Using an Unmanned Aerial System (UAS) to Collect Hyperspectral Imagery of Tidal Wetlands

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4 National Park Service

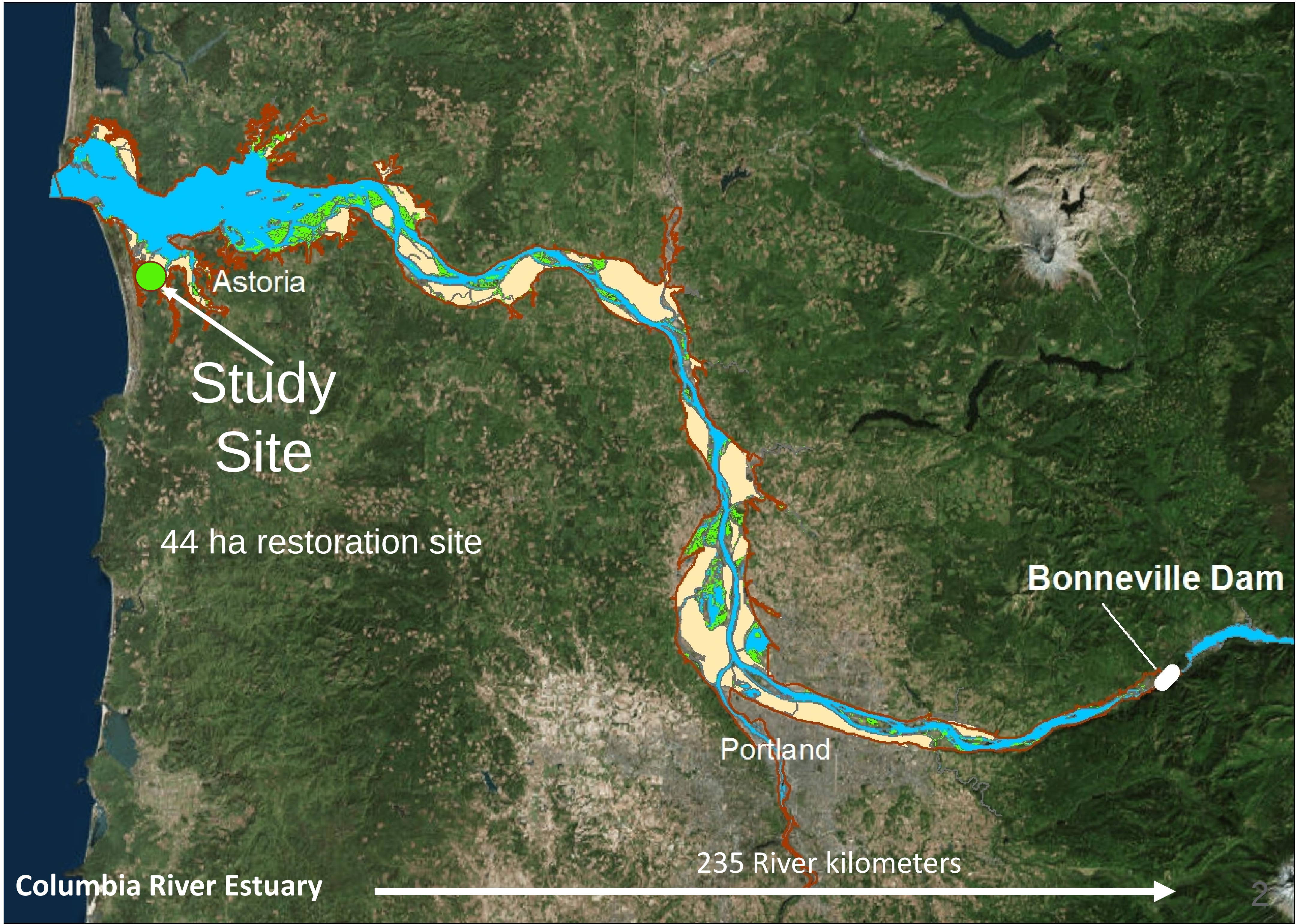
Background and Goal

Wetlands are important for juvenile salmonids and other ecosystem functions.

68% loss of tidal wetlands >20,000 hectares

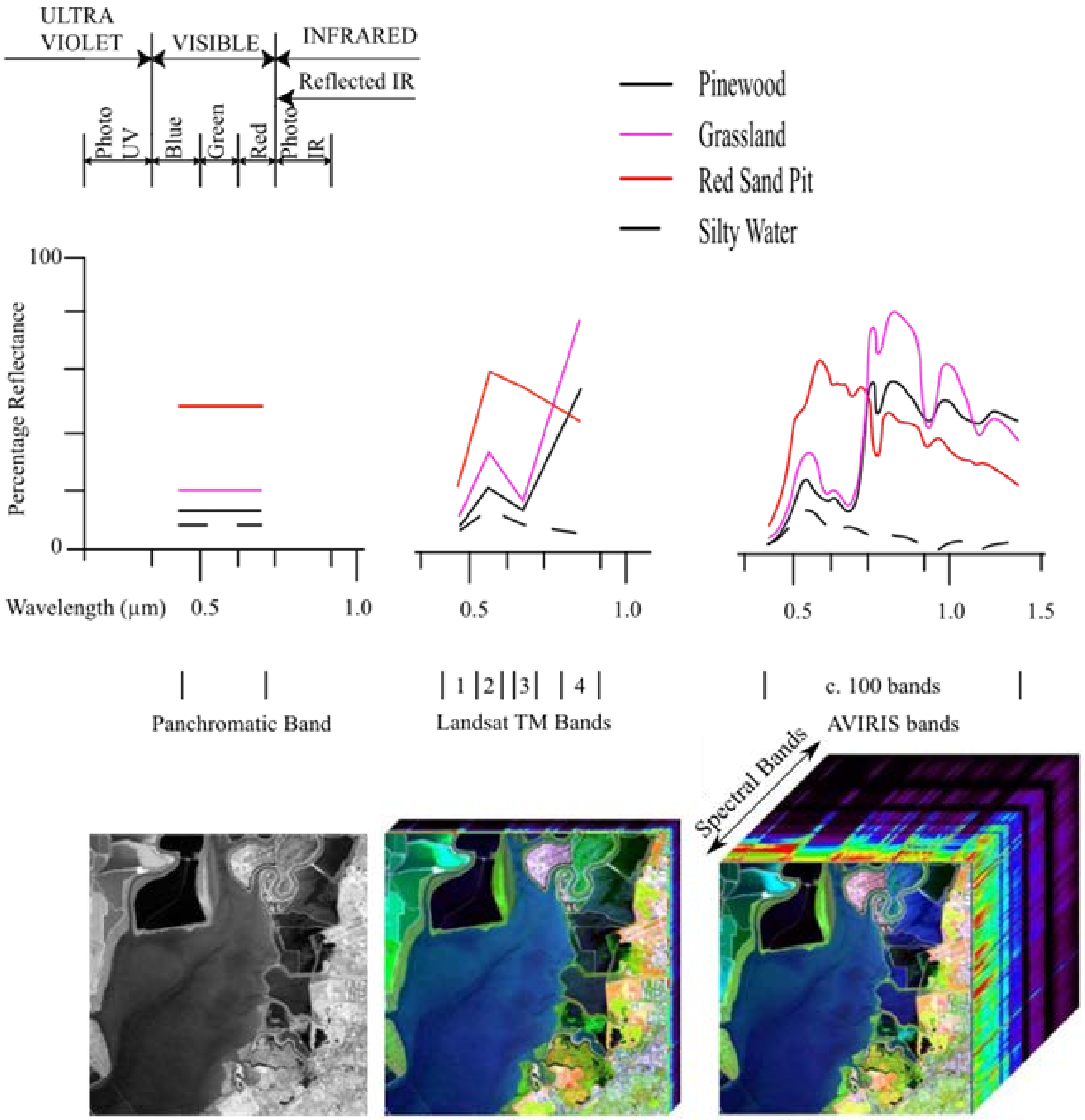
Large-scale restoration program requires comprehensive monitoring.

Goal: Develop UAS with hyperspectral camera to automate wetland classification and inform restoration monitoring.



Approach

- Equip a UAV system with a hyperspectral imager
- Conduct field measurements and build spectral library
- Develop analytics to automate classification
- Test flight methods at additional tidal wetland systems
- Establish protocols to aid evaluation of wetland restoration trajectories and management decision making

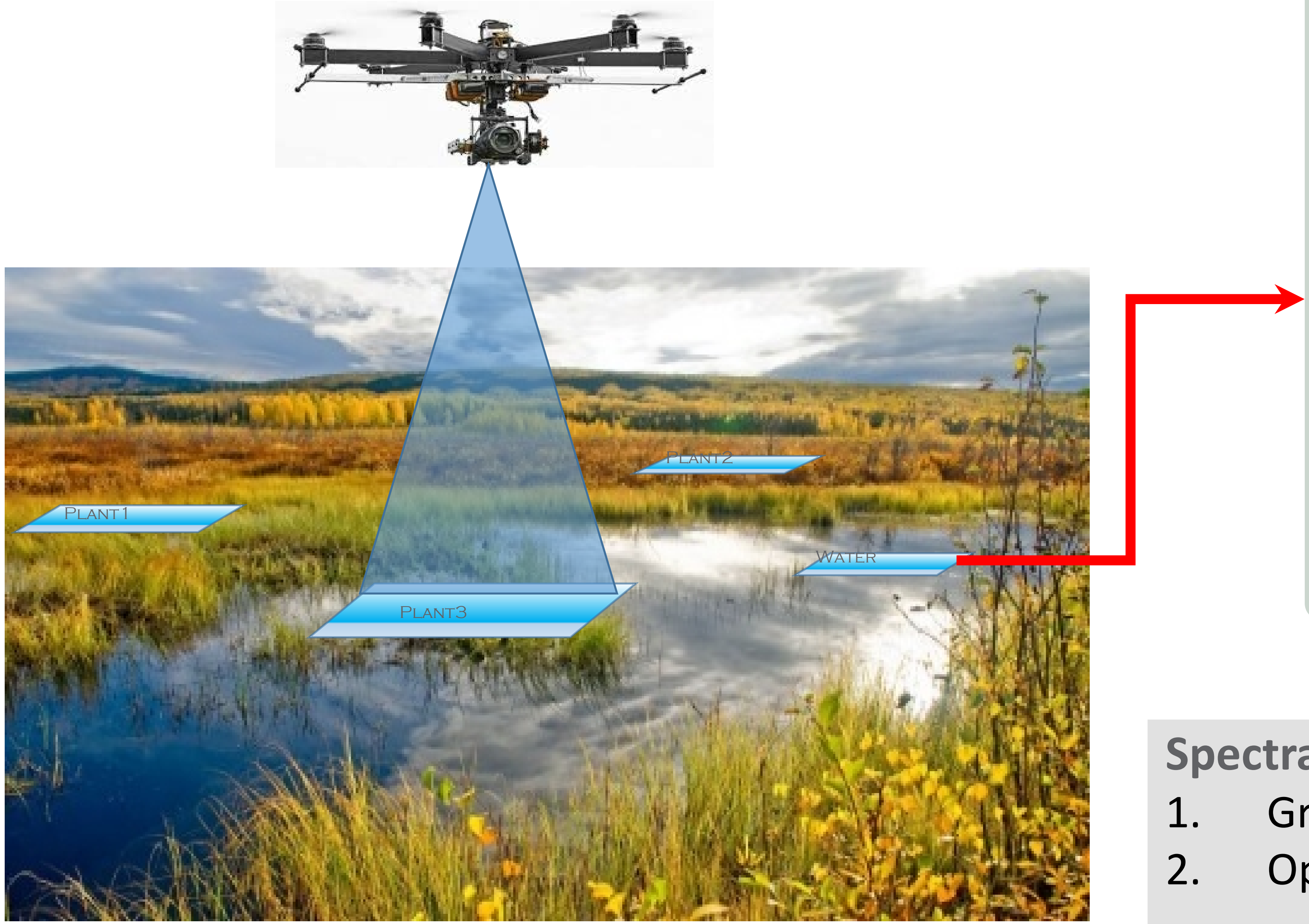


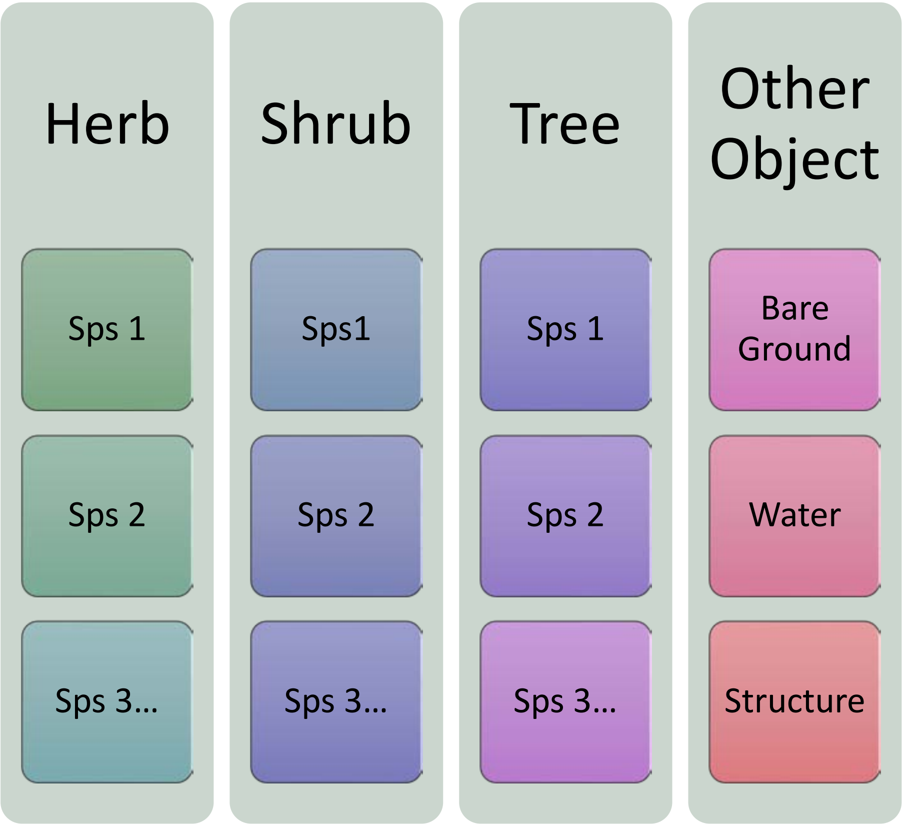
Spectral Library

Catalog of object-specific spectra[1]

Data Acquisition

Spectral signatures of vegetation and other features:





Spectral Library

1. Ground-truthed for PNW wetland habitats
2. Open sourced

1 Zomer et al., 2009

Hyperspectral Imager and Aircraft

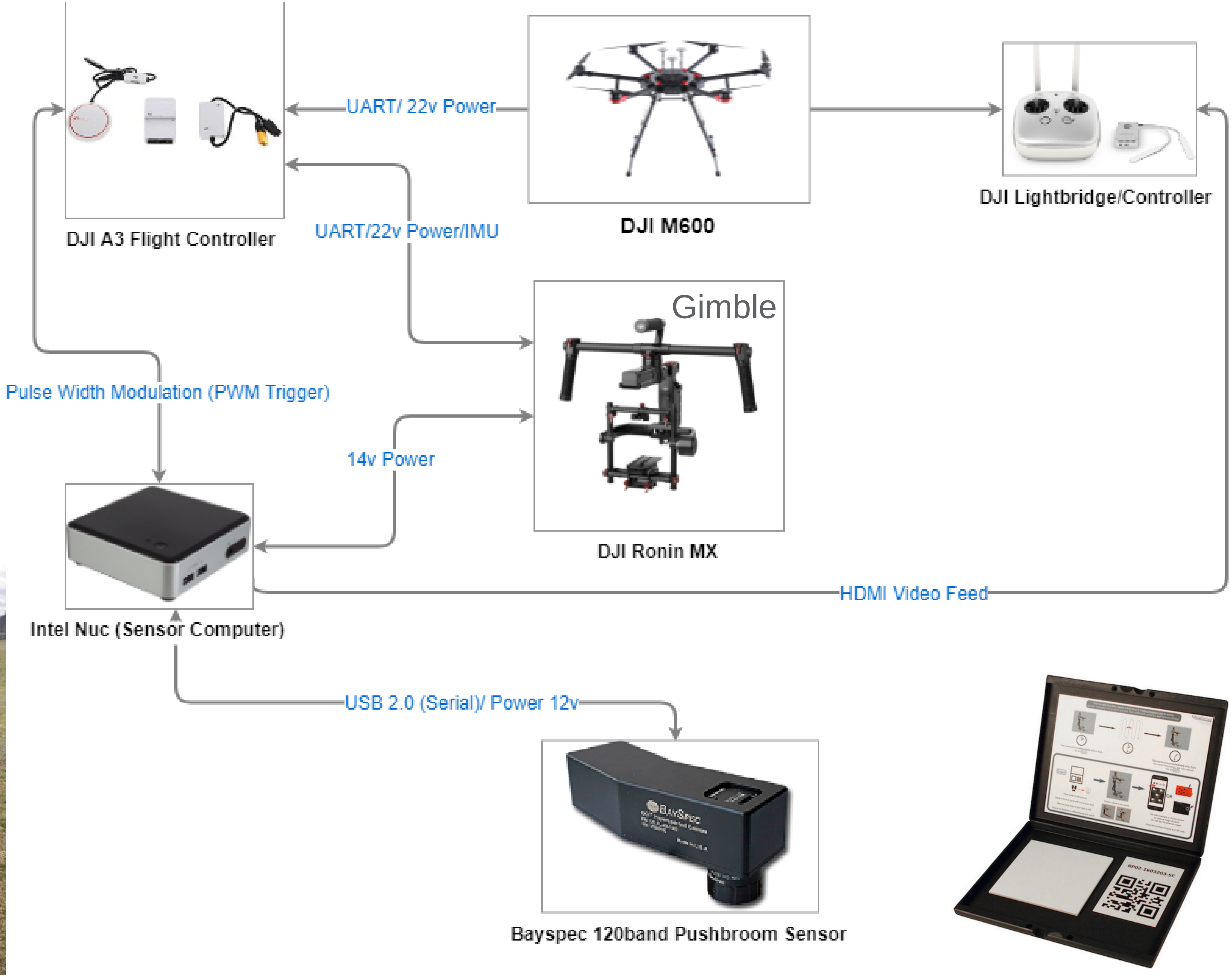
BaySpec OCI-100 BP150

- Pushbroom Hyperspectral Imager
- Spatial Pixels: 2000 pix x scan-length
- Spectral Range: 400-1000nm
- Spectral Resolution: 5nm
- Spectral Bands: 115
- Speed: 60 fps

DJI Matrice 600 Pro (M600)

- Payload of 6 kg
- Ronin MX 3-axis gimbal for stabilization
- Custom built mounting plate for sensor and onboard computer
- Modified battery system to power the sensors and on board computer
- Remote connection to the computer allowed remote shutter control, diagnostics during flight, and sensor calibration

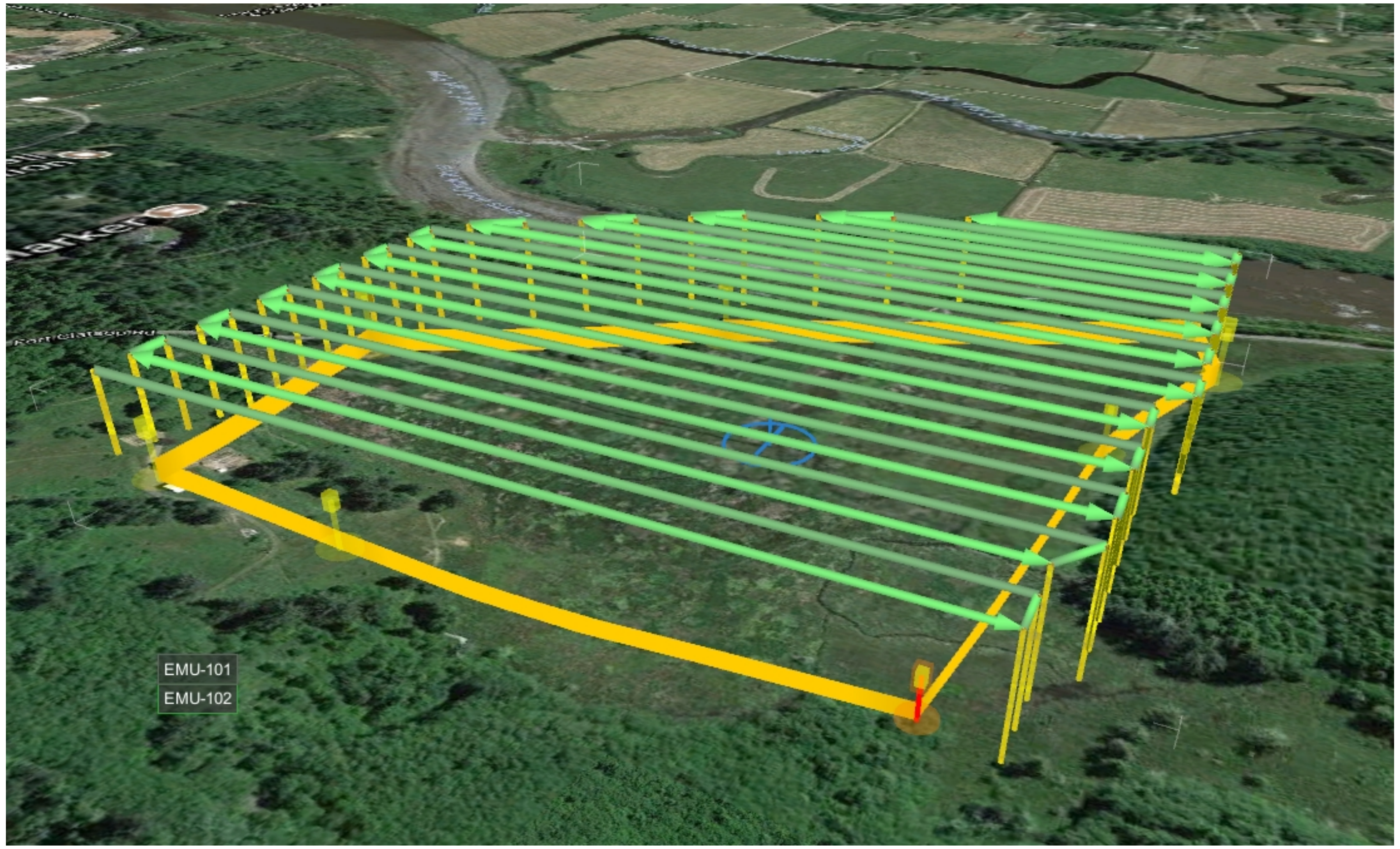
Aircraft Integration



Flight Details

- Used Universal Ground Control Software[1] to plan flight transects
- Maintained low velocity between 1.0 - 1.8 m/second for OCI sensor
- Calibrated each flight for atmospheric conditions including using a calibrated reflectance panel for white balance
- Flight time limited due to heavy payload
- Segmented flights to maximize flight time
- Also captured true-color (RGB) orthrectified imagery in a separate flight

1 SPH Engineering, Latvia



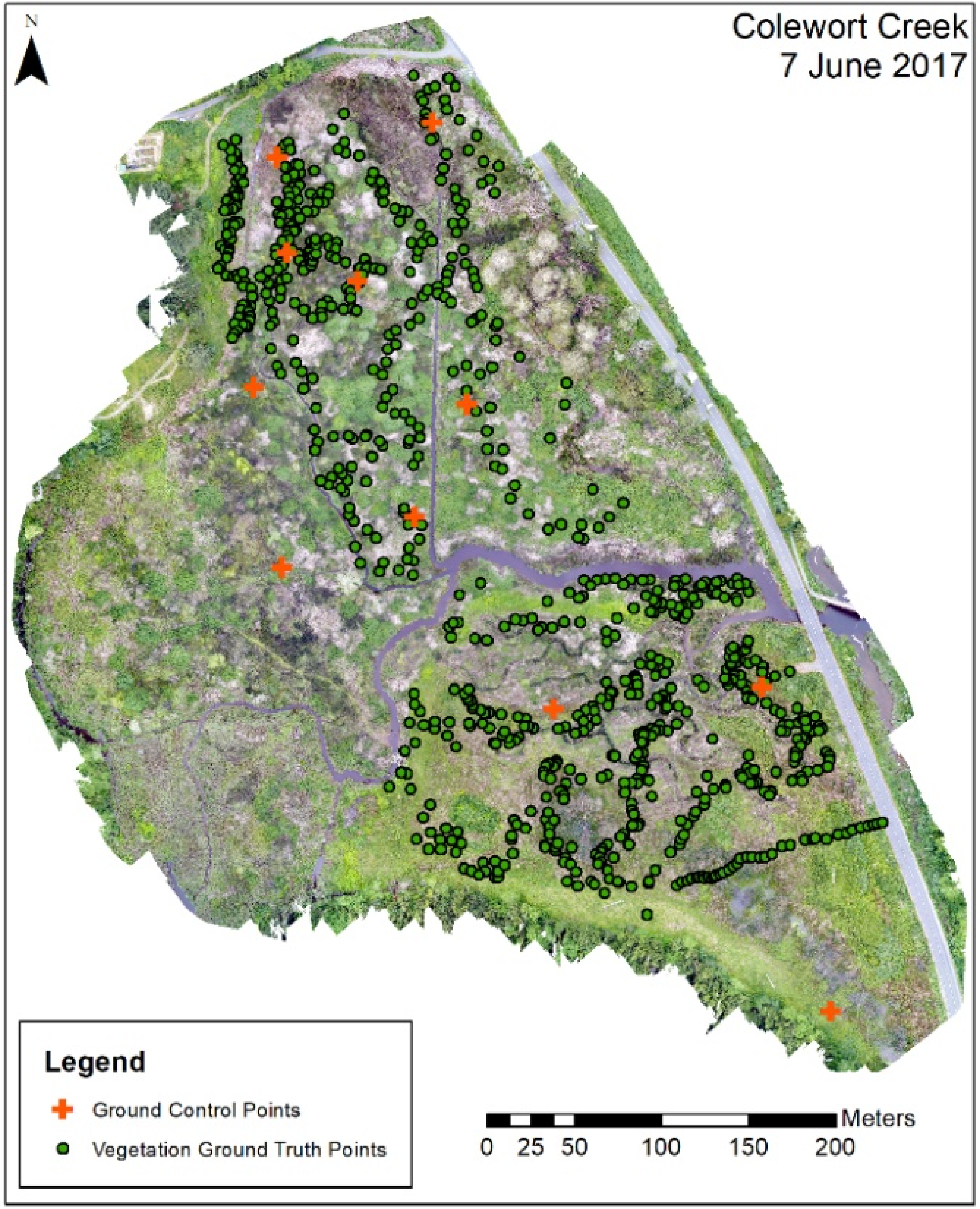
Flight altitude = 70 m

Ground resolution = 2 cm

Flown in June and September

Field Data

- 16 ground control points for georeferencing
  - Real-time kenimatic (RTK) GPS
- 794 reference points collected
  - ID plants to species
  - Estimated percentage of multiple species
  - Documented condition of plants (e.g., lying down, flowering, or dead)



Data Processing and Results

1. Georeferencing
2. Habitat data processing
3. Hyperspectral pre-processing
4. Spectral library development
5. Image classification

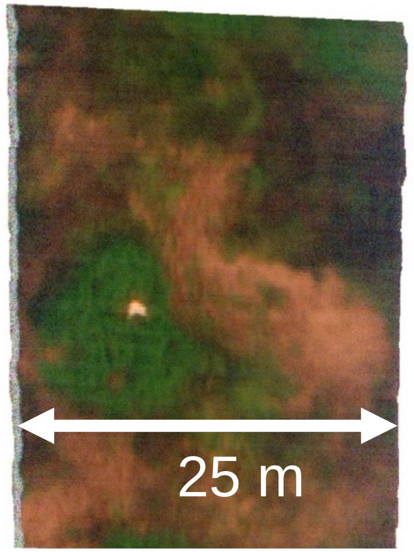
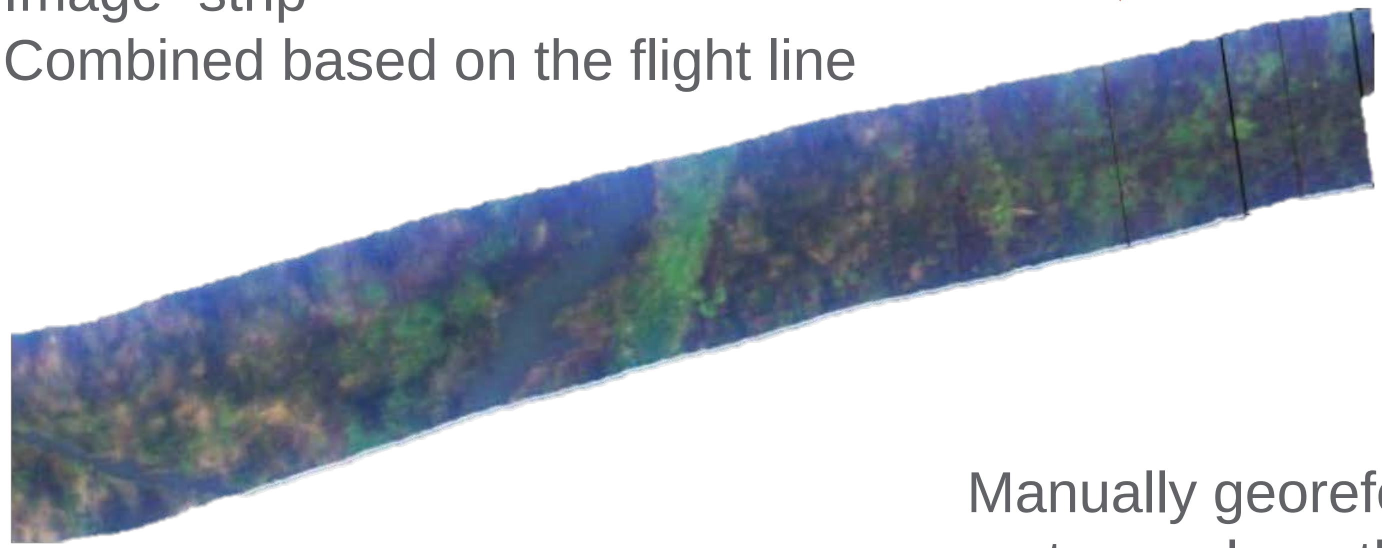
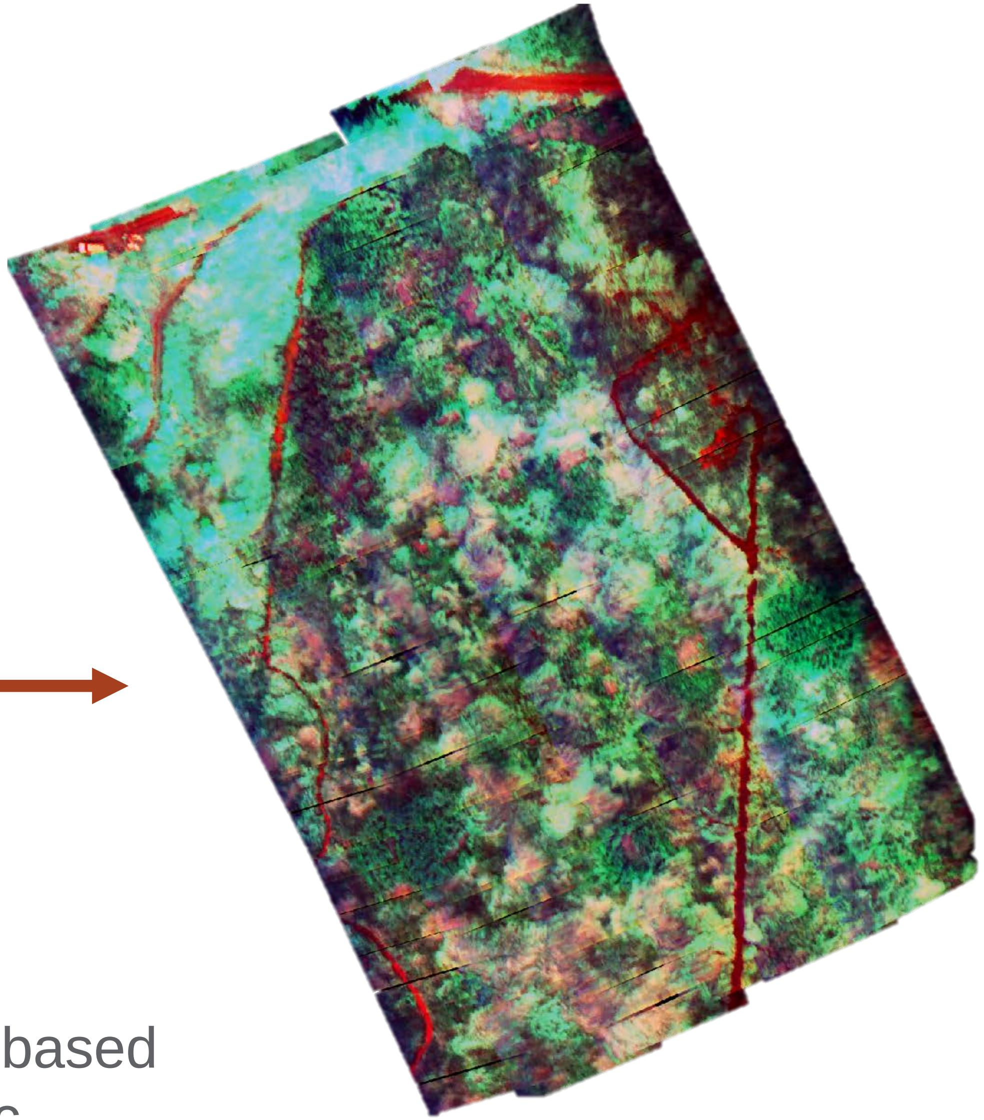


Image “chip”
>1000/site

Image “strip”
Combined based on the flight line





Manually georeferenced based on true-color orthomosaic

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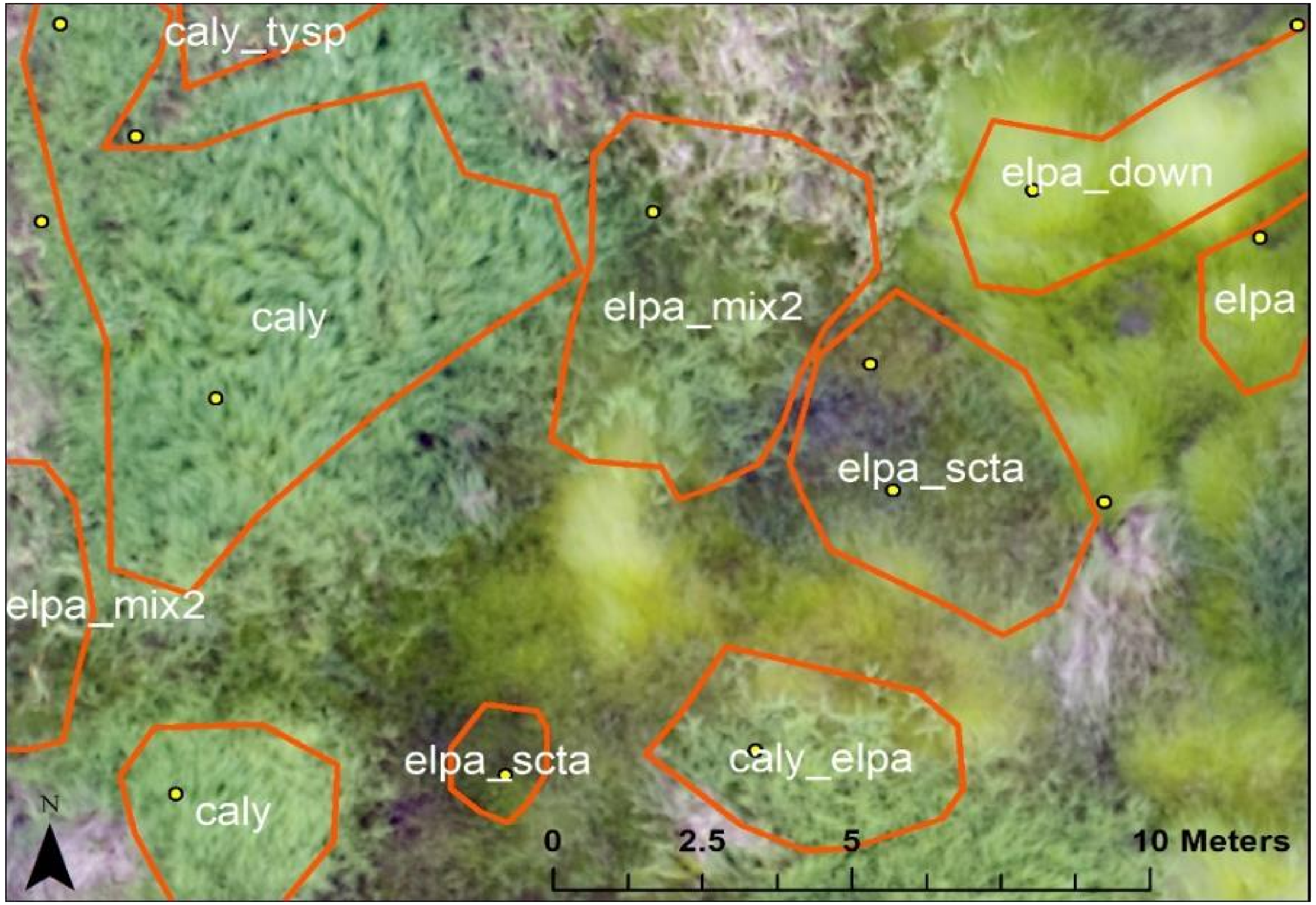
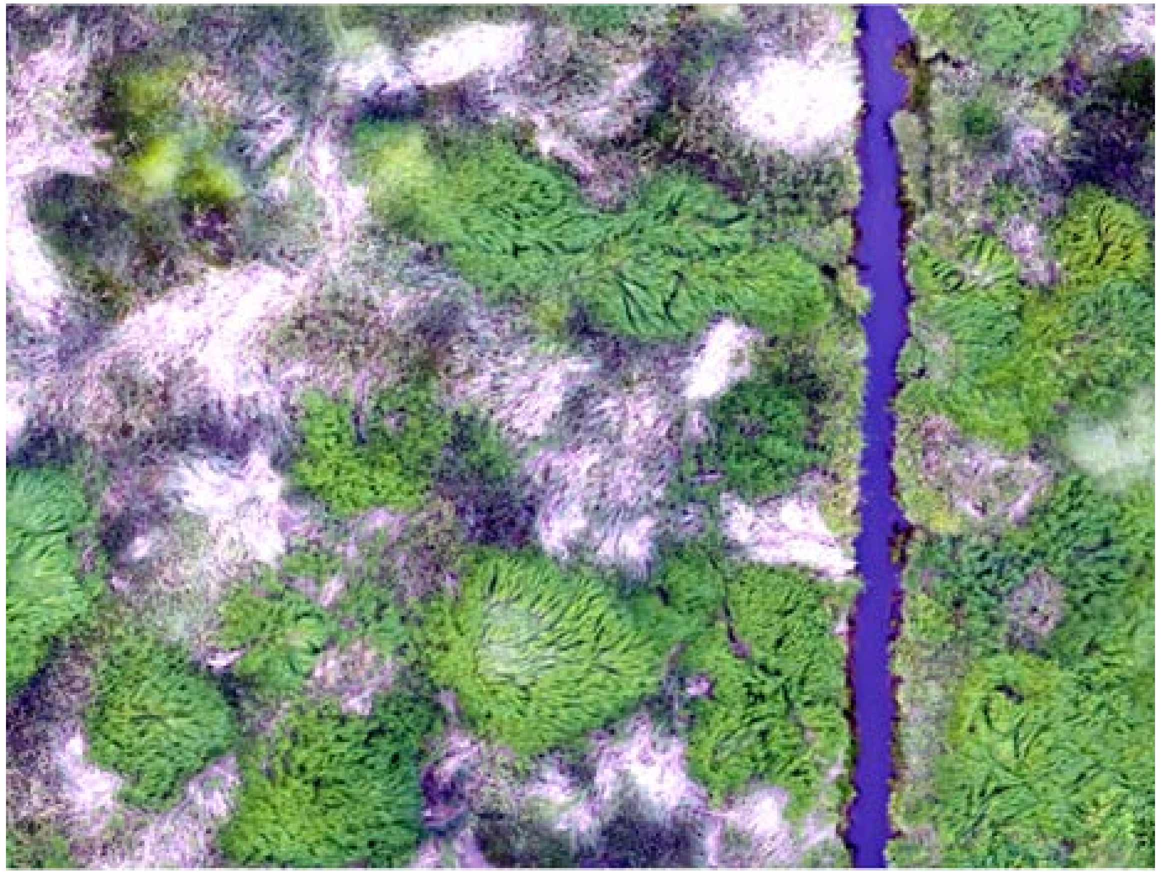
- Developed 77 habitat classes based on field collected GPS data
- Delineated 258 polygons based GPS points and ortho imagery

45 Classes:

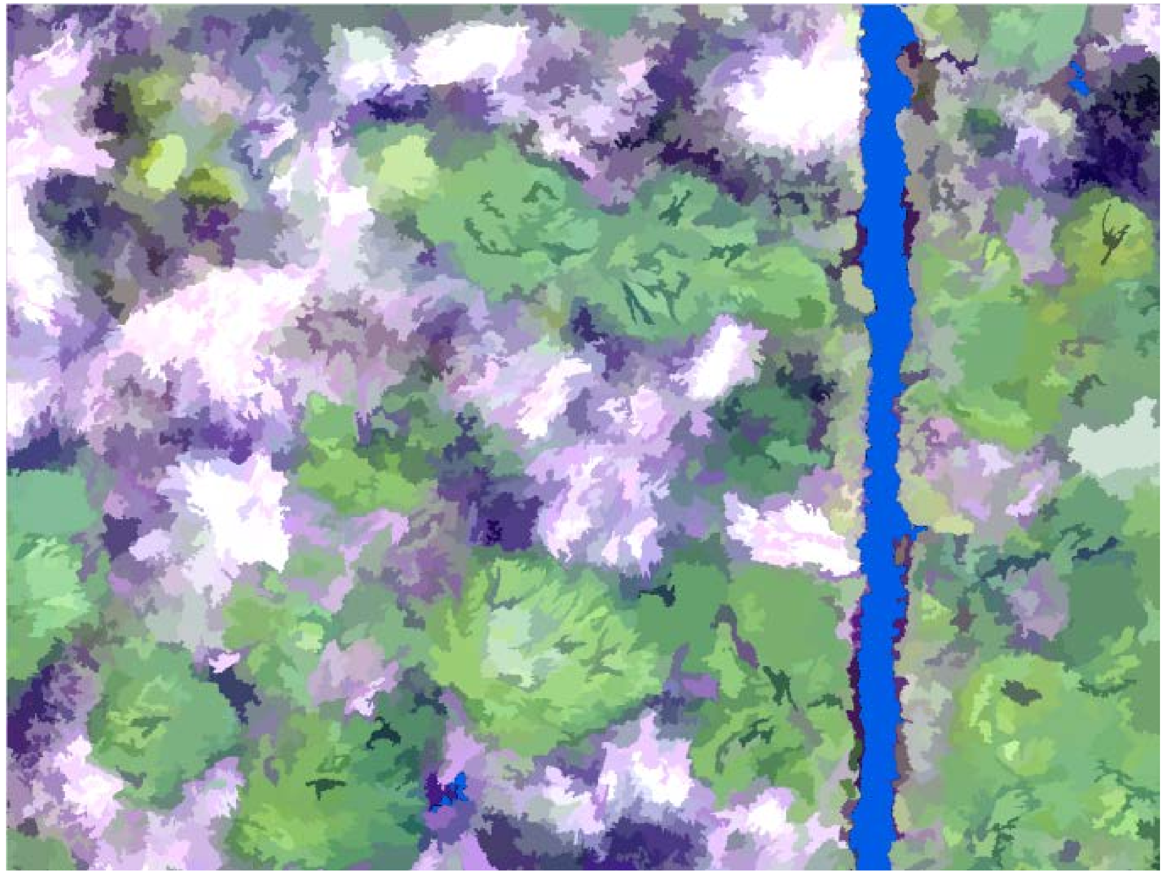
- single species
- co-dominants
- species conditions



Data Processing and Results

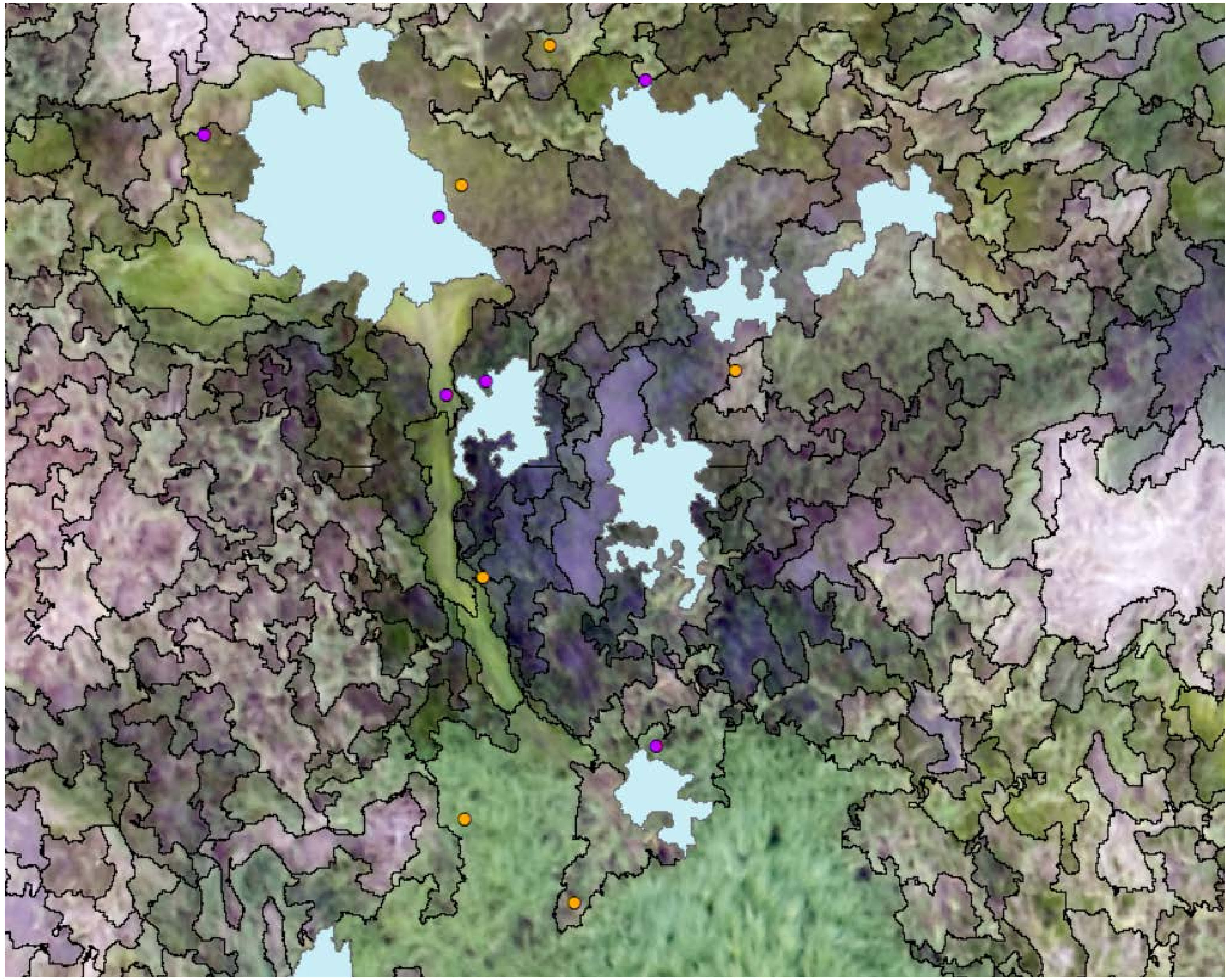


RGB high resolution image



Segmented image using object-based image analysis (OBIA) using ArcGIS Pro

Data Processing and Results



Training polygons: 363
Reference polygons: 353

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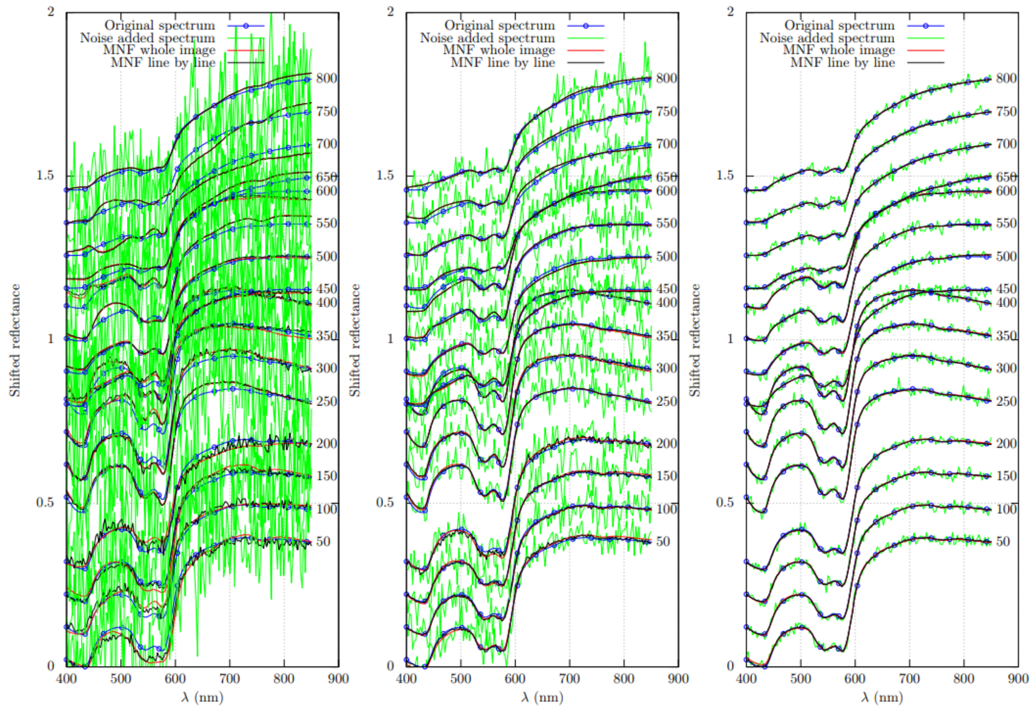

Bjorgan and Randeberg, 2015

- Noise and Dimensionality Reduction
  - Minimum Noise Fraction (MNF)
    - Uses PCA to spectrally and spatially separate noise
  - Data dimensionality reduction
    - ordered by signal to noise ratio
  - Lower bands contain spatial structure and most important information
  - Higher bands contain most of the noise
  - Eliminates spectral bands that don't contribute to classification because of noise or redundancy

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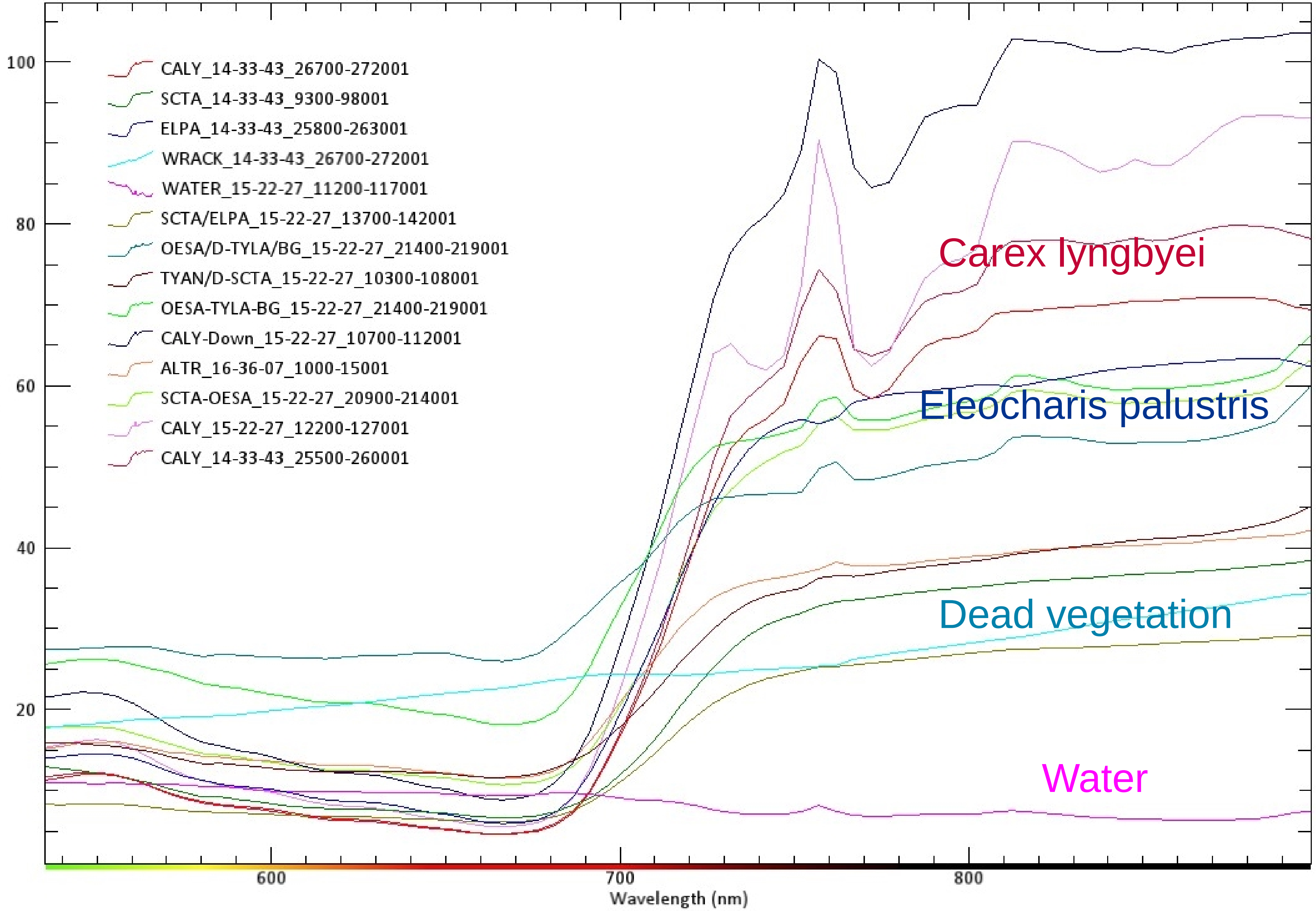

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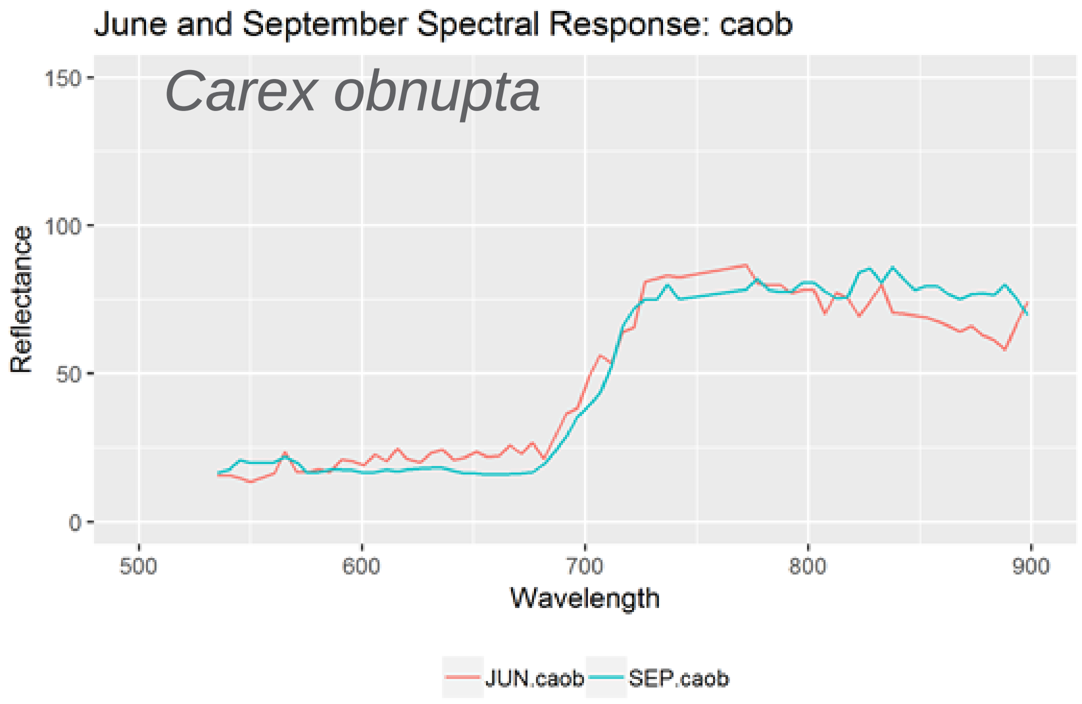

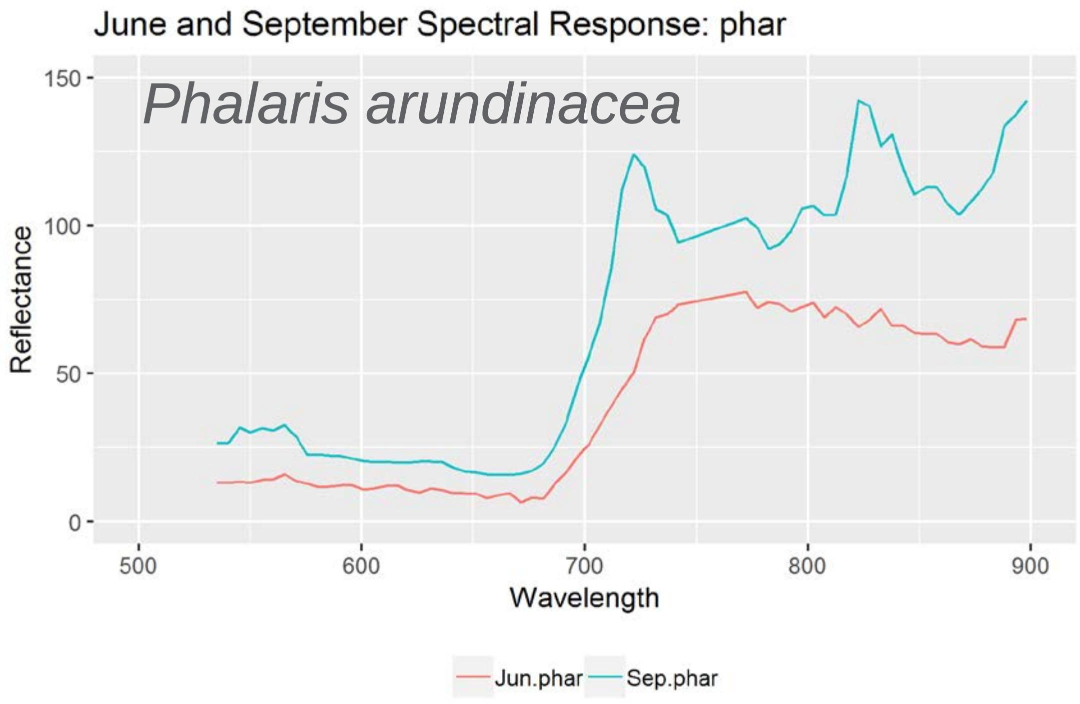

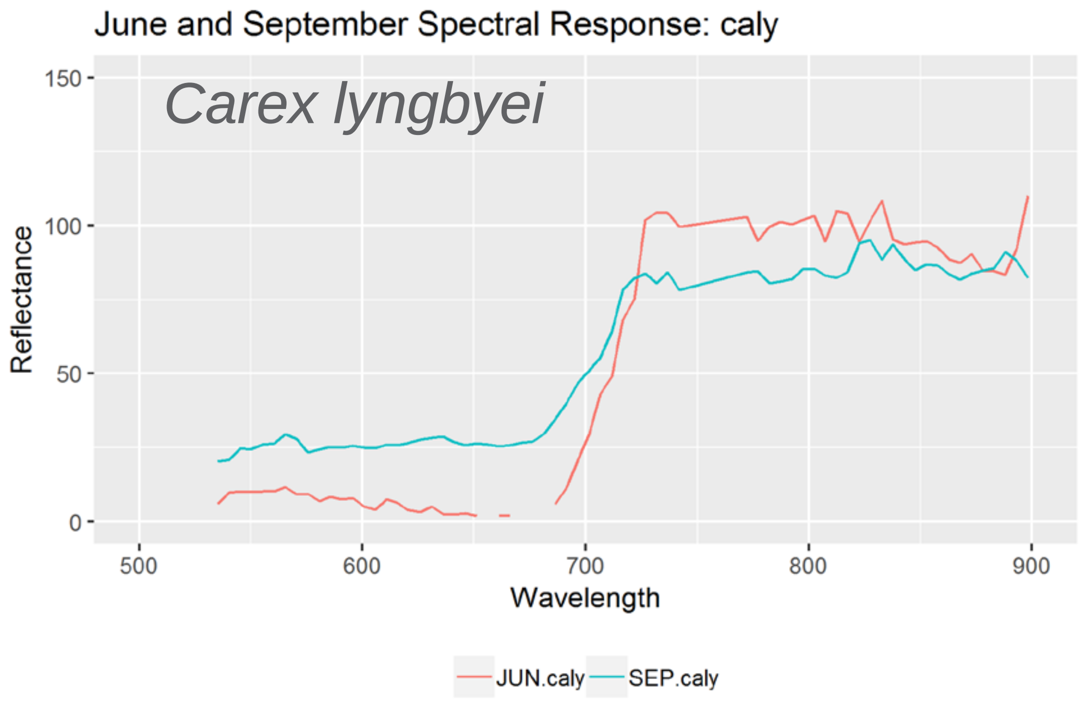

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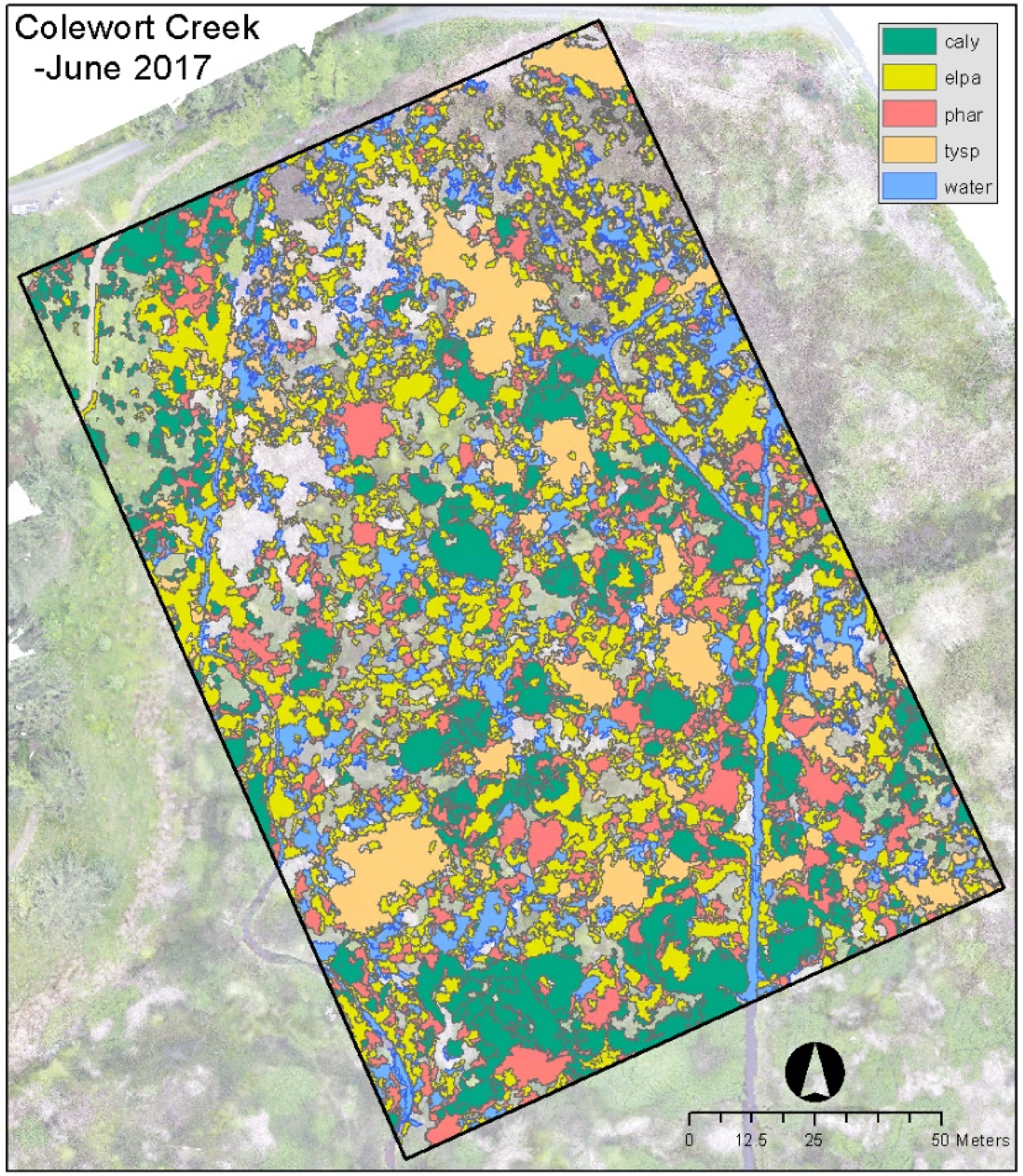
- Used object-based image analysis (OBIA)
  - o Evaluates spatial adjacency of pixels with a similar spectral signature to develop segmentation
  - o Accounts for both spatial and spectral coherence

- Tested multiple classification methods
  - o Determined Spectral Angle Mapper (SAM) provided the best results



Lessons Learned

Challenge	Resolution
Georeferencing imagery	Worked with vendor to develop method to create “strips
	Purchased integrated dGPS that is now offered by vendor
Manual reflectance calibration	Purchased integrated upward looking irradiance sensor that is now offered by vendor
	Add on-the-ground spectral radiometer
Resolution	May not need 2 cm accuracy. 8-10 cm would result in improved flight time, reducing variability
BIG DATA	Dedicated computing resources
Noisy data	OBIA helped, improved georectification will help

Lessons Learned

Challenge	Resolution
Spectral signature variability and duplicity	Use OBIA on RGB ortho imagery to develop polygons and reduce noise
	Evaluate classes to determine if some can be combined
Automated classification	Employ additional analytical methods including deep learning
	Evaluate and test available open-source products such as the ‘hsdar’ R package and SpectralPython (SPy v. 0.18)

Conclusion

- Challenges were faced in utilizing this new integrated technology
- Resolution of the challenges led to development of improved methods
- This study demonstrated the potential utility of hyperspectral-UAS for monitoring habitat restoration outcomes

Future

- Follow-on funding from NOAA UAS office for this year.
  - Collect new data to increase spectral library
  - Compare years to evaluate change at restoration sites
  - Incorporate LiDAR
    - Develop DEM
    - Compare to structure-from-motion (sfm) for accuracy and change detection
    - Biomass estimation

Funding provided by a grant from NOAA-UAS office and NOAA-NMFS

Thank you!