Image Credit: Esri https://www.esri.com/en-us/industries/water-resources/arc-hydro

Innovative On-site and Remote Modeling Techniques to Quantify Biodiversity and Pollinator Habitat Potential

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04/17/24

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Spatial Ecologist

Joy Gu

GIS Developer & Environmental Engineer

Roadmap

1. Remote Sensing and Earth Observation (EO) Resources
2. Informing Your Field Effort
3. Applicable Machine Learning and AI Tools
4. Case Study
5. Implications for Restoration

Image Credit: Esri https://www.esri.com/arcgis-blog/products/arcgis-living-atlas/water/the-most-detailed-map-of-us-waters-that-youve-ever-seen/

Remote Sensing & EO Resources

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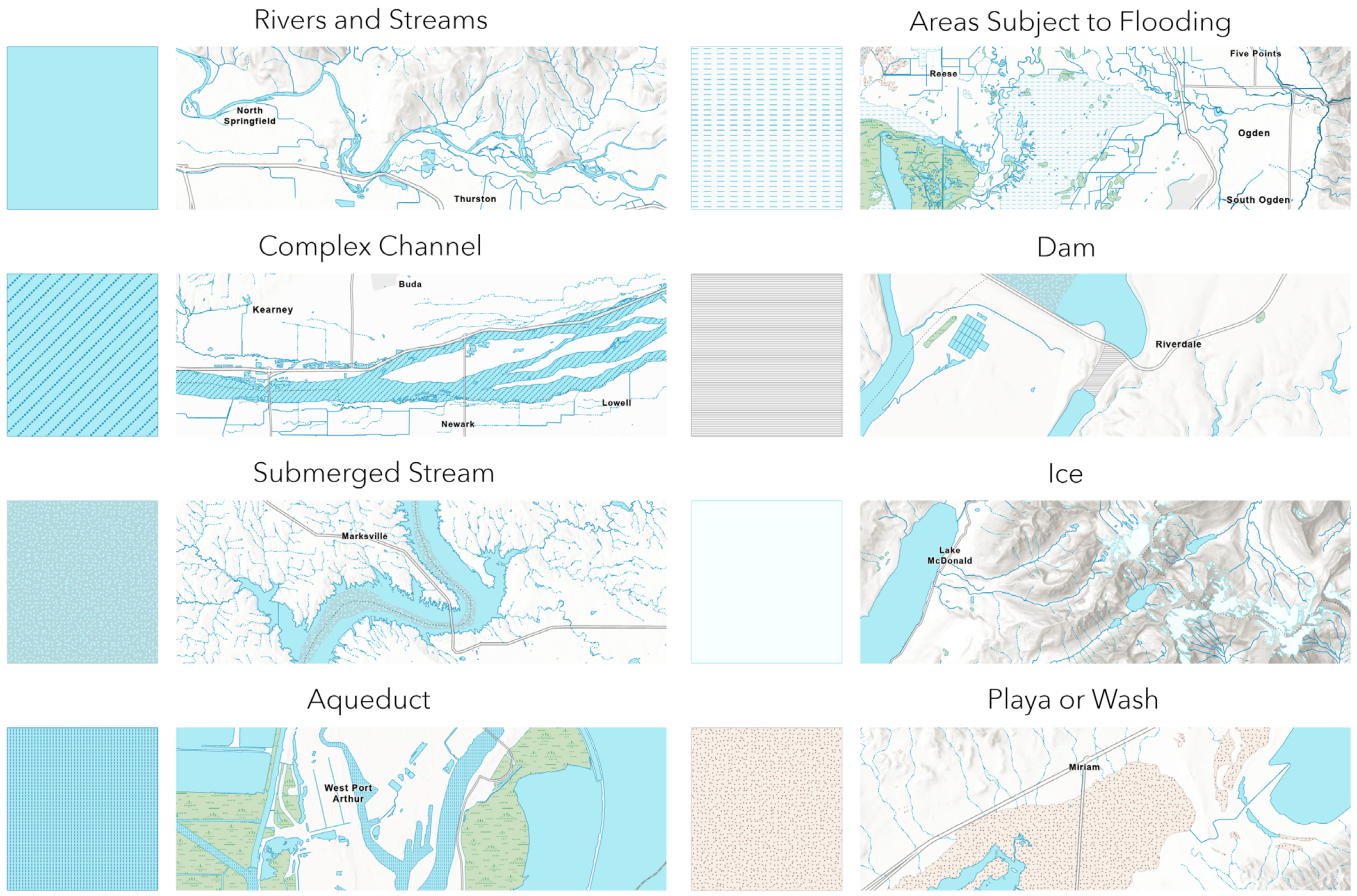

Image Credit: Esri https://www.esri.com/arcgis-blog/products/arcgis-living-atlas/water/the-most-detailed-map-of-us-waters-that-youve-ever-seen/

Hydrology

NHDPlus HR & Arc Hydro

Species Data

NatureServe Explorer Pro

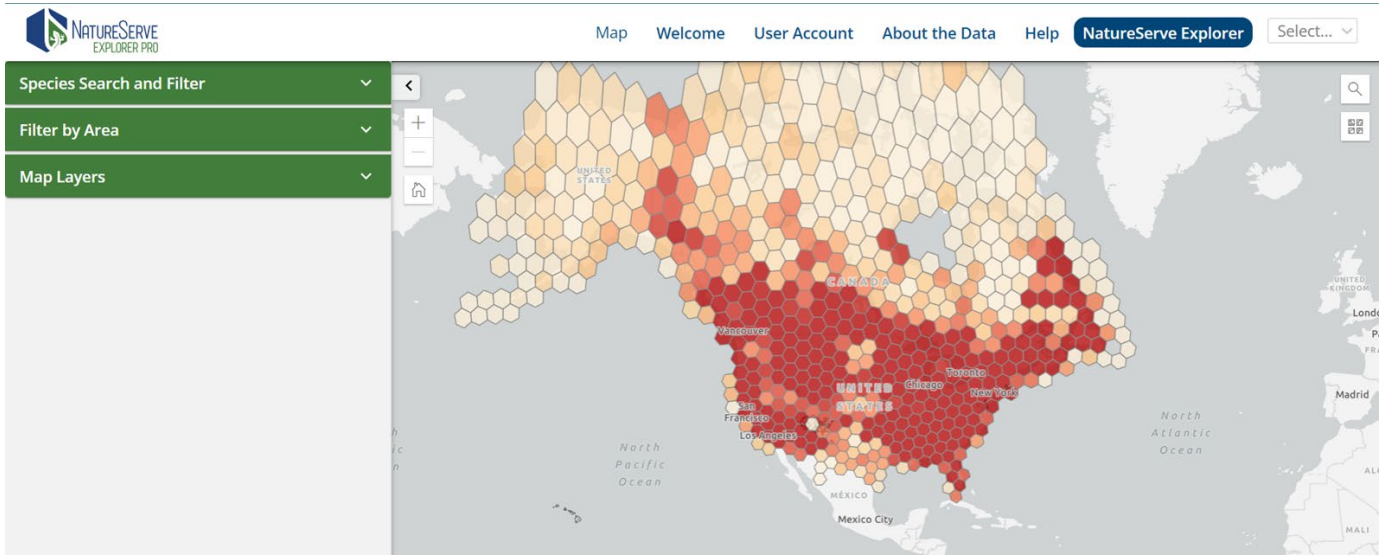

Image Credit: NatureServe https://explorer.natureserve.org/pro/Map

- Species occurrence
- Species distribution

explorer.natureserve.org/pro

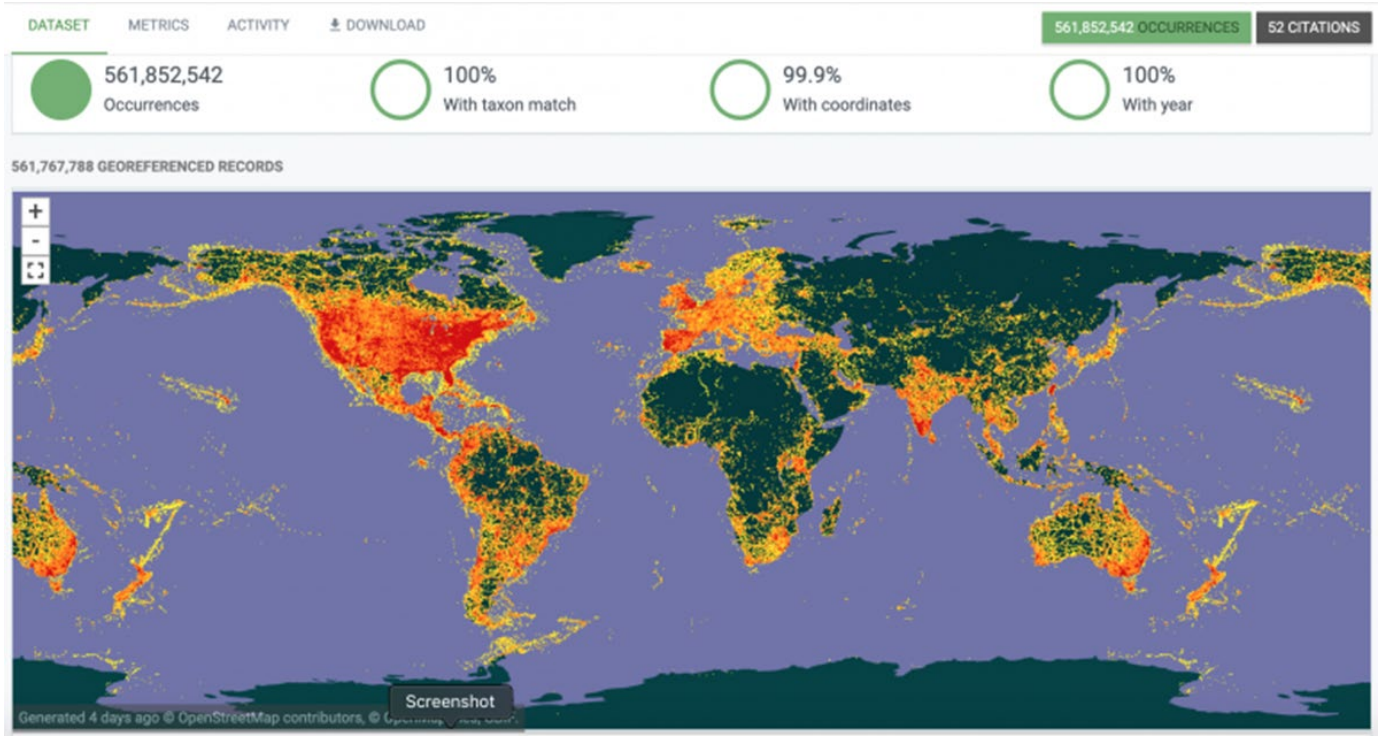

Image Credit: eBird https://ebird.org/camerica/news/ebird-update-brings-gbif-over-1-3-billion-records

Species Data

GBIF Occurrence & Species APIs

- Species occurrence
- Species distribution

https://techdocs.gbif.org/en/openapi/

Image Credit: IUCN Red List https://www.iucnredlist.org/resources/spatial-data-download

Species Data

IUCN Red List Species Range Data

- Species range
- Species distribution
- Species observations

iucnredlist.org/resources/spatial-data-download

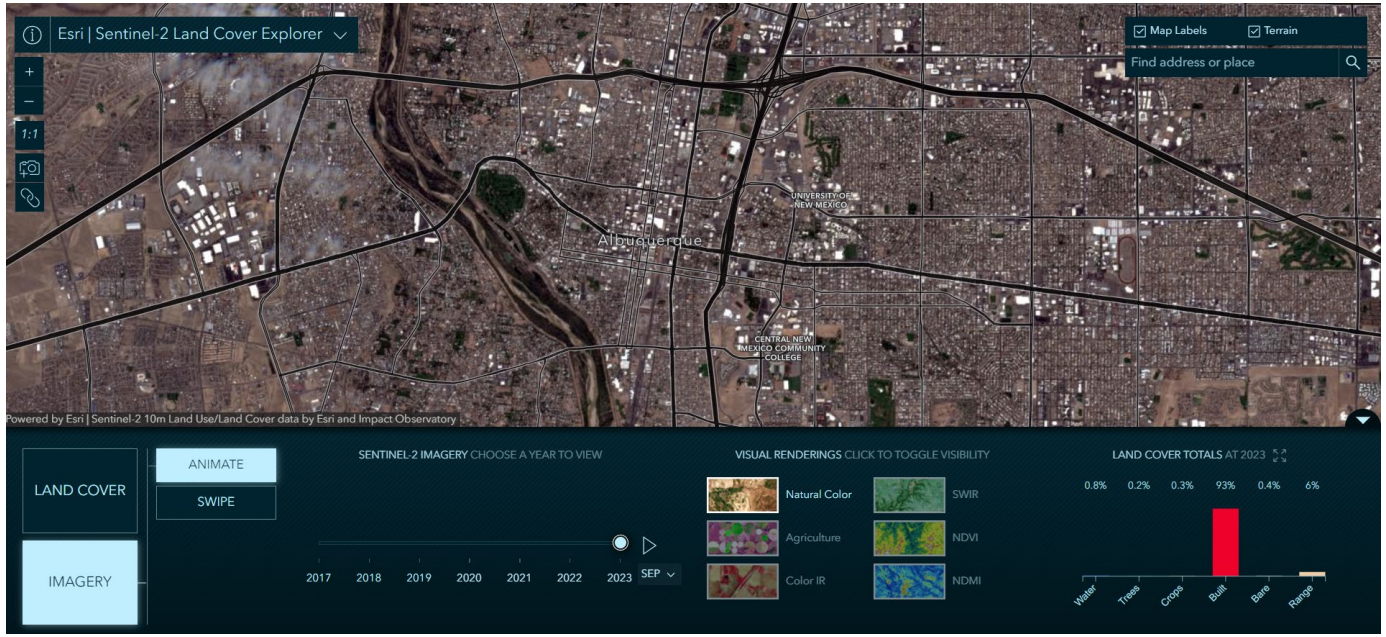

Image Credit: Esri ArcGIS Living Atlas https://livingatlas.arcgis.com/landcoverexplorer/#mapCenter=-106.64243%2C35.08774%2C13.272&mode=step&timeExtent=2017%2C2022&year=2023&showImageryLayer=true&renderingRule=0&month=9

EO Data

Esri Sentinel-2 Explorer

- Multi-year imagery
- Land cover
- NDVI, SWIR, NDMI, IR

livingatlas.arcgis.com/landcoverexplorer

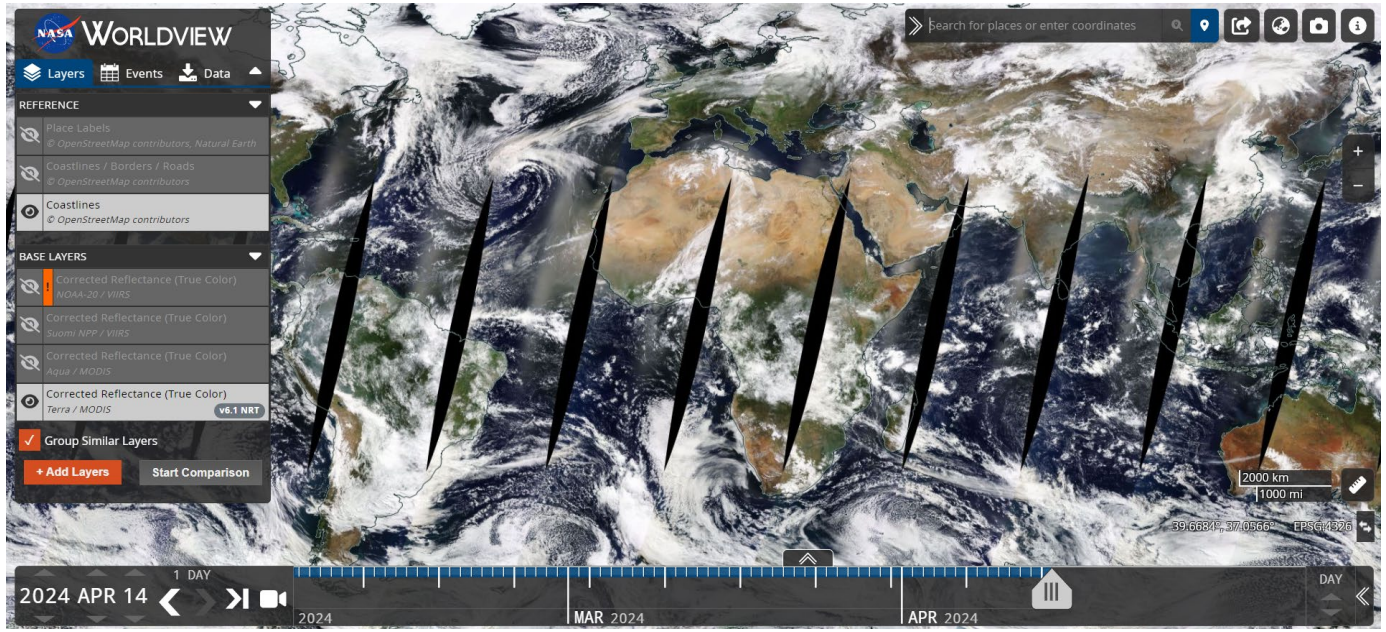

Image Credit: NASA Worldview https://worldview.earthdata.nasa.gov/?v=-138.88141720405915,-63.57842410029713,147.14820852276213,68.07713930391031&t=2024-04-14-T22%3A15%3A22Z

EO Data

NASA Worldview

- Hydrology
- Imagery
- Atmospheric & meteorological data

worldview.earthdata.nasa.gov/

Informing Your Field Effort

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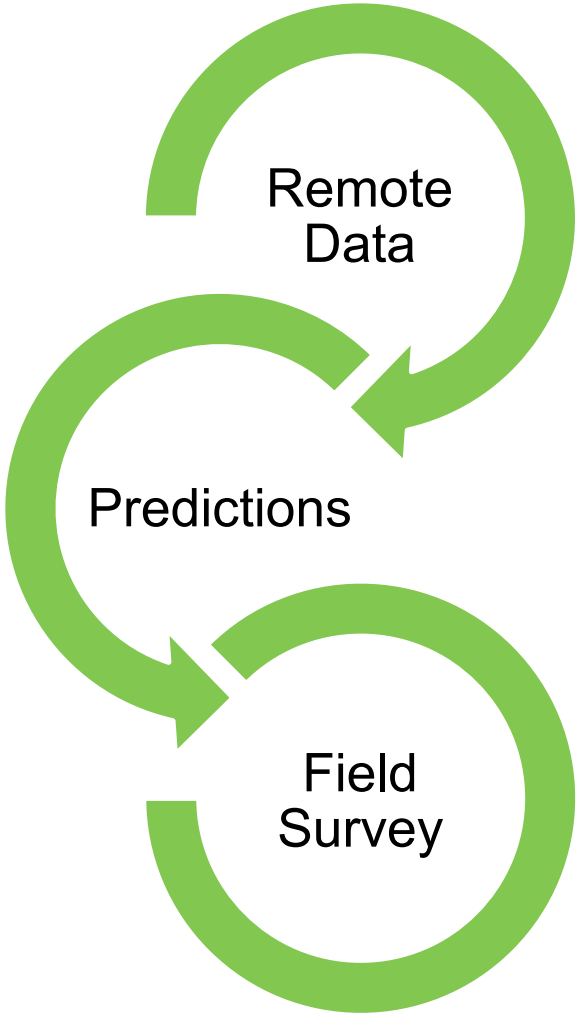
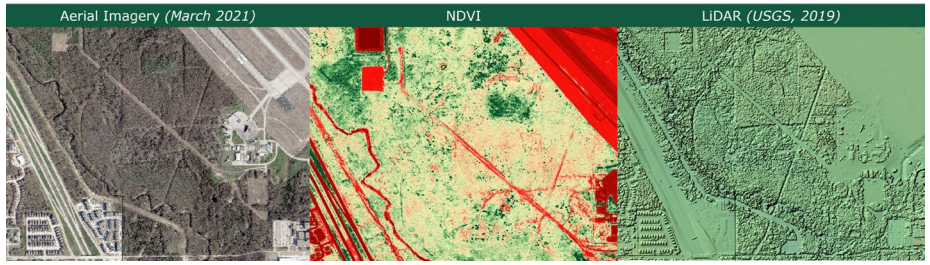
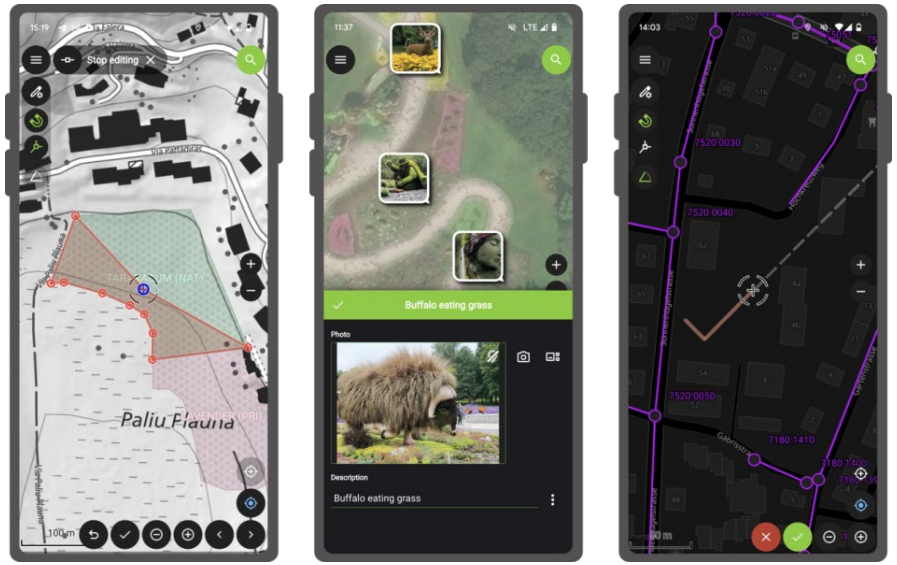
Remote to On-Site

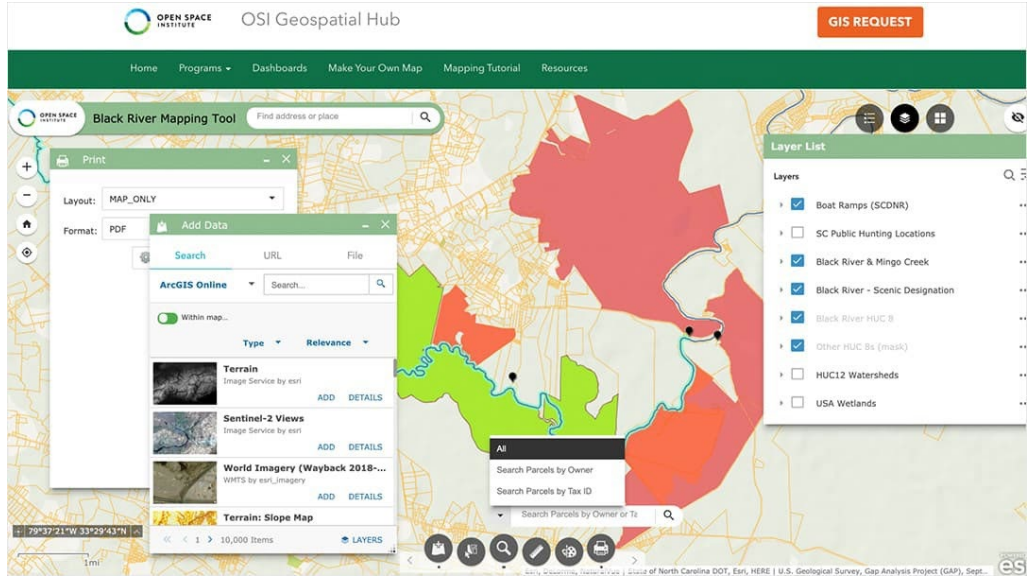




Qfield +
QGIS



ArcGIS Hub,
Field Maps, and
Survey123



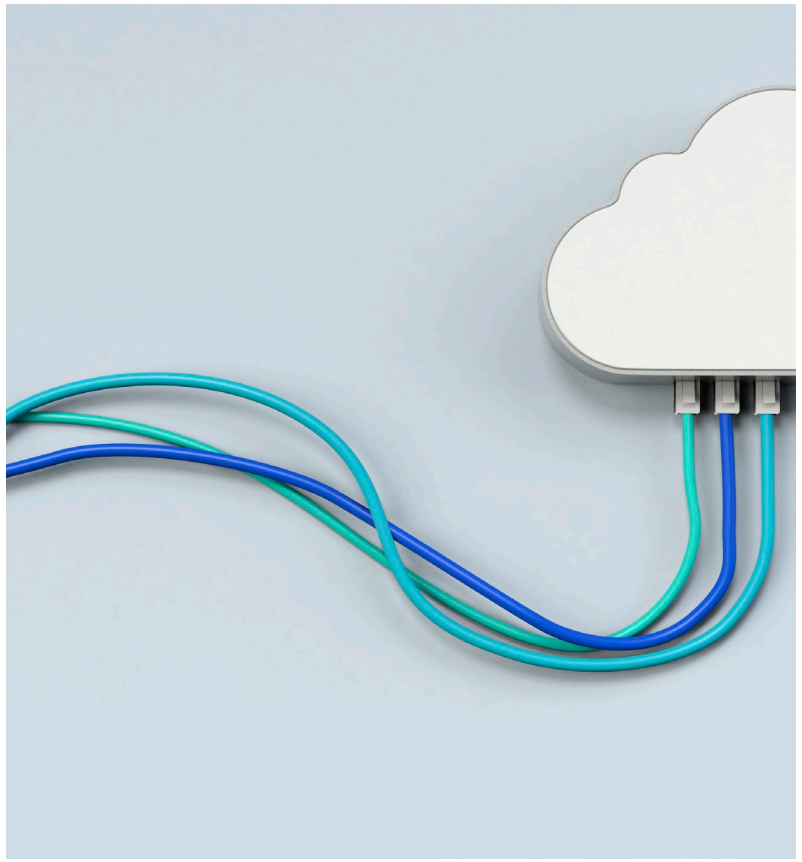
Exhaustive → Efficient

Before

- Full-site visit
- Randomly distributed data collection
- Manual data collection
- Post-field data digitization
- Format and compatibility constraints

After

- Focused visit to key locations
- Optimized location order
- Fast and simple data collection
- No post-field digitization
- Interoperability between formats and programs



Machine Learning, AI, and Other Tools

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For biodiversity assessment

Image Credit: Google Earth Engine https://earthengine.google.com/

Land Cover Analysis

Google Earth Engine (GEE)

Versatile cloud-based platform for data visualization, aggregation, and analysis

earthengine.google.com

AI Tools

Pytorch Wildlife

Image CreditGithub, Microsoft AI for Good Lab
https://camo.githubusercontent.com/52c15bd3ea601fe6ab1238abddb307f651579a8fc169663e50e1304ce2cd9d80/68747470733a2f2f6d6963726f736f66742e6769746875622e696f2f43616d65726154726170732f6173736574732f5079746f7263685f42616e6e65725f7472616e73706172656e74626b2e706e67

A Collaborative Deep Learning Framework for Conservation

github.com/microsoft/CameraTraps

Land Cover Modeling

PEARL

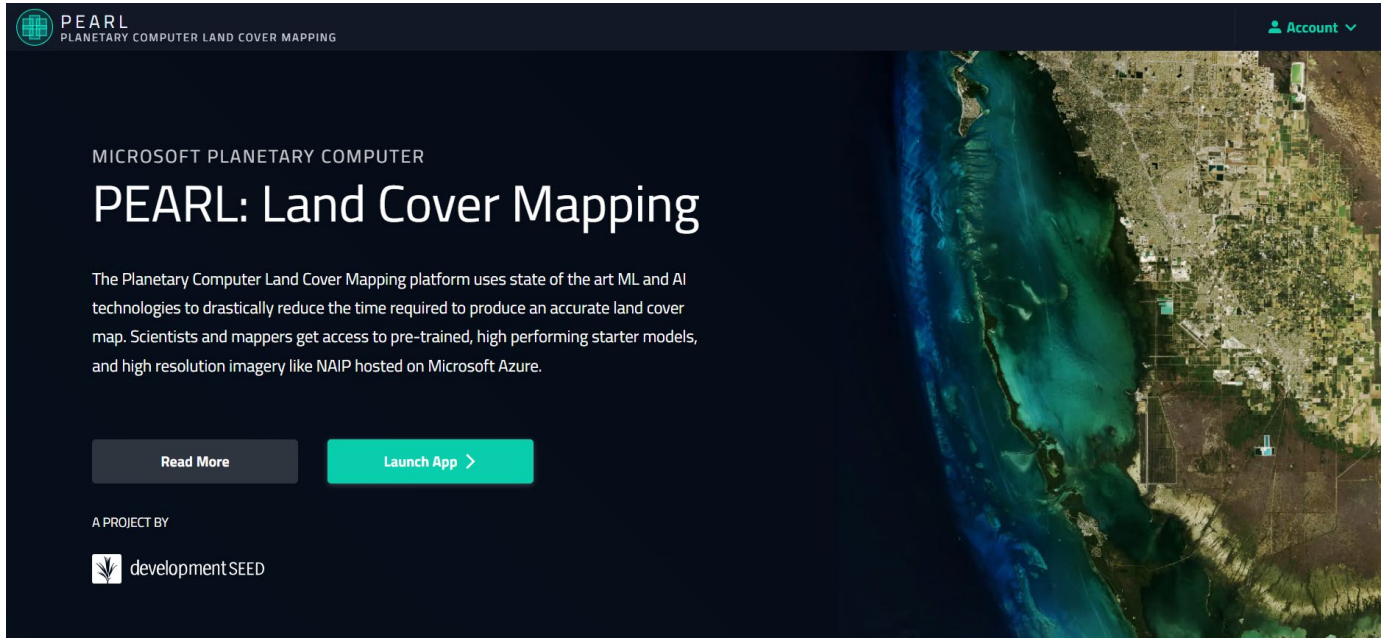

Image CreditGithub, Microsoft AI for Good Lab
https://camo.githubusercontent.com/52c15bd3ea601fe6ab1238abddb307f651579a8fc169663e50e1304ce2cd9d80/68747470733a2f2f6d6963726f736f66742e6769746875622e696f2f43616d65726154726170732f6173736574732f5079746f7263685f42616e6e65725f7472616e73706172656e74626b2e706e67

Using high-resolution imagery with ML + AI to model land cover

github.com/microsoft/CameraTraps

Case Study: Southeast Biodiversity Assessment

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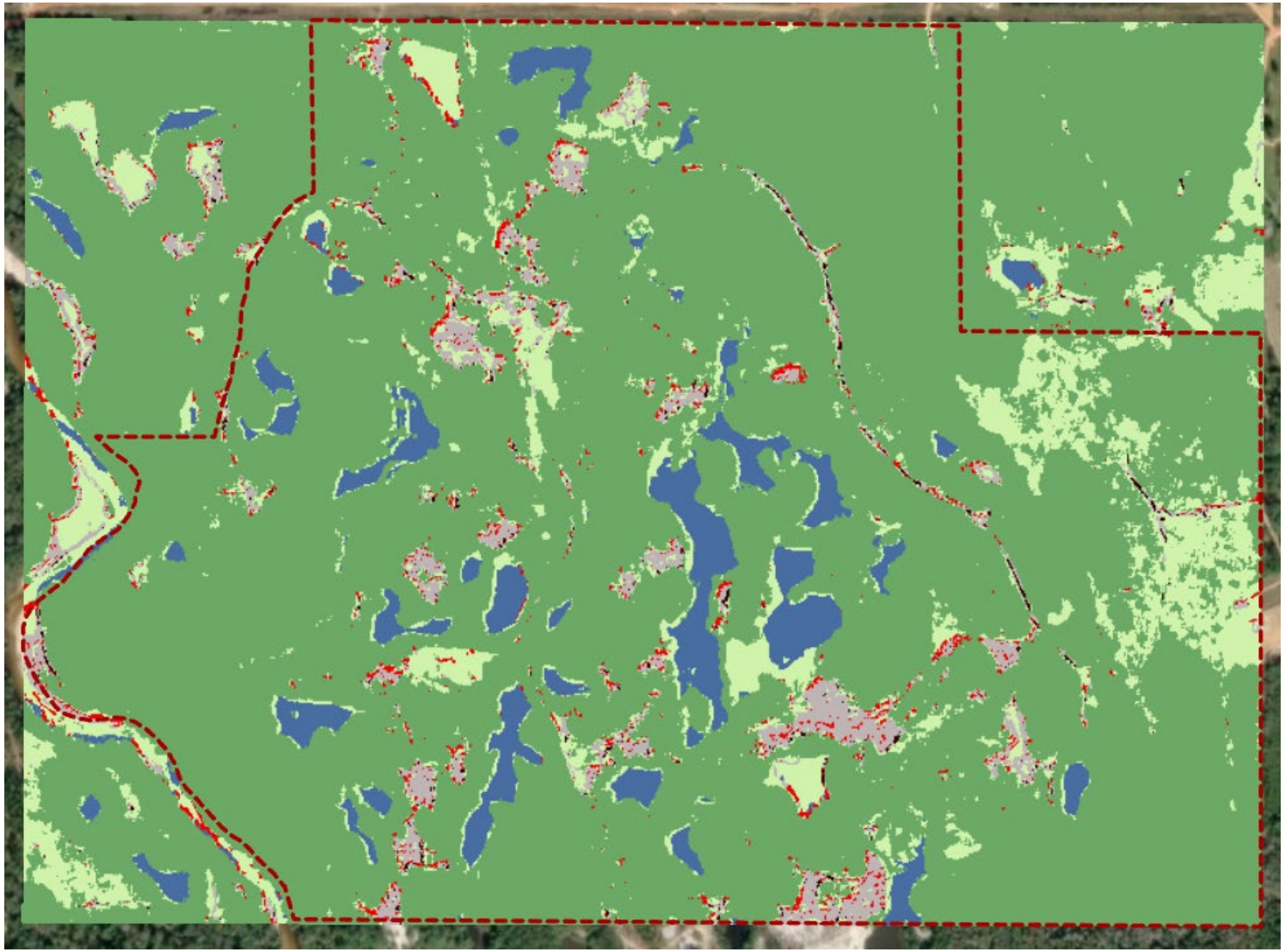
PEARL Output



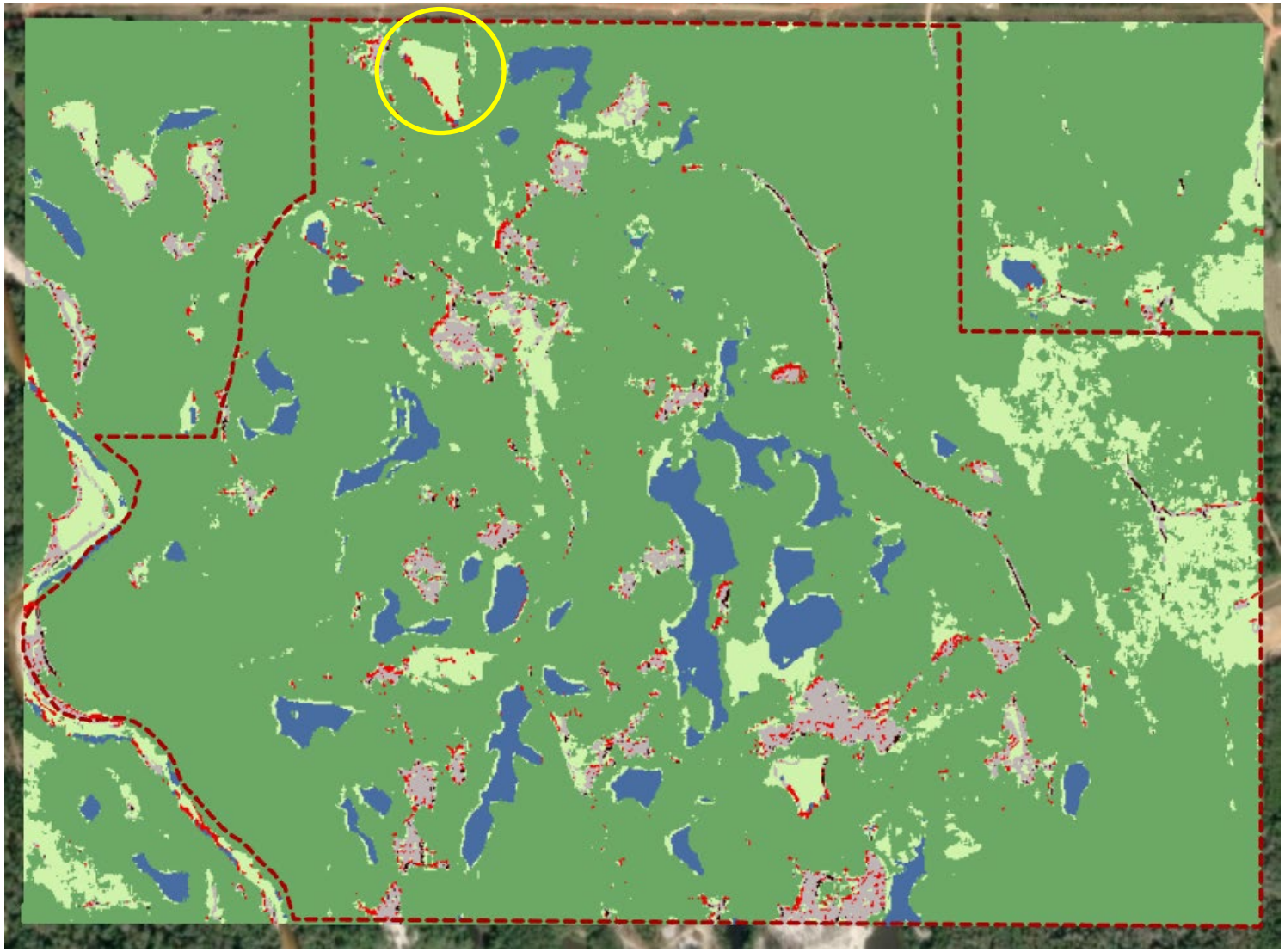
Analysis

CHECKPOINT CLASS DISTRIBUTION

Water	5%
Emergent Wetlands	0%
Tree	81%
Shrubland	0%
Low Vegetation	10%
Barren	0%
Structure	1%
Impervious Surface	3%
Impervious Road	0%

CLASS F1 SCORES

PEARL Output



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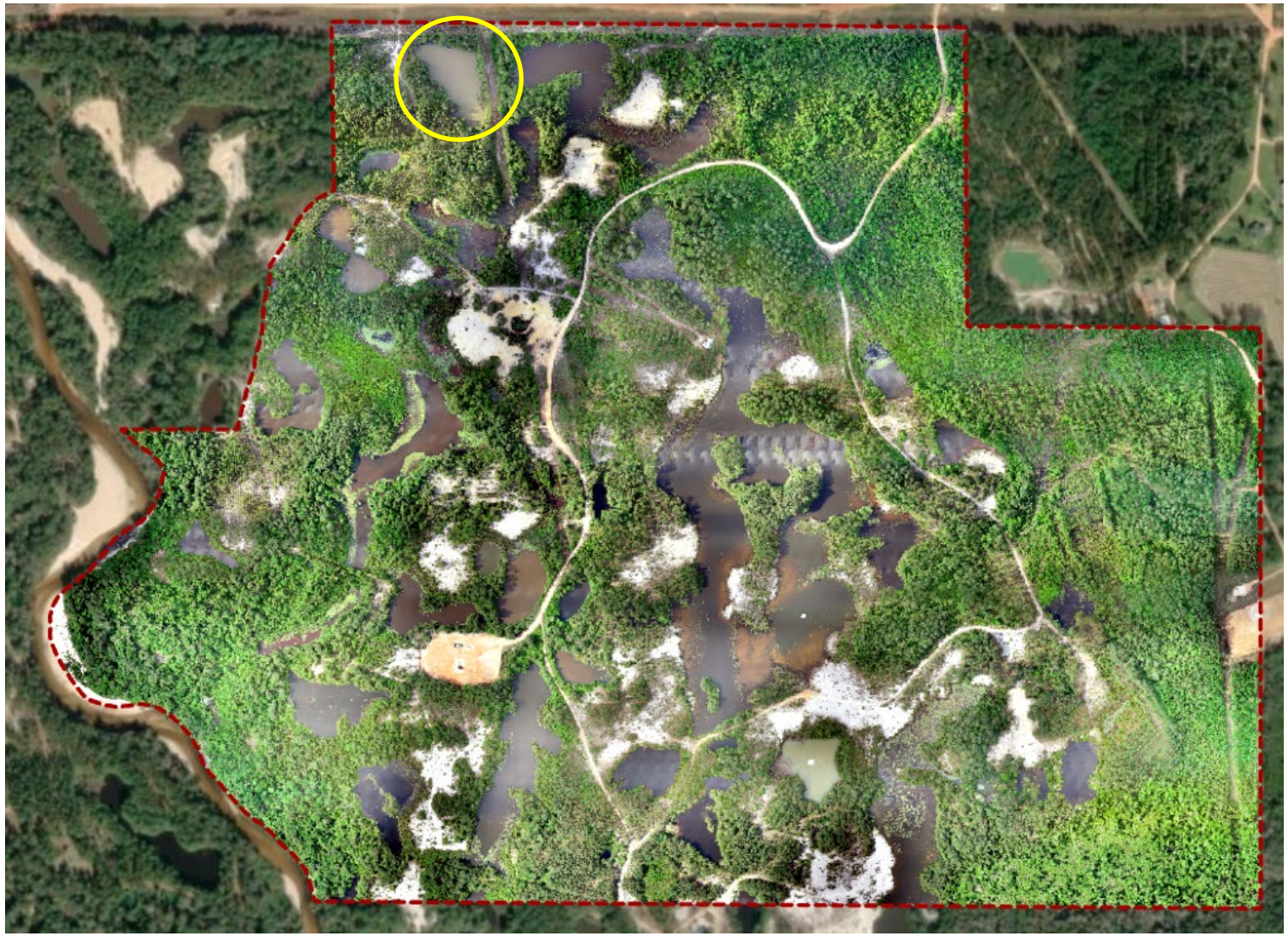
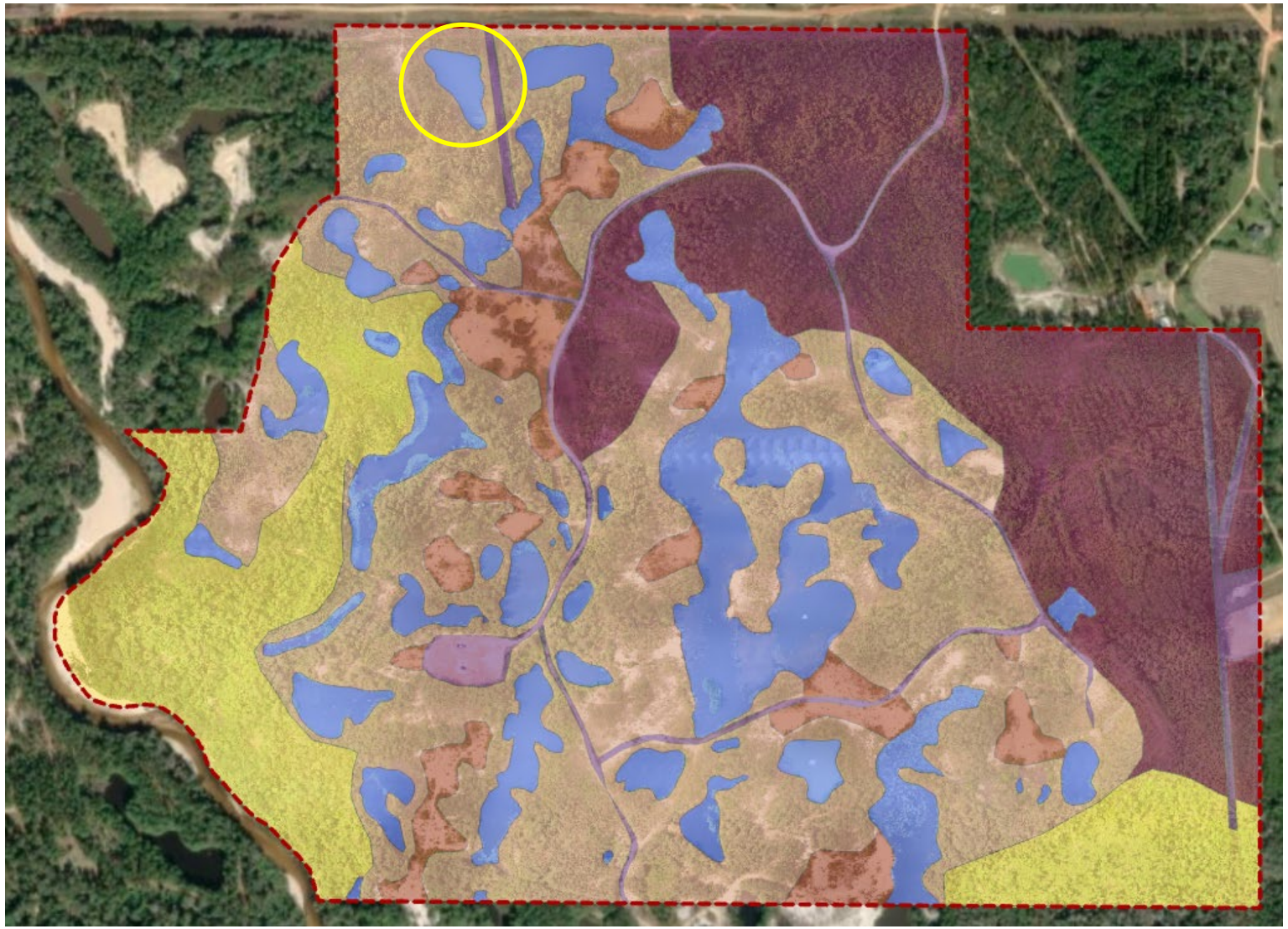
CLASS F1 SCORES

Drone Orthoimagery



PEARL Output



Iterative Training

Model Refinement

- Model built on data from New England
- Re-train using site-specific data across the region
- Save snapshots of the model at different points
- Test and assess accuracy on subsequent sites
  - Look for continued pain points

Result: Habitat prediction model tailored for use in a specific region based on similar data

Conclusion & Implications

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Restoration Implications

- ML + AI tools can be used to extend r emot e sensing and EO data to a greater variety of habitats
- More efficient field work focused on eliminating issues of uncertainty
- Combination of remote and site -specific data can be used to adapt to different s cales of restoration projects
- Variety of data types and customization options from ML + AI tools allow for tailoring to different environments and restoration focuses

Questions?

resanfratello@montrose -env.com

