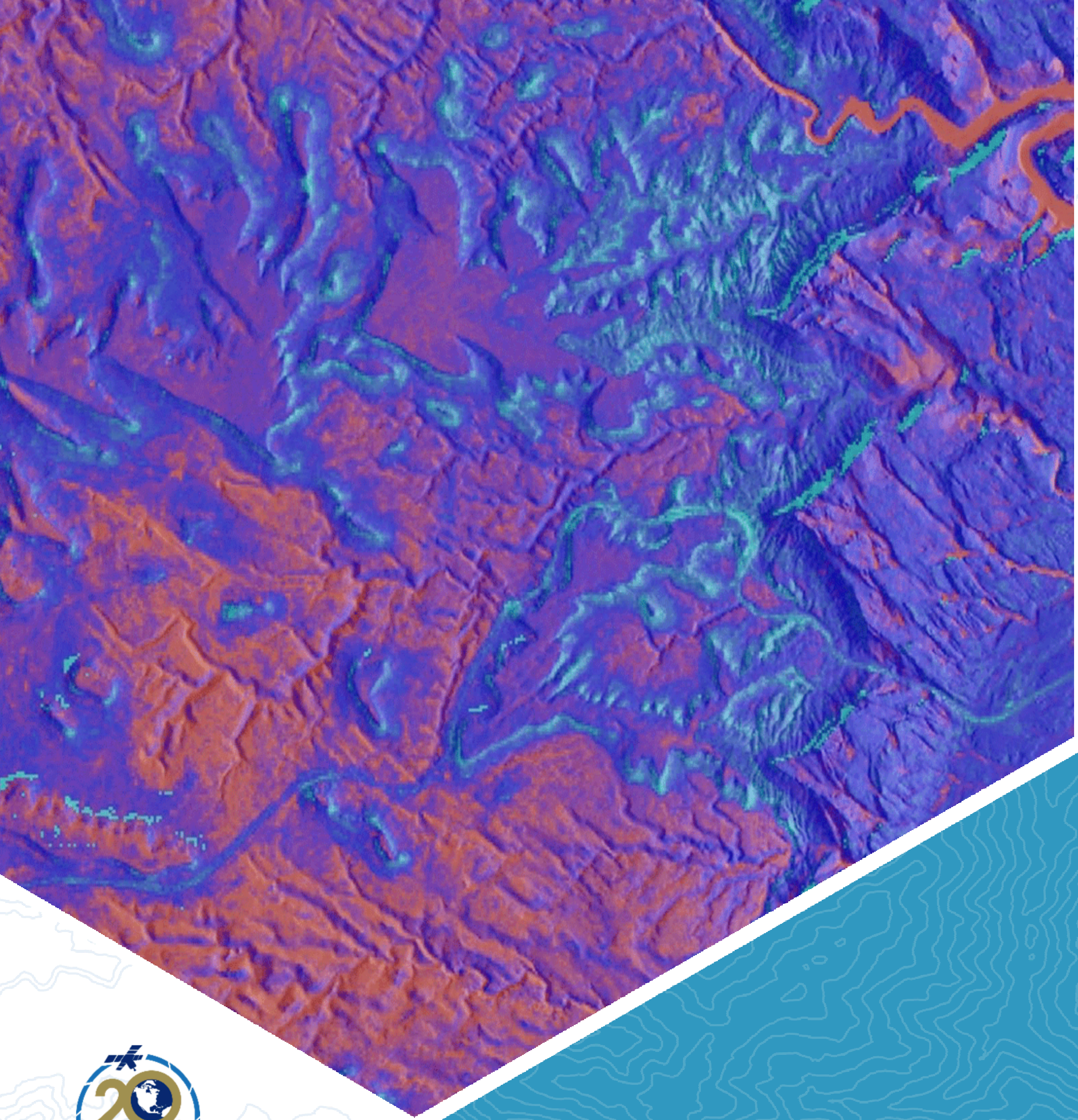

National Aeronautics and Space Administration

Utilizing Landsat to Detect Ephemeral Water Sources in Support of a USGS Feasibility Assessment and Management Strategy of Equids

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Anson Call, Timothy Mayer, & Gary Olds

DEVELOP 20th ANNIVERSARY

Overview

- Wild horses and burros are cultural icons of the American West
- Effective management requires understanding of environmental factors such as cover, forage, and water
- Management areas are located in semi-arid environment
- Surface water in this location is ephemeral
- Goal: Employ NASA Earth observations to identify smaller scale surface water sources




The Sinbad HMA, Utah.
(Image credit: Sarah King, Savannah Summers, Tessa Roos)

Community Concern

Wild burros on the Sinbad HMA, Utah.
(Image Credit: Savannah Summers)

Information is needed for the BLM and USGS to enact informed and effective management decisions.

USGS researcher in Utah.
(Image credit: Jessica Mikenas, USGS)

Shallow ponds in Emery County, Utah.
(Image credit: Michael Freeman, USGS)

Federal agencies support healthy populations of free-roaming burros on the rangelands.

Information regarding water resources for equids in semiarid ecosystems is limited.

Partners

Burros at a watering hole in Sinbad HMA, Utah.
(Image Credit: Savannah Summers)

USGS

Fort Collins Science Center, Ecosystem Dynamics Branch

Dr. Kate Schoenecker, Ecologist

U.S. DEPARTMENT OF THE INTERIOR
BUREAU OF LAND MANAGEMENT

Utah State Office

Gus Warr, BLM Program Manager

BLM and USGS partnered to study burro habitat selection at the Sinbad Herd Management Area

Objectives

1) Testing the feasibility of using NASA earth observations to **detect surface water** at small scales

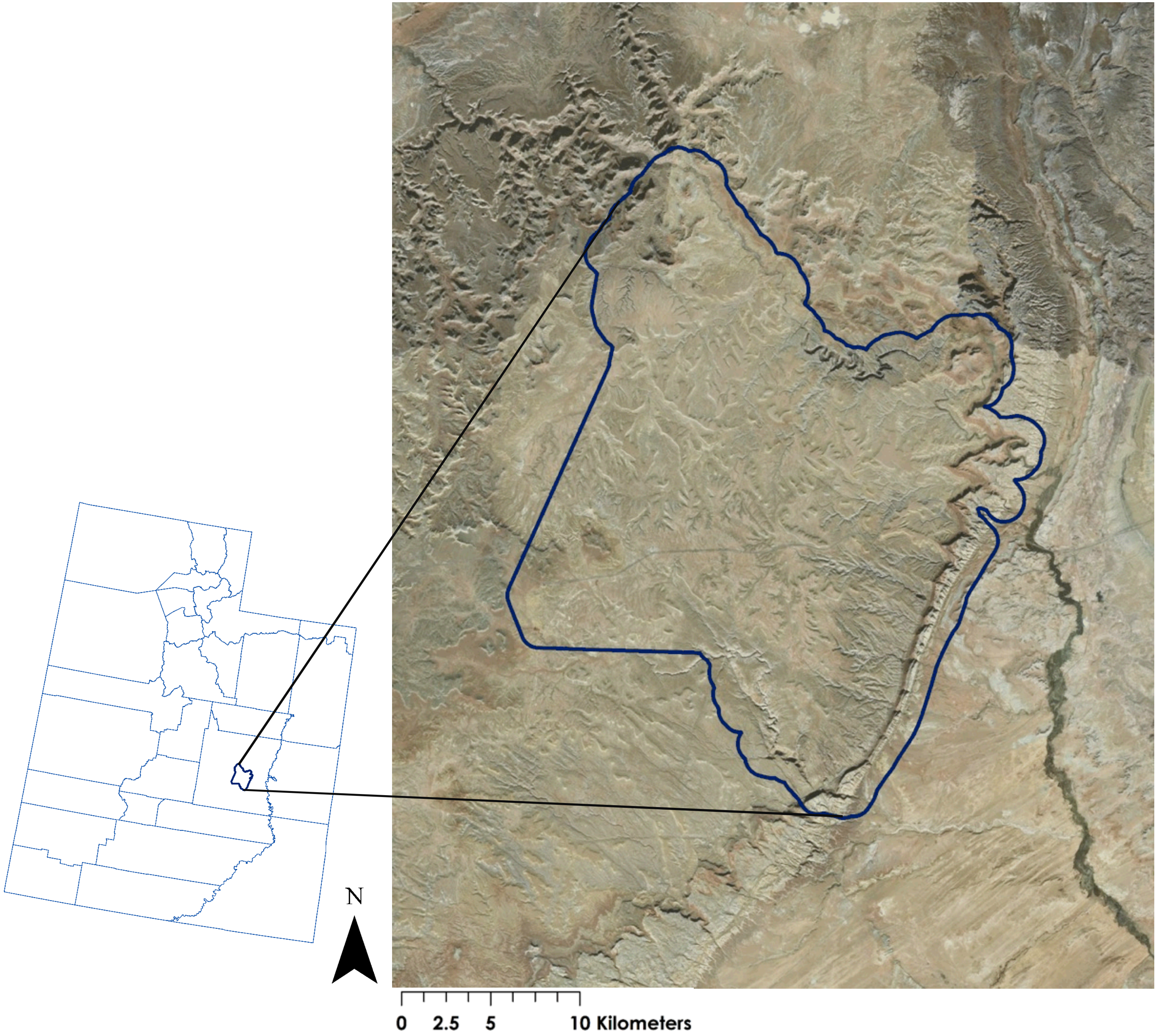
2) Determining the **seasonality** of the available surface water

3) Up-scaling the methods by creating a **toolset** and **tutorial** for use in other regions and organizations

Image Credit: Mike Tweddell, BLM

Study Area

- Sinbad HMA and surrounding area
- Emery County, Utah
- 61,126 ha / 875,071 Landsat pixels
- Semi-Arid with bimodal precipitation regime



Satellites & Sensors

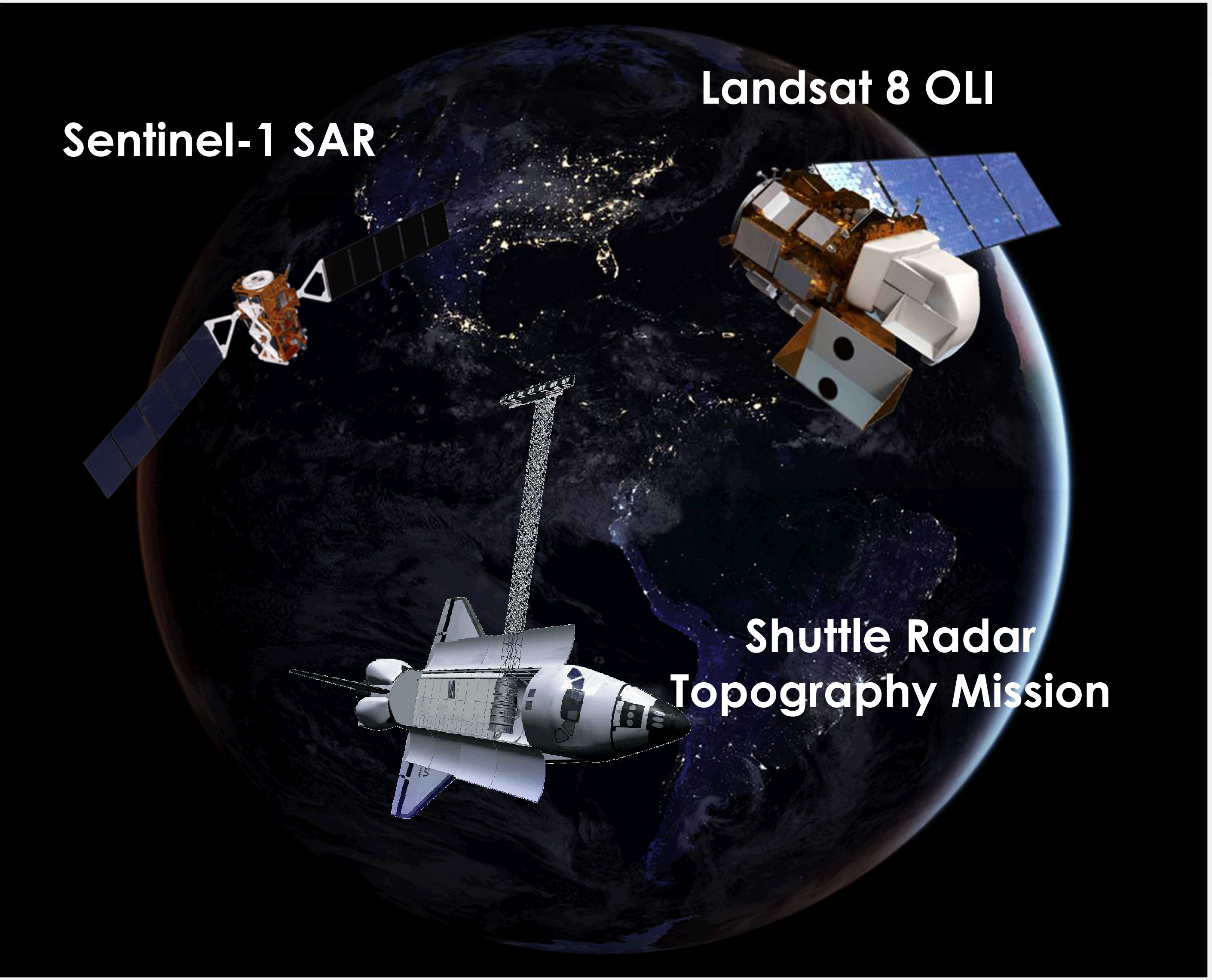
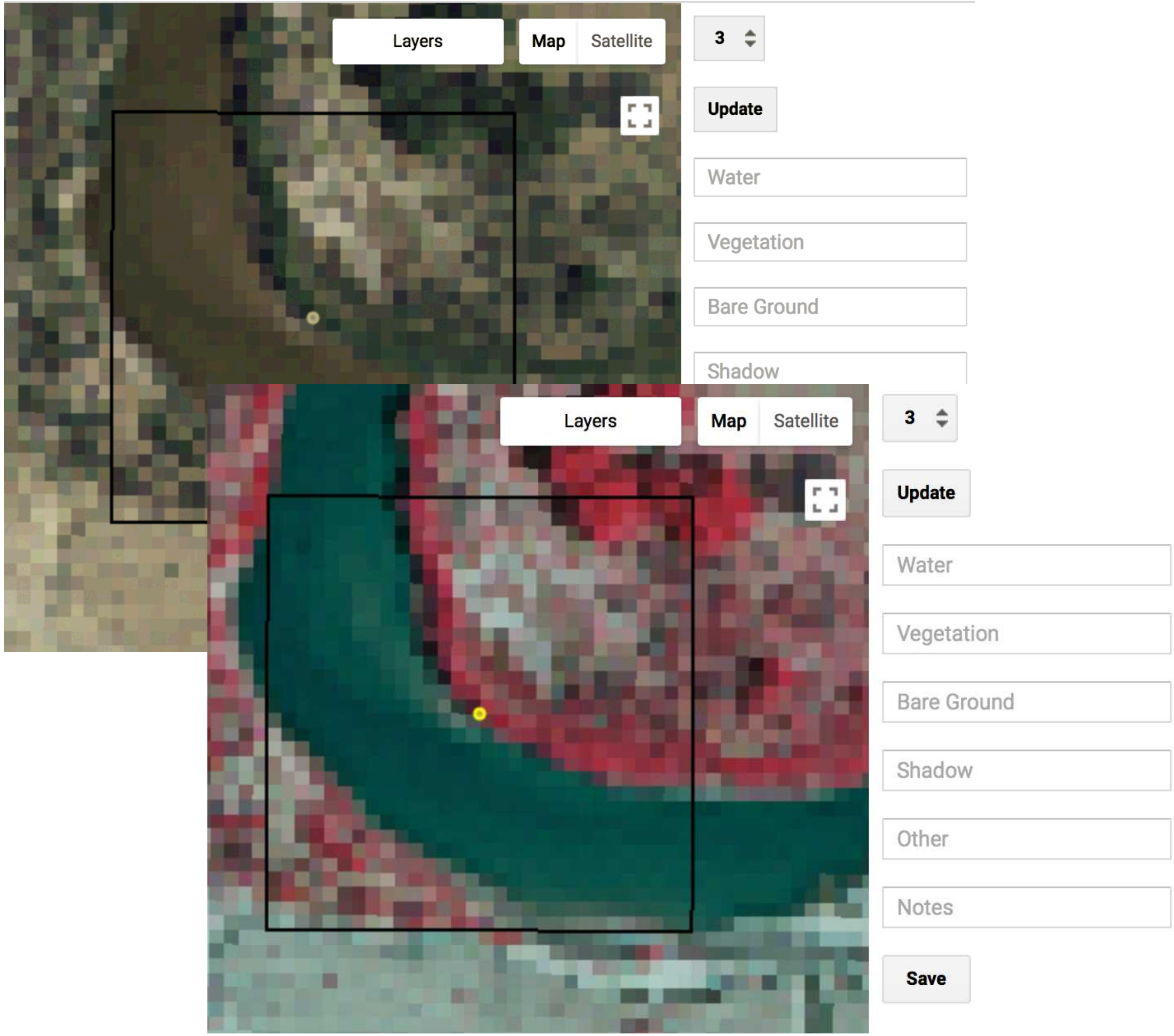


Image Credit: NASA

Platform & Sensor	Data Product	Dates/ Availability	Acquisition Method
Landsat 8 OLI	Collection 1, Tier 1 Raw and TOA Reflectance (Orthorectified) scenes	April 2013 - present	Google Earth Engine
Sentinel-1 SAR	C-band Synthetic Aperture Radar Ground Range Detected, Level-1C	October 2014 - present	Google Earth Engine
STRM	Digital Elevation and Topography Models	June 2015 - present	Google Earth Engine

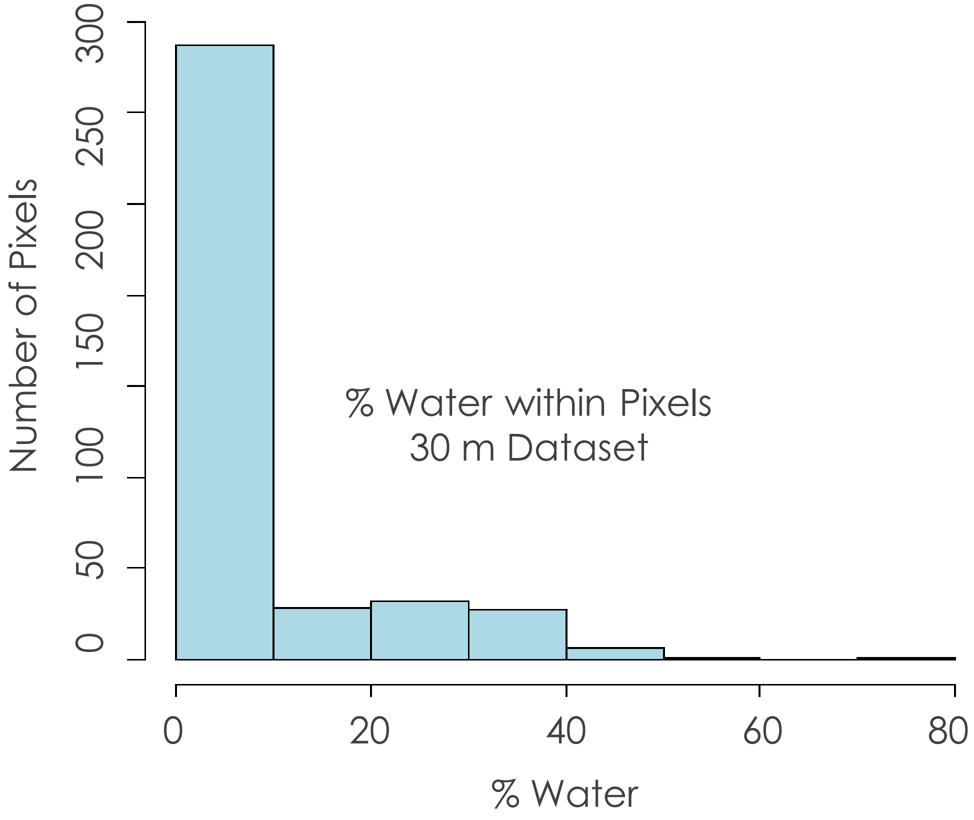
Digital Sampling in Earth Engine

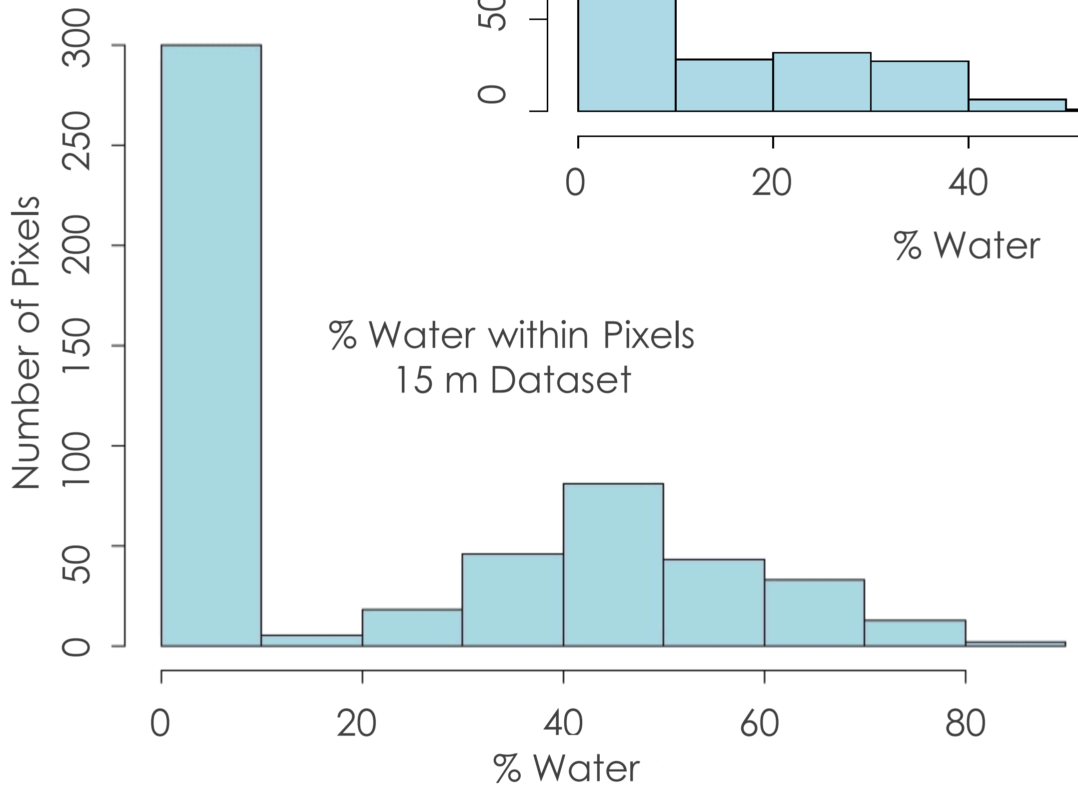


- Two Sampling Efforts
  - 15M Sampling (Panchromatic)
  - 30M sampling
- NAIP imagery to create training data
  - 15M: 299 "dry" points, 242 "wet" points
  - 30M: 226 "dry" points, 206 "wet" points
- Sampling criteria: ocularly survey a single Landsat pixel, estimating cover of 5 different land classes:
  - Water
  - Vegetation
  - Bare ground
  - Shadow
  - Other

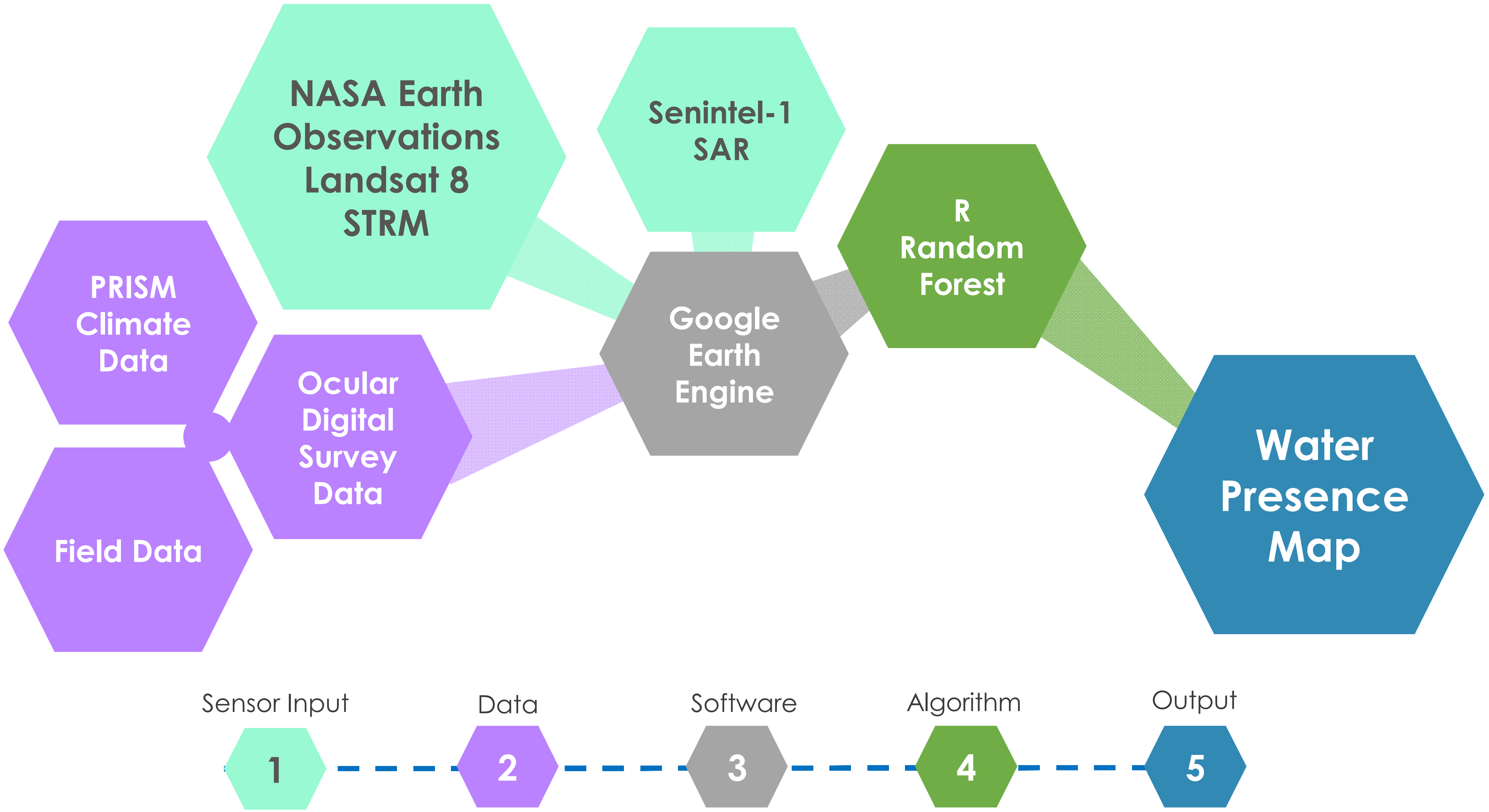
Digital Sampling

- Two Sampling Efforts
- Observed 30M Dataset
  - Highly skewed:
    Few pixels have >40% water
- Observed 15M Dataset
  - Still skewed, but includes more pixels with high percentage of surface water

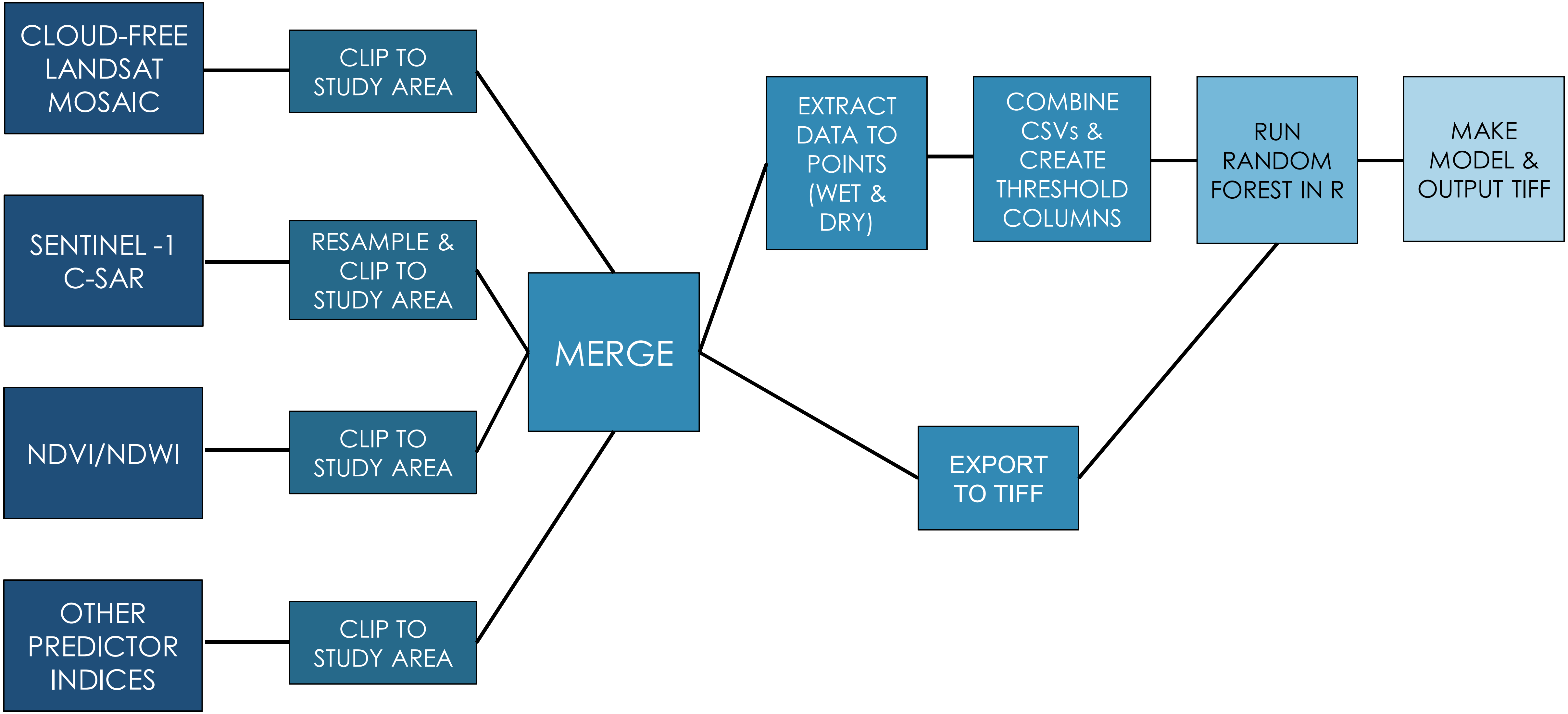


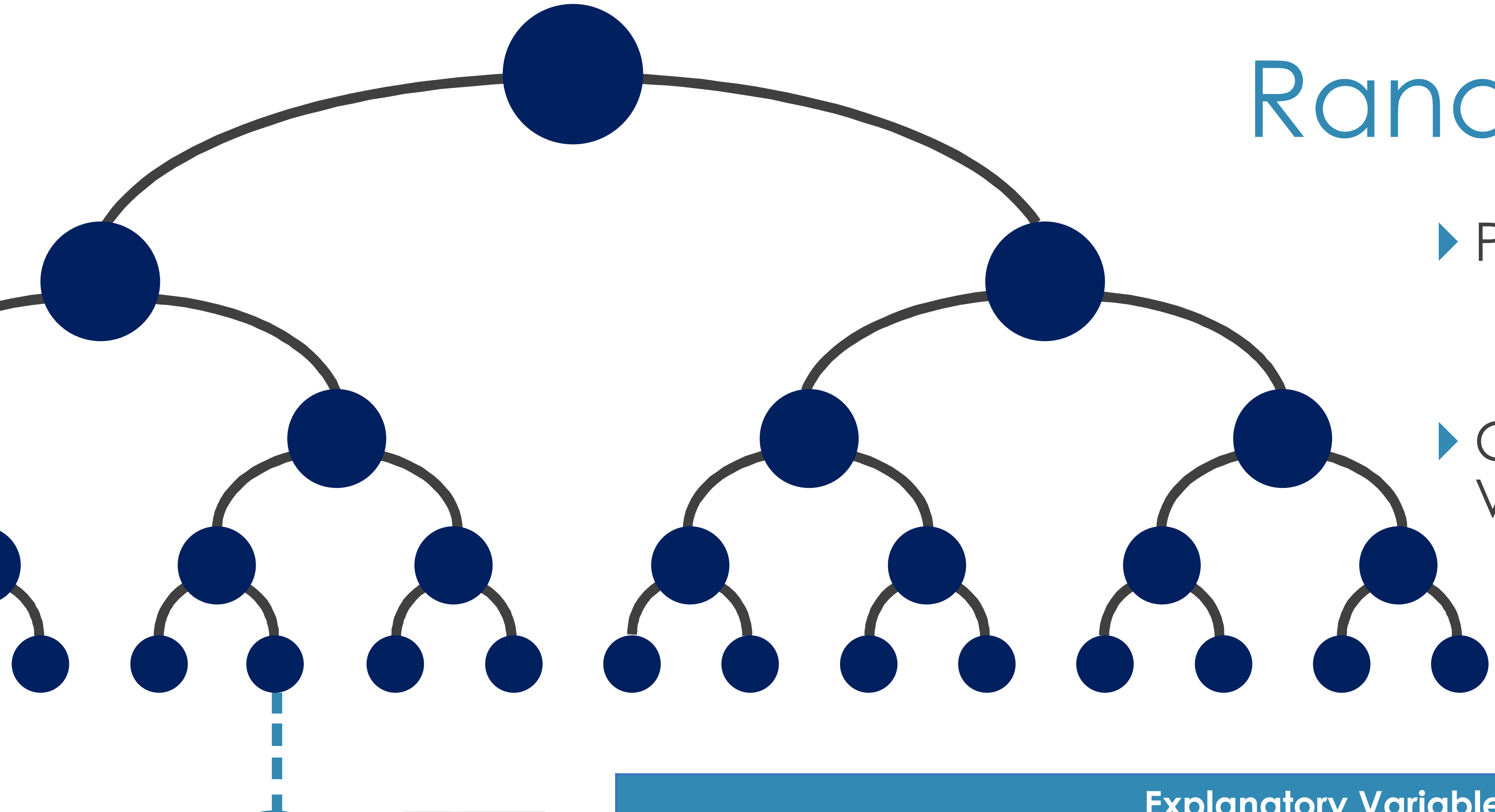


Methodology



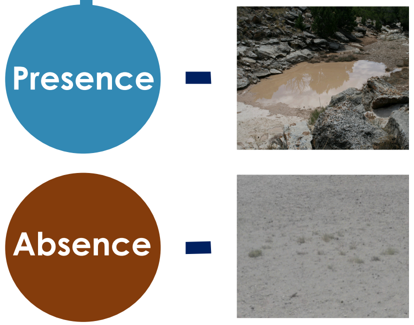
Modeling Workflow





Random Forest

- Process
  - Rank variables using VSURF
  - Covariate correlation plot
- Criteria for Removing Variables
  - Correlated above 0.8
  - Remove least-predictive first

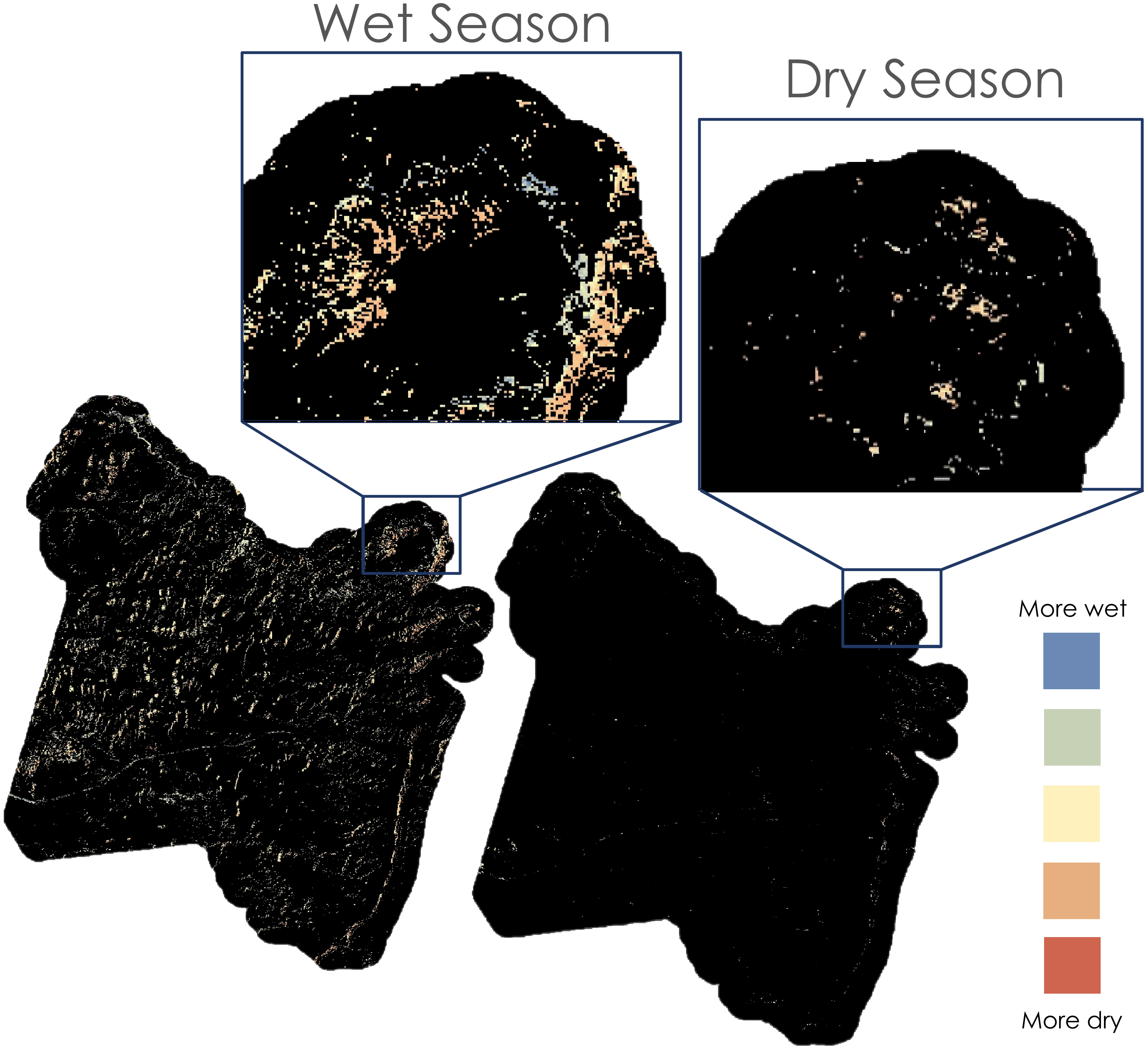


Explanatory Variables			
BLUE	SWIR 1	NBR	Sentinel-1 VV
GREEN	SWIR 2	Tassled Cap B,G,W	Slope
RED	NIR	NDMI	Eastness
PAN	NDVI	GRVI	Northness

Results

Landsat 30m Model

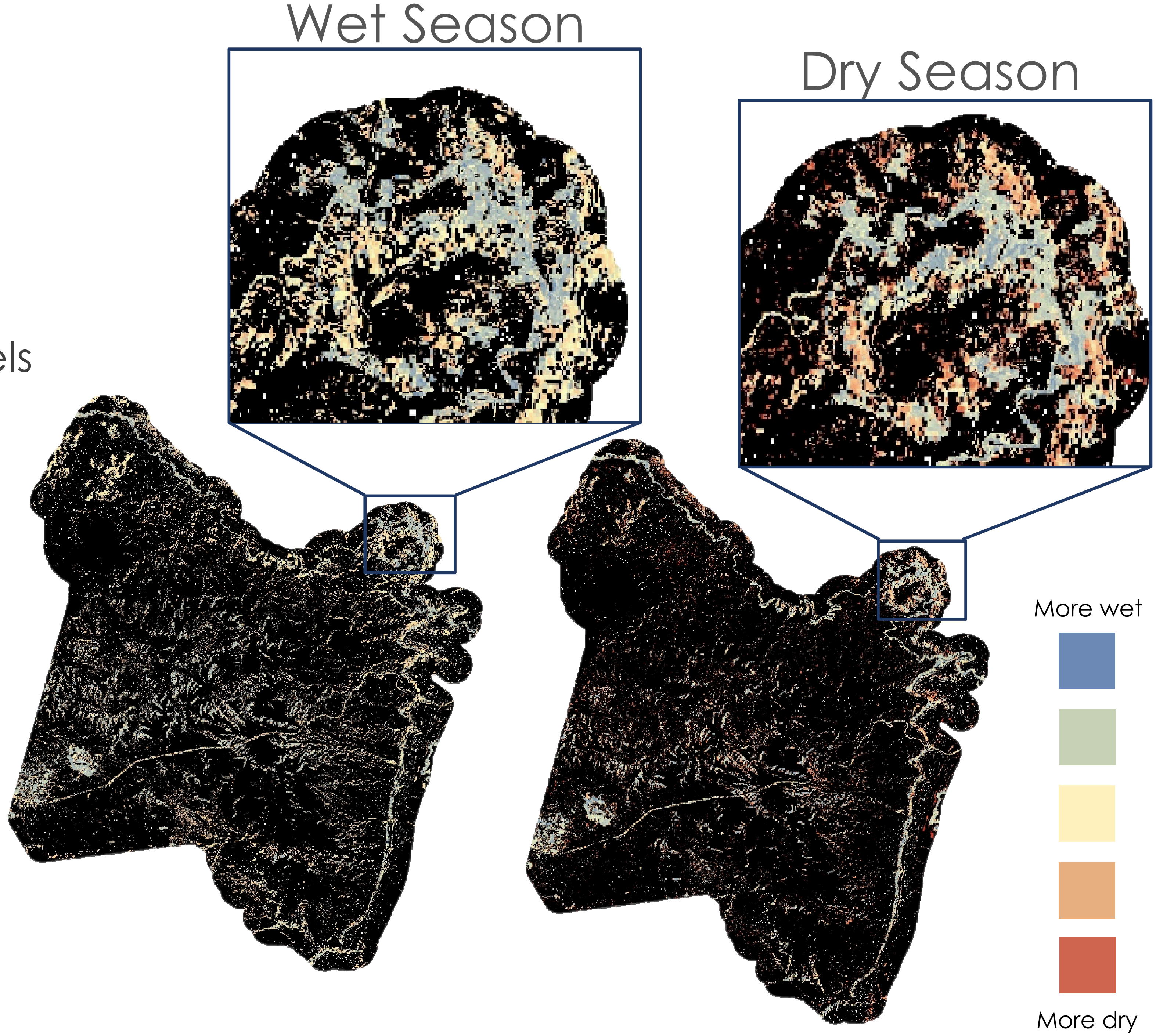
- Two Step Classification models
- Evaluation Metrics
  - Kappa: 0.3284
  - AUC: 0.6347
  - Model Accuracy: 90.7407%
  - Users Accuracy: 30.0%
  - Producer's Accuracy: 50.0%
  - Specificity: 0.3
  - Sensitivity: 0.9694



Results

Landsat 15m Panchromatic Model

- Two Step Classification models
- Evaluation Metrics
  - Kappa: 0.8803
  - AUC: 0.7655
  - Model Accuracy: 94.0850%
  - User's Accuracy: 94.5%
  - Producer's Accuracy: 92.2%
  - Specificity: 0.9454
  - Sensitivity: 0.9373



Conclusions

- Panchromatic model:
  - Higher resolution
  - Improved training effort
  - Provided markedly improved reflectance models
  - More accurately displays ephemeral surface water in distinct seasons
- This may be employed to inform habitat selection models

Image credit: Anson Call

Errors & Uncertainties

- Potential significant influence of mixed pixel training data set
  - Misclassified pixels could result in skewed model results

- NAIP availability resulted in training data sets from the "Dry" season
  - Model was projected to a typical "Wet" season scene

Future Work

- Explore more predictor variables
- Potentially expand the study area to include more HMA's
- Collection of Remote Sensing oriented *in situ* data by teams in the field
  - For "Wet" and "Dry" periods
- Sentinel-2 cross sensor implementation for increased resolution
- Focusing on locations with ample LiDAR data may be useful


Credit: Savannah Summers

Acknowledgements

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