MAPPING NATIVE AND NON-NATIVE RIPARIAN VEGETATION IN THE COLORADO RIVER WATERSHED

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Table of Contents

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INTRODUCTION

The Colorado River is one of the most prominent and important river systems in North America. Its' basin covers over 630,000 km^2 across seven southwestern states in the US and northern Mexico. The Colorado River's headwaters begin at 2,743 m asl at La Poudre Pass in Colorado and, under natural flow regimes, empties into the Gulf of California some 2,333 km downstream. Ephemeral, seasonal, and persistent riparian habitats are found throughout the basin, which harbor and support a disproportionate portion of plant and wildlife species found in the western United States relative to other ecosystems (Knopf 1985, 1988).

Today, water use by municipalities and irrigated agriculture, evaporation from reservoirs, and the invasion of non-native plants have resulted in the river running dry before reaching the sea. More than 40 million people are dependent on the Colorado River for water, and over 4.5 million acres of agriculture are irrigated with this vital resource (BLM 2013). There are 15 dams on the main stem of the Colorado River, and more than 30 dams on its' major tributaries. The reservoirs associated with these dams not only store water for seasonal use and times of drought, but has also led to significant losses from evaporation (as much as 10 percent of the natural flow by some estimates).

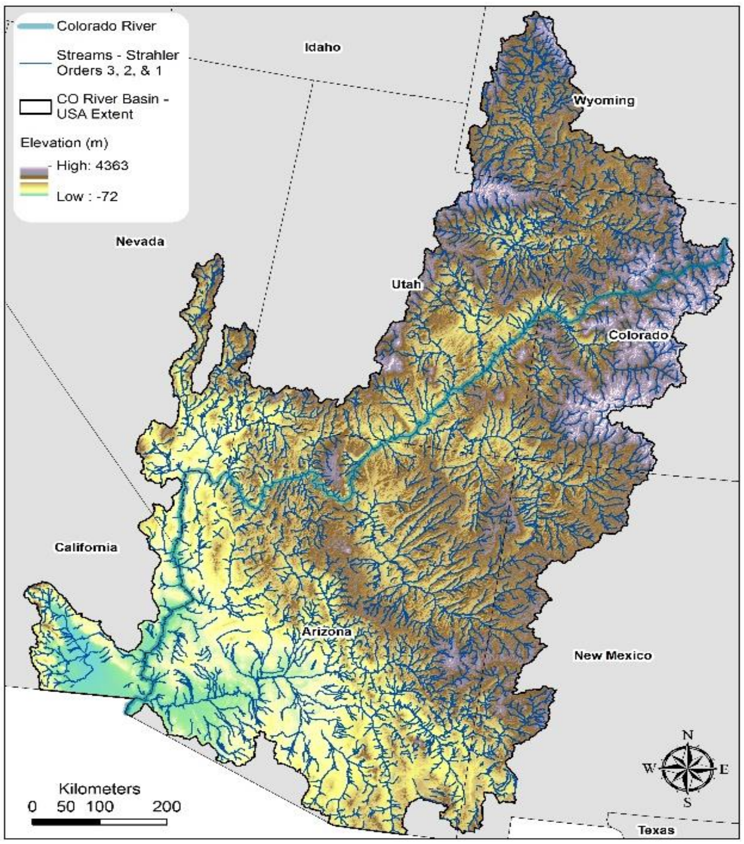

__Figure 1.__ Streams and elevation gradient of the Colorado River Basin.

Anthropogenic activities, such as flow regulation, have also fostered the establishments of invasive species. The species of greatest concern has been tamarisk (*Tamarix* spp.; Figure 2). Not only do these deep-rooted plants displace natural riparian vegetation and deplete water resources, they also alter stream channels, increase fire hazard, alter soil salinity, degrade critical wildlife habitat and increase sediment loading (Sher and Quigley 2013; Shafroth et al. 2005). Another invasive species of increasing concern in the Colorado River Basin is Russian olive (*Elaeagnus angustifolia*). Like tamarisk, Russian olive is often present in large monotypic stands, outcompeting native vegetation (Katz and Shafroth 2003). Both species have raised concerns about the current and future health of riparian zones throughout the Colorado River Basin.

In the last two decades, numerous government and non-government agencies have taken actions specifically toward tamarisk and Russian olive. Management efforts for both of these invasive woody perennials have included mowing, hand-cutting, girdling, chaining, burning and bulldozing, which often require repeated treatment and sometimes are not very effective. In 2001, the tamarisk beetle (*Diorhabda* spp.) was released as a biological control agent in 12 locations of the southwestern US which specifically defoliates Tamarisk. Research concerning the ecological effects of the tamarisk beetle are emerging (Bateman 2013, 2015); however, even in areas where the beetle has been present for years, tamarisk still persists (Sher et al. 2014). To date, no biological control has been introduced for Russian olive. The effectiveness of these treatments varies and continues to be evaluated to improve future management.

Figure 2. *Tamarisk along the Dolores River, CO. Photo by Amanda West*

Given the size and diversity of the Colorado River Basin, the numerous and disparate management strategies, and the ecological concerns accompanying tamarisk and Russian olive, there remains the need to explore and develop methods to map native and non-native riparian vegetation and change over time. There are a number of studies that have mapped tamarisk and Russian olive using remote sensing. However, these studies generally covered small geographic areas and were supported by rich field datasets (Evangelista et al. 2009, Groeneveld and Watson 2008, Ji and Wang 2016, Diao and Wang 2016). These studies provide valuable insights into how to approach mapping tamarisk or Russian olive using satellite imagery at a very local level, but do not provide a framework for scaling up their methods to regional scales. As such, we had the following goals for this project.

GOALS

The goals of this project were to test new spatial modeling and remote sensing methods to:

- Map the riparian corridor in 2006 and 2016 and change in vegetation cover for the Colorado River and its' main tributaries.
- Map tamarisk cover in 2006 and 2016 for the Colorado River and its' main tributaries using Landsat satellite sensors.
- Map Russian olive cover in 2006 and 2016 for the San Juan and Colorado River using Landsat satellite sensors.
- Test Sentinel-2 satellite sensors for detecting tamarisk and Russian olive in target tributaries.

Our methods are summarized below detailing the use of geospatial tools and spatial modeling to map riparian vegetation, detect tamarisk and Russian olive cover. The methods and results of this work, where appropriate, have been published or are in the process of being published in scientific peer-reviewed journals and other public sources.

WORKFLOW

A project of this scale involves multiple inputs, processes and results, often incrementally building upon itself. We compiled a simplified workflow to illustrate the approach we employed and the key products from different components (Figure 3). The details of this workflow will be referred to and discussed below.

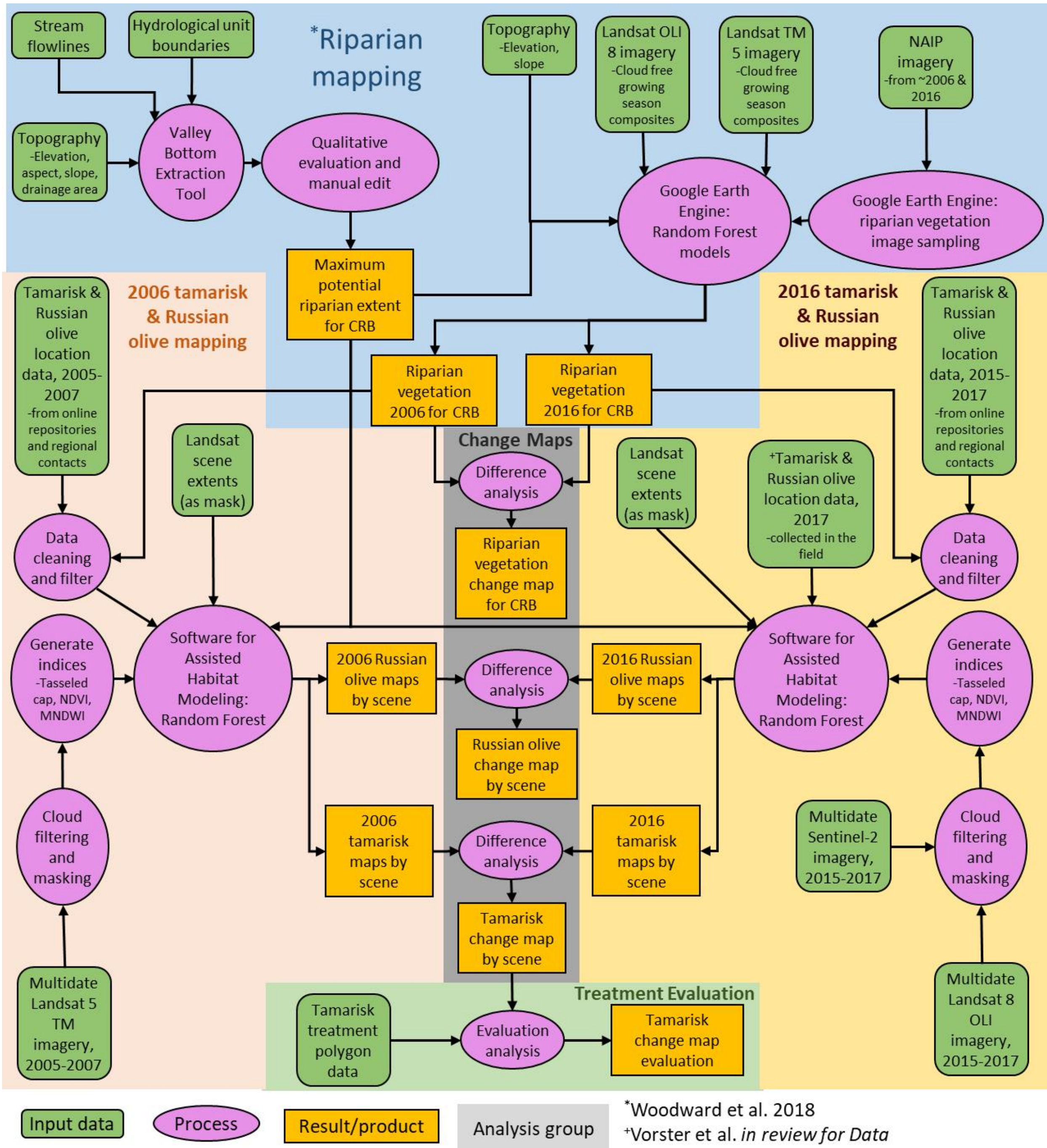

Figure 3. *Conceptual workflow diagram to map riparian vegetation, tamarisk, and Russian olive.*

FIELD DATA

Using remote sensing to map riparian vegetation, particularly single species such as tamarisk and Russian olive, requires georeferenced occurrence locations with estimations of foliar cover to train remote sensing-based models. This project required field data distributed across the Colorado River Basin for 2005-2007 and 2015-2017 providing a one-year buffer on either side of the target years (i.e. 2006 and 2016) to increase our sample size. Additionally, we collected locations where tamarisk and Russian olive were treated to compare temporal changes detected by our analyses with documented treatments. Field data on occurrences and treatments were collected from a number of existing sources (Appendix A) and supplemented by our own field sampling efforts at a few localized areas (Vorster et al.2018).The reliance on existing datasets for tamarisk and Russian olive presented a number of unforeseen challenges and obstacles. Despite accepted minimum standards for sampling and mapping invasive species (See NAWMA 2002), most data were collected using a variety of sampling methods that often lacked detailed descriptions and supporting information, such as percent cover. For example, location data originally collected to determine the potential range of tamarisk or Russian olive may have counted a single seedling as a presence point, which is not detectable by most satellite imagery. We also found that some presence points were recorded in close proximity and not at the actual location of the target species (Figure 4). Other data were recorded as polygons rather than a single point which were unusable due to coarseness and variations with delineations.

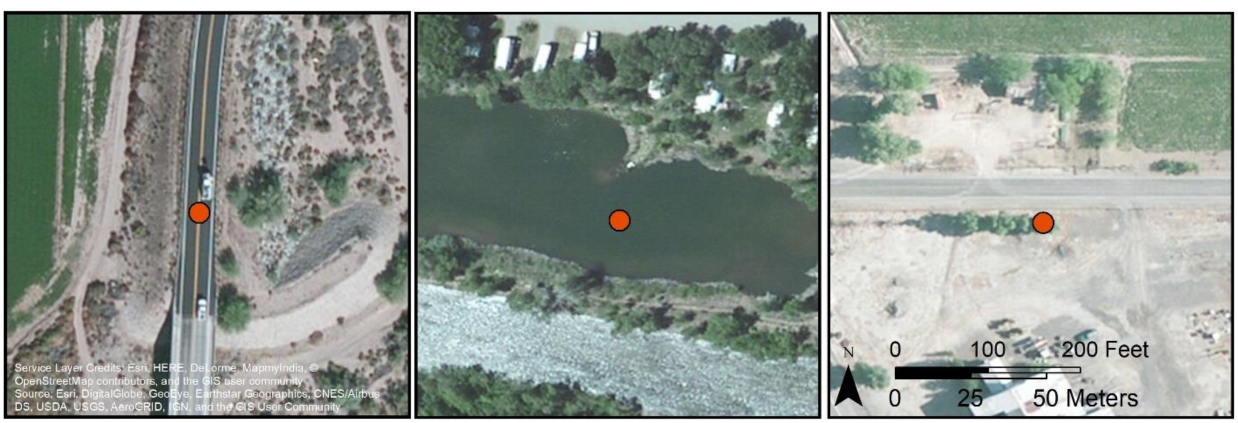

Figure 4. *Examples of problematic location points for mapping tamarisk using remotely sensed imagery that includes a location on a road, in the center of a waterway, and representing a small group of plants in an area otherwise devoid of tamarisk.*

As discussed, these data have inherent issues that can become problematic when used for mapping with remotely sensed imagery. To eliminate some of these errors, we conducted a data vetting and filtering process. The auto-filtering process included removing duplicates, selecting only those that had a date within our time frames of interest, and were located within the extent of our riparian corridor model (see Goal 1 below). After performing the auto-filtering, the number of tamarisk presence points for each Landsat scene ranged from 0 – 430 locations with the majority of scenes having less than 50 (Figure 5). We further filtered the tamarisk presence data by overlaying the 2016 data on aerial imagery and removing presence points that fell in areas with no vegetation or very limited riparian vegetation (i.e., a pixel with one plant surrounded by dirt and road). While this quality assessment process removed non-vegetated presence points, it did not remove presence points that may have been dominated by plant species other than tamarisk. Given the extent of a Landsat scene (~12,000 mi^2 or 31,000 km^2), we had a very limited dataset to use for model development.

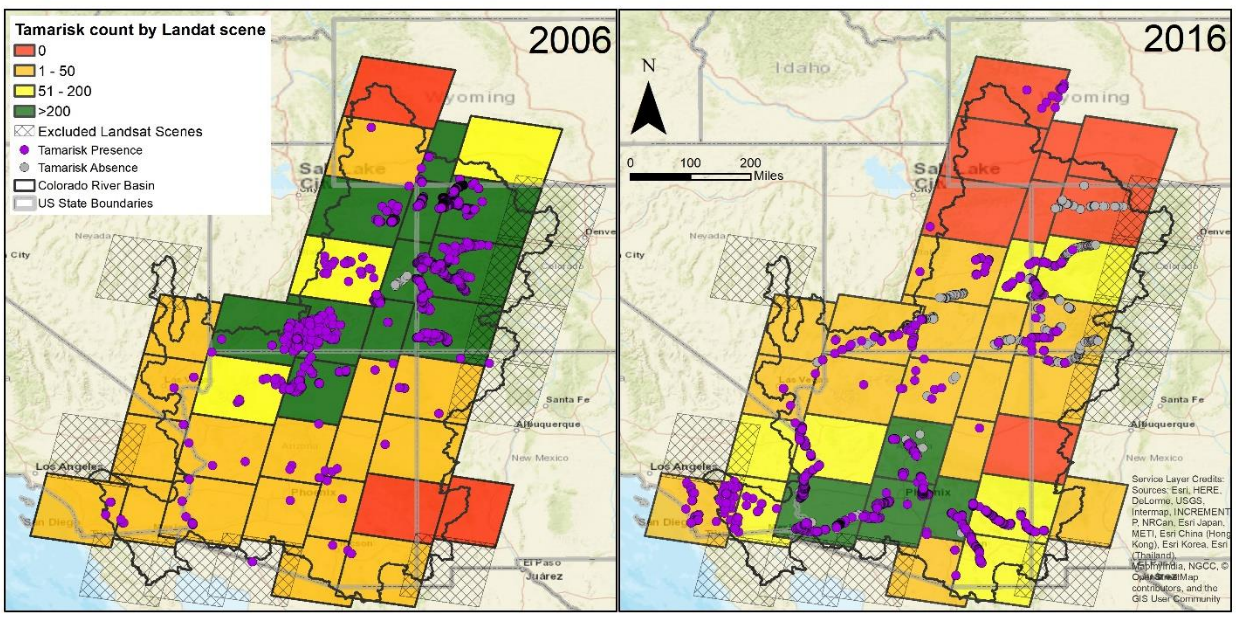

__Figure 5.__ Maps showing tamarisk data availability by Landsat scene extent within the Colorado River Basin for 2006 and 2016.

Field data were clustered in certain areas across the Colorado River Basin (Figure 5). This presented another challenge since we mapped tamarisk and Russian within single footprints of Landsat satellite imagery scenes. Furthermore, data availability for a given scene often did not match between study periods. Only one scene had enough data to map tamarisk in both 2006 and

2016. We supplemented existing data for our 2016 models with our own field data collection, targeting areas that were easily accessible, had limited existing field data and covered the overlapping region of two Landsat scenes (further described below).

Data Repositories

Our collection of existing field data began by downloading data from the large online repositories, including Global Biological Information Facility (GBIF), Biodiversity Information Serving Our Nation (BISON), EDDMapS, Citizen Science/NIISS (IBIS) and iMAP invasives. These repositories hold hundreds of thousands of species occurrence records. Some are primarily museum-based records, while others rely on citizen science programs. We downloaded 299,314 occurrences of tamarisk and Russian olive from these sources. Although these sources produce large quantities of the records, the quality is more often unsuitable for satellite remote sensing. After performing an auto-filter of the data to meet the project needs, we retained

Site Data

In addition to large online repositories, we conducted an intensive effort to contact government and non-government stakeholders within the Colorado River Basin that were likely to have tamarisk or Russian olive data. We contacted over 150 organizations that ranged from National Parks to counties and non-profit groups (Appendix A). The data we acquired included tamarisk and Russian olive points and treatment polygons in addition to tamarisk beetle locations. These data were originally collected for a variety of purposes with a wide range of protocols. Most of the data represented local efforts along a particular stretch of river or within the bounds of an administrative unit (e.g., National Park or a specific river).

Supplemental Data Collection

We collected 3,829 plots during summer 2017 to supplement existing field data gathered from other sources (Figure 6). Using 7.32 m radius circular plots, we recorded percent cover and height of each species in in representative land cover and vegetation along the Colorado, Dolores, Green, Virgin, and Yampa Rivers in Colorado and Utah. These plots were used to test preliminary tamarisk models of percent cover and were utilized as presence/absence points for subsequent modeling. We also developed and implemented an extremely efficient method for sampling presence locations of tamarisk, Russian olive, and other riparian vegetation types (Vorster et al. 2018). In this method, presence locations were marked over high-resolution aerial imagery on electronic tablets as field crews visited sites either on foot or in a vehicle. This method allowed for efficient collection across large areas. Presences were only recorded where tamarisk or Russian olive comprised greater than 50% of the cover of a roughly 7 m radius area as viewed from above. Tamarisk presence points were classified to account for tamarisk beetle impacts as either live (where live tamarisk is the dominant form), mixed (where live tamarisk is mixed with dead tamarisk), dead (where nearly all the tamarisk is dead), or defoliated (where tamarisk foliage has a reddish appearance from tamarisk beetle defoliation). This data was collected along easily-accessible stretches of the Animas, Colorado, Dolores, Escalante, Fremont, Gila, Little Colorado, Paria, San Juan, San Miguel, San Pedro, San Rafael, Santa Clara, Verde, and Virgin Rivers and McElmo Creek in Colorado, Utah, Nevada, Arizona, New Mexico, and California.

GEOSPATIAL DATA

We collected over 3.5 terabytes of Geographic Information System (GIS) and remotely sensed data for this project (Table 1). These data were used for a number of processes ranging from defining analysis extents to modeling variables (Figure 3, Table 1). The remotely sensed satellite imagery from the Landsat mission comprised the bulk of the geospatial data we acquired, which were used to generate indices for model development (Appendix B). A subset of the indices most important to this project and their descriptions are as follows:

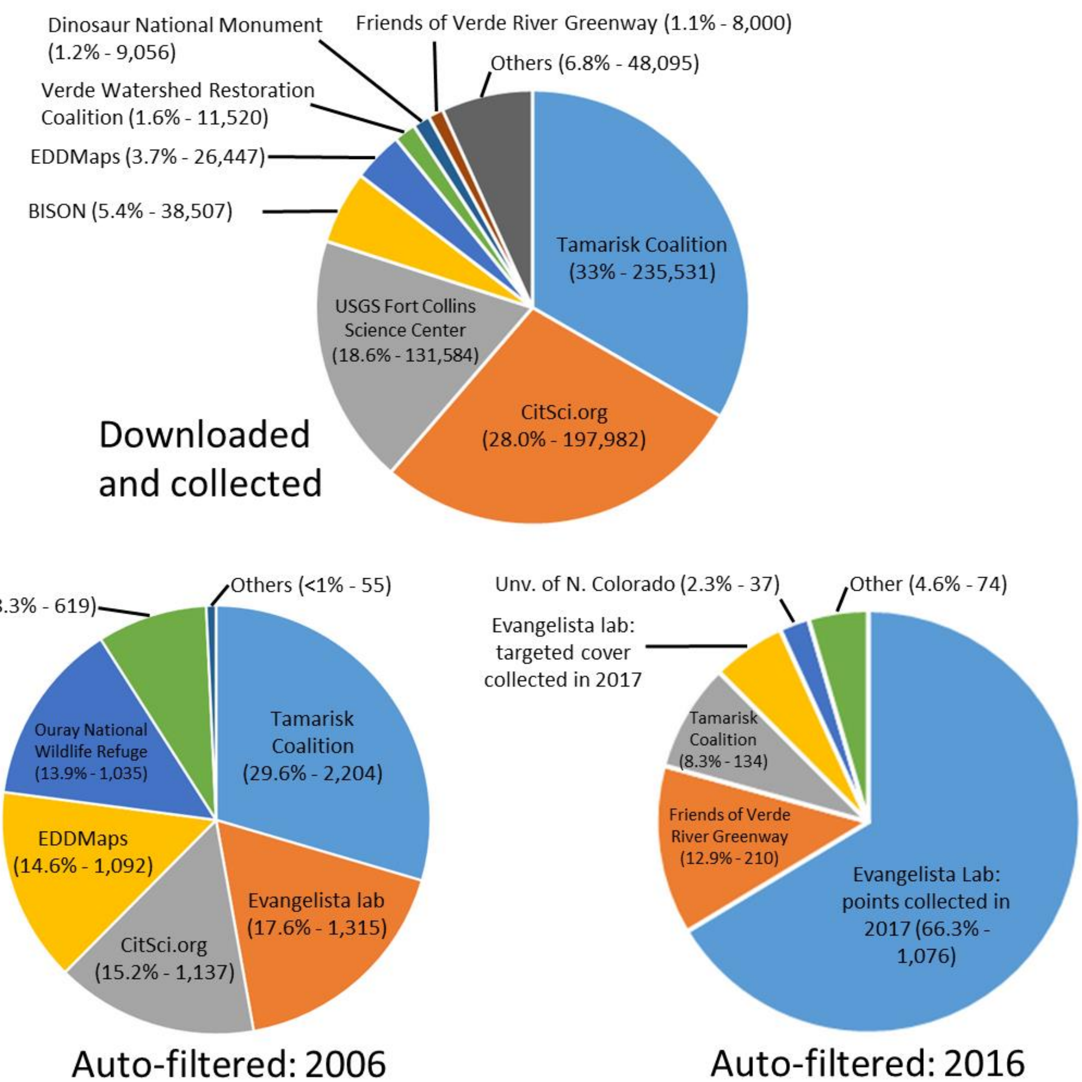

Figure 6. *Source and quantity of downloaded and collected tamarisk presence points across the Colorado River Basin and the data suitable for modeling in 2006 and 2016 after performing the automated filter*

Modified (MNDWI) and Normalized Difference Water Index (NDWI): These indices are both meant to distinguish water from non-water features. They use a band from the visible spectrum and a shortwave infrared (SWIR) band. Because we are mapping riparian systems it is important to exclude active stream channel, this indices allows us to do so.

Green Normalized Difference Vegetation Index (GNDVI): GNDVI is a measure of a plant's greenness or photosynthetic activity. It can be helpful is distinguishing variation between species.

Specific Leaf Area Vegetation Index (SLAVI): SLAVI has been used to determine the specific leaf area. This can identify areas of greater canopy coverage.

Tasseled Cap indices: The tasseled cap indices are a linear transformation of the spectral bands that create three new bands to represent brightness, greenness, and wetness. These are useful for vegetation mapping and are more interpretable than original bands.

Table 1. *Geospatial data acquired and used for riparian, tamarisk and Russian olive mapping in the Colorado River Basin.*

Name	Description	Resolution	Use	Source
Stream flowlines	A network of flowlines representing ephemeral streams, as well as 'artificial paths' (virtual flowlines) within waterbodies.		Developing VBET model, general mapping	USGS National Hydrography Dataset (NHD)
Hydrological unit boundaries	Hydrological units that indicate the level or scale of the watershed. Larger units indicate smaller hydrology basin areas.		Partitioning Colorado River Basin for VBET modeling	USGS National Hydrography Dataset (NHD)
EPA level III ecoregions	Level III EPA ecoregions in the continental U.S. that can be used for different applications in terrestrial- and aquatic- based research and environmental assessment.		Partitioning the riparian vegetation mapping	U.S. Environmental Protection Agency
WRS-2 Landsat scene extents	The worldwide reference system (WRS) path/row scene boundaries and geographic coordinates for Landsat images globally.		Clipping all Landsat images to the same geographic extent. Grid system to define modeling extents.	USGS Landsat Path/Row shapefiles

Elevation	High resolution digital elevation model of the Colorado River Basin.	10 meters	Developing VBET model, deriving aspect, slope, flow accumulation,	National Elevation Dataset from USGS National Map
Aspect	High resolution aspect layer derived from the elevation model of the Colorado River Basin.	10 meters	Developing VBET model, Riparian vegetation mapping	Derived from Elevation
Slope	High resolution slope layer derived from the elevation model of the Colorado River Basin.	10 meters	Developing VBET model, Riparian vegetation mapping	Derived from Elevation
National Agriculture Imagery Program (NAIP) aerial imagery	Very high resolution aerial imagery collected less than 10% cloud coverage during the agricultural growing seasons in the continental US.	1 meter	Digital sampling for riparian mapping and Russian olive mapping, map base layer, qualitative riparian, tamarisk and Russian model evaluation	US Department of Agriculture (USDA)
Landsat 5 TM imagery	Satellite sensor with seven spectral bands in the visible near-infrared, and mid infrared frequencies and includes a thermal band. Revisits the same location on the Earth every 16 days.	30 meters	Riparian vegetation, tamarisk and Russian olive mapping for 2006, deriving ecological indices	NASA and USGS
Landsat 8 OLI and TIRS imagery	Satellite sensor with nine spectral bands in the visible, near-infrared, and short wave infrared frequencies and includes a panchromatic, cirrus band and two thermal infrared sensor bands.	30 meters	Riparian vegetation, tamarisk and Russian olive mapping for 2016, deriving ecological indices	NASA and USGS
Sentinel-2A	Freely available European Space Agency (ESA) imagery collected at both a higher spatial and temporal resolution than Landsat.	10-20 meters	Case study comparison to Landsat when modeling tamarisk and Russian olive at select tributaries in Colorado River Basin	European Space Agency (ESA)

GOAL 1: MAPPING THE RIPARIAN CORRIDOR OF THE COLORADO RIVER AND ITS' MAIN TRIBUTARIES

Summary

• Employed a recently-developed approach to map the maximum riparian corridor extent in the Colorado River Basin (Shapefile download: Colorado State University Library)

• Developed novel Google Earth Engine scripts to digitally-sample riparian vegetation in the Colorado River Basin

• Created riparian vegetation maps of the Colorado River Basin for 2006 and 2016 using Google Earth Engine (Mapbook Atlas book: Colorado State University Library)

• Analyzed change in riparian vegetation for the Colorado River Basin, finding an overall increase in riparian vegetation between 2006 and 2016 (Mapbook Atlas book: Colorado State University Library)

• All methods, results and discussion related to the riparian vegetation mapping have been prepared as a peer reviewed publication (Woodward et al. 2018)

Riparian zones are delineated in numerous ways; their definition is usually dependent on the research approach or agency targets (Appendix C). Generally, they are described as the transition between terrestrial and freshwater ecosystems (Gregory et al. 1991) and defined by topographic, vegetation, and soil components. Riparian zones are dynamic regions with complex heterogeneous landscapes formed by frequent disturbances (Swanson et al. 1988). They are challenging to map across large spatial scales due to variations in species composition linked to elevation and climate (Congalton et al. 2002; Goetz 2006; Hollenhorst et al. 2006; Salo et al. 2016). Fixed buffers along streams have been broadly employed in delineating riparian zones; however, they do not capture temporal or spatial fluctuations of wet soils and vegetation. The potential maximum extent of riparian zones can be captured by identifying its' geomorphology. Within this area, temporal fluctuations in riparian zone vegetation may be evaluated with spectral imagery (Congalton et al. 2002; Clerici et al. 2013). For our purposes, this is how we approached modeling riparian vegetation along the Colorado River and its' tributaries.

First, we delineated areas that could potentially hold riparian vegetation. To do this, we used the recently described Valley-bottom Extraction Tool (VBET) developed by Gilbert et al. (2016). This ArcGIS Toolbox tool uses high resolution topographic information and stream flowlines to develop a delineation of valley bottoms, which is often defined as the "maximum riparian corridor extent" (Illhardt et al. 2000). These results were then qualitatively evaluated and manually edited to remove any superfluous channels or over/under estimations of extent using the refinement and editing process detailed in Gilbert et al. (2016). The network of streams and riparian areas within the Colorado River Basin is extensive and detailed, therefore we only manually edited the VBET results along streams that were less than or equal to Strahler stream order "3" (USGS National Hydrologic Database, 2016) since these were the primary streams of interest for tamarisk and Russian olive detection. Overall, these results provided a suitable approximation of the maximum riparian corridor extent in the Colorado River Basin. Higher error rates in the VBET models were encountered in areas where streams of largely different sizes merged. In addition, areas of large flat, floodplain areas also proved to be difficult to classify. However, the overall result provided a key output that we used in subsequent models.

Once we narrowed the Colorado River Basin to areas that represent the maximum riparian extent, we moved to map riparian vegetation within this extent for both 2006 and 2016. To accomplish this, we first developed novel scripts in Google Earth Engine to digitally collect riparian vegetation presence and absence across the Colorado River Basin using high resolution (1 m^2 or higher) National Agriculture Imagery Program (NAIP) imagery

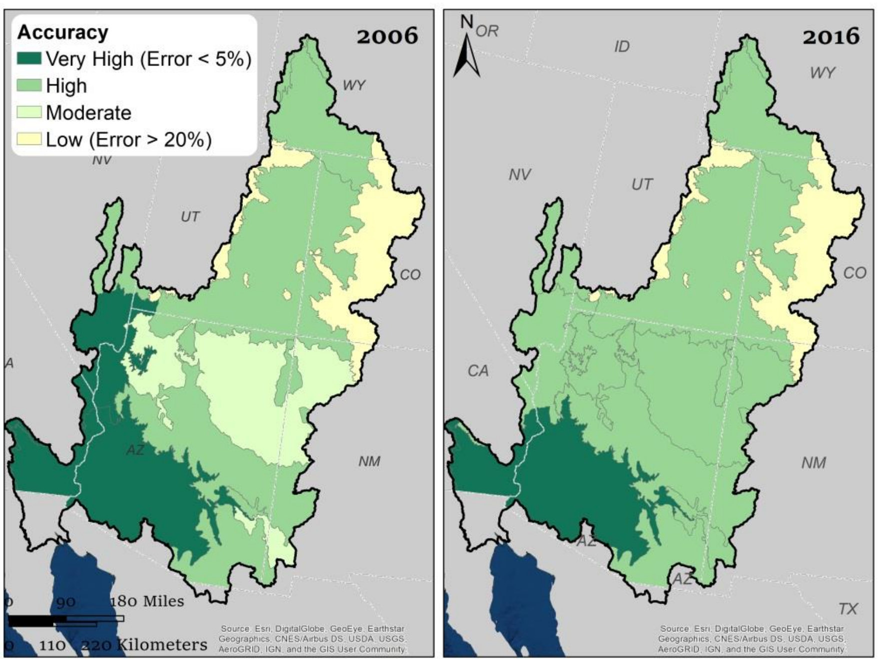

Figure 7. Riparian vegetation model accuracy for 2006 and 2016.

for each state that was closest to 2006 and 2016. This amounted to a total of 14,446 riparian vegetation presence points and 17,604 absence points.

We continued to use Google Earth Engine to perform the riparian vegetation mapping. To accomplish this, we divided the Colorado River Basin into ecologically meaningful regions based on the Environmental Protection Agency (EPA) level III ecoregions. This allowed us to tailor models to environmental conditions specific to each ecoregion. We used Landsat cloud free growing season composites for environmental variables, including NDVI, SAVI, MNDWI, Tasseled cap transformation, and the original bands (Figure 3). Using the digitally sampled data and these environmental layers, we developed random forest (Breiman 2001) models of riparian vegetation for each ecoregion in 2006 and 2016 (Woodward et al. 2018). When combined, these created a continuous riparian vegetation map for the Colorado River Basin for each year.

Models performed well, overall, with Out of bag (OOB) errors ranging from 2% - 35%, depending on the ecoregion. To help illustrate the uncertainly surrounding these models, we created error maps by ecoregion for each year (Figure 7). As expected, ecoregions further north and encompassing mountainous regions had lower accuracy than those further south in less mountainous and arid environments where riparian vegetation can be easily distinguished from other cover types.

After mapping riparian vegetation, we performed a difference analysis to map the change in riparian vegetation from 2006 to 2016. This provided a map of the persistence, loss and gain of riparian vegetation across the Colorado River Basin at a 30 m resolution (Figure 8). To our knowledge, this provided the first comprehensive, high-resolution map of riparian vegetation and vegetation change for the entirety of the Colorado River Basin. The change analysis showed an overall net increase amounting to 63,350 ha of riparian vegetation in the Colorado River Basin. The ecoregions with the largest gains included the Sonoran basin and the Mojave Desert while greatest losses occurred in the Southern Rockies and the Central Basin.

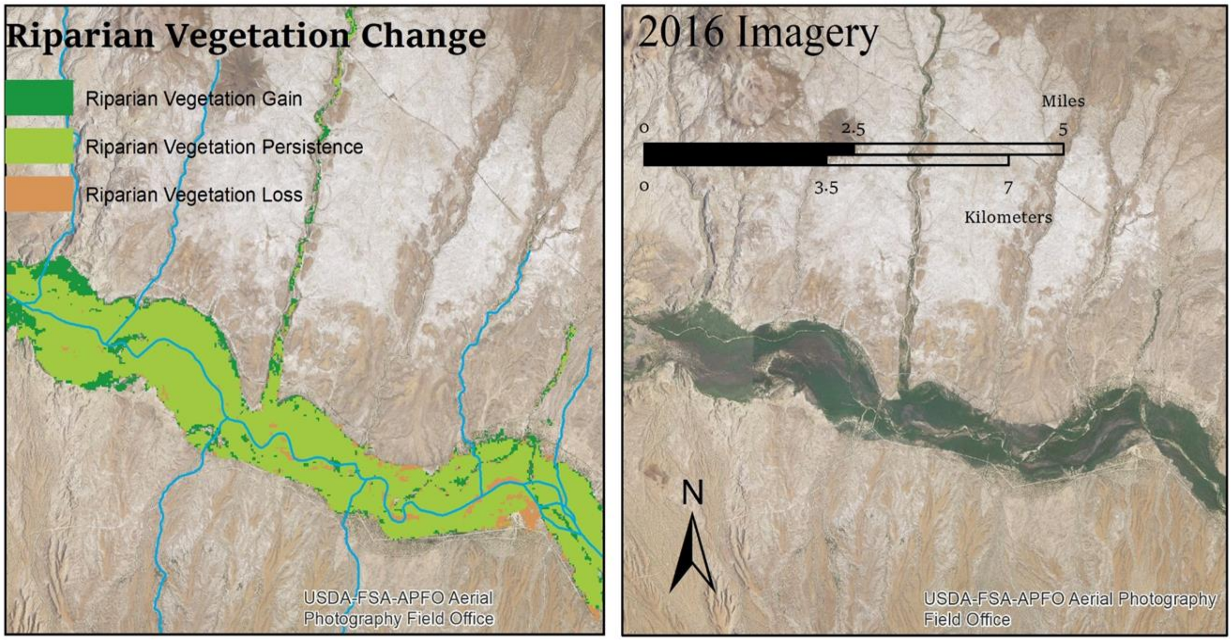

Figure 8. *Riparain vegetation change (2006-2016) example along the Gila River, AZ*

Given the scale, resolution and complexity of our analyses there are some important caveats to consider when interpreting these results. One of the most important is the definition of riparian areas, which has no universal definition and differs from one application to another. Our definition was specific to the data available and objective and may not fit the needs for certain end-uses. The characteristics and availability of remotely sensed data is also important to consider. Much of the riparian vegetation is found in deep, winding canyons that obscure reflectance signals from satellites making modeling and mapping of these areas difficult. Lastly, the variability in riparian vegetation across the Colorado River Bain varies greatly from alpine environments to arid deserts. As such, our map may likely over predict riparian vegetation in high elevation environments. Change maps should be interpreted cautiously, as changes shown may reflect actual change, or they may be due to model errors when comparing the two years.

The mapping of riparian vegetation for 2006 and 2016 was a key step to mapping tamarisk and Russian olive. By reducing the landscape to only those areas within the maximum riparian extent and then further to only areas with existing riparian vegetation, we were able to narrow future tamarisk and Russian olive mapping to this specific area of interest.

GOAL 2: MAPPING TAMARISK ALONG THE COLORADO RIVER AND ITS' MAIN TRIBUTARIES

Summary

• Found most available field data did not meet the standards needed for mapping

• Performed and evaluated multiple methods to map tamarisk using freely available data over large scales (Appendix D)

• Identified data and methods most appropriate for mapping tamarisk across large scales using remotely sensed imagery

• Created maps of regions where data were suitable for mapping (PDF map: posted to Colorado State University Library)

• Evaluated change maps by comparing output to known treatment locations

As described in "Field Data", the team conducted an extensive data collection effort, first by contacting multiple government and non-government organizations located within the Colorado River Basin that were likely to have tamarisk occurrence data. This effort resulted in a diverse set of location features for tamarisk, potentially suitable for basin-wide mapping. We then conducted a field sampling campaign to fill some of the data gaps in 2016.

We approached tamarisk mapping in the Colorado River Basin by developing maps by Landsat scene extents. This served three purposes. First, by modeling by each Landsat scene, we avoided complications that arise when mapping over multiple scene extents since the images would be captured on different dates which can cause issues related to sun angle, clouds, haze, and phenology (Young et al. 2017). Second, this allowed us to portion the study area into manageable sizes for computational purposes (a single Landsat 8 OLI image is over 3 GB in size). Finally, by mapping at smaller extents, we could tailor the methods for mapping to match the environmental conditions in the region without having to generalize over the entire Colorado River Basin. While this approach provided significant benefits, there were also some disadvantages. Most importantly, we were restricted to only using the occurrences that were located within each Landsat scene for modeling. Ultimately, this significantly reduced the sample size for each model. As previously mentioned, we also used the results from Goal 1 to help narrow the focus of the tamarisk mapping (Figure 3). We only modeled tamarisk within the riparian areas which help eliminate non-vegetated areas, agriculture fields, and water while also reducing the processing extent.

Selecting the environmental predictor variables to include in the models to map tamarisk was also important to consider. To capture the phenological pattern of tamarisk and co-occurring species in the Colorado River Basin, we included representative Landsat images for each month for each year modeled when possible (i.e., 2006 and 2016). We widened our imagery timeframe to 2005-2007 and 2015-2017 to increase the images available due to potential cloud cover issues. Since the number of variables considered for each model could reach upwards of 150, we had to reduce this number before conducting our analyses. We used environmental variables that were ecologically interpretable (e.g., NDVI), showed promise for distinguishing tamarisk, and retained much of the information in the original (e.g., tasseled cap transformations) image (Evangelista et al. 2009).

When mapping species distributions using remotely sensed imagery, field data with a measurement of percent cover associated with the location is ideal. This allows methods by which the data can be filtered to only include locations that can be detected by the remotely sensed imagery (West et al. 2016). Of all the data we gathered, less than 1% of the records had adequate cover data associated with them for 2006 or 2016. This prompted us to modify our methods to use binary presence absence/background data to develop our models.

We began our modeling process using scenes that had an adequate number of occurrence points and were in regions familiar to the team. There are numerous methods that can be used to map a species occurrence across the landscape. Therefore, we tested dozens of potential methods to identify approaches that would perform the best given our objectives. Items that we explored included: location of presence points (e.g., within VBET output or within riparian model results), background point amount and distribution, type and number of environmental variables considered, and modeling algorithm. We conducted over 100 exploratory models using a multiple modeling approaches. During these tests, we discovered that the auto-filtering we performed on the data was still not sufficient to provide data suitable for this purpose. As such, we overlaid all 2016 location points on NAIP imagery and classified each point into three classes: poor quality, intermediate quality and high quality. This was the final set of presence points that we used to develop tamarisk models for 2016. We did not perform this visual evaluation on 2006 data due to time and imagery limitations. Although this visual evaluation further reduced the data available, it improved model performance.

Given the challenges we had with developing consistent and accurate maps of tamarisk, we also conducted an in-depth phenological analysis comparing the spectral signatures of tamarisk and co-occurring species. Using the auto-filtered data, we performed a time-series analysis to map each species signal over a year based on image availability. Our goal was to detect when tamarisk reflectance could be significantly different from other vegetation types. Our analysis confirmed that distinguishing tamarisk from other vegetation types given the data and imagery available is difficult and variable depending on location (Figure 9).

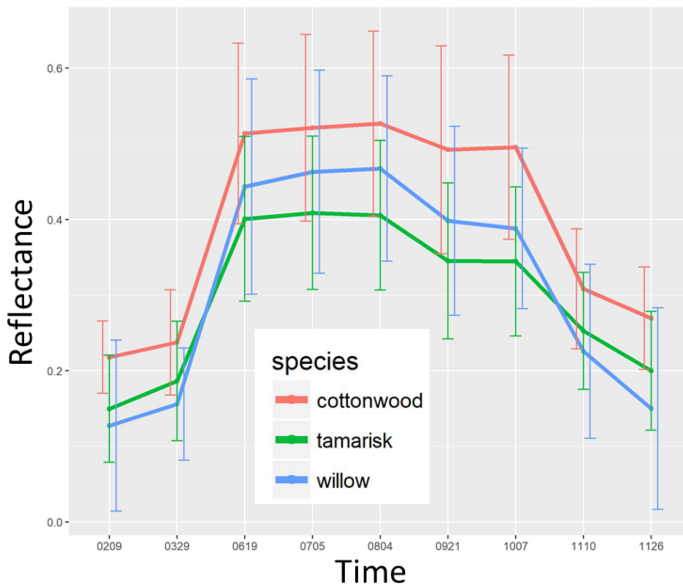

Figure 9. *Annual time series of NDVI signatures for tamarisk, cottonwood and willow showing the limited spectral signature separation. Brackets show plus and minus one standard deviation.*

Our final models for 2016 were developed using only the auto-filtered and visually cleaned presence points that fell within riparian vegetation as defined by our models outlined in the “Goal 1” section. Due to the limited availability and reliability of absence data, we used background points that fell within the maximum riparian extent that we developed. Our earlier testing showed that the random forest model algorithm performed the best of the five algorithms considered, which we used for our final 2016 models. All our models were developed using Software for Assisted Habitat Modeling (SAHM) in the VisTrails platform developed by the US Geological Survey at the Fort Collins science Center (Morisette et al. 2013). We mapped six Landsat scenes for 2016. These scenes included the Blue, parts of the Colorado, Dolores, Gila, Green, Salt, San Carlos, San Francisco and San Pedro Rivers.

All models performed well when statistically evaluated (Table 2). However, a qualitative visual assessment appeared to show a general over prediction of tamarisk in most regions. This was especially true in regions that had diverse and patchy vegetation, such as portions along the Verde and Gila Rivers. While we were only able to map six Landsat scenes successfully for 2016, we attempted to map many other areas, but the models simply did not perform well - predominantly due to the lack of quality data.

Table 2. *List of 2016 successful tamarisk model evaluation metrics.*

Path/ Row	General Location	Train AUC	Test AUC	Train Sensitivity	Test Sensitivity	Train Specificity	Test Specificity
38/37	Lower Gila River	0.95	0.95	0.87	0.73	0.88	0.95
37/37	Middle Gila	0.98	0.98	0.93	0.78	0.93	0.97
36/37	Lower Verde	0.95	0.95	0.90	0.72	0.89	0.96
37/36	Verde River	0.97	0.97	0.92	0.69	0.92	0.97
35/37	Upper Gila	0.94	0.94	0.87	0.58	0.87	0.95
36/33	Dolores River	0.89	0.88	0.81	0.74	0.84	0.87

We were only able to successfully model one Landsat scene for 2006, but this provided an area to test the ability of this method to quantify the current extent of tamarisk cover and how it has changed in the past decade. Using the Landsat scene that covers the Dolores River and the upper part of the Colorado River, we developed advanced methods to quantify and map tamarisk distribution and its change between 2006 and 2016. We used a two-step classification method to predict the percent cover of tamarisk within our study area. We combined a presence/absence model with a continuous model to develop percent cover maps of tamarisk for 2006 and 2016. We were able to use this approach, which differs from the approach described above, because we had sufficient high quality cover field data available. The results were differenced to create a map of change (Figure 10).

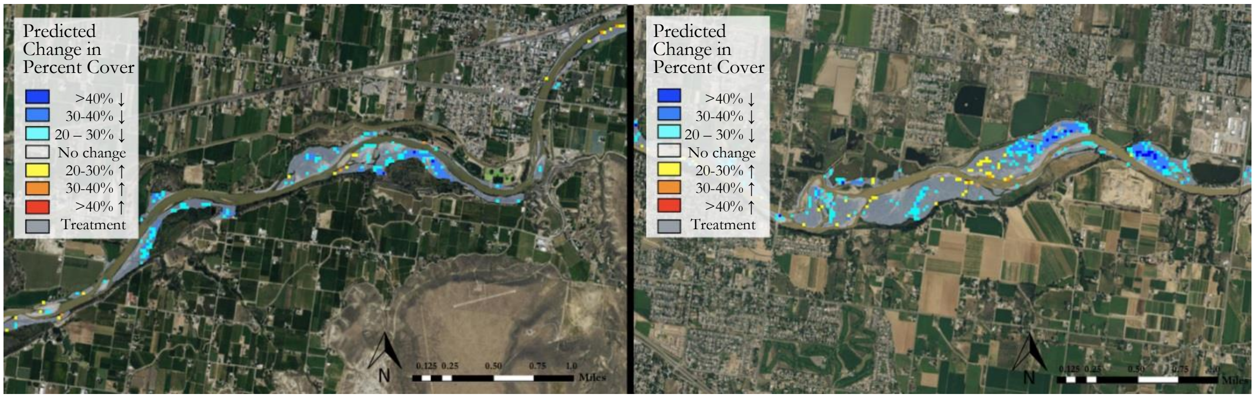

Figure 10. *Change in percent tamarisk cover between 2006 and 2016 in two tamarisk management areas on the Colorado River. Colored pixels represent areas where the predicted percent of tamarisk changed great than 20% from 2006 to 2016. Grey polygons outline treatment areas*

We found tamarisk cover detected by our models decreased from 2006 to 2016 in the Dolores River and Upper Colorado River region. Tamarisk cover was shown to decrease by 186.7 km^2, accounting for 4.5% of the potential riparian area. This change in tamarisk cover could represent an ecologically real effect in response to various management efforts. However, it is also important to consider the differences in the abilities of Landsat 5 and Landsat 8 models to distinguish tamarisk cover (see below).

Once we had a change map, we evaluated agreement between the detected change and treatment polygon data from the Dolores River Restoration Partnership by overlaying the treatment polygons onto the change map (Figure 3). We also compared two modeling algorithms for this particular evaluation; random forest and Maxent. Overall, we found agreement between treatment polygons and detected decrease in tamarisk (Figure 11). This was encouraging and suggests that in regions with the quantity and quality of data for multiple time steps, these methods can be used to provide spatial results of tamarisk cover change.

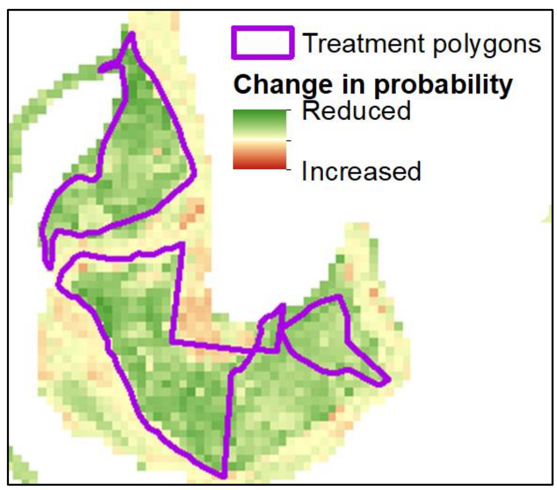

Figure 11. *Evaluation of treatment polygons when compared to tamarisk difference maps along the Dolores River. Green areas show where tamarisk probability decreased and red where it increased.*

GOAL 3: MAPPING RUSSIAN OLIVE ALONG THE COLORADO RIVER AND ITS' MAIN TRIBUTARIES

Summary

• Limited field data for Russian olive occurrences in the Colorado River Basin

• Augmented existing data with novel digital sampling method and compared results

• Mapped Russian olive along the San Juan River for 2006 and 2016 using four modeling methods

• Found digitally sampled data performed better for 2006 than existing data but was equal to high quality field data for 2016-2017

• Model performed well, statistically, but there was variation in the spatial predictions across modeling methods

• The availability of larger, consistently sampled and application specific field data would improve model results

Russian olive, like tamarisk, is having significant impacts in the Colorado River Basin by degrading riparian habitat and preventing regeneration of the dominant native species (Reynolds & Cooper 2010) (Figure 12). Although Russian olive has been established throughout the basin for decades, there has been limited spatial data collected on this species. Due to this lack of data, we restricted our analysis to only targeted riparian areas in the Colorado River Basin to develop methods and evaluate results. We selected stretches of the San Juan and upper Colorado Rivers as case studies; however, we found the latter area was too poor to develop reliable models. Russian olive is visually distinct in both field surveys and satellite imagery because of its' silver-gray color (Hamilton et al. 2006; Madurapperuma, Oduor, Anar, and Kotchman 2013). After close inspection of Russian olive presence and absence data from 2005-2006, we concluded the data were not suitable for satellite imagery analyses. Therefore, an additional digital sampling approach was employed. Similar to the riparian vegetation sampling, this was performed using NAIP imagery in Google Earth Engine. We used ocular estimation to create points of Russian olive cover along the San Juan River. We also selected areas absent of Russian olive using in nearby locations. This was done for the 2005-2006 and 2015-2017 time frames. We refer to these points hereon as our digitally sampled points.

Figure 12. *Russian olive along the banks of the Colorado River near Rifle, Colorado. Photo credit: Meghan Vahsen*

We again restricted our analysis to the maximum riparian corridor extent as defined by our VBET analysis (see Goal 1) and used the random forest model to develop maps of Russian olive. We developed models using the field and digitally sampled points along with the indices and bands from the remotely sensed imagery. This produced binary maps of Russian olive presence and absence in the study area for 2006 and 2016 (Figure 13).

Models developed using field data collected in 2005 and 2006 over-predicted because these data used were not collected specifically for remote sensing purposes**.** For example, an ocular assessment of these data points revealed that many points marked as presence represented single trees or stands that were small enough that they would not dominate the spectral reflectance within a single pixel**.**

Excluding the model trained on Landsat 5 field data, all random forest models had out of bag errors below 6% and AUC values greater than 62%. This suggests that Russian olive lends itself well to remote sensing detection due to its unique spectral signature. Digital and field sampled points generally yielded comparable percent cover of Russian olive in 2016. Even though models contained similar percent cover, they showed some disagreement on the spatial distribution of Russian olive. Discrepancies between field and digital models were due to the way data was collected. The field data were collected from a number of sources and with inconsistent sampling methods. Alternately, digital data were collected using the same methods with remote sensing modeling in mind.

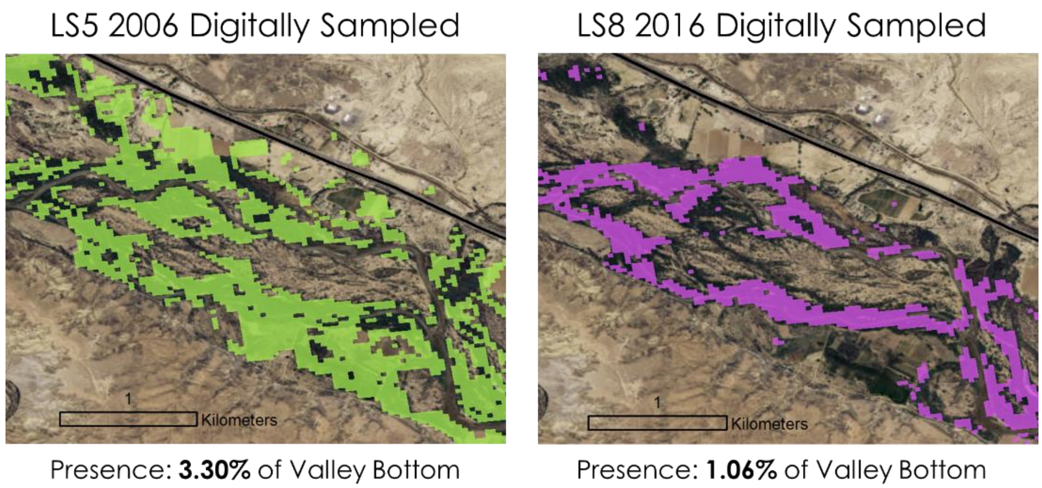

Figure 13. *Model results and coverage of Russian olive along the San Juan River in 2006 using Landsat 5 imagery and in 2016 using Landsat 8 OLI imagery*

All classification models in SAHM were generally very accurate based on statistical evaluation metrics; no significant differences between model performances were found except when using different datasets (field vs. digital). Even though the overall statistical accuracy was similar between models, spatial distribution varied. One SAHM evaluation tool, the ensemble map, generated a distribution map showing where models spatially agreed and disagreed, so we have high confidence in the map where they all agree. Each model was trained on a unique data set (i.e., unique by year of imagery and by data collection method), so it is difficult to compare models across time. Differences in image quality, data acquisition, radiometric resolution, etc., could cause differences in model output across sensors. This was validated by our results when applying a model generated from Landsat 5 imagery to Landsat 8 imagery and points.

GOAL 4: TEST SENTINEL-2 MULTI-SPECTRAL INSTRUMENTS FOR DETECTING TAMARISK AND RUSSIAN OLIVE

Summary

• Compared Landsat imagery to the more recently launched European Sentinel-2A imagery when developing models of tamarisk and Russian olive

• Found differences between models but difficult to discern if the difference was entirely due to sensor choice

• Higher-resolution Sentianl-2A models showed more details with slightly denser tamarisk predictions, however the difficulty is using Sentinel-2A data is prohibitive, especially at larger scales

With the recent availability of Sentinel-2 as a freely available resource for long-term remotely sensed imagery, we were interested in comparing mapping methods described above with Landsat imagery. Although there are many similarities between the two sensors, there are also many nuanced differences that can have major impacts for mapping. One of the key differences is the pixel resolution. Sentinel has four bands at 10 m resolution and another six bands at 20 m. Landsat bands are limited to 30 m. The higher resolution and the fact that it is freely available is the primary impetus to evaluate Sentienl-2A to Landsat. However, beyond resolution there are a number of challenges with Sentinel-2A. Since this is a relatively new satellite, there is no long-term monitoring data. In addition, the ease of access, download reliability and data structure are all much more difficult with Sentienl-2A compared to Landsat. While these issues are still being worked on, using Sentienl-2A data for mapping purposes is much more challenging than Landsat. Even so, a comparison between the two sensors is warranted and can provide valuable insights as to how to approach mapping species in the future. We conducted two case studies that were largely completed by the NASA DEVELOP teams (see Accomplishments) that used and compared both sensors for mapping tamarisk and Russian olive.

Case Study 1: Tamarisk mapping on the Dolores River

First, we tested the two sensors by mapping tamarisk in an area where we had the best available data, along the Dolores River. A subset of the original field and digitally sampled data from 2016 was used to train the Sentinel-2A model. This subset contained all data points that fell within the extent of the Sentinel-2A scene. This area covered a smaller proportion of the Landsat scene, but included much of the Dolores River (Figure 14). We created models for predicted percent cover and presence/absence. Due the lack of an independent validation data set, model performance was tested against the data that was used to train the model.

We tested a wide variety of remotely sensed predictor variables (bands and indices) captured during the growing period of April to September. Random forest models were used to determine which set of predictors worked best for each model. While no set of predictors was the same for any two models, there were commonalities in the predictors selected across the sensors and between sensors.

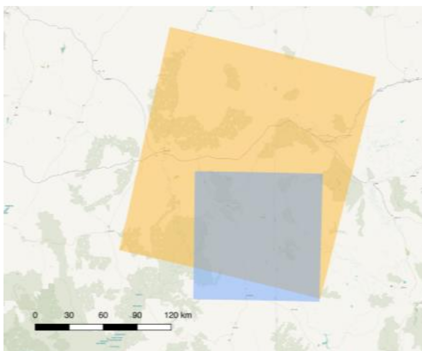

Figure 14. Overlay of Landsat scene Path 36, Row 33 in yellow and Sentinel-2 tile T12SXH (Military Grid System) in blue

We found that models developed with Landsat 8 imagery and Sentinel-2A imagery predicted considerably different tamarisk presence and percent cover (Figure 15). Within the Sentinel-2A scene, the Landsat 2016 percent cover model predicted 5.9% of the riparian corridor to be tamarisk cover, while the Sentinel 2016 model predicted 14.8% to be tamarisk cover. To perform a change detection analysis between the two models, the Sentinel-2A model was resampled to 30 m. A threshold of greater than 20 percent change in cover was used to produce the change detection map. The results show that 2.2 km^2 of land was mapped as having a higher percent cover by Landsat, whereas 26.8 km^2 was mapped as having a higher percent cover by Sentinel-2A. It is important to note that due to the different spatial extents of the Landsat and Sentinel scenes, the Sentinel model was trained with a subset of the Landsat 2016 training data. To improve this comparison the same training data should be used for both models.

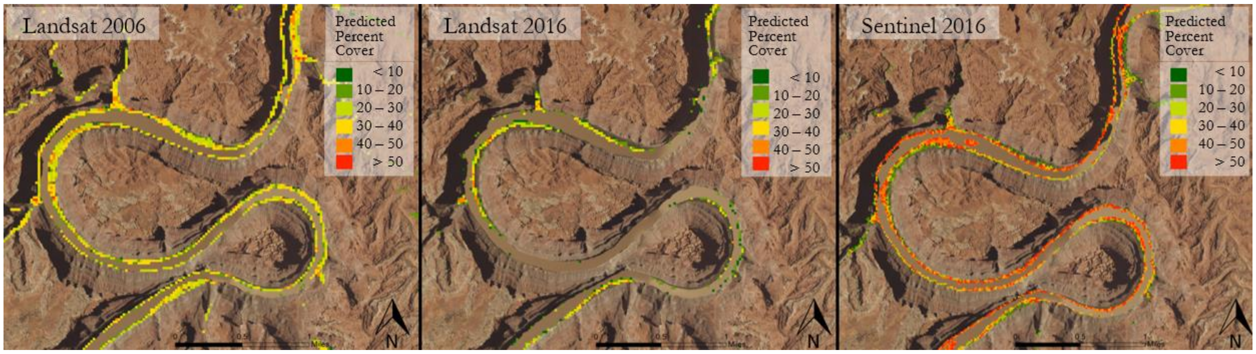

Figure 15. *Predicted tamarisk cover for Landsat 2006, Landsat 2016, and Sentinel 2016 models. Maps show percent tamarisk cover from the continuous model for areas that were predicted as presences by the binary model*

The results of the cross platform analysis between the Landsat 8 and Sentinel-2 show that Landsat 8 predicts lower tamarisk cover per pixel than models that used Sentinel-2 imagery. However, this may be primarily due to resampling methods to make the models comparable. Due to the different scene extents and spatial resolution between Landsat 8 and Sentinel-2, it is difficult to state which better represents true tamarisk cover without having ground reference data.

Case Study 2: Russian olive mapping on the San Juan River

Using the data and methods described in Goal 3, we compared models using Landsat and Sentinel-2A to map Russian olive. We developed and evaluated each of the statistical models fit in SAHM and compared their accuracy using various test statistics. Random forest models that used Landsat imagery performed well according to evaluation statistics. Sentinel-2A had higher model performance metrics than Landsat-8, suggesting that Sentinel-2A may be well-suited for detecting Russian olive presence. Sentinel-2A distinguished this species with more precision due to its higher spatial resolution, and yielded a more accurate boundary between vegetation and water (Figure 16). A comparison map showed that 6.4 km^2 mapped as Russian olive by the Landsat 8 model was not predicted as presence by the Sentinel-2 model. This accounted for 65.3% of the area predicted to be Russian olive by the Landsat 8 model. Similarly, 5.1km^2 mapped as Russian olive by the Sentinel-2 model was not predicted as Russian olive by the Landsat 8 model. This accounted for 58.6% of the area predicted to be Russian olive by the Sentinel-2 model (Table 3, Figure 16). Both models were trained with the same dataset so this variability is due to differences between the sensors. This is another case where evaluation statistics show strong performance, but qualitative evaluation indicates greater inaccuracies.

Table 3. Modeled area of Russian olive cover

Data Set	Percent Area of Valley Bottom Detected as Russian Olive (%)		Area Detected as Russian Olive (km^2)	
	Digital	**Field**	**Digital**	**Field**
LS5	3.30	63.75	113.25	2166.43
LS8	1.06	1.46	35.92	49.30
LS8 subset	1.42	N/A	9.77	N/A
Sentinel	1.26	N/A	8.69	N/A

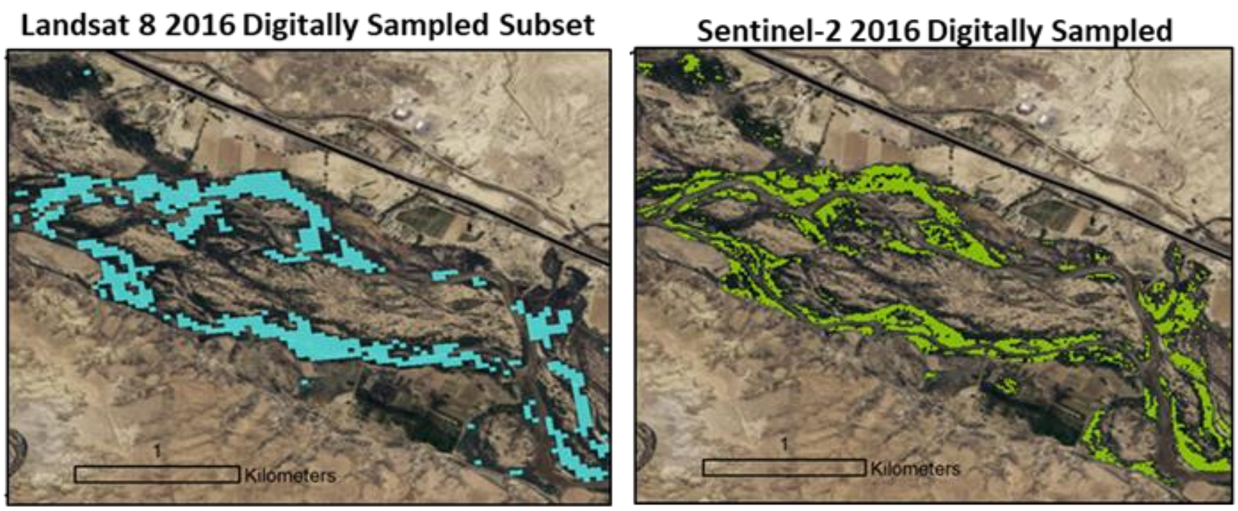

Figure 16. *Comparison of binary model outputs created for 2016 using Landsat 8 and Sentinel-2A imagery. Areas shaded blue in the Landsat map and green in the Sentinel-2A map represent Russian olive distribution.*

MAJOR ACCOMPLISHMENTS

This project propelled our team to critically evaluate existing data and knowledge concerning riparian vegetation and invasive species distribution within the Colorado River Basin while exploring novel methods and resources to accomplish our goals. During the process, we delivered a wealth of outcomes and achievements, while involving dozens of scientists, technicians, young professionals and students. With the appropriate data and modeling methods, change maps can be used to identify regions where the change is most significant. An evaluation of the change map in a known region of tamarisk management showed that our models did identify a substantial decrease in tamarisk. Continued validation efforts would greatly improve the overall confidence in the predictive capabilities of the models. The results of this study are a promising next step for project partners to utilize remote sensing to monitor the efficacy of management efforts throughout the Colorado River Basin and inform future management strategies.

Products

Product	Description
Vorster et al. 2018 for *Data*	Peer review publication describing the wide-scale novel tablet data collection of point data that included tamarisk, Russian olive, and co-occurring riparian vegetation
Woodward et al. *2018* in *ISPRS International Journal of Geo-Information*	Peer reviewed publication describing VBET and riparian mapping for Colorado River Basin
Maximum riparian corridor extent	A shapefile the covers the Colorado River Basin created using the recently-described Valley-bottom Extract tool (VBET)
Riparian vegetation digital Mapbook atlas	Riparian vegetation for 2006, 2016 and the change between years for the Colorado River Basin available through the Colorado State University Library
High-resolution elevation spatial layer	10 meter elevation layer for entire Colorado River Basin available through the Colorado State University Library
Targeted 2017 cover field data	Spreadsheet and shapefile of targeted cover data collected in 2017 in the Green River area, upper Colorado River and Dolores River
Tamarisk occurrence for 2016 digital Mapbook atlas	Select tamarisk modeling results for 2016 in a Mapbook atlas
Presentation of Results	Organized session and five presentations at the Tamarisk Coalition Annual Conference in 2018
Field data database	Most comprehensive and up-to-date dataset for tamarisk and Russian olive in the Colorado River Basin (Cannot be shared entirely due to data use agreements)
Remote sensing imagery	Landsat 5 TM and Landsat 8 OLI imagery for Colorado River Basin representing 2006 and 2016. Includes raw downloads and

	ecologically relevant derived indices amounting to over 3.5 TB of spatial data
Cloud cover estimation script	Automated cloud cover estimation script for Landsat imagery
Vegetation index generation script	Automated index generation script for Landsat imagery
R Markdown script	Automated script to create fully reproducible results is easy to view format of select methods and analyses
Google Earth Engine code	Google Earth Engine code to perform digital sampling and random forest modeling of riparian vegetation

NASA DEVELOP

The NASA DEVELOP program is a part of NASA's Applied Sciences Program and has been established to address environmental and public policy issues through interdisciplinary research projects that take advantage of NASA Earth observation platforms. The program builds capacity with partnering organizations and the young professionals who engage in the research projects. The Fort Collins NASA DEVELOP Node in collaboration with the Colorado State University Natural Resources Ecology Laboratory (NREL) and USGS Fort Collins Science Center conducted three 10-week research projects associated with this project. This program offers an opportunity for young scientists to engage with real world science applications using NASA imagery. The three projects focused on 1) an exploratory analysis to map the valley bottoms and riparian vegetation change along the Verde River in Arizona, 2) mapping tamarisk cover change in the area around the Dolores River, comparing performance of two satellites, Landsat and Sentinel 2, and 3) mapping Russian olive distribution along the San Juan River in 2006 and 2016, comparing the same two satellites. Much of their work is included in this report and related products.

Figure 17. *Summer NASA DEVELOP team collecting field data along the Green River. Photo by Anthony Vorster*

The highlight for the young scientists was a week of field sampling along the Dolores, Green, Price, San Rafael, and Colorado Rivers (Figure 17). The team learned the challenges and rewards of field work. Most of the crew had never seen this region, so they quickly developed a deep appreciation of this beautiful landscape and were lucky enough to have several wildlife and petroglyph encounters. This project exposed the team to the process of monitoring invasive species, from the field work through analysis and communication of results. The work from this term was presented to public lands managers at the 14th biannual conference of Science and Land Management in Flagstaff, Arizona, GIS Day at Colorado State University, CO, and the Annual Earth Science Applications Showcase in Washington DC.

PROJECT CONSTRAINTS AND CAVEATS

As with any research project, there are constraints and caveats that are important to identify. Given the scale and short timeline of this project, we had to make a number of assumptions and generalizations that could otherwise be fully investigated. Below we summarize some of the main constraints and caveats encountered during the project.

Field Data

Field data are an essential component to any spatial modeling effort. The need for high quality and time-specific data was one of the major constraints for the project. Although the original quantity of data gathered for the study area was large, once we auto-filtered and vetted these only a fraction of the total remained revealing a lack of point coverage for the Colorado River Basin (Figure 6). The data we gathered were collected for a number of reasons not necessarily suited for mapping the species at a specific time. Many did not have a date associated with them or lacked percent cover. In addition, there were geolocation errors (Figure 4) and the variability in polygon data forced us to drop those data from consideration. Lastly, there was a lack of high-quality absence data for similar reasons. Absence data (e.g., locations of co-occurring species such as cottonwood, willow, and mesquite) can dramatically improve classification models and without this we had to rely on randomly generation background locations, which are less preferable. We attempted to overcome some of these limitations by collecting our own data designed to quickly sample large regions and digitally sample when feasible (e.g., riparian vegetation and Russian olive – see above). While this data did improve models, time constraints and the inability to sample retroactively prevented a suitable dataset for the entire Colorado River Basin.

Remotely Sensed Imagery and Application Specific Data Collection

Remotely sensed imagery can be a powerful and rich data source for mapping species distributions. However, these data have a number of limitations. First is the availability of usable satellite imagery. Although Landsat sensors revisit the same spot on the Earth every 16 days, the image quality can be compromised by weather and atmospheric conditions. As such, we had to conduct an extensive cloud, cloud shadow, and snow filtering and masking analysis on the imagery which reduced the number of images available for each model. Although the resolution of Landsat images is considered to be appropriate for landscape scale analyses, it is relatively coarse when mapping a specific species that can have narrow and patchy occurrence across the landscape. Even when patches exists that are large and homogenous, these will be a mixing of pixels on the edge of the patch that will include co-occurring species, water, or another type of land cover that will dilute the tamarisk signal. Further, there is often a disconnect between measurements taken in the field and remote sensing analysis. Field measurements are often points or small plots representing only a few individual plants but for remotely sensed analyses, larger plot sizes representing multiple individuals over a larger area are ideal for constructing robust models. Also, when performing change detection between 2006 and 2016, we relied on two different Landsat sensors; Landsat 5 TM and Landsat 8 OLI. Although they were designed to collect similar data there are important differences and these may change the prediction of models between years. This could result in change maps that show differences between sensors in addition to changes in the distribution of a

Figure 17. *An example of tamarisk in the foreground that would be classified as "defoliated" in this dataset. Photo credit: Amanda West*

species. Finally, differences in seasonal phenology across the study area with tamarisk and native riparian vegetation were found to be significant, but the signature between tamarisk and other riparian vegetation did not show to be very different when using Landsat imagery (Figure 9). Without a different sensor with greater spectral or grain resolution this is a difficult constraint to overcome.

Management and Tamarisk beetle

One major challenge for mapping tamarisk has been the impacts of the tamarisk beetle across the Colorado River Basin. Unlike many other management actions, the tamarisk beetle has varied and cyclic impacts to tamarisk. This has major impacts to remote sensing analysis. During our field data collection, we encountered numerous locations where tamarisk beetles were active. However, their presence resulted in a mixed appearance of tamarisk. Some locations showed relatively healthy tamarisk but we found beetles on the live plants. Other locations had tamarisk that were completed dead. We also encountered many locations with characteristics between these two extremes. For example, we came across stands of tamarisk that were a mix of live and dead tamarisk. And in other areas, the tamarisk had a red appearance from tamarisk defoliation (Figure 18). This wide range of appearance for tamarisk can have a major impact on model development. Further, the appearance can change rather quickly in the span of a growing season resulting in multiple signals for the same location in a short timeframe. As we developed models of tamarisk occurrence, we discovered areas that had active beetle activity were difficult to accurately map given these conditions. For instance, the beetle activity further reduced the available field data for modeling because even in areas with extensive data collection we did not have adequate data representing live tamarisk to develop models. In addition, those areas that had a live-dead tamarisk mix added confusion to model results.

Modeling

When developing models, there are numerous parameters that need to be set. Normally, these are extensively researched in relation to the task at hand or are compared using sensitivity testing which involves running numerous tests and comparing the results to find settings that perform the best. Given the scale and timeline of this project, we could not fully parameterize every model and had to generalize or approximate. To fully parameterize each model would have required significant amount of time and additional data exploration. However, through our model testing, we found that "one size does *not* fit all". Although we modeled the same species across scene, different approaches work better depending on the scene which is likely a function of data quality and quantity, environment and other vegetation. Further, our testing and a review of the literature showed random forest to be one of the best model algorithms for our purposes but, ideally, multiple algorithms should be compared and perhaps combined to create more reliable predictions.

Others

Another limitation is the fact that we had numerous people conducting field data collection, digital data collection and developing maps. While we developed standardized protocols for all these processes, we expect to see some person-to-person variability in data collection and model procedure.

RECOMMENDATIONS

Field Data

- Quality assessment of existing field data is required before modeling
- Standardized and coordinated intensive field sampling campaign needed across the study area
- Important to collect field data oriented towards remote sensing analyses
    - Capture data at similar scale as pixel resolution
    - Collect vegetation cover data rather than presence/absence data when resources allow
    - Field data must align with timing of imagery, especially in areas with active tamarisk beetle
- Digital sampling for Russian olive is a possible efficient alternative to field sampling, although available aerial imagery may not be suitable in all areas

- There are many existing sources of data scattered across stakeholders in the Colorado River Basin, significant work remains to gather, standardize and organize these data

Remote Sensing

- Scripts for processing large amounts of imagery to handle cloud and snow issues
- Google Earth Engine NAIP digital sampling approach is effective
- Model Sentinel-2 at 10 meters
- Landsat imagery may not be the best sensor for mapping tamarisk in tributaries where tamarisk cover is low or occurs in narrow strips along rivers. Alternative, commercial, sensors could be used if only interested in current distribution.
- Model large landscapes (such as the Colorado River Basin) in smaller portions due to the many issues that arise with cross-scene normalization of imagery

Landsat vs Sentinel

- Sentinel is still new and as such there are a number of items related to downloading the imagery, preprocessing the imagery and interpreting model results for this new data source. And while we found more refined model predictions and detail in the resulting maps, it would be very difficult to scale any analysis up to larger regions given the current system.
- Due to its novelty, Sentinel-2A is difficult to use in mapping purposes, currently, but it may become a valuable option in the future as the data are made more readily available and additional satellites are added to the program for a shorter revisit durations
- Landsat imagery is still the most appropriate imagery for historical remote sensing analysis and Landsat 8 continues to deliver quality data that is easily harmonized with previous collections.

Modeling

- Use of the Software for Assisted Habitat Modeling (SAHM) for modeling (preprocessing, evaluation, provenance, etc.) was effective, especially for a multi-model and large scale project
- Testing a number of algorithms was helpful when possible, although random forest appears to consistently perform well
- If more percent cover data or absence data were available, it would be preferable to modify the modeling approach to a continuous regression framework or at least a presence/absence framework rather than presence/background
- Limiting predictions to the maximum possible riparian extent was effective for limiting over-prediction outside of the riparian zone
- Evaluation statistics alone are not sufficient and may be misleading—models must also be qualitatively evaluated

Portions of this report were originally drafted for inclusion in the ISPRS International Journal of Geo-Information

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APPENDICES

Appendix A. List of contacted stakeholders

Partner	State	Contact
Aquatic Ecologist, PhD with the University of Arizona	UT	David Walker
Archuleta County Weed & Pest Program	CO	Ethan Proud
Arizona Cooperative Extension, Yavapai County	AZ	Jeff Schalau
Arizona Interagency Weed Action Group	AZ	NA
Arizona Invasive Plant Program	AZ	John Richardson
Arizona Native Plant Society	AZ	NA
Arizona Pest Management Center, IPM Program Manager & Assoc. Director	AZ	Dr. Al Fournier
Ashley National Forest (which is affiliated with Flaming Gorge National Recreation Area)	UT, WY	Matthew Lee (Geospatial Data Manager), then in touch with Cherette Bonomo (Flaming Gorge Rangleand Management Specialist)
AZ Dept. Ag, Plant Services, Phoenix Operational Unit	AZ	Keith Miller
AZ Dept. Ag, Plant Services, Tucson Operational Unit	AZ	Edward Carr
AZ Dept. Ag, Plant Services, Yuma Operational Unit	AZ	Tony Joseph
BLM Assessment, Inventory and Monitoring	All	
BLM Assistant Field Manager	NA	Karen Simms
BLM AZ Office	AZ	Lisa Thornley, State Program Lead: Invasive and Noxious Weeds, Native Plant Conservation & Forestry

BLM CA Office	CA	Steven Walterscheid
BLM CO Office	CO	Jay Thompson (riparian program lead)
BLM Grand Junction Field Office	CO	Doug Diekman
BLM National Invasive Species Information Management System	All	Tenille Lenard
BLM Nevada Office	NV	
BLM NM Office	NM	Calvin Deal (BLM NM GIS lead)
BLM Rock Springs Office	WY	Jim Glennon (suggested by Kenneth Henke)
BLM UT Office	UT	
BLM WY Office	WY	Kenneth Henke
Boulder County Weed Coordinator County Parks & Open Space	CO	Steve Sauer
Carbon County Weed and Pest	WY	
Carbon County Weed Supervisor	UT	Brian Ostwald
Chaffee County Weed Department	CO	Kayla Malone
Clark County, Desert Conservation Program	NV	Caryn Wright
Clear Creek County	CO	Julie Whisenand
CO Dept. of Ag.	UT	Patty York, Early Detection and Rapid Response Specialist
Coconino County Cooperative Extension	AZ	Derek Bowerman
Colorado State University Graduate Degree Program in Ecology	AZ	Erin Cubley
Colorado State University Graduate Degree Program in Ecology	CO	Graham Tuttle
CSU Extension Gilpin County	CO	Irene Shonle
Daggett County Weed Supervisors	UT	Carol Gardener
DIGIT Lab, University of Utah	UT	Phoebe McNeally

Dinosaur National Monument	CO	Tamara Naumann and Peter Williams (Biological Science Technician)
Dixie National Forest	UT	Michael Golden
Dove Creek Mandatory Weed Control District	CO	Oma Fleming
Escalante River Watershed Partnership	UT	Stephanie Minnaert, Public Lands Project Coordinator
Fremont County Weed and Pest	WY	
Friends of Verde River	AZ	Anna Schrenk
Garfield County Road & Bridge Dept.	CO	Steve Anthony
Gila National Forest	NM	Bethany Davidson
Gila Rivershed Partnership	AZ	NA
Gila Watershed Partnership of Arizona	AZ	Dan Bove
Glen Canyon National Recreation Area	UT, AZ	John Spence, chief scientist
Graham County Cooperative Extension	AZ	Bill Brandau
Grand Canyon Weed Management Area	AZ	NA
Grand County	CO	Amy Sidener
Grand County Weed Supervisor	UT	Tim Higgs
Grand Staircase-Escalante National Monument	UT	Matt Betenson, assistant monument manager
Grand Staircase-Escalante National Monument (BLM)	UT	Amber Hughes
Gunnison Weed Coordinator County Weed District	CO	Jon Mugglestone
Hinsdale County	CO	Alice Attaway
http://cal-ipc.org/ip/mapping/index.php	CA	NA
http://pest.ceris.purdue.edu/state.php?code=AZ	CA	NA
https://www.wildlife.ca.gov/Data/BIOS	CA	NA
Imperial Weed Management Area	CA	Rachel Nilson
Jackson County Noxious Weed Program	CO	Janie Brands

Kane County Weed Supervisor	UT	Bert Harris
La Plata County Noxious Weed Program	CO	Ben Bain
Larimer County Land Stewardship Manager	CO	Casey Cisneros
Lincoln County Weed and Pest	WY	
Maricopa County	AZ	Theresa Pinto
Mesa County Weeds and Pest District	CO	Teresa Nees
Middle Colorado Watershed Council	CO	Nate Higginson
Mineral County	CO	Drew Marino
Moffat County Weed and Pest Management	CO	Jessica Counts
Mohave County Extension Director	AZ	Rob Grumbles
Montezuma County Weed Program	CO	Bonnie Loving
Nature Conservancy	AZ	Dr. Paul Brown
Nevada Department of Wildlife	NV	Brad Hardenbrook
Nevada Division of Forestry, Southern Region	NV	Cayenne Engel
New Mexico Forest and Watershed Restoration Institute	NM	Withnall, Katahdin
NMDA Natural Resources Specialist - San Juan Soil and Water Conservation District	NM	Melissa May
NMSU Extension Weed Specialist	NM	Kert Young, PhD
North American Weed Management Association	NA	NA
Northern Arizona University	AZ	Carol Chambers
Northern Arizona Weed Council	AZ	NA
Northern Nye Weed Management Association and Tonopah Conservation District	NV	Susan Wharff
Noxious Weed Program Coordinator-Arizona Department of Agriculture	AZ	Dr. Francis E. Northam
Noxious Weed Program Manager	CO	Scott Griffin

Noxious Weeds - Conservation Department	CO	
NPS - Exotic Plant Management Team	All	Jennifer Sieracki
NPS - Sonoran Desert Inventory and Monitoring Network	AZ	Sarah Studd
Ouray County Weed Control	CO	Ron Mabry
Ouray National Wildlife Refuge	UT	Diane Penttila
Pitkin County Public Works	CO	Melissa Sever
Potential Databases of Interest:	NA	NA
Rio Grande County Weed District	CO	Brianna Brannan
Riverside-Corona Resource Conservation District	CA	Kerwin Russell
Robinett Rangeland Resources (Prev. USDA Natural Resources Conservation Service)	AZ	Dan Robinett
Routt County Weed Program	CO	Greg Brown
Saguache County Center Conservation District	CO	Brenda Anderson
Same as Chaffee	CO	Same as Chaffee
Same as Graham and Pima, AZ	AZ	Same as Graham and Pima, AZ
Same as Graham, AZ	AZ	Same as Graham, AZ
Same as Pima, AZ	AZ	Same as Pima, AZ
San Diego Weed Management Area	CA	
San Francisco Peaks Weed Management Area	AZ	Scott Harger
San Juan County	CO	Mark Reavis
San Juan County Weed Supervisor	UT	Jim Eberling
San Miguel County Weed Control Program	CO	Ron Mabry
Sonoran Desert Museum - Invaders Program	AZ	Website Form
Sonoran Institute	AZ	Website form
Southern Nevada CWMA	NV	John Jones

Southern Utah-Northern Arizona Cooperative Weed Management Area	NA	NA
Southwest Conservation Corps	CO	Mike Wight and Emily
Southwest Vegetation Management Association	AZ	
State Noxious Weed Program Manager	UT	Rich Riding
State Weed Coordinator. New Mexico Dept. of Agriculture	NM	Jim Wanstall
Sublette County Weed & Pest District	WY	
Summit County Weed Coordinator Noxious Weed Program	CO	Ben Pleimann
Summit County Weed Supervisors	UT	Jack Marchant
Sweetwater County Water and Power	WY	Dan Matson
Sweetwater County Water and Power	WY	Dan Matson
Tamarisk Alliance CA	CA	Nicole Norelli
Tamarisk Coalition	ALL	Stacy Beaugh, Exec. Director
Tamarisk Coalition	ALL	Rusty Lloyd
Tamarisk Coalition	ALL	Ben Bloodworth, Program Coordinator
Tamarisk Coalition	AZ	Melissa McMaster
Tamarisk Coalition	CO	Shannon Hatch
Tamarisk Coalition	CO	David Varner
Tamarisk Coalition, Desert Rivers Collaborative	CO	Shannon Hatch
Teller Park Conservation District	CO	Marisa Nuezil
Teton County Weed and Pest District	WY	
The Nature Conservancy	NM, UT, CO	Dave Gori, Robert Findling
The Nature Conservancy	CO	Nathan Moyer and Celene Hawkins
Tonto Weed Management Association	AZ	NA

Tucson Mountain Weedwackers	AZ	NA
U.S. Bureau of Land Management, Southern Nevada District	NV	Aleta Nafus
U.S. Fish and Wildlife Service, Desert NWR Complex	NV	Kevin DesRoberts
UC Denver	ALL	Anna Sher
Uinta County Water and Power	WY	Chris Aimone
Uinta County Water and Power	WY	Chris Aimone
Uintah County Weed Supervisor	UT	Nathan Belliston
University of Arizona Cooperative Extension	AZ	Christopher Jones
University of Northern Colorado	CO	Dr. James Dunn
University of Northern Colorado	CO	Dr. Salo
UofA County Extension Director	AZ	Ed Martin
UofA County Extension Director & Agent	AZ	Barry Tickes
UofA County Extension Director & Agent	AZ	Kim McReynolds
UofA Extension Weed Specialist - The School of Plant Sciences	AZ	William McCloskey
UofA Noxious Weeds/Range Management Specialist & Professor	AZ	Larry Howery
Upper Gila Watershed Alliance	NM	Patrice Mutchnick
US Bureau of Reclamation-San Juan River Endangered Fish Recovery Program	NM, UT, CO	Mark McKinstry
US Bureau of Reclamation-Upper Colorado Region	ALL	Kathleen Callister (Environmental Resources Division Chief)
USFS Intermountain Region Invasive Species Coordinator	NA	Warren J. Ririe
USGS	NA	Pam Nagler
USGS Fort Collins Science Center	ALL	Eduardo Gonzalez
USGS Fort Collins Science Center	ALL	Pat Shafroth

USGS Fort Collins Science Center	ALL	Michael Scott
USGS Fort Collins Science Center	NA	Chris Jarchow
USGS Grand Canyon Monitoring and Research Center		Emily Palmquist, Laura Durning
Utah Division of Wildlife Resources	UT	Christian Edwards
Verde Valley Weed Management Area	AZ	NA
Washington County Weed Superintendent	UT	Bonnie Davis
Wayne County Weed Supervisor	UT	Rex Griffiths
West Yavapai Weed Management Area	AZ	NA
Zion National Park	UT	Laura Schrage and Dave Firmage

Appendix B. List of derived indices from Landsat TM and OLI TIRS imagery

Derived Indices from Landsat Imagery
Corrected Transformed Vegetation Index (CTVI)
Difference Vegetation Index (DVI)
Enhanced Vegetation Index (EVI)
Two-band Enhanced Vegetation Index (EVI2)
Global Environmental Monitoring Index (GEMI)
Land Surface Water Index (LSWI)
Modified Normalized Difference Water Index (MNDWI)
Modified Soil Adjusted Vegetation Index (MSAVI)
Modified Soil Adjusted Vegetation Index 2 (MSAVI2)
Normalized Difference Vegetation Index (NDVI)
Corrected Normalized Difference Vegetation Index (NDVIC)
Normalized Difference Water Index (NDWI)
Normalized Ratio Vegetation Index (NRVI)
Ratio Vegetation Index (RVI)
Soil Adjusted Total Vegetation Index (SATVI)_
Soil Adjusted Vegetation Index (SAVI)
Specific Leaf Area Vegetation Index (SLAVI)

Simple Ratio Vegetation Index (SR)
Transformed Vegetation Index (TVI)
Thiam's Transformed Vegetation Index (TTVI)
Weighted Difference Vegetation Index (WDVI)

Appendix C. Defining riparian areas: a comparison of definitions. Modified from University of Arizona 2007 Cooperative Extension Report "Understanding Arizona's Riparian Areas")

U.S. Department of Agriculture Natural Resource Conservation Service (USDA-NRCS, 2005)	"Riparian areas are ecosystems that occur along watercourses or water bodies. They are distinctly different from the surrounding lands because of unique soil and vegetation characteristics that are strongly influenced by free or unbound water in the soil. Riparian ecosystems occupy the transitional area between the terrestrial and aquatic ecosystems. Typical examples would include floodplains, streambanks, and lake shores."
U.S. Forest Service (USFS, 2000)	"Riparian areas are geographically delineated areas, with distinctive resource values and characteristics that are comprised of the aquatic and riparian ecosystems, floodplains, and wetlands. They include all areas within a horizontal distance of 100 feet from the edge of perennial streams or other water bodies…. A riparian ecosystem is a transition between the aquatic ecosystem and the adjacent terrestrial ecosystem and is identified by soil characteristics and distinctive vegetation communities that require free and unbound water."
Bureau of Land Management (BLM, 1999)	"A riparian area is an area of land directly influenced by permanent water. It has visible vegetation or physical characteristics reflective of permanent water influence. Lake shores and stream banks are typical riparian areas. Excluded are such sites as ephemeral streams or washes that do not exhibit the presence of vegetation dependent upon free water in the soil."
U.S. Fish and Wildlife Service (FWS, 1998)	"Riparian areas are plant communities contiguous to and affected by surface and sub-surface hydrologic features of perennial or intermittent lotic and lentic water bodies (rivers, streams, lakes, or drainage ways). Riparian areas have one or both of the following characteristics: (1) distinctively different vegetative species than adjacent areas, and (2) species similar to adjacent areas but exhibiting more vigorous or robust growth forms. Riparian areas are usually transitional between wetlands and upland."

U.S. Environmental Protection Agency (EPA) and National Oceanic and Atmospheric Administration (NOAA) Coastal Zone Management Act (EPA, 1993)	"Riparian areas are vegetated ecosystems along a water body through which energy, materials and water pass. Riparian areas characteristically have a high water table and are subject to periodic flooding and influence from the adjacent waterbody. These systems encompass wetlands, uplands, or some combinations of these two land forms. They will not in all cases have all the characteristics necessary for them to be classified as wetlands."
Society for Range Management and Bureau of Land Management	"A riparian area is a distinct ecological site or combination of sites in which soil moisture is sufficiently in excess of that available locally, due to run-on or subsurface seepage, so as to result in an existing or potential soil-vegetation complex that depicts the influence of that extra soil moisture. Riparian areas may be associated with lakes, reservoirs, estuaries, springs, bogs, wet meadows, muskegs and intermittent and perennial streams. The distinctive soil-vegetation complex is the differentiating criteria."
Lowrance et al., (1985)	"Riparian areas - Complex assemblage of plants and other organisms in an environment adjacent to water. Without definite boundaries, it may include streambanks, floodplain, and wetlands, ... forming a transitional zone between upland and aquatic habitat. Mainly linear in shape and extent, they are characterized by laterally flowing water that rises and falls at least once within a growing season."
National Research Council (NRC, 2002)	"Riparian areas - Transitional between terrestrial and aquatic ecosystems and are distinguished by gradients in biophysical conditions, ecological processes, and biota. They are areas through which surface and subsurface hydrology connect waterbodies with their adjacent uplands. They include those portions of terrestrial ecosystems that significantly influence exchanges of energy and matter with aquatic ecosystems (i.e., a zone of influence). Riparian areas are adjacent to perennial, intermittent, and ephemeral streams, lakes, and estuarine–marine shorelines."

Appendix D. A subset of the total combination of presence data, background data, environmental variables and model algorithms used to explore the best approach to map tamarisk in the Colorado River Basin.

Model Number	Path Row	Year	Presence data type	Presence data extent	Background type	Background method	Background extent	Vars used (short description e.g., TCap)	Model (RF or Maxent)
001	37/34	2016	Cleaned points	Riparian	Background	Random	VBET	TCAP - NDVI - MNDWI	RF
002	38/34	2016	Cleaned points	Riparian	Background	Random	VBET	TCAP - NDVI - MNDWI	RF
003	38/37	2016	Cleaned points	Riparian	Background	Random	VBET	TCAP - NDVI - MNDWI	RF
004	37/37	2016	Cleaned points	Riparian	Background	Random	VBET	TCAP - NDVI - MNDWI	RF
005	36/37	2016	Cleaned points	Riparian	Background	Random	VBET	TCAP - NDVI - MNDWI	RF
006	37/36	2016	Cleaned points	Riparian	Background	Random	VBET	TCAP - NDVI - MNDWI	RF
007	35/37	2016	Cleaned points	Riparian	Background	Random	VBET	TCAP - NDVI - MNDWI	RF
008	35/33	2016	Point&Cvr>20%	VBET	None	na	na	Full - None Removed	BRT
009	35/33	2016	Point&Cvr>20%	VBET	None	na	na	Full - None Removed	GLM
010	35/33	2016	Point&Cvr>20%	VBET	None	na	na	Full - None Removed	RF
011	35/33	2016	Point&Cvr>20%	VBET	None	na	na	Full - Correlated Removed	RF
012	35/33	2016	Point&Cvr>20%	Riparian	Background	KDE	VBET	TCAP - NDVI - MNDWI (Non Removed 35 cov)	RF
013	35/33	2006	Point&Cvr>20%	VBET	Background	KDE	VBET	TCAP - NDVI - MNDWI	Maxent
014	35/33	2006	Point&Cvr>20%	Riparian	Background	KDE	VBET	TCAP - NDVI - MNDWI	Maxent
015	35/33	2006	Point&Cvr>20%	Riparian	Background	KDE	Riparian	TCAP - NDVI - MNDWI	Maxent
016	35/34	2006	Point&Cvr>20%	VBET	Background	KDE	VBET	TCAP - NDVI - MNDWI	Maxent
017	35/34	2006	Point&Cvr>20%	Riparian	Background	KDE	VBET	TCAP - NDVI - MNDWI	Maxent
018	35/34	2006	Point&Cvr>20%	Riparian	Background	KDE	Riparian	TCAP - NDVI - MNDWI	Maxent
019	35/33	2006	Point&Cvr>20%	VBET	Background	Random	VBET	TCAP - NDVI - MNDWI	RF
020	35/33	2006	Point&Cvr>20%	VBET	Background	Random	VBET	TCAP - NDVI - MNDWI	Maxent
021	35/33	2006	Point&Cvr>20%	Riparian	Background	Random	VBET	TCAP - NDVI - MNDWI	RF
022	35/33	2006	Point&Cvr>20%	Riparian	Background	Random	VBET	TCAP - NDVI - MNDWI	Maxent
023	35/33	2006	Point&Cvr>20%	VBET	Background	Random	Riparian	TCAP - NDVI - MNDWI	RF
024	35/33	2006	Point&Cvr>20%	VBET	Background	Random	Riparian	TCAP - NDVI - MNDWI	Maxent
025	35/34	2006	Point&Cvr>20%	VBET	Background	Random	VBET	TCAP - NDVI - MNDWI	RF
026	35/34	2006	Point&Cvr>20%	VBET	Background	Random	VBET	TCAP - NDVI - MNDWI	Maxent
027	35/34	2006	Point&Cvr>20%	Riparian	Background	Random	VBET	TCAP - NDVI - MNDWI	RF

028	35/34	2006	Point&Cvr>20%	Riparian	Background	Random	VBET	TCAP - NDVI - MNDWI	Maxent
029	35/34	2006	Point&Cvr>20%	VBET	Background	Random	Riparian	TCAP - NDVI - MNDWI	RF
030	35/34	2006	Point&Cvr>20%	VBET	Background	Random	Riparian	TCAP - NDVI - MNDWI	Maxent
031	36/33	2006	Point&Cvr>20%	Riparian	Background	KDE	VBET	TCAP - NDVI - MNDWI	RF
032	36/33	2006	Point&Cvr>20%	Riparian	Background	Random	VBET	TCAP - NDVI - MNDWI	RF
033	36/33	2006	Point&Cvr>20%	Riparian	Background	Random	VBET	TCAP - NDVI - MNDWI	Maxent
034	36/33	2006	Point&Cvr>20%	Riparian	Background	Random	VBET	TCAP	RF
035	36/33	2006	Point&Cvr>20%	Riparian	Background	Random	VBET	TCAP	Maxent
036	36/33	2006	Point&Cvr>20%	Riparian	Background	Random	Riparian	TCAP - NDVI - MNDWI	RF
037	36/33	2006	Point&Cvr>20%	Riparian	Background	Random	Riparian	TCAP - NDVI - MNDWI	Maxent
038	36/33	2016	Point&Cvr>20%	Riparian	Background	Random	VBET	TCAP - NDVI - MNDWI	RF
039	36/33	2016	Point&Cvr>20%	Riparian	Background	Random	VBET	TCAP - NDVI - MNDWI	Maxent
040	36/33	2016	Point&Cvr>20%	VBET	Background	Random	VBET	TCAP	RF
041	36/33	2016	Point&Cvr>20%	VBET	Background	Random	Riparian	TCAP	RF
042	38/34	2006	Point&Cvr>20%	VBET	Background	Random	VBET	TCAP	RF
043	38/34	2006	Point&Cvr>20%	VBET	Background	Random	Riparian	TCAP	RF
044	38/34	2006	Point&Cvr>20%	Riparian	Background	Random	Riparian	TCAP	RF
045	38/34	2006	Point&Cvr>20%	Riparian	Background	Random	Riparian	TCAP	Maxent
046	35/33	2006	Point&Cvr>20%	Riparian	Absence	na	VBET	TCAP	RF
047	35/33	2006	Point&Cvr>20%	Riparian	Background	Random	VBET	TCAP	Maxent
048	37/33	2006	Point&Cvr>20%	Riparian	Absence	na	VBET	TCAP	RF
049	37/33	2006	Point&Cvr>20%	Riparian	Background	Random	VBET	TCAP	Maxent
050	36/33	2016	Point&Cvr>20%	VBET	Absence	na	VBET	Full (Bands, Indices, Tcap)	RF
051	36/33	2016	Point&Cvr>20%	VBET	Background	KDE	VBET	Full (Bands, Indices, Tcap)	Maxent
052	36/33	2016	Point&Cvr>20%	VBET	Absence	na	Riparian model	Full (Bands, Indices, Tcap)	RF
053	36/33	2016	Point&Cvr>20%	VBET	Background	KDE	Riparian model	Full (Bands, Indices, Tcap)	Maxent
054	36/33	2016	Point&Cvr>20%	VBET	Absence	na	VBET	TCAP	RF
055	36/33	2016	Point&Cvr>20%	VBET	Background	KDE	VBET	TCAP	Maxent
056	36/33	2016	Point&Cvr>20%	VBET	Absence	na	Riparian model	TCAP	RF
057	36/33	2016	Point&Cvr>20%	VBET	Background	KDE	Riparian model	TCAP	Maxent
058	36/33	2016	Point&Cvr>20% w/2016 field data	VBET	Absence	na	VBET	TCAP	RF

059	36/33	2016	Point&Cvr>20% w/2016 field data	VBET	Background	KDE	VBET	TCAP	Maxent
060	36/33	2016	Point&Cvr>20% w/2016 field data	VBET	Absence	na	Riparian model	TCAP	RF
061	36/33	2016	Point&Cvr>20% w/2016 field data	VBET	Background	KDE	Riparian model	TCAP	Maxent
062	36/33	2016	Point&Cvr>20% w/2016 field data	VBET	Background	Random	VBET	TCAP	RF
063	36/33	2016	Point&Cvr>20% w/2016 field data	VBET	Background	Random	Riparian model	TCAP	RF
064	36/33	2016	Point&Cvr>20% w/2016 field data	VBET	Background	Random	Riparian model	TCAP	Maxent
065	36/33	2006	Point&Cvr>20%	VBET	Background	KDE	Riparian model	TCAP	RF
066	36/33	2006	Point&Cvr>20%	VBET	Background	Random	Riparian model	TCAP	RF
067	36/33	2006	Point&Cvr>20%	VBET	Background	Random	Riparian model	TCAP	Maxent
068	36/33	2006	Point&Cvr>20%	VBET	Background	Random	VBET	TCAP	RF
069	36/33	2006	Point&Cvr>20%	VBET	Background	Random	VBET	TCAP	Maxent
070	36/33	2006	Point&Cvr>20%	VBET	Background	na	VBET	Full (Bands, Indices, Tcap)	RF
071	36/33	2006	Point&Cvr>20%	VBET	Background	na	VBET	Full (Bands, Indices, Tcap)	BRT
072	36/33	2006	Point&Cvr>20%	VBET	Absence	KDE	VBET	Full (Bands, Indices, Tcap)	RF
073	36/33	2006	Point&Cvr>20%	VBET	Absence	KDE	VBET	Full (Bands, Indices, Tcap)	RF
074	36/33	2006	Point&Cvr>20%	Riparian	Background	KDE	Riparian model	Full (Bands, Indices, Tcap)	RF
075	36/33	2006	Point&Cvr>20%	Riparian	Background	KDE	Riparian model	Full (Bands, Indices, Tcap)	BRT
076	37/35	2006	Cvr>20%	VBET	Background	Random	VBET	Full (Bands, Indices, Tcap)	BRT
077	37/35	2006	Cvr>20%	VBET	Background	Random	VBET	TCAP	Maxent
078	37/35	2006	All Point&Cvr	VBET	Background	Random	VBET	Full (Bands, Indices, Tcap)	RF
079	37/35	2006	All Point&Cvr	VBET	Background	Random	VBET	TCAP	Maxent
080	37/35	2006	All Point&Cvr	VBET	Background	Random	Riparian model	Full (Bands, Indices, Tcap)	RF

081	37/35	2006	All Point&Cvr	VBET	Background	Random	Riparian model	TCAP	Maxent
082	37/35	2006	All Point&Cvr	VBET	Background	KDE	VBET	TCAP	RF
083	36/33	2016	Point&Cvr>20% w/2016 field data	VBET	Background	Random	Riparian model	TCAP	Maxent
084	36/33	2016	Point&Cvr>20% w/2016 field data	VBET	Background	Random	Riparian model	TCAP	RF
085	36/33	2016	Point&Cvr>20% w/2016 field data	VBET	Background	Random	Riparian model	Full (Selected using Spectral Graphs)	Maxent
086	36/33	2016	Point&Cvr>20% w/2016 field data	VBET	Background	Random	Riparian model	Full (Selected using Spectral Graphs)	RF
087	36/33	2016	Point&Cvr>20% w/2016 field data	VBET	Background	Random	VBET	TCAP	Maxent
088	36/33	2016	Point&Cvr>20% w/2016 field data	VBET	Background	Random	VBET	TCAP	RF