



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

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- 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. (Credit: Sarah King, Savannah Summers, Tessa Roos)

Community Concern



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

Federal agencies support healthy populations of freeroaming burros on the rangelands. Information is needed for the BLM and USGS to enact informed and effective management decisions.



USGS researcher in Utah. (Credit: Jessica Mikenas, USGS)



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

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







USGS

Dr. Kate Schoenecker, ecologist

BLM

- Gus Warr, BLM Program Manager
- BLM and USGS partnered to study <u>habitat selection</u> of burros on the Sinbad Herd Management Area

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

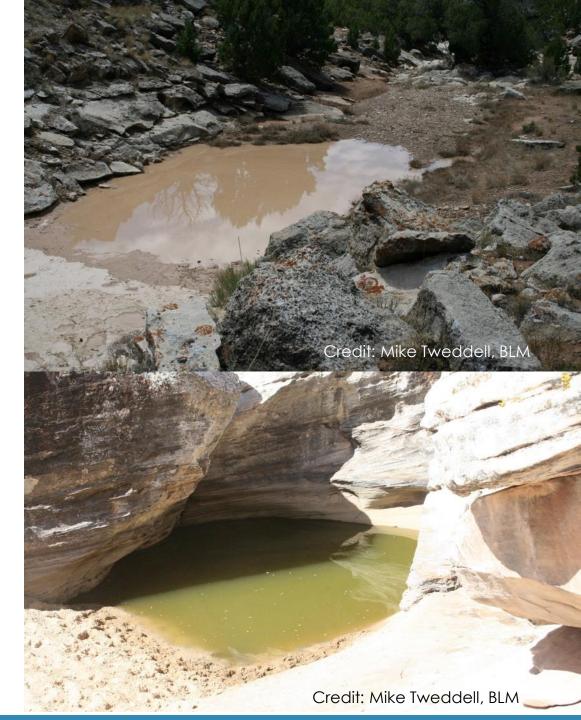


Our study objectives include:

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

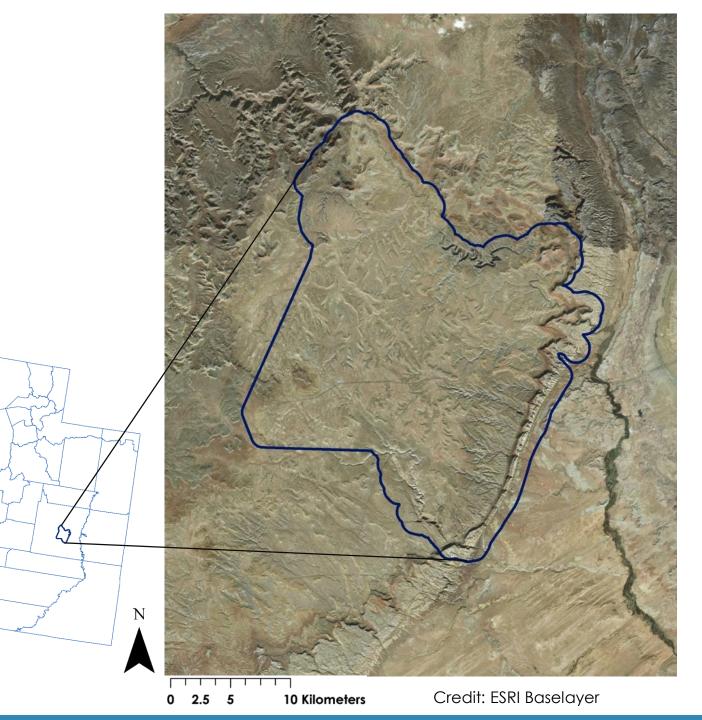
2) Determine the **seasonality** of the available surface water

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





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

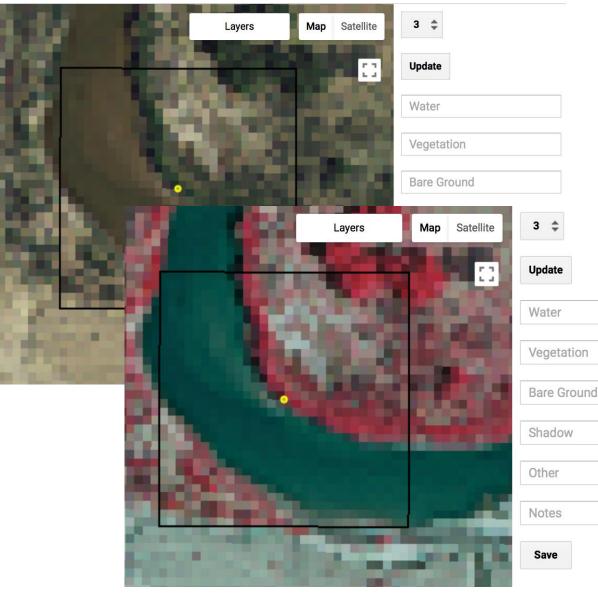






Platform and Sensor	Data Product	Dates/ Availability	Acquisition Method
Landsat 8 OLI	Collection 1, Tier 1 Raw and TOA Reflectance (Orthorectified) scenes	April 2013 - present	Google Earth Engine
Sentinel-1 SAR	C-band Synthetic Aperture Radar Ground Range Detected, Level- 1C	October 2014 - present	Google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

Used 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 Effort

- Two Sampling Efforts
- Observed 30M Dataset
 - Highly skewed: few pixels have

300

250

200

150

100

50

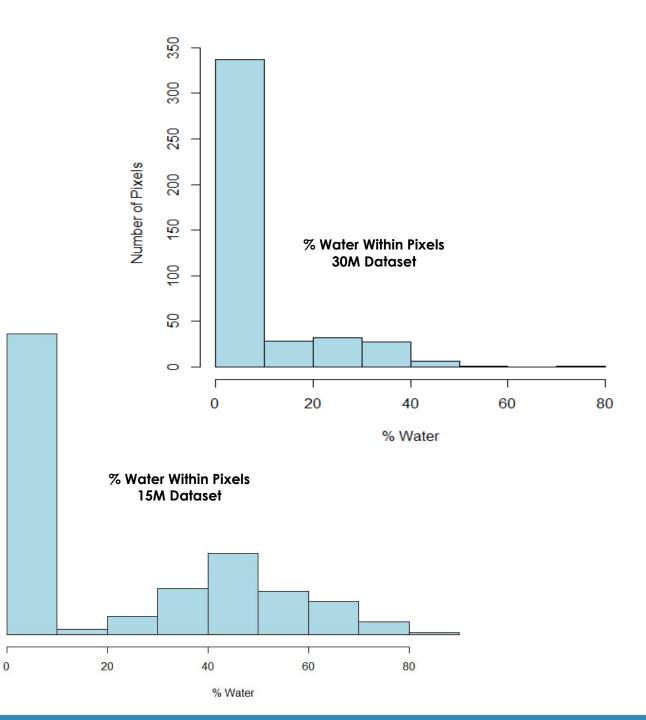
0

Number of Pixels

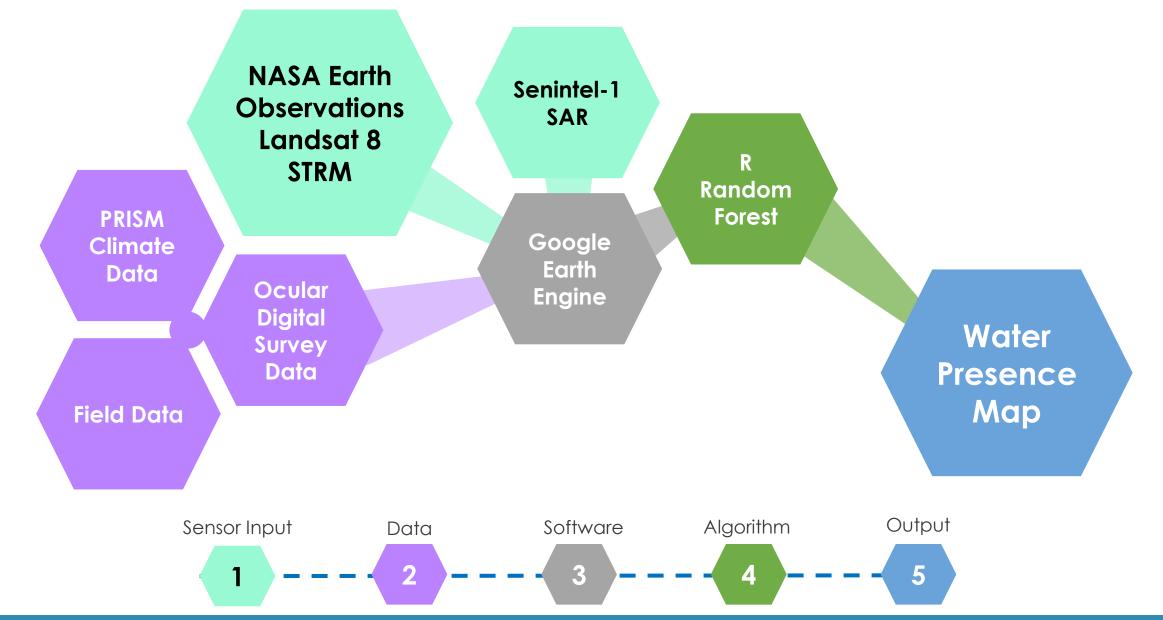
>40% water

- Observed 15M Dataset
 - Still skewed, but includes more
 - pixels with high percentage of

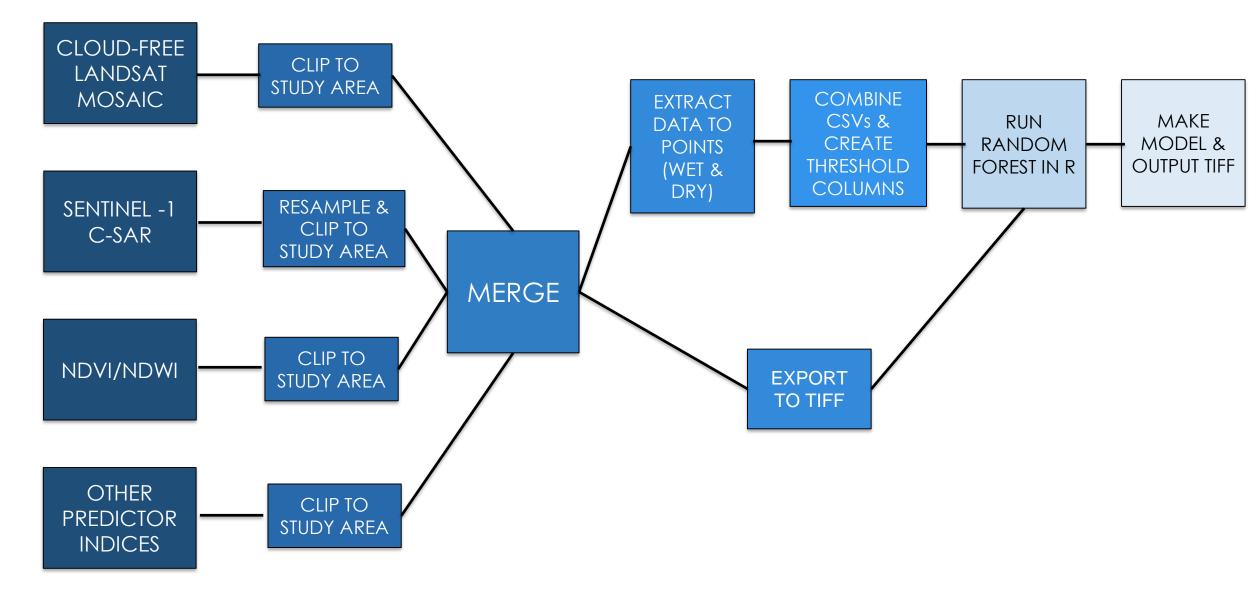
surface water







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	

Presence

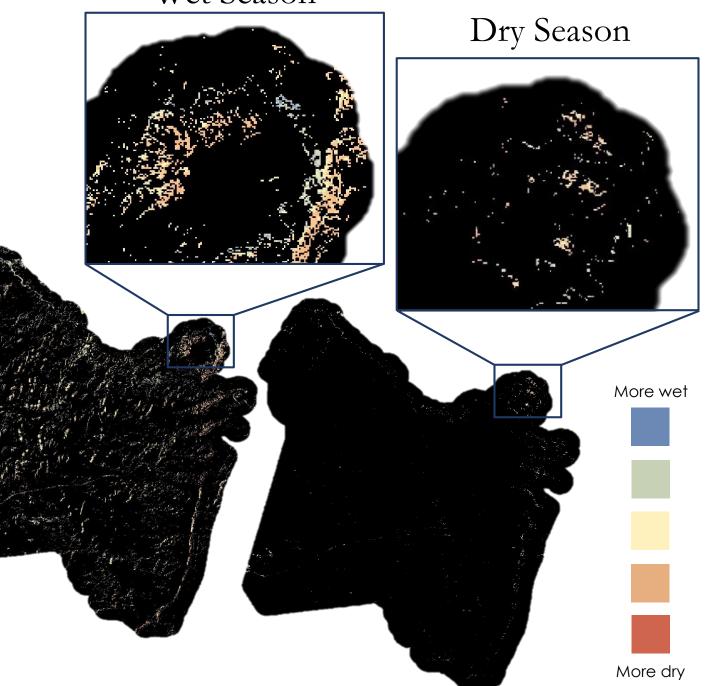
Absence



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

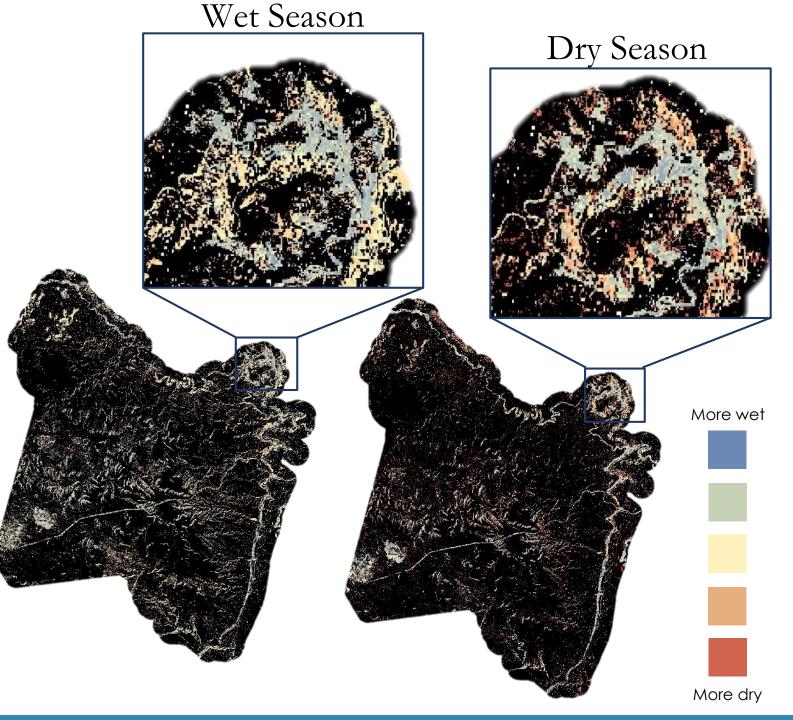






Landsat 15m Panchromatic Model

- 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





- 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





Potential significant influence of

mixed pixel training data set.

- Miss classified 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.



Credit: Anson Call



- 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 as well





- Dr. Paul Evangelista (Natural Resource Ecology Laboratory, Colorado State University)
- Dr. Catherine Jarnevich (USGS, Fort Collins Science Center)
- Nick Young (Natural Resource Ecology Laboratory, Colorado State University)
- Dr. Kate Schoenecker (USGS, Fort Collins Science Center)
- Dr. Sarah King (Ecosystem Science and Sustainability, Colorado State University)

This material contains modified Copernicus Sentinel data (2017), processed by ESA



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