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Vegetation Mapping in a Dryland Ecosystem Using Multi-Temporal Sentinel-2 Imagery and Ensemble Learning

Josh Enterkine
Boise State University

Megan Gallagher
Boise State University

Nancy Glenn
Boise State University

Lucas Spaete
Boise State University

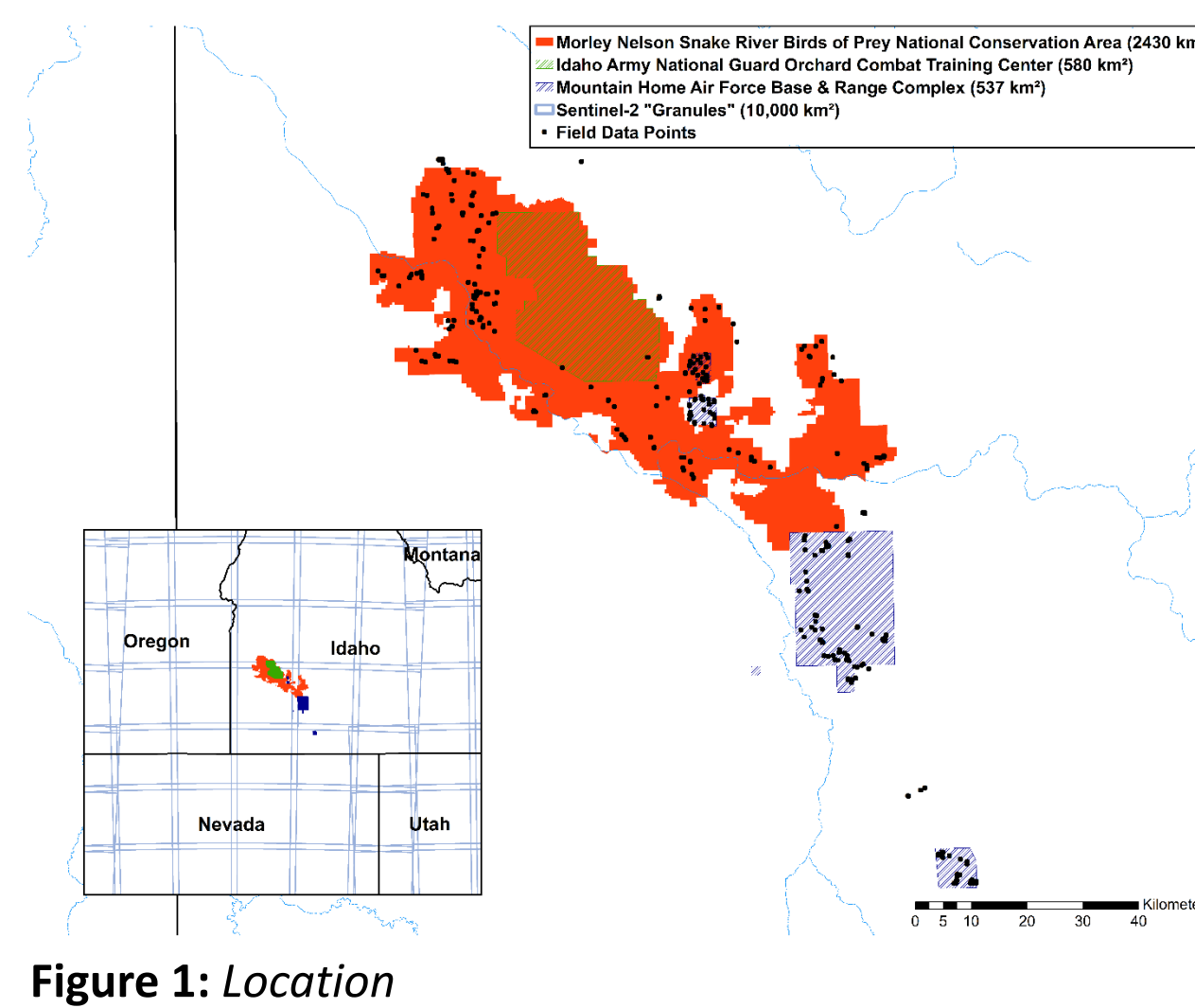
1. Background

Motivation:

- Mapping vegetation in dryland ecosystems is important for conservation and restoration efforts, rangeland management, and fire prediction.
- Relatively low fractions of vegetative cover (e.g. shrubs and bunchgrasses) make mapping and quantifying vegetation in dryland ecosystems challenging.
- New imaging systems, machine learning algorithms, and powerful computing platforms enable large-scale remote sensing studies of vegetation cover and phenology that can be quickly updated or modified.

Location:

- Our field study area is a National Conservation Area (NCA) that supports North America's highest density of nesting raptors.
- The NCA multi-use area has military training, grazing, power generation, and recreation
- Elevation ranges from 687 to 1111 m above sea level
- Annual precipitation is 0-20 cm in SW, to 30-36 cm in NE



Data:

- We used the following data in this study:
 - 8 cloud-free dates of Sentinel-2 satellite imagery (Table 1)
 - 34 spectral indices for each date (e.g. *Normalized Difference Vegetation Index*, or 'NDVI')
 - 215 field data 'signature plots' of vegetation and land cover types (Figure 6 in 3. Results) for training and validation

Table 1: Imaging Dates with < 10% Cloud Cover

2016-03-30
2016-04-19
2016-06-28
2016-07-18
2016-07-28
2016-09-16
2016-09-26
2016-11-05

2. Methods

Processing Environment: Google Earth Engine

- Google Earth Engine (GEE) is a cloud-based platform developed to access and analyze remote sensing and other large-scale spatial data. (Figure 2)
- JavaScript or Python API
- Google servers host data, process script
- Free for research, education, and non-profit use

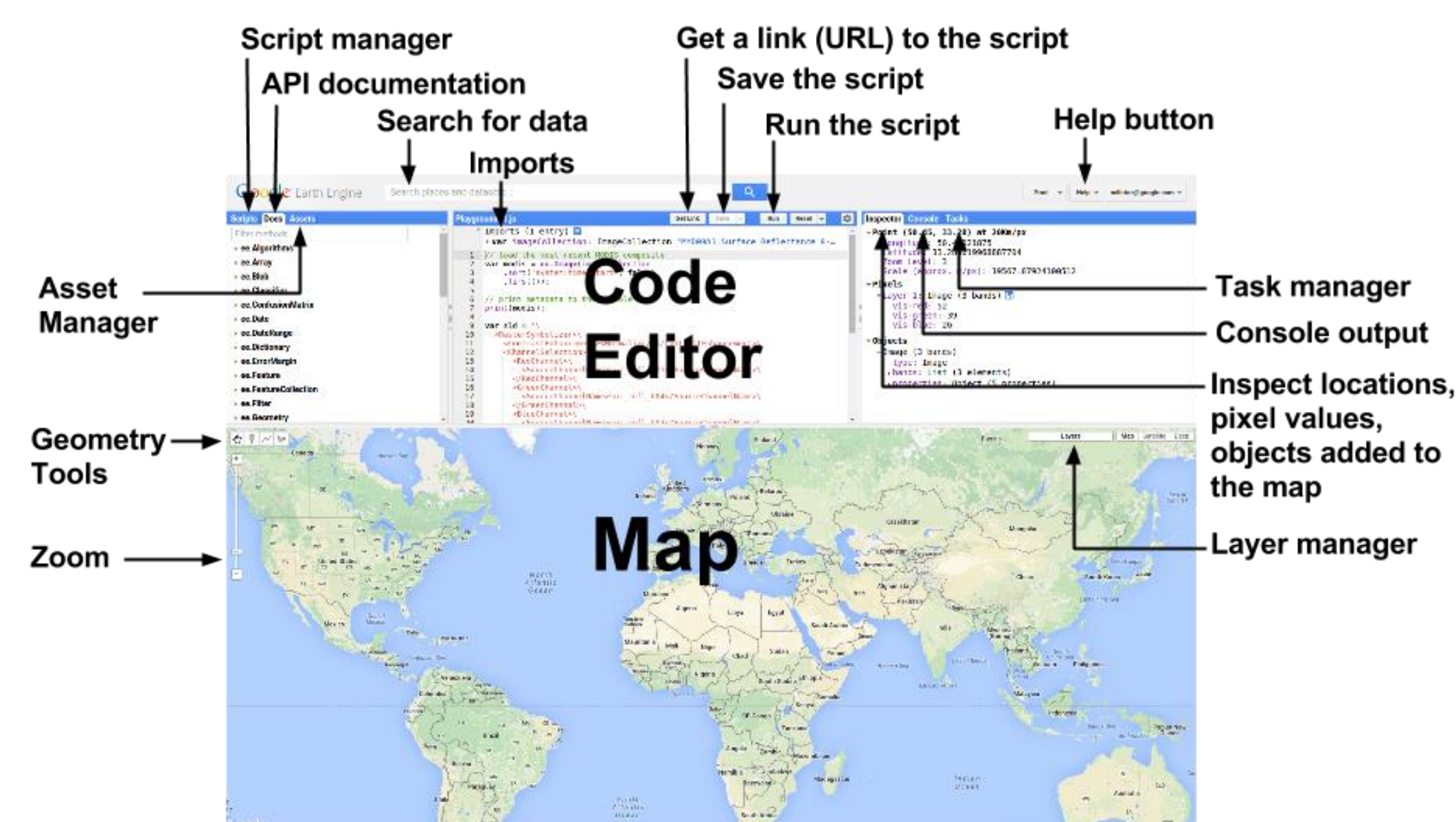


Figure 2: Schematic of Google Earth Engine Code Editor interface⁵

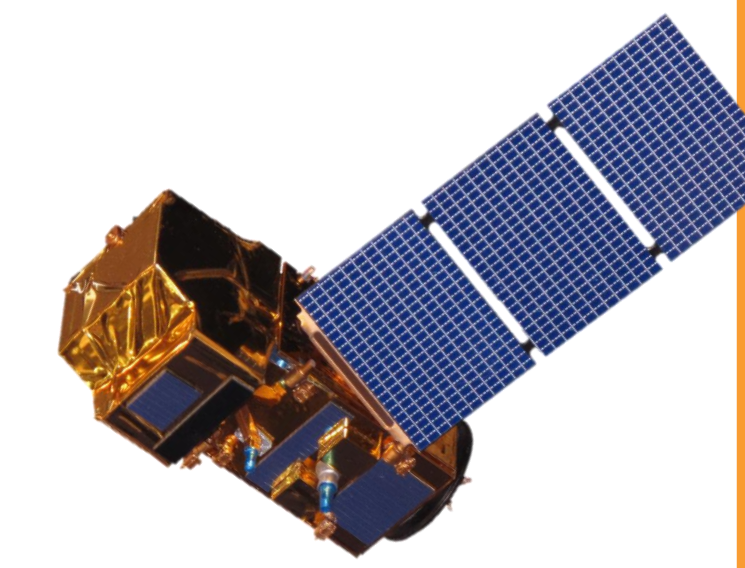
2. Methods (continued)

Remote Sensing Data: Sentinel-2

- The two Sentinel-2 satellites are part of the Global Monitoring for Environment and Security (GMES) programme, a joint initiative of the European Commission and the European Space Agency.
- Designed to monitor land cover and coastal waters as a continuation of the SPOT and Landsat missions. (Table 2)
- Sentinel-2A was launched on 23 June 2015, Sentinel-2B on 7 March 2017.²

Table 2: Sentinel-2 Satellite Constellation and Sensor Characteristics²

Number of Satellites	2
Orbit Altitude	786 km
Swath Width & Data-take Length	290 km by 15,000 km - see Figure 5
Revisit Time	5 days (equator), 2-3 days (mid-latitudes) - see Figure 4
Spectral Instrument	13 in visible, near infrared, and shortwave infrared 12 bit - see Figure 3
Ground Sampling Distance	10 m, 20 m, 60 m
Products Levels	L1-B (Top-of-atmosphere radiance, 25 km by 23 km tiles or 'granules') L1-C (TOA reflectance, orthorectified and spatially-registered, 100 km by 100 km 'granules') L2-A (Bottom-of-atmosphere reflectance, 100 km by 100 km tiles) *processed user-side with SNAP Toolbox
Data Access	ESA's Copernicus Data Hub, USGS' Earth Explorer, Google Earth Engine, Sinergise Sentinel Hub



Model of Sentinel-2 Satellite. Photograph by Roma, Wikimedia Commons, Cc-by-sa-2.0-fj

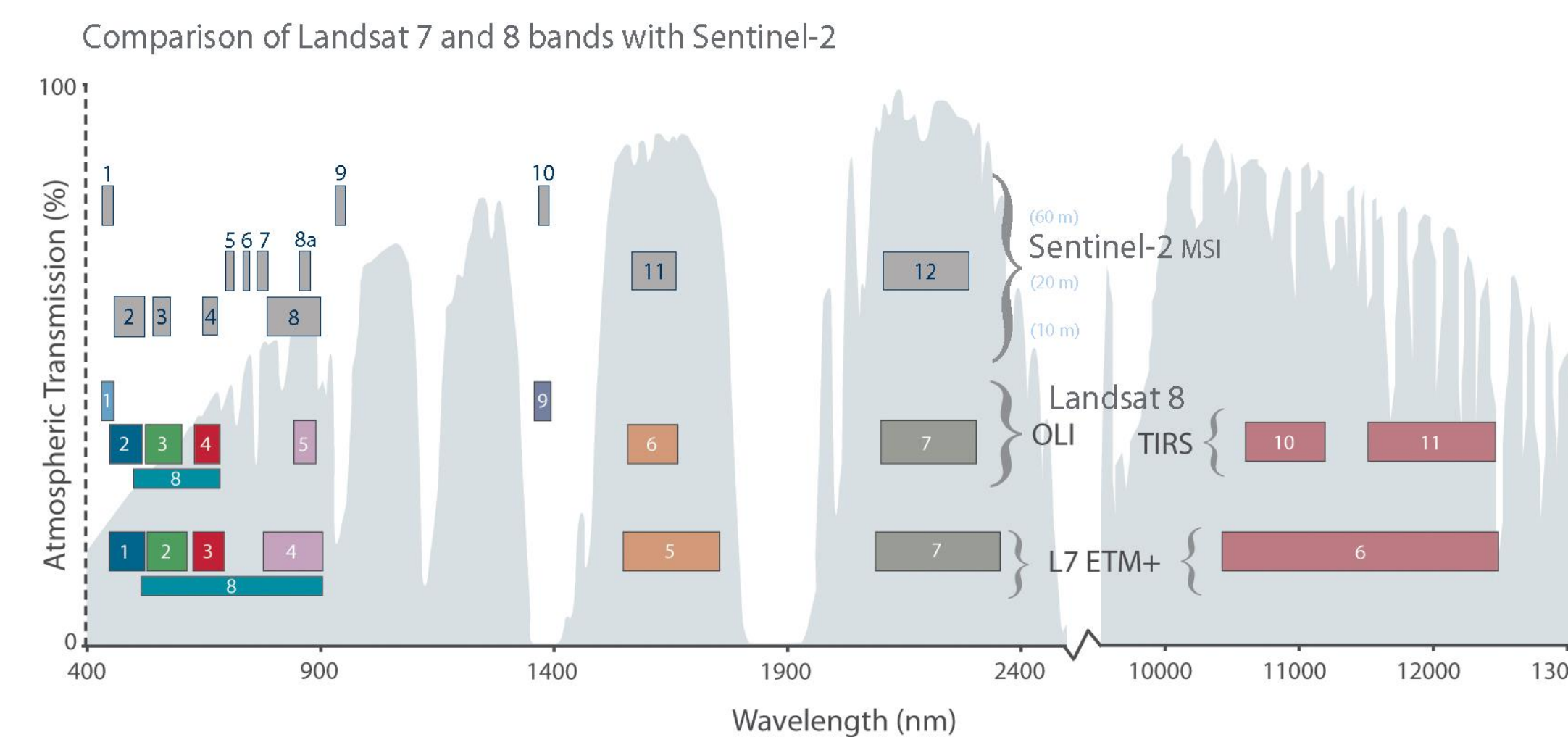


Figure 3: Sentinel-2 Spectral and Spatial Resolution vs. Landsat 7 & 8³

Caveats:

- S-2 naming changed after 6 December 2016; processing different
- Confusion between 'tile' and 'granule'; early revisit times not consistent
- S-2-specific algorithms in early stages of implementation

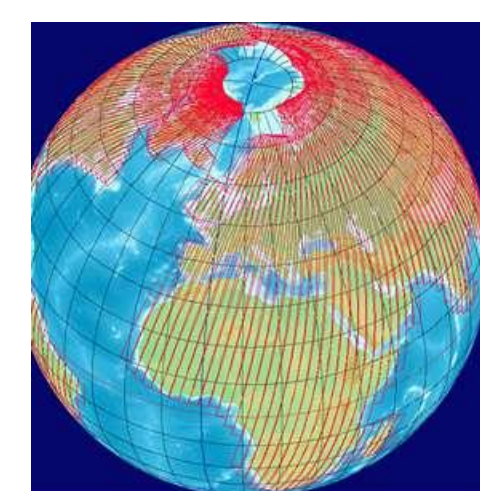


Figure 4: Sentinel-2 Data-Take²

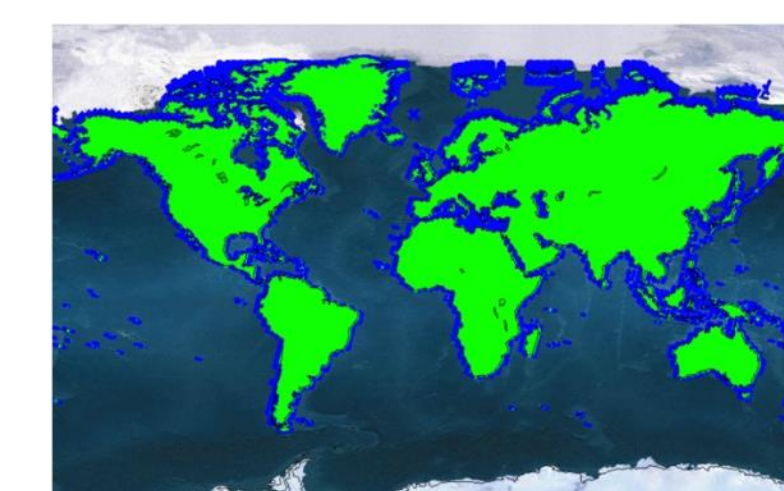


Figure 5: Sentinel-2 Coverage²

Classification Method: Random Forest

- Random Forests (RF) is an ensemble machine-learning algorithm that grows a 'forest' of decision trees.¹
- RF uses bagging and random feature selection to select data for each tree, and 'votes' on the best decision tree.¹
- Implementation:
 - Data randomly subset 70%
 - 500-tree forest, $\sqrt{\text{number of variables}}$ per split, out-of-bag sampling
 - Independent validation with remaining 30% of training data

3. Results

Results: Classification

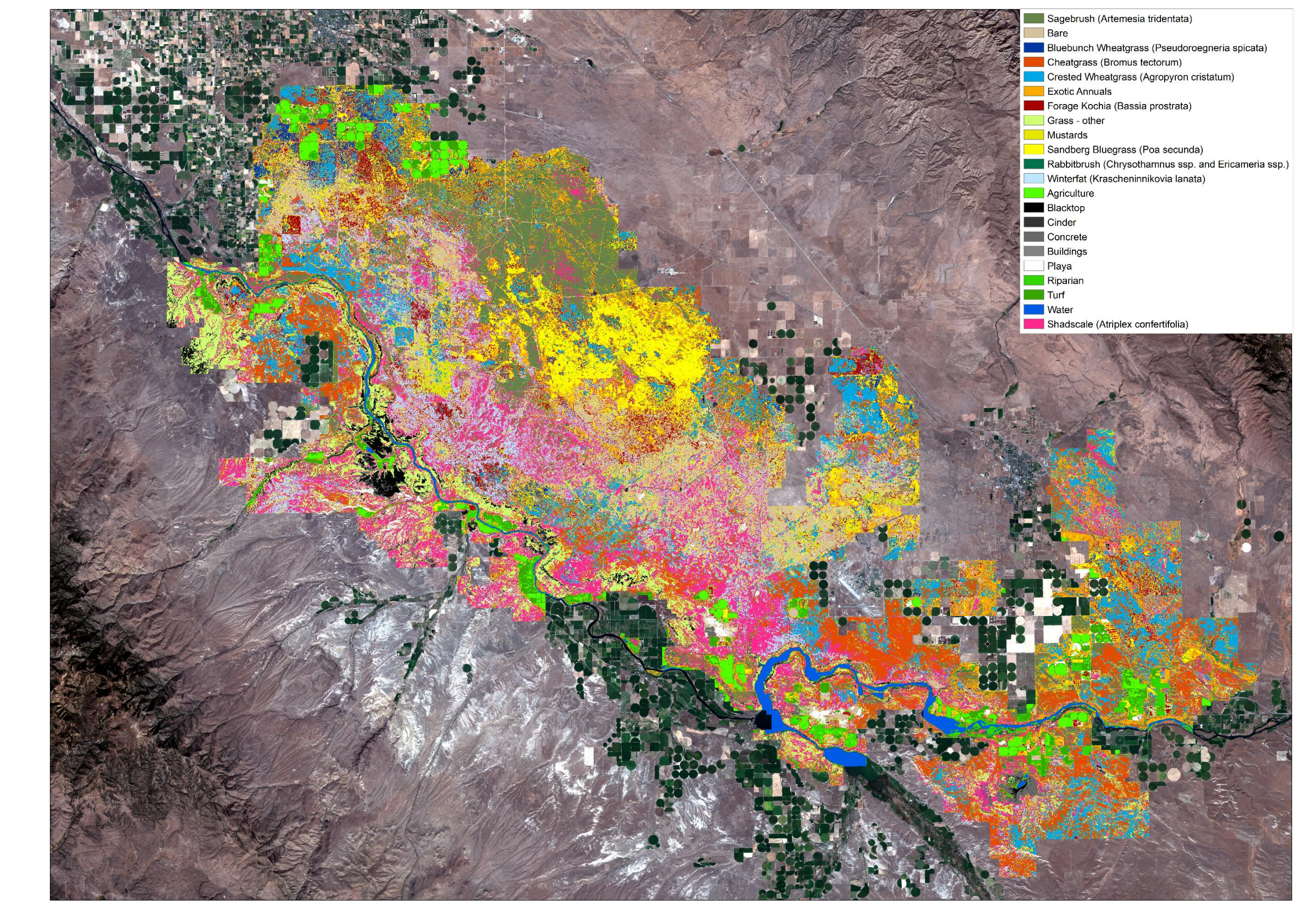


Figure 6: Classification Output, section

28,516 km² (10 m × 10 m) pixels → 300 million pixels in 1 hour

4. Conclusions

Take-away Messages

- S-2 offers advantages over Landsat (higher temporal, spatial, and spectral resolution) and MODIS (higher spatial resolution)
- GEE is efficient for processing, enabling different approaches for difficult topics (e.g. dryland vegetation)
 - Classification method easily changed or compared (SVM, CART, etc.)
 - Study area and date range flexible
 - Can add ancillary data
- Multi-temporal imagery and Random Forests leverage differences in phenology between similar species (Figure 7)

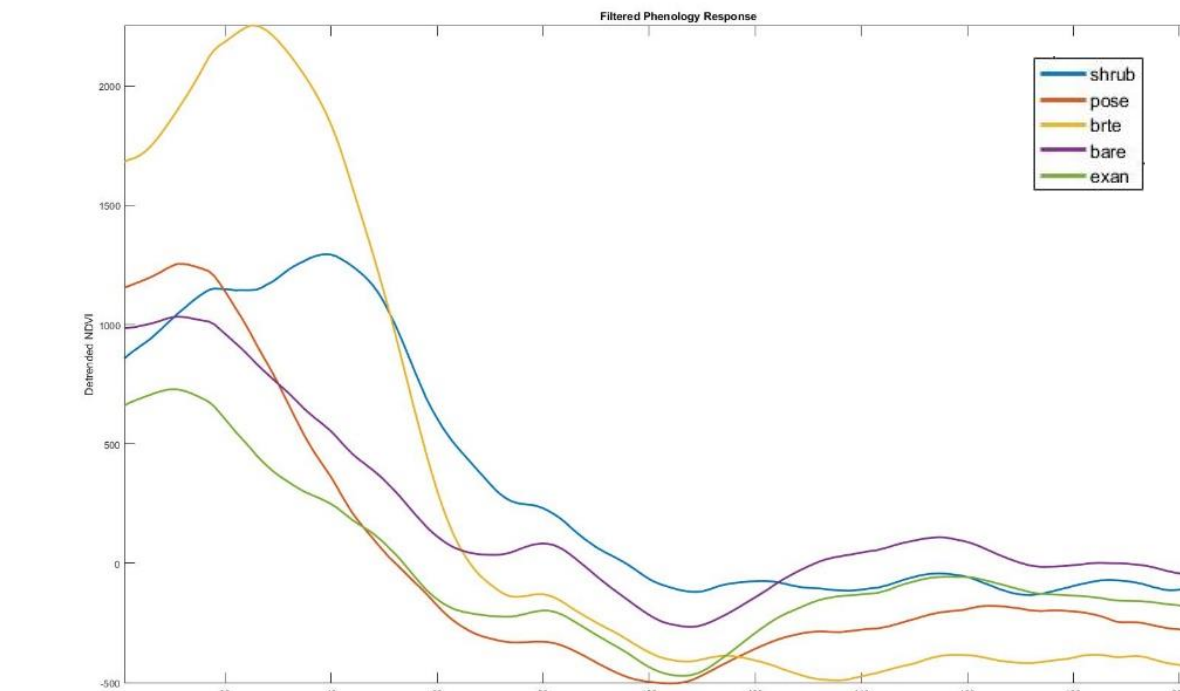


Figure 7: Sample of phenology (by NDVI) from Feb-Sept, courtesy of Megan Gallagher⁴

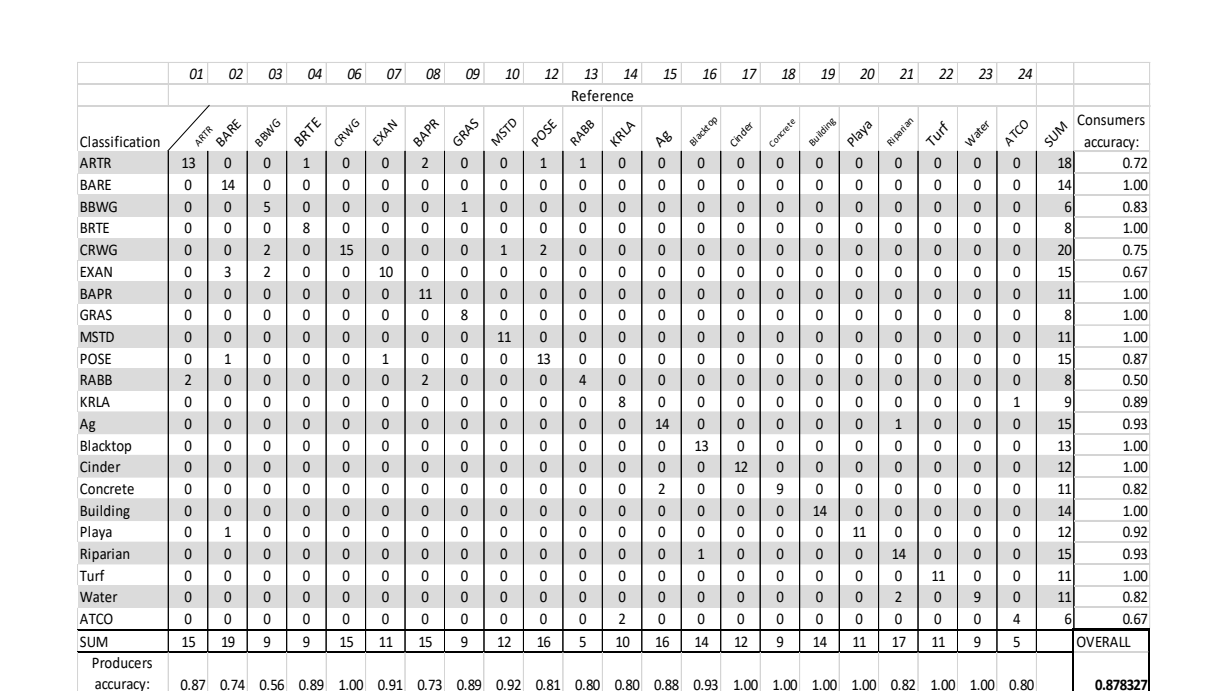


Figure 8: Confusion Matrix

Acknowledgements

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References

1. Breiman, L. (2001). *Random Forests*. Machine Learning. 45, 5–32
2. European Space Agency. <https://earth.esa.int/web/guest/missions/esa-operational-eo-missions/sentinel-2>
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