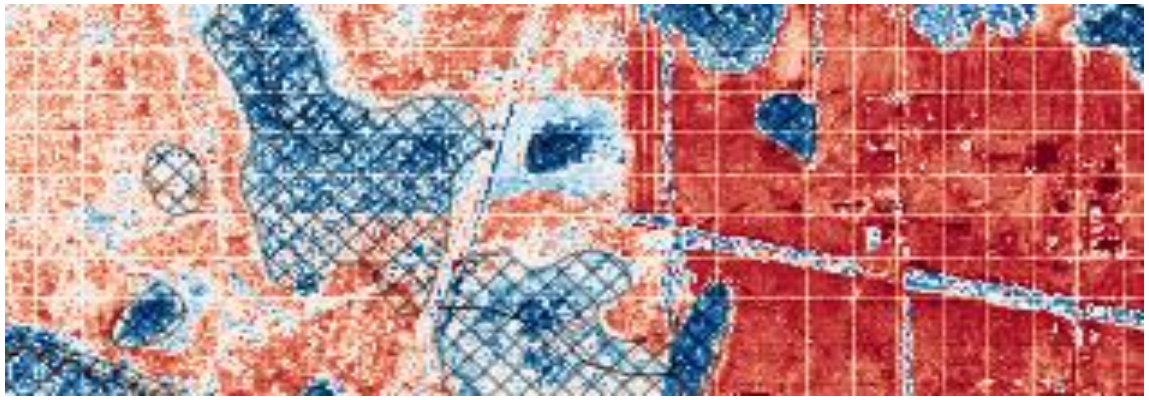
Source: European Space Agency Sentinel 2 MSI

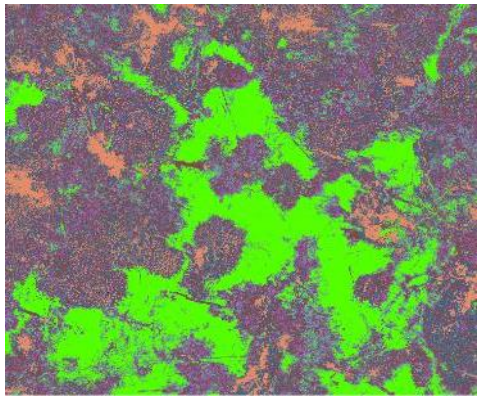
3

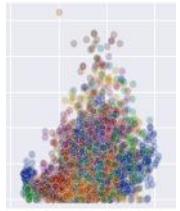
We are finally seeing the promise of machine learning being delivered, but environmental applications are lagging.

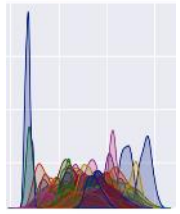


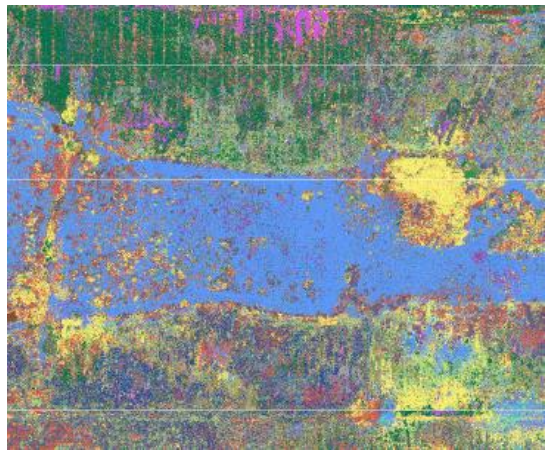


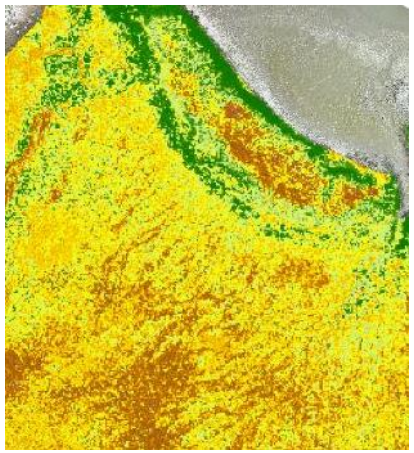


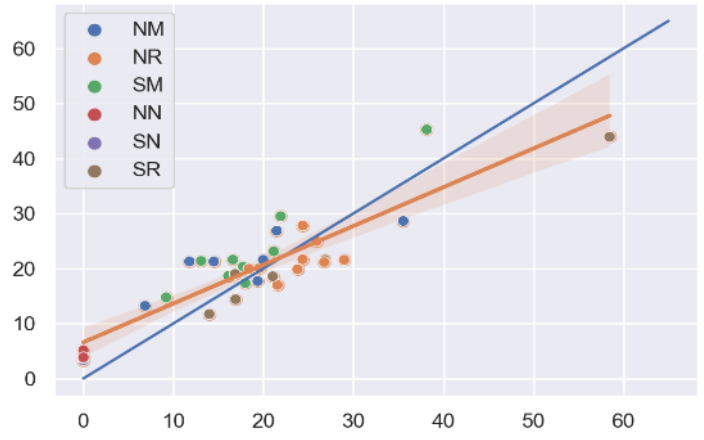


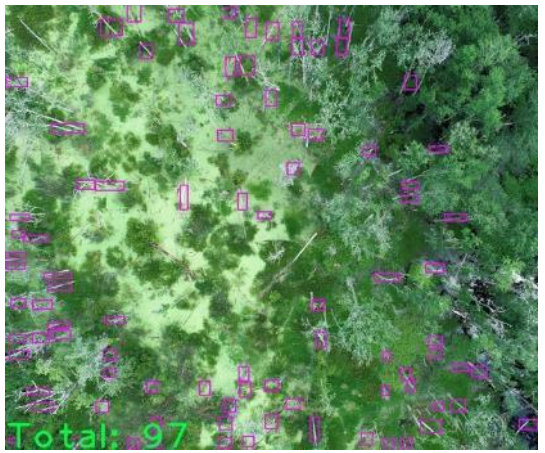








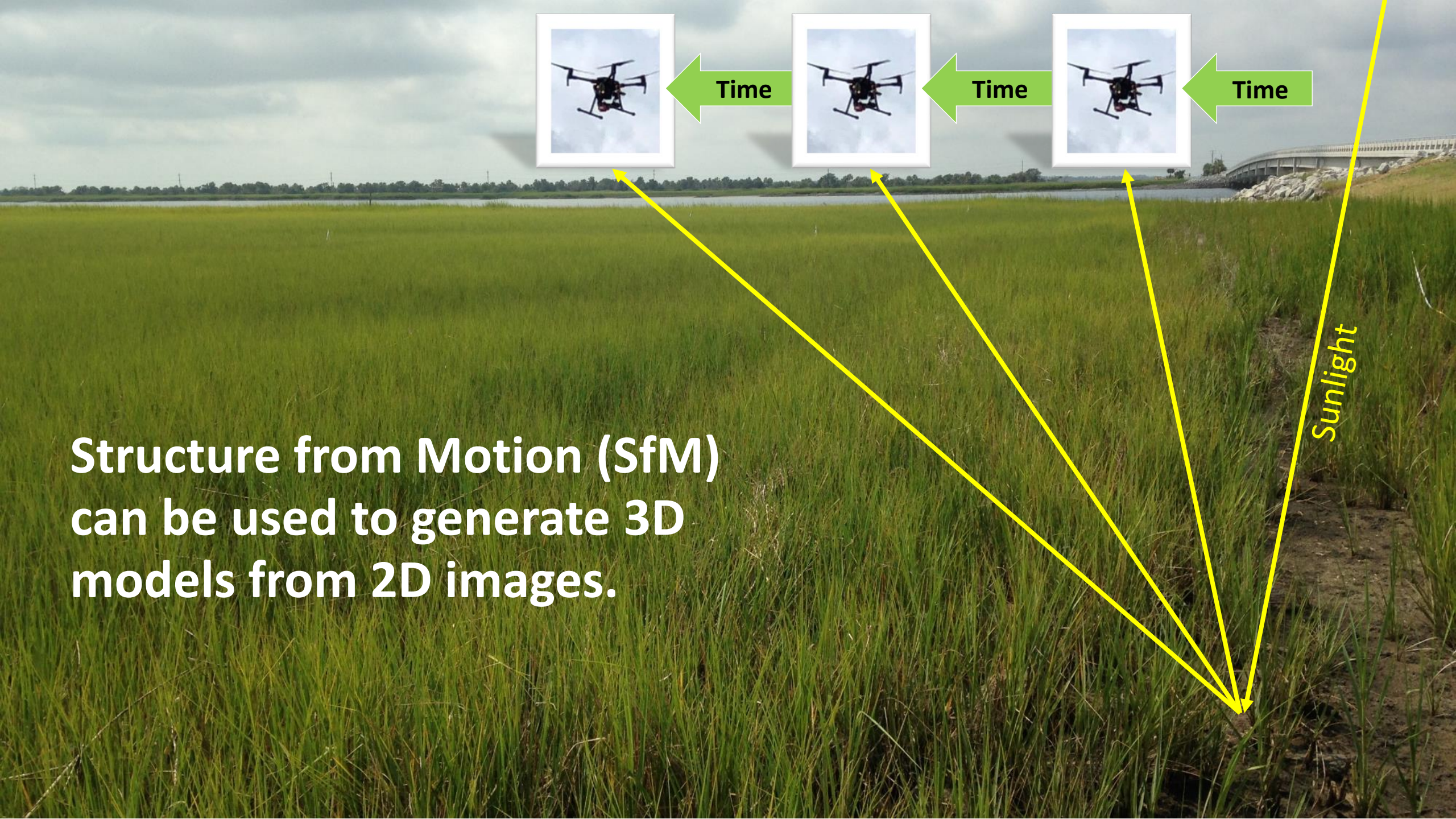




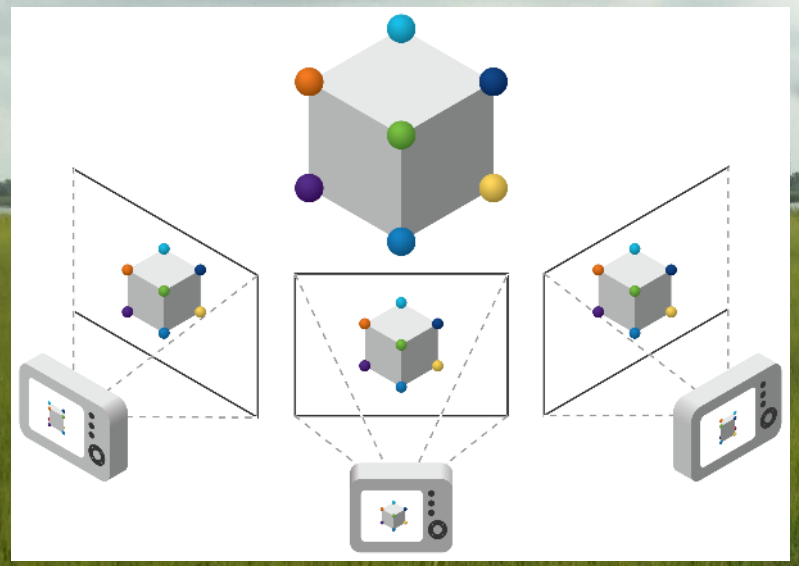
Agenda

Methods & Sensors

Monitoring



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



Time

Time

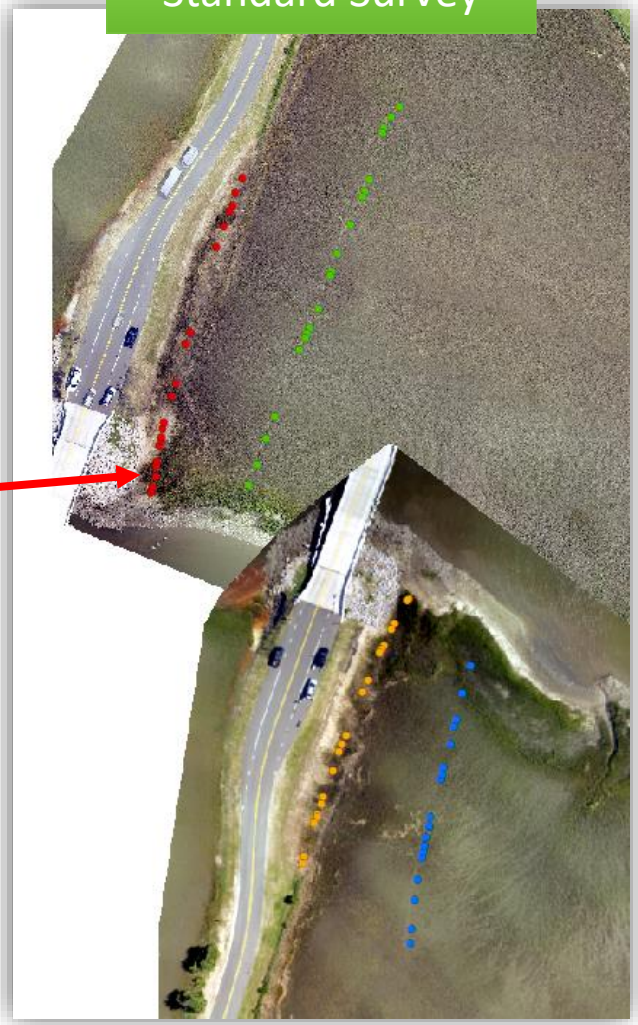
Time

Sunlight

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

Drones can be used to get near survey-grade elevations under the right conditions.

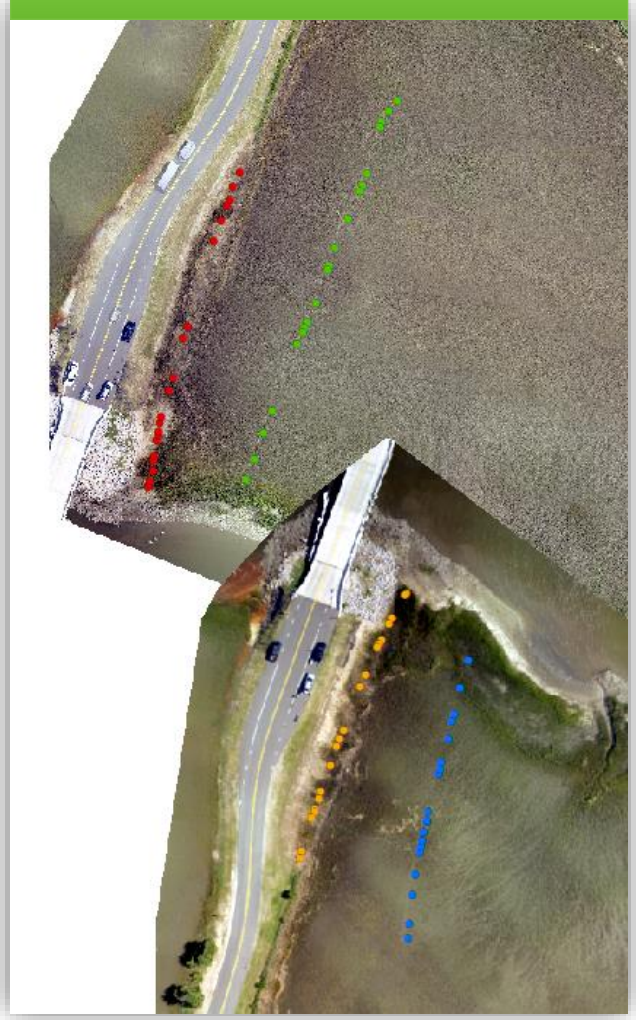
Standard Survey



=

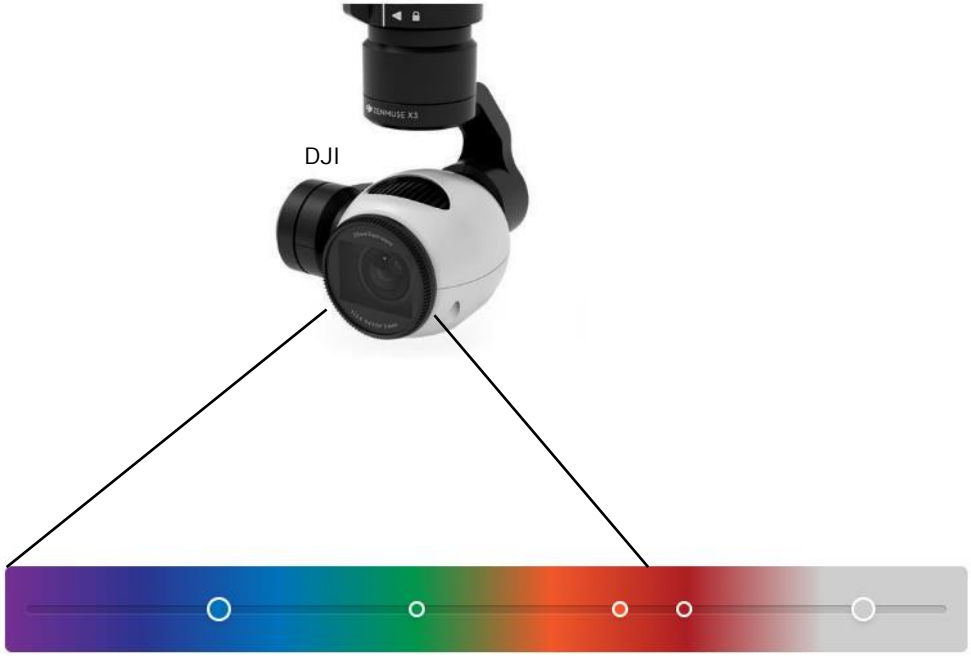
~0.07 ft

Drone-derived Elevations

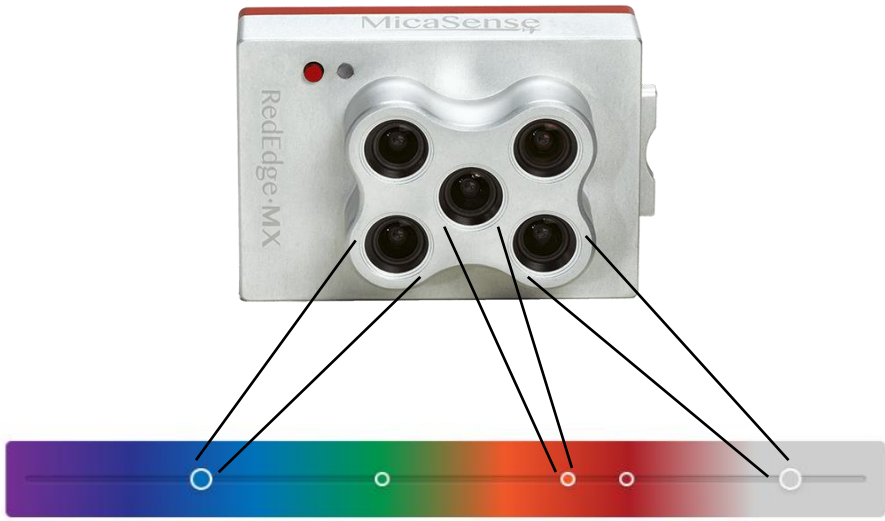


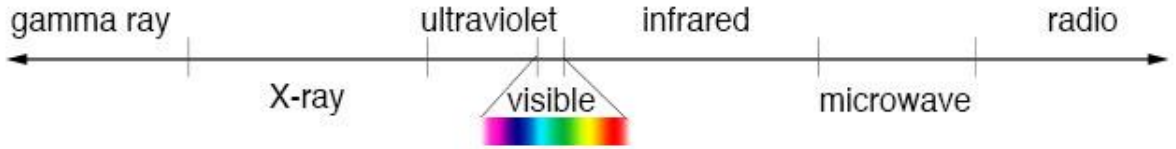
Multispectral sensors collect visible and non-visible portions of the electromagnetic spectrum.

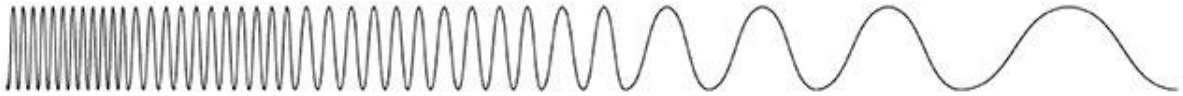
DJI



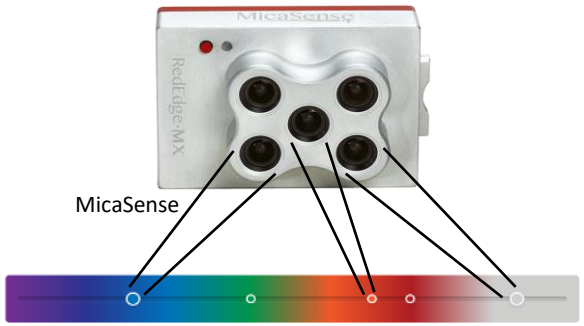
MicaSense



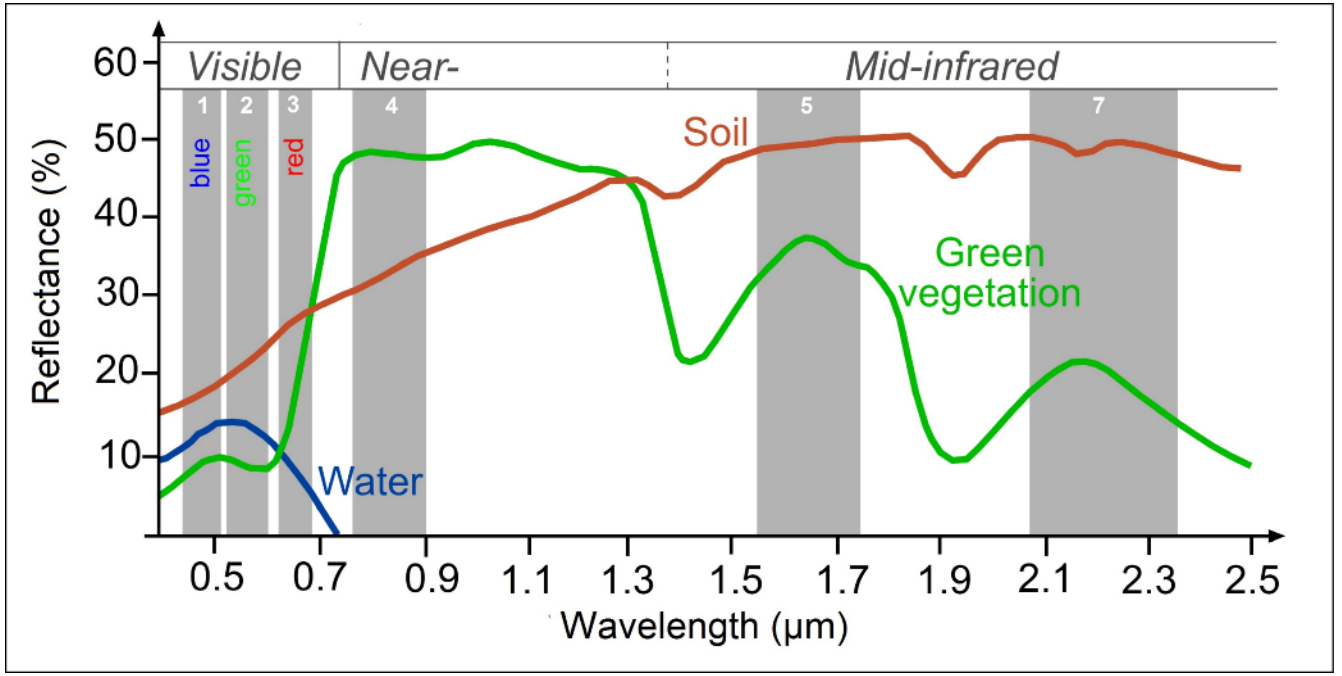




Multispectral data provides information on spectral signatures of land cover.

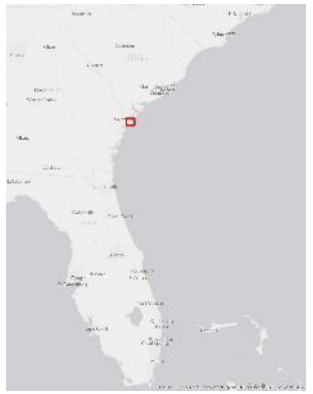


Spectral signatures



Source: NASA

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

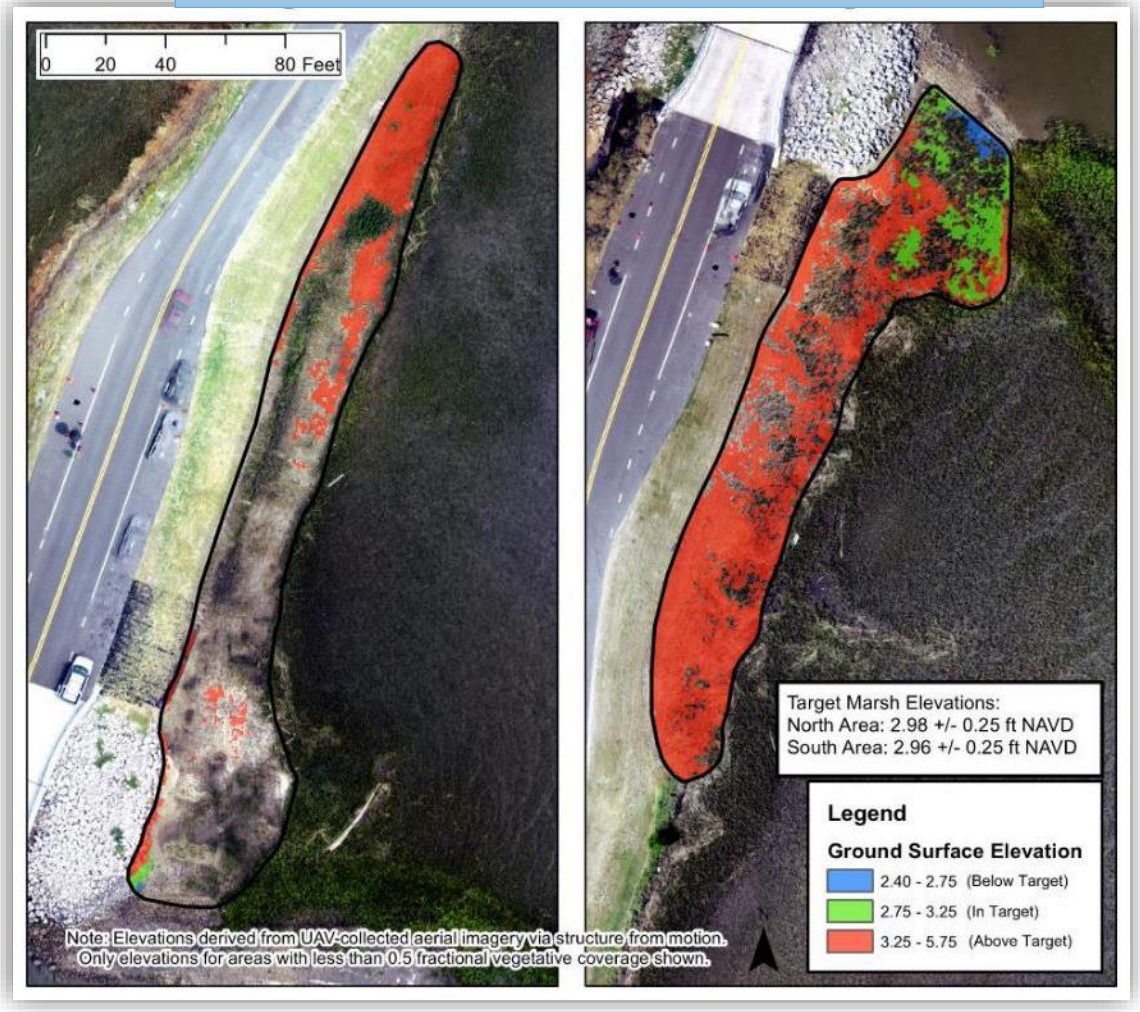


CDM Smith monitored a nature-based solution project at the mouth of the Savannah River.

Marsh Restoration

Drone data revealed that the contractor graded too high.

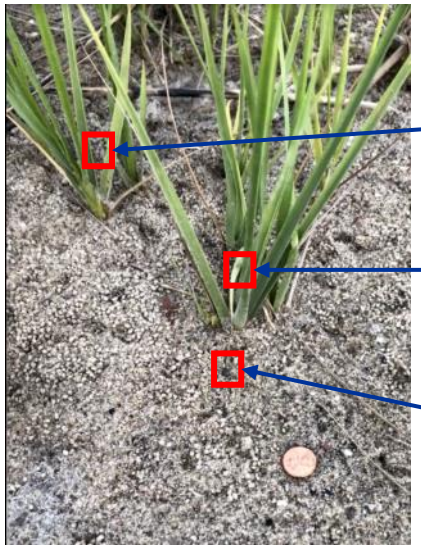
Areas out of spec for target grading



High resolution pixels identify individual *Spartina* plugs.

Fractional Vegetation Coverage (FVC)

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



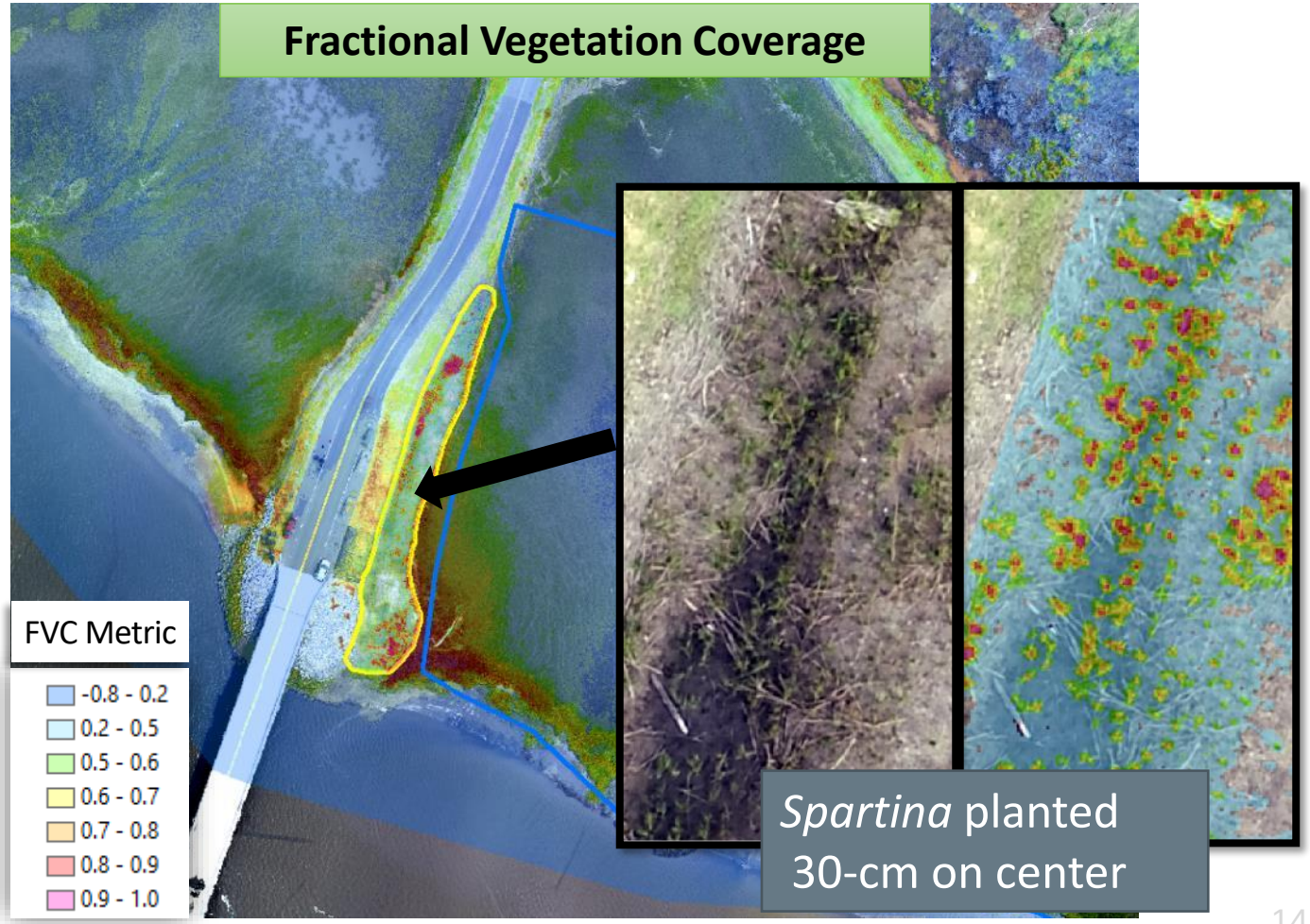
NDVI of Target

$NDVI_{veg}$ (100%)

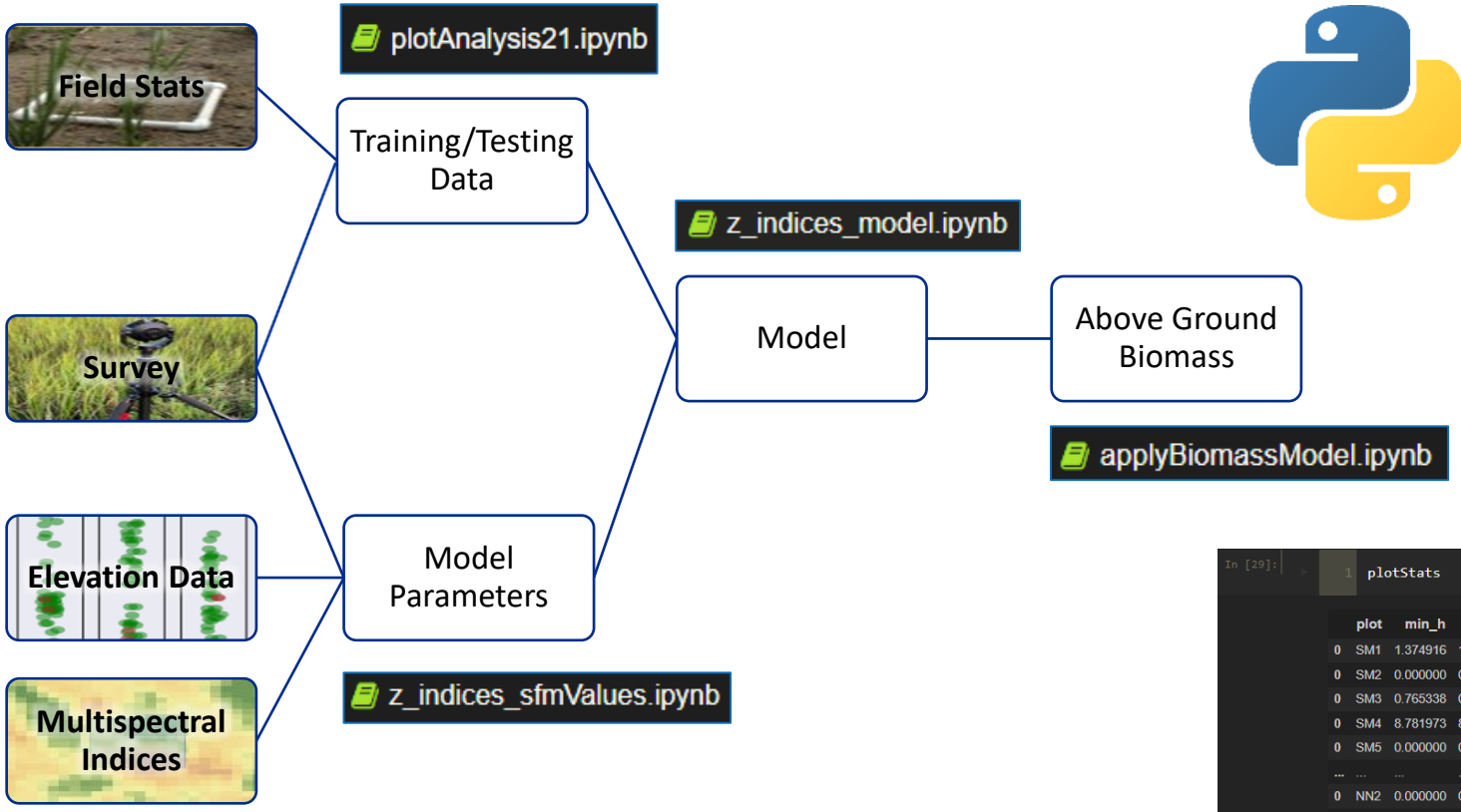
$NDVI_{soil}$ (100%)

Mitigation Area

Reference Area



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




```python
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:
```

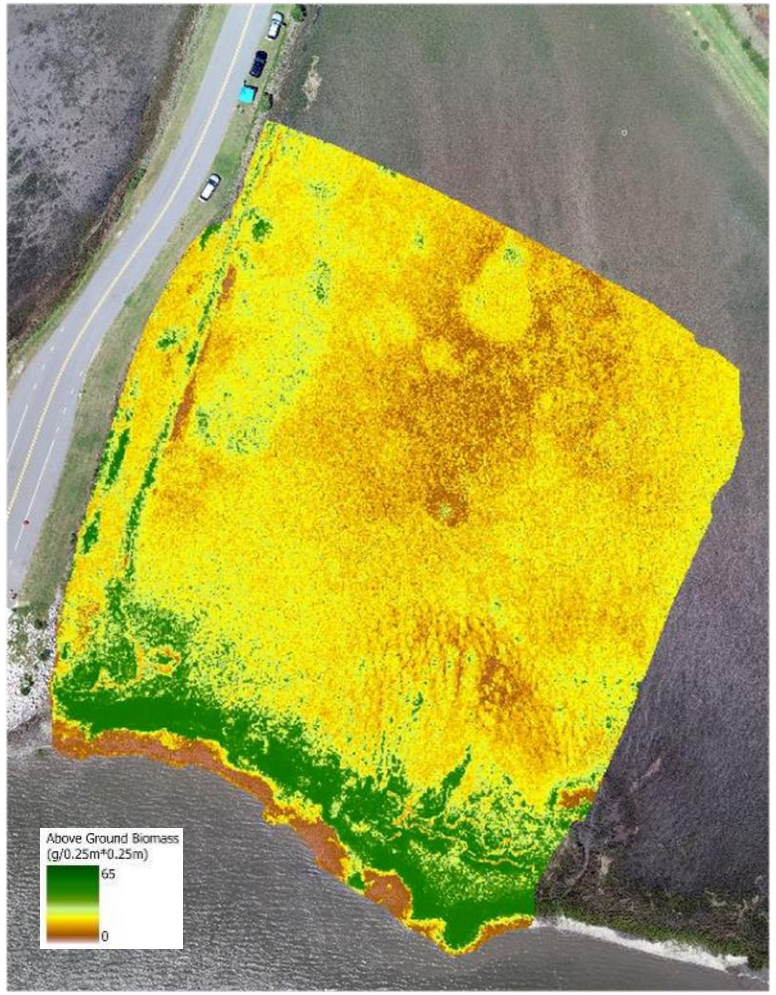
```
In [29]: plotStats
```

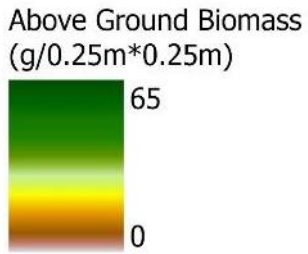
	plot	min_h	p5_h	p25_h	p50_h	p75_h	p90_h	max_h	mean_h	std_h	...	ndvi_std	ndviPV
0	SM1	1.374916	1.441972	1.710196	2.045476	2.243596	2.362468	2.441716	1.954036	0.440293	...	0.031970	12.0
0	SM2	0.000000	0.000000	0.978388	4.090376	11.999936	16.660328	21.433496	7.354360	7.499678	...	0.024759	16.0
0	SM3	0.765338	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

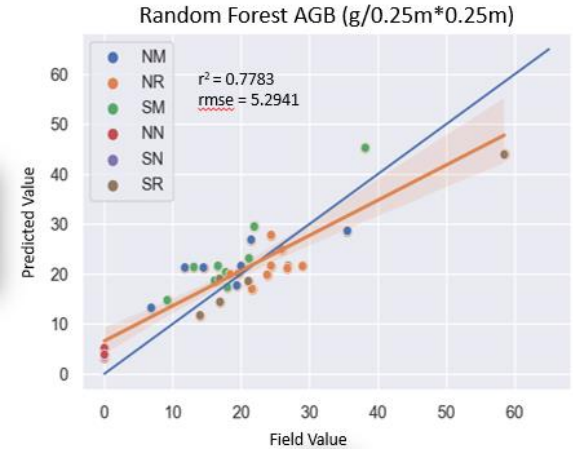
86 rows × 43 columns

The machine learning model can output site wide biomass.

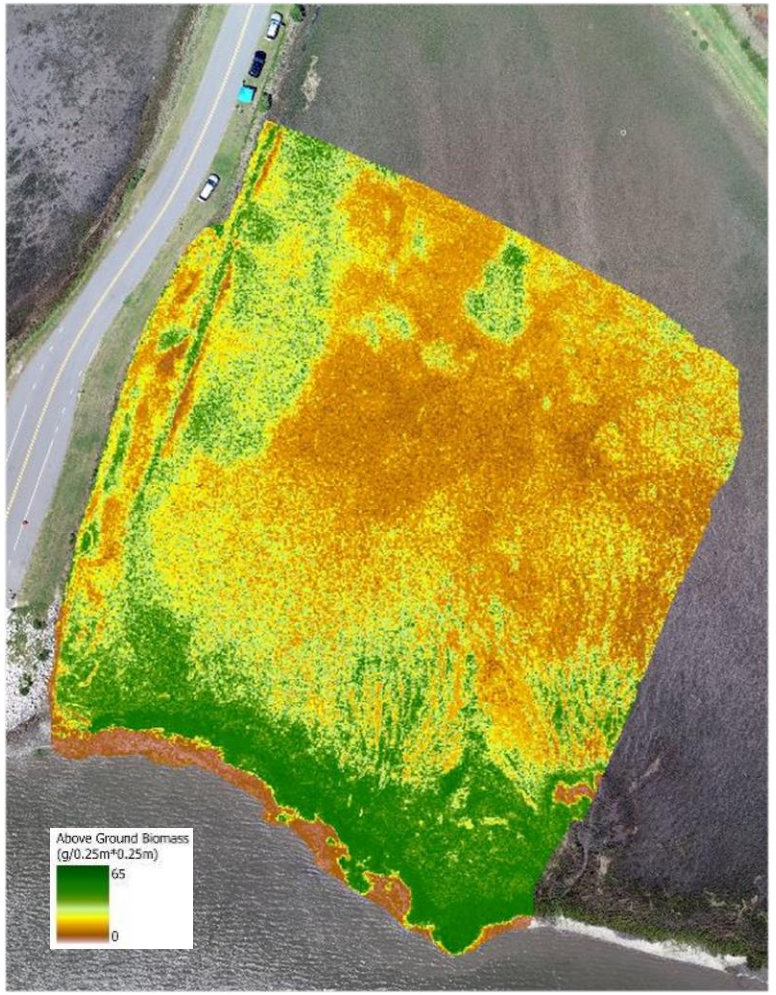
2021





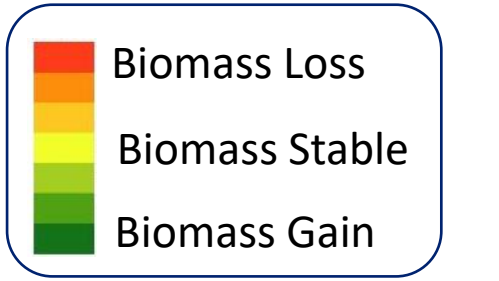


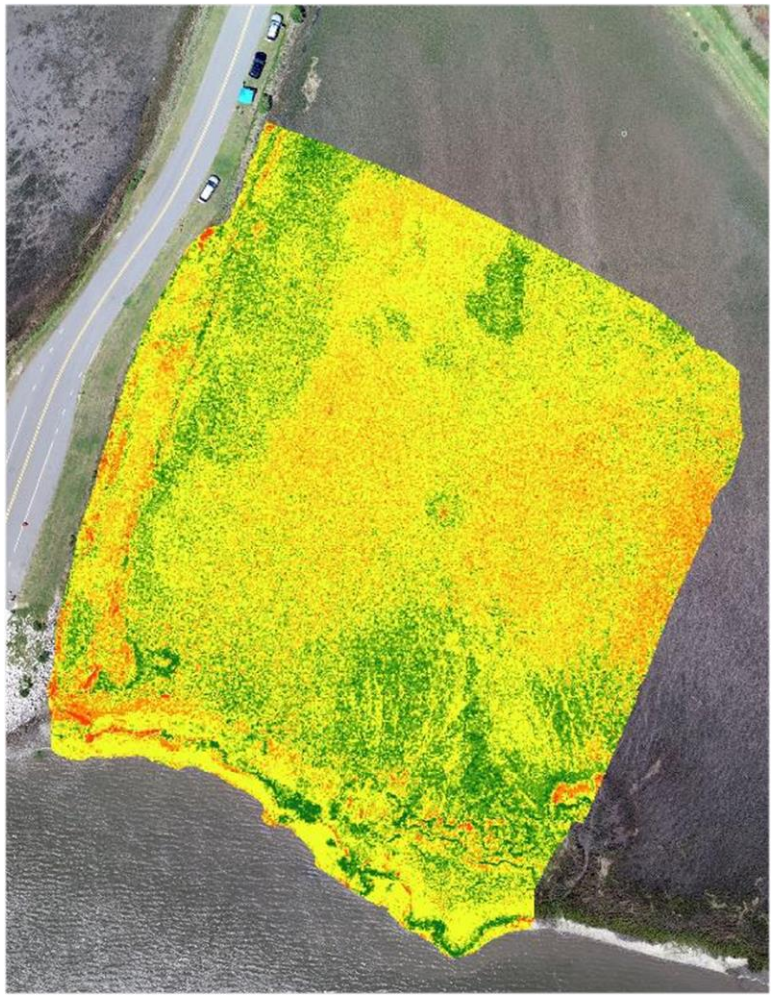
2022



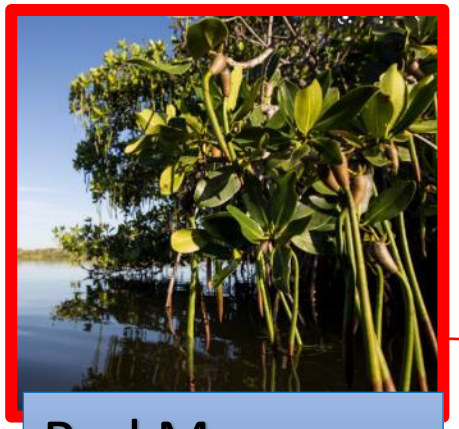
Machine learning model results allow for easy identification of biomass loss and gain over time.

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

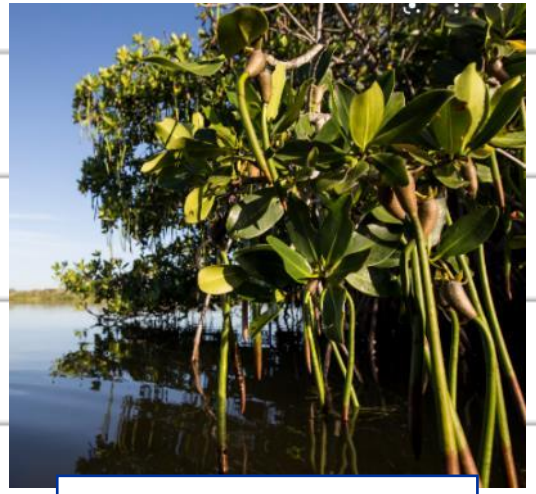
Flight Path

Drone-derived Aerial

10-band Dual Camera

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

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.

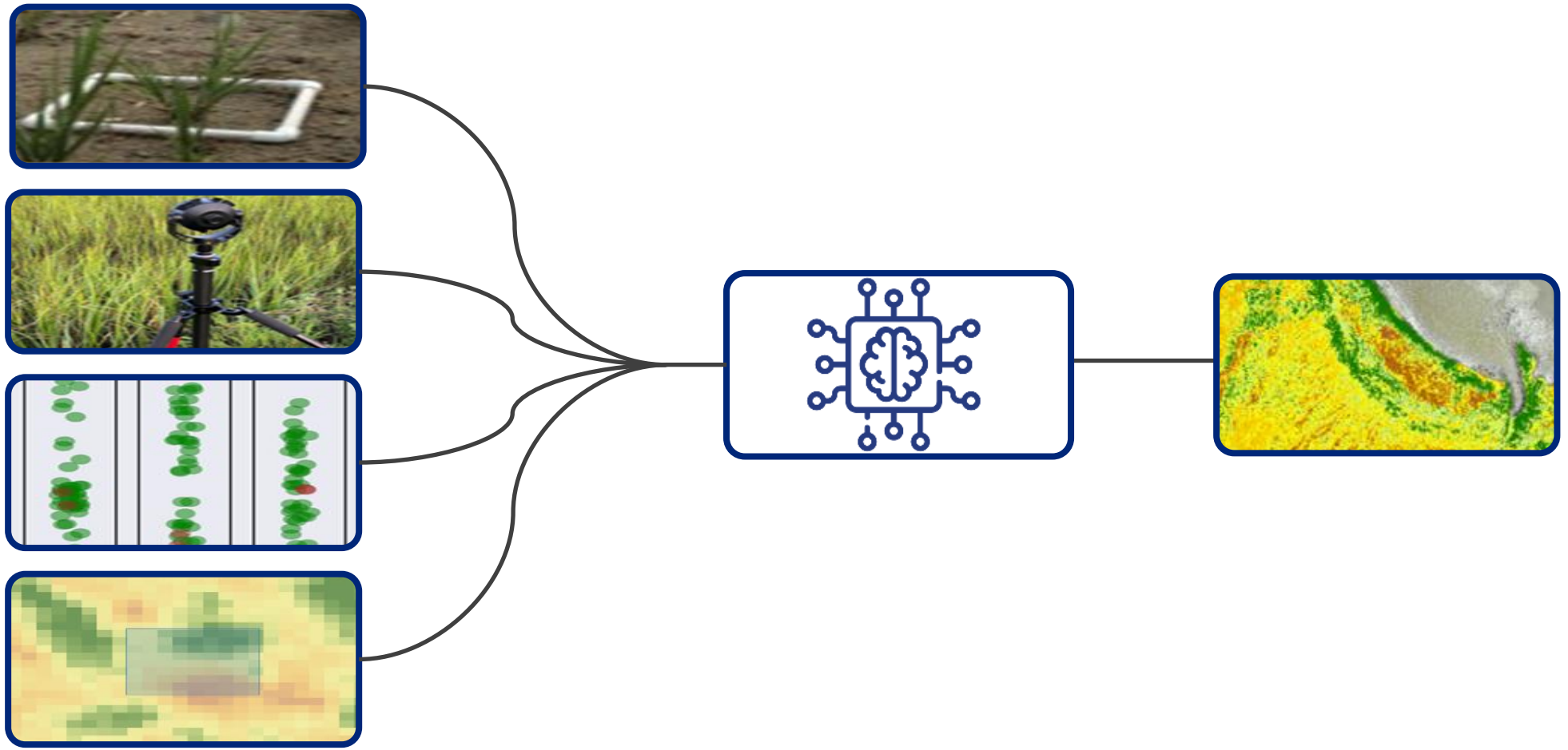
Plane-based Mapping

Image: Courtesy of SurvTech

High-resolution/Efficient Collection

Time-consuming Field Transects

Machine learning will a play a vital role in understanding coastal ecosystems.



cdmsmith.com/skywave
brownbv@cdmsmith.com
407-660-6300

sky wave™

at CDM Smith