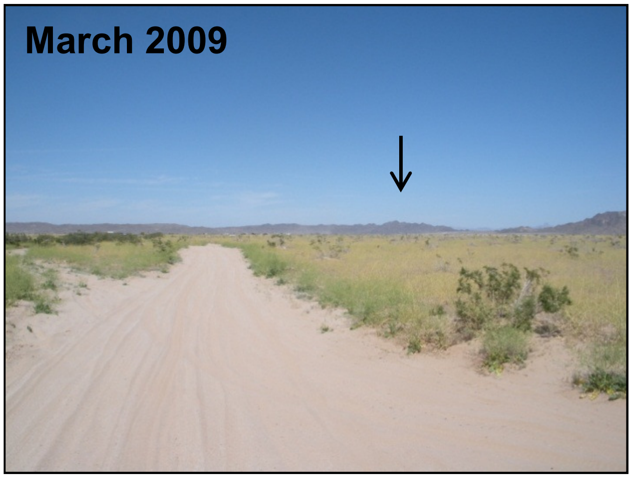
A New Time Series Remote Sensing Approach to Mapping Fine Fuels in Sonoran Desert Ecosystems



Final Report, Project ID: **10-1-04-7**

October 27, 2015

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Abstract

Annual grasses and forbs comprise the dominant fuel bed layer in hot desert portions of Sonoran Desert in Arizona. Many parts of the Sonoran Desert are dominated by non-native invasive grasses and forbs that can increase the potential for uncharacteristic large and severe wildfires. Sonoran Desert thornscrub and upland vegetation is unaccustomed to fire can be slow to recover representing a loss of animal habitat and biodiversity. This research focused on developing remote sensing-based methods to map fine fuels and target invasive plants red brome (*Bromus madriteneis*), Sahara mustard (*Brassica tournefortii*), African buffelgrass (*Cenchus ciliaris*), Mediterranean grasses (*Schismus* spp.), and arugula (*Eruca vesicaria v. sativa*). Invasive plants were hypothesized to show a competitive advantage over native species such as growing cycle differences that can be recognized using high temporal resolution satellite imagery such as the Moderate Resolution Imaging Spectroradiometer (MODIS) and Landsat Thematic Mapper (TM). We used a stratified random field sampling design and Habitat Suitability Models (HSM) for each target invasive species to sample sites with ≥0.90 suitability across a 66,541 Km^2 study area. Field plots and sub-plots were designed to sample within MODIS (250 m) and TM (30 m) pixels. Point intercept and comparative yield methods were used to estimate plant cover and biomass. We used time-series imagery and phenenology metrics from spectral vegetation indices such as the Normalized Vegetation Index (NDVI) to estimate fine fuel biomass, cover, and invasive plant occurrence for the study area. Field sampling from 2011 and 2012 measured a total of 744 plots and 3,701 subplots. Herbaceous biomass and fine fuel production was extremely low on plots averaging <50 kg/ha because of little or no rainfall prior to the growing season. The TM sensor experienced a mechanical failure and was not used. MODIS image-based models of fine fuels proved difficult with poor prediction under trace biomass conditions. Additional biomass models from plots measured in 2014 that used Landsat 8 NDVI provided improved fine fuel prediction for semidesert grassland sites ($r^2 = 0.56$). Novel plant phenology-based models developed in Google Earth Engine using MODIS and other predictor variables produced accurate models for the two most abundant invasive plants in the study area *Schismus* spp. (AUC = 0.88) and *B. tournefortii* (AUC = 0.86). Our results indicate that greater flexibility to sample sites during higher productivity years for hot desert for developing fine fuel biomass models. However, follow-on studies suggest that growing season NDVI values preceding large fires in the study area can be used to predict areas of high fuel hazard and risk.

Background & Purpose

Substantial research and development has been devoted to mapping and characterizing forest fuels, as wildfire activity on forest lands is often at the forefront of public attention. Satellite based burned area estimates indicate that contemporary grass- and shrublands rival or surpass the number of forest hectares burned annually within the continental US (Zhang and Kondragunta 2008). Non-forested landscapes frequently lack sufficient methods to capture the spatial and temporal variation in fuel-bed composition and structure necessary to evaluate potential fire behavior, hazard, and risk.

This research addresses BLM\JFSP Project Announcement No.FA-RFA-10-0001 Task 4, "*Improved fuels mapping in non-forested ecosystems*" for the Sonoran Desert. Native and non-native annual and perennial grasses and forbs comprise a majority of the flammable fuel-bed material in southwestern desert ecosystems (Esque and Schwalbe 2002). Variation in seasonal and annual precipitation mediates plant production cycles such that elevated rainfall periodically increases the amount and continuity of fine fuels (Patten 1978). Enhanced fuel beds consist of herbaceous plant biomass that fills interspaces between desert cacti, shrubs and other woody vegetation (Brooks and Matchett 2006). These conditions may persist for only a single fire season (June to September), or shorter durations, but have the potential to greatly augment fire hazard, risk and behavior in a given season or year (Esque and Schwalbe 2002).

Fire is historically considered to be an infrequent and low intensity disturbance event in southwestern desert vegetation types (Weiss and Overpeck 2005). However, the Sonoran Desert in Arizona experienced several large and severe wildfires following an extremely wet winter in 2004 and 2005, consuming as much as 10,000 ha of upland desert scrub vegetation in a single event (e.g., the King Valley Fire). In native and non-native dominated vegetation types, uncharacteristic fires of this magnitude are of particular concern since recovery of pre-disturbance vegetation and critical habitat for federally listed endangered plant and animal species may not occur for centuries (Hobbs et al. 1992, Esque and Schwalbe 2002, Esque et al. 2003).

Indeed, the long-term effects of non-native invasive plants on the seasonality, frequency and severity of desert wildfires are a recognized threat to biodiversity in desert ecosystems (Brooks et al. 2004). Burned areas can become establishment sites for non-native invasive plants, which, in-turn, promote an 'invasive grass/fire cycle' atypical of desert plant communities (D'Antonio and

Vitousek 1992). Of vital concern are a marked increase in non-native plant invasions by species, such as red brome (*Bromus madriteneis*), Sahara mustard (*Brassica tournefortii*), African buffelgrass (*Cenchus ciliaris*), and Mediterranean grasses (*Schismus* spp.), which can dramatically increase fine fuels accumulation on a site (Esque and Schwalbe 2002). These species have been linked to more frequent large fires in Sonoran and Mojave Desert ecosystems that have evolved primarily in the absence of fire (Weiss and Overpeck 2005, Swetnam and Beatancourt 1998, Tellman 2002).

Remote sensing is rapidly becoming an indispensable tool for monitoring plant phenology related to global change (Cleland et al. 2007), detecting non-native plant invasions (Lass et al. 2005), and quantifying fine fuels conditions on arid lands (Wessels et al. 2007, Verbesselt et al. 2006). Recent work has shown that invasive plants can be identified based on annual and interannual phenological differences from native vegetation (Bradley and Mustard 2006, Peterson 2005). For example, earlier timing of green-up relative to native plants has been used to map the distribution of the invasive annual cheatgrass (*Bromus tectorum*) (Bradley and Mustard 2006), while interannual variability in response to precipitation anomalies has been used to map the distribution of cheatgrass (Peterson 2005) and the non-native perennial Lehman lovegrass (*Eragrostis lehmanniana*) in Southwest desert environments (Huang and Geiger 2008).

Study Description & Location

This project focused on developing novel phenology-based remote sensing techniques to map native and non-native fine fuels production and occurrence across a 66,541-km^2 region of the Sonoran Desert (**Figure 1**). Accurate and efficient field-based measurements of herbaceous biomass were used to parameterize models responsive to interannual variation in plant production. To accomplish this, we established new sampling protocols to train and test landscape- and region-scale (100 to>10,000 km^2) models of herbaceous plant distribution, composition, and biomass (Wang et al. 2014). Spectral vegetation indices from satellite imagery were also related to plant processes, fine fuels accumulation, and the spatial extent of fuels to model where and when fire ignitions are more likely result in large fires (Gray et al. 2014).

The study area included BLM (11,600 km^2) and adjacent lands in the Sonoran Desert of southwestern Arizona (**Figure 1**). The area contains important levels of ecosystem heterogeneity and contiguous expanses of native habitats affected by large-scale fire and other disturbance factors. The dominant plant communities are typified by the Sonoran Desert scrub, Arizona Upland, and Lower Colorado River Valley subdivisions (Brown 1994).

Long-term average (1952-2007) precipitation from weather data collected at the nearby Yuma Proving Ground (YPG) and Kofa National Wildlife Refuge (KNWR) was 93 mm and 175 mm, respectively, and mean minimum (Dec.) and maximum (July) temperatures ranged between 5.9 °C (YPG) and 39.8 °C (KNWR) (Western Regional Climate Center 2009, www.wrcc.dri.edu/newweb.htm). Elevations range from <100 m in the lowlands to over 1500 m in the Dome Rock Mountains in the western part of the study area. Considerable topographic relief results from numerous small mountain ranges separated by expansive desert valleys, plains, and bajadas. Between 1970 and 2005, 1500 unique fire ignition events were recorded on the study area (Desert Research Institute 2006, www.cefa.dri.edu). Thirty-one percent of these events have occurred since 2000 and most were initiated in the agriculture and traffic corridors immediately adjacent to BLM lands.

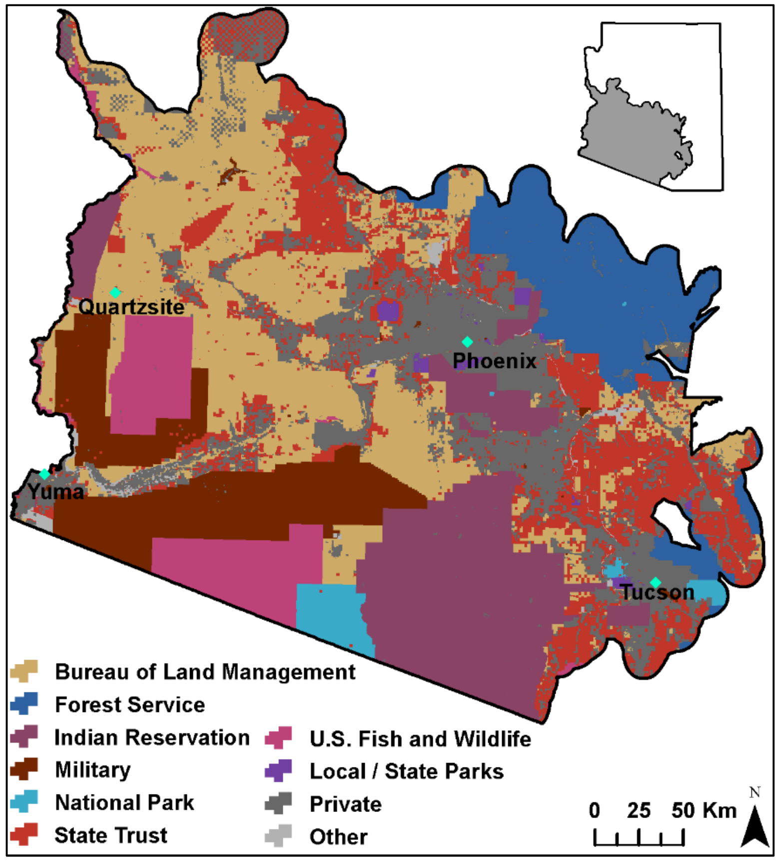


Figure 1. The 35,354-km^2 study region located in southwestern Arizona and land jurisdictions considered for sampling.

Objectives and methods for this project were focused on determining the relative contribution of native and non-native herbaceous grasses and forbs to fine fuel biomass in the Sonoran Desert study region. Each objectives outlined below was developed in conjunction with the matching project entitled "*Integrating spatial models of non-native plant invasion, fire risk, and wildlife habitat to support conservation of military and adjacent lands in the Sonoran Desert*" funded by the Department of Defense, Strategic Environmental Research and Development Program (SERDP; project RC-1722).

Principal study objectives were as follows:

1. Design and develop a cross jurisdictional sampling protocol for common and targeted non-native invasive plant species and fine fuels in the region.
2. Establish new sampling protocols to rapidly quantify fuel bed characteristics and biomass of herbaceous desert vegetation.
3. Develop and test remote sensing and phenology-based methods to distinguish and map herbaceous fine fuels (native vs. non-native) and biomass.
4. Improve methods to characterize fine fuel components of Sonoran Desert vegetation utilizing differences in phenology trajectories and spectral characteristics to distinguish native and non-native invasive plant groups.

Key Findings

A focus on non-native invasive plants and quantifying fine fuels required new techniques to effectively sample suitable sites across the study region for each target non-native invasive plant species; red brome (*Bromus rubens*), Sahara mustard (*B. tournefortii*), African buffelgrass (*C. ciliaris*), Mediterranean grasses (*Schismus* spp.), and arugula (*Eruca vesicaria v. sativa*). The spatial distribution of each species varied depending on invasion potential and degree of establishment (i.e. long-term vs. relatively recent introductions) in the study region (Wang et al. 2014).

Objective 1. Sampling design

A novel model- and random sampling-based approach was taken to effectively measure target invasive plant occurrence and fine fuel production across the study area. Existing invasive plant databases and plant occurrence locations were initially used to model species habitat suitability and develop a stratified random sampling design for the study area. A similar study by Crall et al. (2013) found that using HSMs to target sampling efforts for invasive plants improved sampling efficiency and detection rates above that of a non-targeted sampling design (e.g., completely randomized or gradient-based sampling). Habitat suitability model (HSM) and sampling details for this study are outlined in Wang et al. (2014). HSMs resulted in detecting at least one of the target plant species on 77% of plots in 2011 (Wang et al. 2014). Sample sites were selected for each target species for locations within 90th percentile habitat suitability values for 2011 and 70th percentile suitability values for 2012. Therefore, key findings from 2011 and additional constraints placed on sample site selection improved detection rates to target plant species on 96% of plots in 2012 (**Table 1**).

Table 1. Number and percentage of detections of five target species by plot and subplot sampled in the Sonoran Desert of Arizona during our 2011–2012 field seasons.

	2011 Detections		**2012 Detections**	
Species	**Plot (n = 238)**	**Subplot (n = 1,171)**	**Plot (n = 506)**	**Subplot (n = 2,530)**
Schismus spp.	133 (56%)	505 (43%)	473 (93%)	2020 (80%)
B. tournefortii	113 (47%)	329 (28%)	260 (51%)	748 (30%)
B.madritensis	15 (6%)	54 (5%)	11 (2%)	13 (0.5%)
E. vesicaria	14 (6%)	32 (3%)	26 (5%)	77 (3%)
C. ciliaria	21 (9%)	46 (4%)	3 (0.6%)	3 (0.1%)

Wide spread and abundant invasive plants such as *B. tournefortii* showed a high degree of correspondence between predicted detection rates using generalized linear models (GLM) and habitat suitability (**Figure 2**). Invasive plants that were regionally rare, but locally abundant in the study region such as *C. ciliaris* and *E. vesicaria* showed a weak relationship between modeled detection rate and habitat suitability.

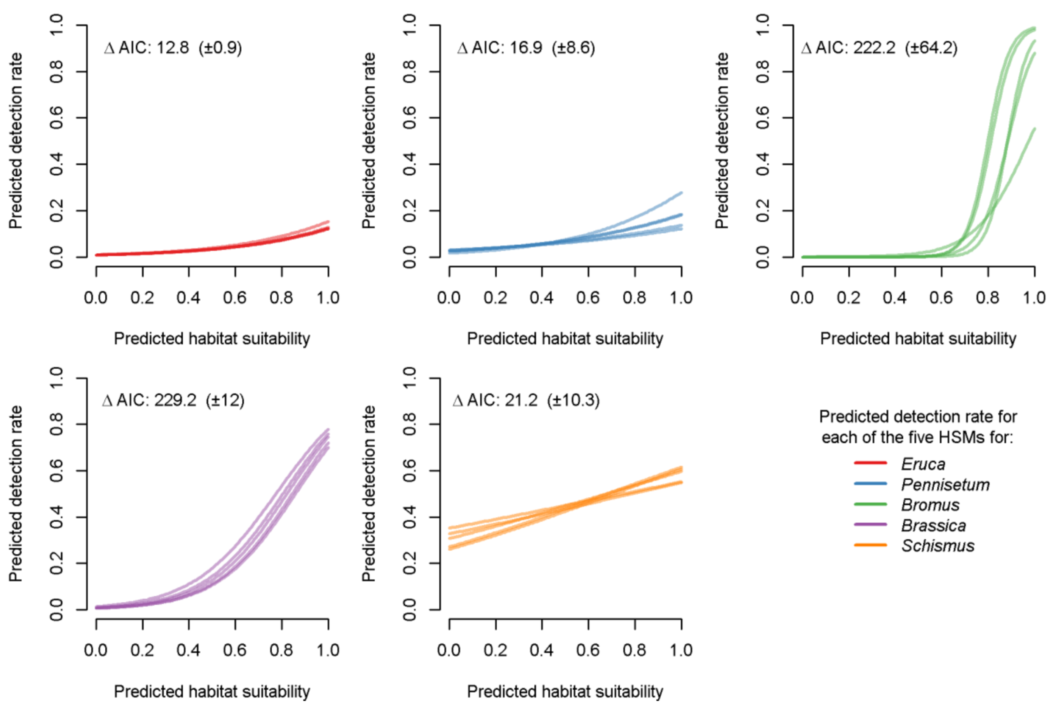


Figure 2. Relationship between predicted habitat suitability and modeled detection rate at subplots for each of the five habitat suitability models for each target invasive species. We used a generalized linear model to fit regression line between binary field detections in 2011 and predicted habitat suitability. Detections were modeled using a binomial distribution and a logit link function. For each target species, we show the average delta Akaike Information Criterion (ΔAIC) ±95% confidence interval for models of detection rate that included predicted habitat suitability versus models that included an intercept term only.

Subplots sampled in the field also showed good agreement between areas predicted to have high or low levels of habitat suitability and the number of target species detected. Two or more target species were typically detected in areas showing high habitat suitability for multiple species (**Figure 3**).

Objective 2. Protocols to efficiently quantify fuel bed characteristics for herbaceous desert vegetation

New field techniques to measure Sonoran Desert fine fuels were developed to complement conventional point intercept and modified comparative yield sampling methods that are widely applied in arid grass and shrublands (BLM 1996, Marsett et al. 2006). We also considered the use of Moderate Resolution Imaging Spectroradiometer (MODIS) and Landsat Thematic Mapper (TM) satellite remote sensing systems for invasive plant occurrence, herbaceous biomass, and fine fuels modeling to appropriately develop plot sampling techniques. Therefore, nested subplots and plots were co-registered with 30m TM and 250m MODIS pixels selected using HSM models (**Figure 4A, B**). Plots and subplots were measured during the peak annual and herbaceous plant productivity

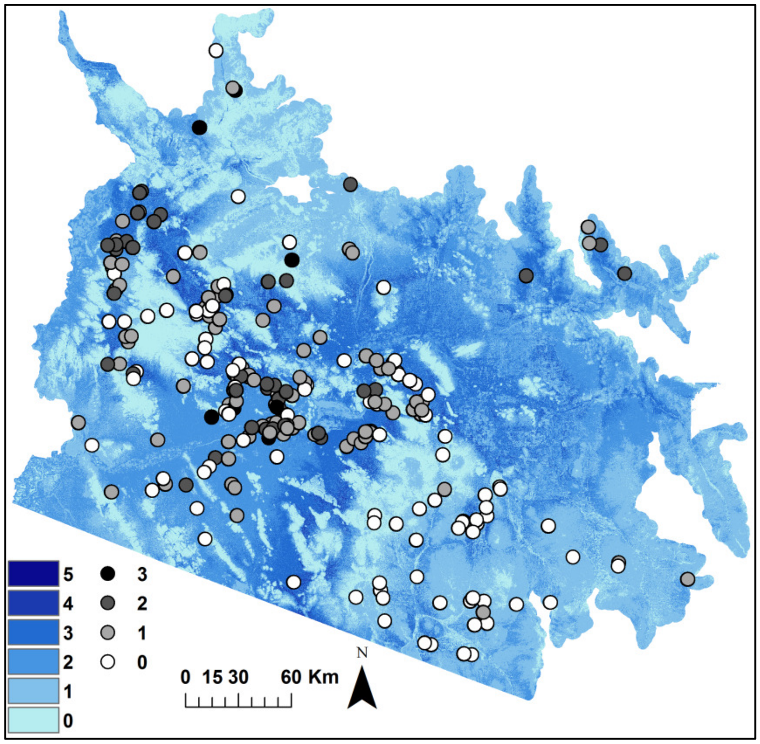


Figure 3. Number of species (black, gray, and white circles) detected in our study area in 2011. Colored areas show the number of habitat suitability models (Model 4 for winter annuals and Model 5 for Pennisetum) with predicted high habitat suitability (70th percentile). Darker colors indicate greater spatial overlap of high suitability across species.

period for the study area that is typically between January and March of each year (Marushia et al. 2010).

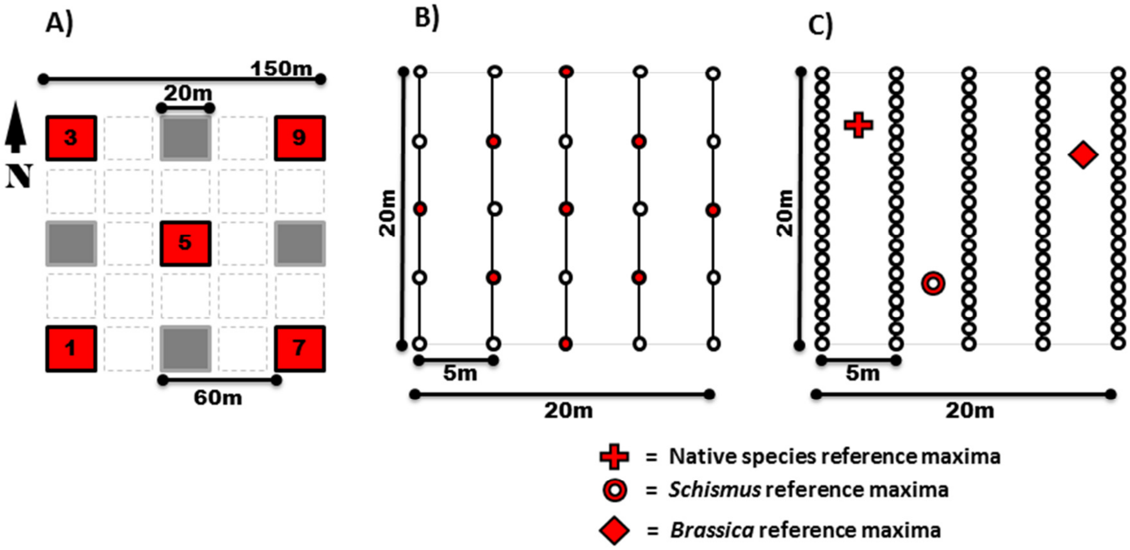


Figure 4. Nested pixel plot design used to sample plants in the Sonoran Desert of Arizona. A) Plots were co-registered with the resolution and location of a MODIS image pixel, and included five nested subplots, each co-registered with the resolution and location of a Landsat TM image pixel. Target and alternate (used when the target subplot was inaccessible) subplots are in red and gray, respectively. B) Within each subplot, five point-intercept transects were established to measure attributes of species composition and herbaceous biomass at 5 m (n = 25) intervals in 2011. C) The point sample interval was increased to every 1 m (n = 100) in year 2012 in addition to using comparative yield methods to estimate biomass on subplots (red symbols for samples clipped and weighed).

Destructive and comparative yield biomass estimates were used on a 0.33 m^2 circular micro-plot at 9 of the 25 point intercepts to estimate biomass from MODIS and TM pixel data. Biomass samples collected within micro-plots were placed into separate bags containing invasive plants from the current year's production, target invasive plants from the previous year, native plants from the current year, and native plants from the previous year. Field separated biomass was used to facilitate plant drying, weighing, and data entry for each category.

For a subset of subplots (n = 45), a spectrometer sampling protocol was developed to collect reflectance data using an ASD Inc. FieldSpec Max3 (350nm - 2,500nm range) from each of the 9 micro-plots (n = 405) where biomass samples were collected. A pistol grip and fiberoptic cable assembly were mounted on a specialized non-reflective (black) pole and leveling device to obtain un-shadowed spectral reflectance measurements from each 0.33 m^2 circular biomass collection point. To measure reflectance from only the clipping area, spectrometer measurements were recorded from 1.3 m above the ground with the bare fiber cable end equivalent to a 25° field of view. All spectral measurements were taken prior to biomass clipping and calibrated to field illumination conditions with a white reference spectralon disk. Spectral samples were collected at point locations averaging 20 measurements for each of five separate spectra, taken in less than five seconds per each intercept once equipment and foreoptics were in position.

Combined old and new herbaceous biomass (total biomass) was used as the principle response variable and spectral reflectance values as predictor variables using partial least squares regression (PLSR) models. PLSR is useful for analyzing highly correlated spectral data that is typical of high resolution spectrometers. All spectral values highly impacted by water vapor absorption and suspended solids such as dust, were removed prior to analysis. Resulting models indicated that field spectrometer measurements were likely impacted by extremely low biomass productivity on nearly all sites. Herbaceous biomass collected from plots ranged from 0 to 110 g, with a majority the data points showing no herbaceous biomass. As a result, very low variation was explained (29% maximum) by PLSR models with a maximum of 9 orthogonal factors and a maximum of 12% of the variance explained (6 factors) using 10 fold cross validation (**Figure 5**). Most samples were dominated by surface material such as rock, sand, soil crusts or dry woody material, resulting poor model performance when only trace amounts of herbaceous biomass exist within a micro-plot.

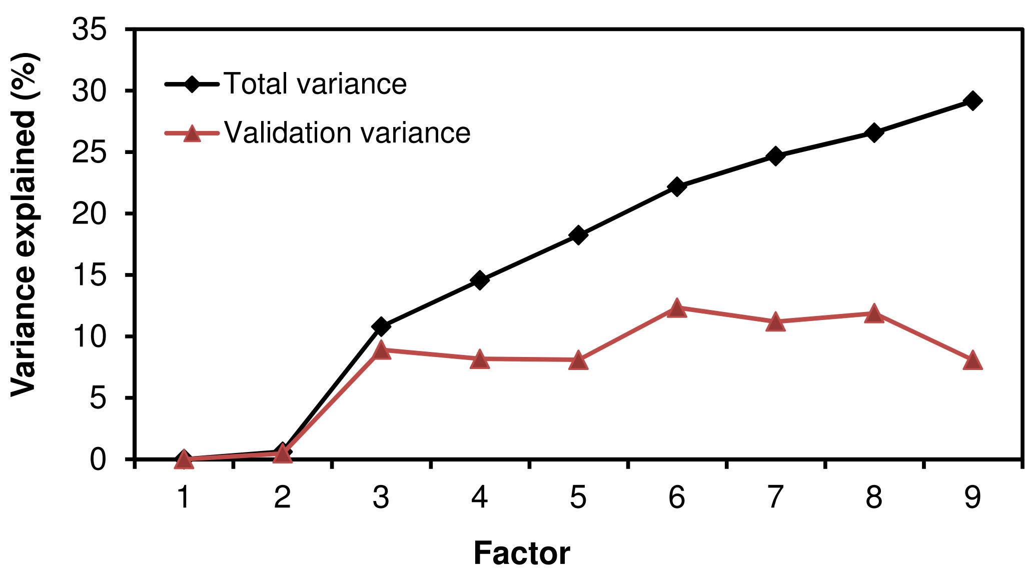


Figure 5. Partial least squared regression results indicating total amount of variance explained by

the model and variance explained from 10-fold cross validation with an increased number of orthogonal factors.

Spectrometer base-sampling methods may likely show improved results in grassland areas with consistently high herbaceous plant productivity. For this study, years 2011 and 2012 were marked by below average or no rainfall. Overall biomass estimates on subplots from comparative yield and destructive sampling were typically <17 kg/ha (**Figure 6**), compared to relatively wet years in the western Sonoran Desert that may range as high as 3,000 kg/ha in areas heavily invaded by buffelgrass (Martin et al. 1995). We briefly outline new JFSP project work that has greatly improved herbaceous biomass field sampling using a Decagon Devices AccuPAR LP-80 ceptometer and Leaf Area Index (LAI) below in the Ongoing Work section (see also Whitbeck and Grace 2006).

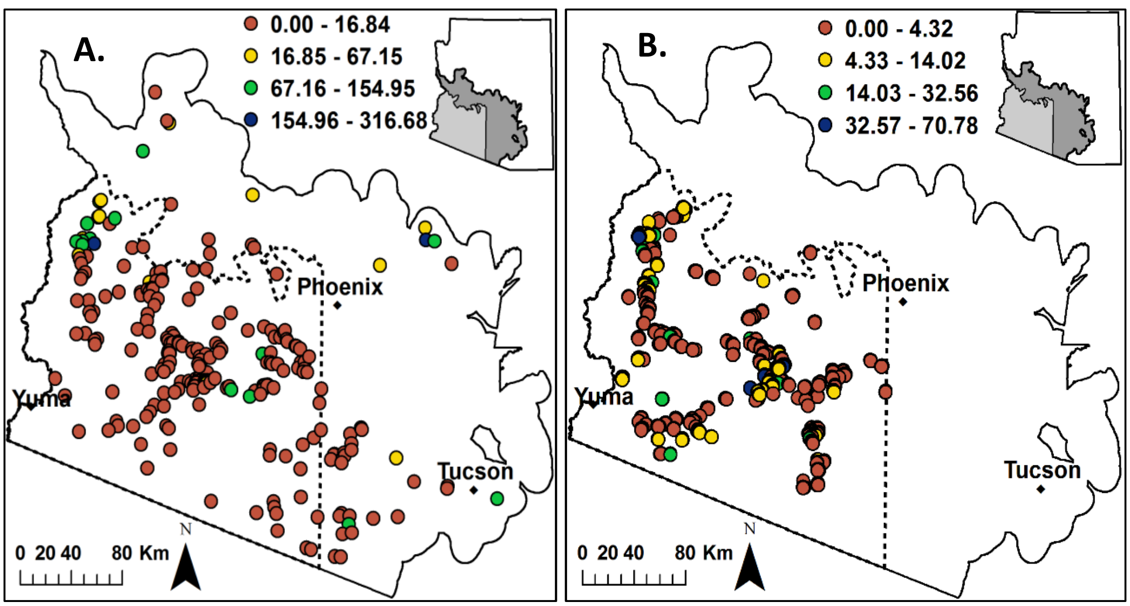


Figure 6. Extremely low biomass (kg/ha) estimates estimated for subplots measured during below average or no rainfall years A) 2011 and B) 2012. Sampling was limited to a smaller area in year 2012 lite gray inset map.

Objective 3: Develop and test remote sensing and phenology-based methods to distinguish and map desert herbaceous fine fuels (native vs. non-native) and biomass

Fuel parameters are not well quantified for desert landscapes because of high interannual variability and less attention paid to areas typically with lower fire potential. However, recent decades have shown increased fire behavior primarily in hot desert regions because of an increased abundance of non-native invasive annual grasses and forbs (Brooks 1999). Fuel models for the Sonoran Desert can change dramatically from year to year depending on rainfall and fine fuel production. We focused empirical herbaceous cover and biomass models on using

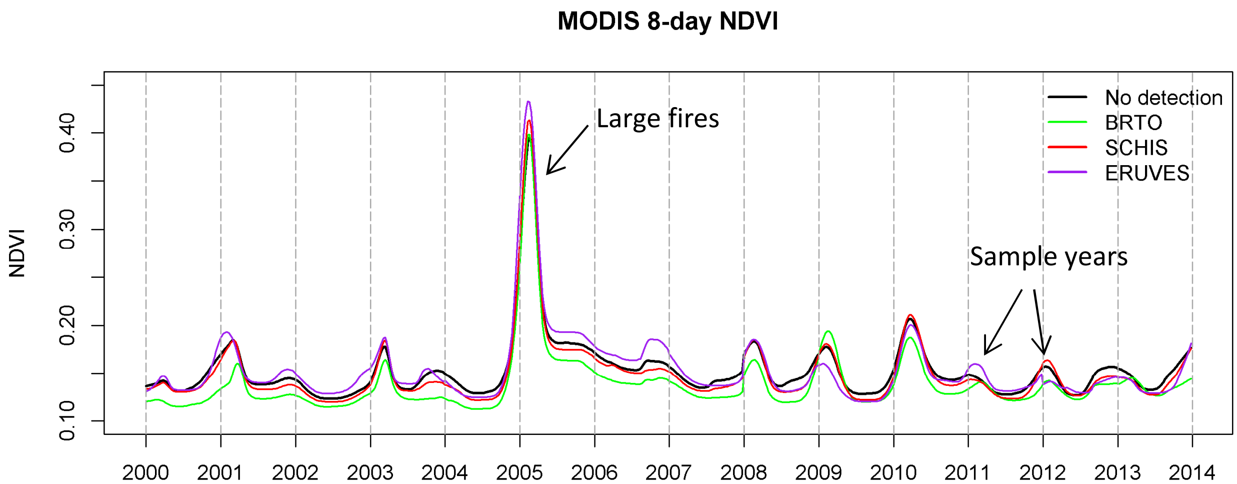


Figure 7. MODIS 8-day NDVI time-series data for plots with *B. tournefortii* (BRTO), Schismus spp. (SCHIS), *E. vesicaria* (ERUVES) or without targeted non-native plants (No detection). Year 2005 experienced several uncharacteristically large fires in the study area whereas the 2011 and 2012 sample years experienced below average rainfall, low fuel production and no fire activity.

MODIS and TM time-series imagery and spectral vegetation indices (VI) such as the Normalized Difference Vegetation Index (NDVI) to develop improved methods for estimating arid land fine fuel production and biomass. NDVI is calculated using red and near infrared (NIR) spectral ranges as Red-NIR/Red+NIR that is known to be sensitive to plant greenness, Leaf Area Index (LAI), biomass, and vigor (Huete et al. 2002). Improved methods to map fine fuels over time were sought as principal objective for this research because the five years preceding this study showed rapid increases in non-native plant production contributing to greater fuel-bed continuity (**Figure 7**).

Fine fuels on our plots were mainly comprised of annual grasses and forbs. Separate live and dead fine fuel measurements were made on plots. We found low fuel accumulation present on plots from the previous year's production, which can quickly break down and blow away in hot desert environments. Nevertheless, cover models were developed and tested for live and live + dead herbaceous biomass on a plot.

This aspect of the project was exceptionally difficult because of the low level of productivity observed for the Sonoran desert study area for 2011 and 2012 (**Figures 6, 7**). Areas of high target invasive plant productivity observed in previous years showed little or no fine fuel production during the field study (**Figure 8**). In addition, the higher spatial resolution TM sensor experienced a mechanical failure and was taken off line in November of 2011. Contingencies were used to aid in developing this aspect of the study because of the trace amounts of biomass measured in the field. We were less likely to accurately estimate herbaceous biomass and cover at the spatial scale of MODIS or TM pixels with low level and diffuse annual plant productivity. Therefore, we acquired higher spatial resolution SPOT-5 (10 m pixels) and Worldview-2 (WV2; 2 m pixels) imagery for a large portion of the study area in 2012 through the USGS commercial data purchased imagery program (https://lta.cr.usgs.gov/UCDP). Images were acquired during the peak productivity period for 2012 concurrent with field sampling. Higher spatial resolution satellite imagery generally lacks the time series capability of MODIS and TM imagery that are consistently acquired for desert regions. In addition, a separate effort was taken to use herbaceous biomass data collected in 2013 and 2014 from more productive Sonoran semidesert grasslands on Buenos

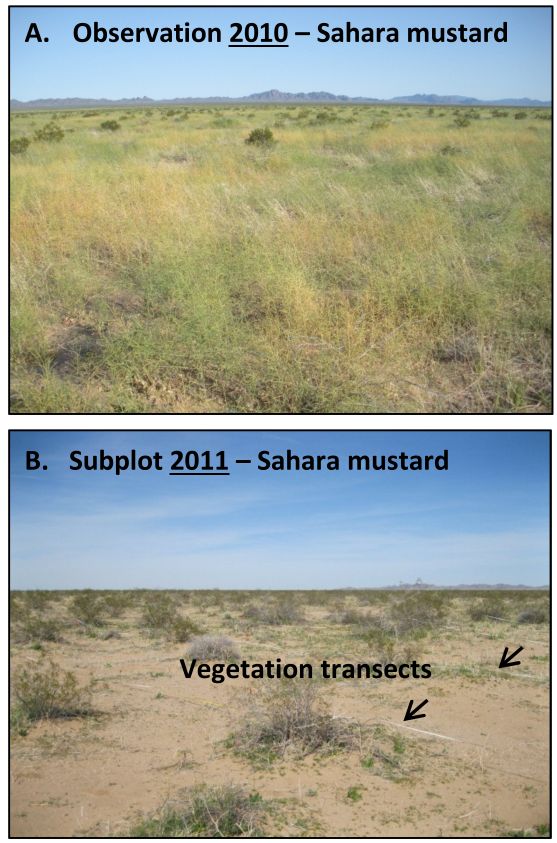


Figure 8. Study site biomass conditions for close to the same location in A) a year previous to the study period (March 23, 2010) and B) during the study period (March 11, 2011). Only a small number of sun-bleached stems from the previous year's Sahara mustard invasion can be seen in year 2011 as most stems have blown away.

Aires National Wildlife Refuge (BANWR; JFSP Project 13-1-16-16), east of the principal study area (*n* = 136 plots). Biomass on BANWR plots averaged 605 kg/ha as compared to 51 kg/ha and 44 kg/ha on average for plots within the JFSP-SERDP study area for 2011 and 2012 respectively. Approximately 550 kg/ha of continuous herbaceous biomass is needed to carry a fire in the Sonoran desert (Wade Reaves, personal communication).

For fine fuel cover and biomass predictive models, we used ordinary least squares (OLS) regression and Random Forest regression trees (Breiman 2001). We found that of the various satellite remote sensing platforms used to predict herbaceous biomass fine fuels cover in the SERDP-JFSP study area, MODIS performed the best when using intensively sampled 2012 plots and plant cover (r^2 = 0.63 live, r^2 = 0.64 live + dead; **Table 2**). NDVI from higher temporal resolution MODIS imagery provided a flexible platform to match annual herbaceous plant cover at or close to the time of sampling. In addition, improvements to the subplot sampling design also aided in good cover prediction. None of the herbaceous biomass models developed for the JFSP-SERDP study area performed well with such low annual plant production measured on plots. We anticipated that higher spatial and spectral resolution WV2 imagery (8 visible and near infrared) spectral bands would show improved cover and biomass estimates however this was not the case also because of extremely low productivity (Sankey et al. 2014).

Landsat 8 was launched in February of 2013, replacing TM and Enhanced Thematic Mapper (ETM+) sensors. From our more recent semidesert grassland plots sampled for fine fuels on BANWR semidesert grassland site, Landsat 8 NDVI in addition to other environmental and disturbance variables performed better for predicting herbaceous biomass (r^2 = 0.56), with the use of imagery closest to the sampling date (**Table 2**). Herbaceous cover estimates however performed poorly for these plots. Analyses for BANWR plots are still preliminary as other plots are currently being measured in addition to developing VI such as the Soil Adjusted Total Vegetation Index (SATVI) and Total Vegetation Fractional Cover (TVFC) following Marsett et al. (2006). We have also acquired high spatial (2 m – 4 m) and spectral resolution (16 visible and infrared spectral bands) Worldview 3 imagery during the peak summer growing season (September) in 2015 to test fine fuel cover and biomass model relationships with spectral VI.

Table 2. Herbaceous biomass model estimates from plots on JFSP-SERDP and JFSP-BANWR study areas.

Model Type	Image source	Project	Sample year	Predictors[1]	Pixel scale (m)	Response variable	R^2
OLS quadratic model with square-root transformed response	SPOT5	JFSP-SERDP	2012	Max NDVI	10	Biomass	0.18
OLS quadratic model	SPOT5	JFSP-SERDP	2012	Nearest NDVI	10	Cover	0.25 & 0.26[1]
OLS	WV2	JFSP-SERDP	2012	NDVI-B7, NDVI-B8[2]	30	Biomass	0.16
OLS	WV2	JFSP-SERDP	2012	NDVI-B7, NDVI-B8[2]	30	Cover	0.36
OLS quadratic model with log-root transformed response	eMODIS[2]	JFSP-SERDP	2012	Nearest NDVI	250	Biomass	0.17
OLS quadratic model	MODIS	JFSP-SERDP	2012	Nearest NDVI	250	Cover	0.63 & 0.64
Random forest	Landsat 8	JFSP-BANWR	2013 & 2014	NDVI covariates (nearest, interpolated NDVI, integrated NDVI, growing season maximum, mean and SD of NDVI at the plot, and maximum post-growing season NDVI) + environmental predictors (years since last burn, vegetation height, fire frequency, landform, elevation, slope, and northness)	30	Biomass	0.56
Random forest	Landsat 8	JFSP-BANWR	2013 & 2014	Same as above	30	Cover	0.24

[1]R-squared coefficient on left is from predictions for live biomass only and the coefficient on the right is from the sum of live and dead biomass.
[2]eMODIS 8- to 10-day composited NDVI layers

In the absence of strong biomass model performance for the study area, we used the relationship between contemporary fire occurrence, Landsat TM NDVI, and other environmental variables to model the likelihood of large fires. We characterized fires occuring between 1989 and 2010 as either 'large' (i.e. ≥ 20 ha) or 'small' (i.e. < 20 ha) fires. Twenty hectares represents a low-end estimate of large fire size in desert fuels and is a threshold that characteristically identifies years when the annual fuel load is sufficient for fire spread (W. Reaves, BLM, pers. comm.). We used fire occurrence data from two national level datasets (Finney et al. 2011, Short 2013 and Fire Program Analysis, www.fpa.nifc.gov). A random sample of fires that burned < 20 ha was eliminated from the dataset to establish a parsimonious 4:1 ratio of small to large fires (Brillinger et al. 2003). A mixed effects logistic regression model to estimate the relative probability of a large fire given a historical ignition event and conditioned on environmental covariates (fixed effects).

We accounted for the direct effect of fine fuel loads on large fire probability using time-series analysis and seasonal NDVI summaries. As a spatially and temporally 'dynamic' variable, it can be used to estimate fire risk over large, contiguous extents (Maselli et al. 2003). Yearly maximum NDVI in a given area was considered a proxy for the annual build-up of fuel (Box et al. 1989). To estimate yearly maximum NDVI values for 1988 to 2010 we obtained Landsat TM scenes covering our study area (n = 1114, temporal resolution = 16 days) from the US Geological Survey (USGS) Global Visualisation Viewer (http://glovis.usgs.gov, accessed November 2012). Our model included variables of the year-of-fire maximum NDVI value as well as the maximum NDVI value of the year before the fire.

We used the model-averaged regression coefficients and a Geographic Information System (GIS) to implement the full model and produce probabilistic, spatially explicit maps for two analysis years (1996 and 2005) at a 30-m pixel resolution. We chose these years to illustrate dynamic large fire probability in a moderate fine fuel scenario (1996) and high fine fuel scenario (2005), and we refer to these as moderate and high large fire probability scenarios. For 1996, we reasoned that fuel loads were affected primarily by the wet winter of 1994 and therefore only moderately abundant. Fine fuels were uncharacteristically abundant across the study area in 2005. Further details are found in Gray et al. (2014).

The compiled fire occurrence dataset included 316 small and 79 large fires that burned within the study area between 1989 and 2010. Over these 22 years, large fires burned a total of

57,000 ha. The extremely high fire year of 2005 saw the greatest number of large fires (n = 36) and highest total area burned (51,700 ha). The median size of a large fire in 2005 was 95 ha, whereas the 22-year median size of a large fire was only 60 ha.

The AIC of our full model of large fire probability was 71 units less than (i.e. better than) a null model containing only the random effects. The Hosmer–Lemeshow test did not indicate a significant lack of fit (P = 0.25). The ROC value for this model was 0.85, suggesting excellent discrimination. Among explanatory variables, areas with high maximum annual NDVI (w + (j) = 1.00), low elevation (1.00) and low road density (1.00) were the most strongly associated with higher large fire probability. Low vegetation heterogeneity was a strong predictor (0.90), as were south-facing slopes (0.80). Maximum NDVI as a lagged variable was less influential than the year-of-fire maximum NDVI, but was still a strong predictor (0.70). Topographic roughness was also a strong predictor of large fire probability (0.58), but less than the other variables we considered.

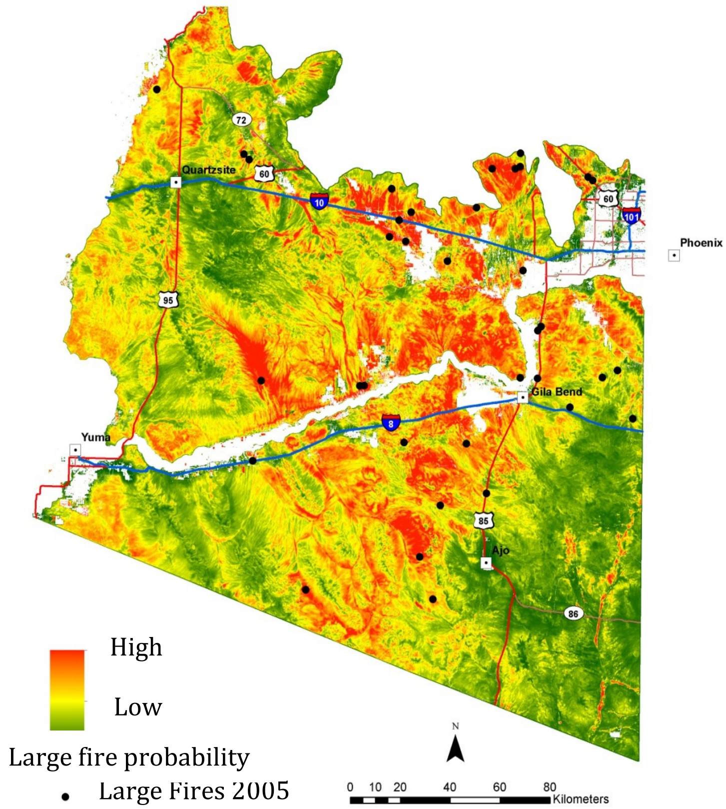


Figure 9. Map-based prediction of large fire probability in the lower Sonoran Desert of southwestern Arizona, based on 2005 conditions (i.e. high large fire probability). The ignition points of large (≥20 ha) fires that burned in 2005 are represented by black dots.

Random effects ranged from <10 to >300% of normal winter precipitation. The best linear unbiased predictors for the random effects (Faraway 2005) revealed that precipitation anomalies in the two antecedent winters had different predicted effects on large fire probability, but without discernible pattern.

Maps of the moderate (1996) and high probability (2005; **Figure 9**) scenarios showed very different patterns of large fire probability across the study area. In 1996 there were only a few isolated patches of very high large fire probability (e.g., >60%), whereas in 2005 there were much more widespread and spatially contiguous areas of very high probability. Over the entire study area, the mean probability of large fire was 0.13 (s.d. = 0.08) and 0.37 (0.21) in 1996 and 2005.

Objective 4: Improve methods to characterize fine fuel components of Sonoran Desert upland vegetation utilizing differences in phenology trajectories and spectral characteristics to distinguish native and non-native invasive plant groups

Non-native invasive plants are an increasingly dominant proportion of annual fine fuel bed composition in southwester deserts, which can encourage a more frequent grassland fire cycle than has previously been acknowledged (de'Antonio and Vitousek 1992, Van Devender et al. 1997). This aspect of the project focused on mapping the distribution of principal in non-native invasive plants *B. tournefortii* and *Schismus* spp. to help estimate areas potentially vulnerable to fire in relatively high productivity years (**Table 1**). All other target invasive plants in the study area were infrequently encountered on plots.

We developed two spatial modeling approaches to detect areas likely be invaded by *Schismus* spp. and *B. tournefortii*. The first was a satellite image time-series approach which assumed that target invasive plants had unique phenology patterns (Marushia et al. 2010). As seasonal rainfall is spatially heterogeneous in the study area, we used varying spatial model weights to account for uneven growing season conditions. We termed this new method a Spatially Weighted Ensemble (SWE) approach where a number of "local" models have been trained using a spatial subset of the field data and, by logical extension, are "tuned" to the local discriminating conditions of that spatial subset (Olsson et al. *in revision*). A second approach used a broader suite of satellite VI, spectral bands, and other environmental variables stored and processed within Google Earth Engine (GEE) and the Google Cloud. The two approaches are further outlined with a description of key findings below.

For the first approach, we used time-series VI and phenology and growing season metrics such as NDVI amplitude, maximum, start-of-season and end-of-season NDVI from MODIS imagery to characterize growing season differences between target non-native and native plants for developing predictive models to map probability of occurrence. To develop the SWE modeling approach, the spatial arrangement of plots within a subset of plots were used to derive an interpolated surface for each local model, described as an area of influence. The local models were then combined using linear combination, but with spatially varying weights. The weights of each local model were normalized at each cell such that the sum of weights is equal to one, and these weights are used to combine model values in a linear weighted sum. We tested a variety of spatial interpolations and weighting schemes, including a hybrid between spatial weights and performance-based weights. Performance-based weighting integrates multiple contributing models into an ensemble wherein the weights are augmented by each model's performance on a validation dataset, thus using intrinsic validation to guide weighting. For these models, we used the Random Forest algorithm to predict the likelihood of *Schismus* spp. and *B. tournefortii* occurrence using 2011 field data.

We compared the performance of SWE to "regional models" that also used the Random Forest algorithm to estimate invasive plant occurrence, but lacked spatial weighting. Our results indicated that SWE models performed similarly according to Cohen's kappa (k) that was observed for the regional models. For *Schismus* spp. k = 0.435 for the regional model and k = 0.429 the SWE model. For *B. tournefortii* k = 0.561 for the regional model and k = 0.576 for the SWE model. We used each model type to map invasive plant occurrence (**Figure 10 A-D**) and compare differences (**Figure 10 E-F**). Regional and SWE model outputs were also comparable with the exception of a few areas with much higher levels of occurrence predicted by the SWE model particularly with *B. tournefortii* (**Figure 10 E-F**). Higher SWE model predictions were consistent for sites with sandy soil conditions and greater levels of *B. tournefortii* cover during high productivity years.

We developed a second phenology-based approach to estimate invasive plant occurrence, but considered a broader set of predictor variables using GEE as an analysis platform. The use of phenology variables alone with SWE or regional Random Forest models did not show good performance as observed from low Cohen's kappa values above. As an alternative, we fit a single occurrence model for each species considering meteorological, geomorphological, and vegetation and surface reflectance variables simultaneously. Plots from both 2011 and 2012 were used for these models While it is possible to confound remote sensing-based occurrence models with measures of habitat suitability (Bradley et al. 2012), we believe that the coarse spatial resolution of environmental predictor variables (250m pixels), in addition to the way in which we derived the vegetation and surface reflectance variables, helped to alleviated this concern (**Table 3**).

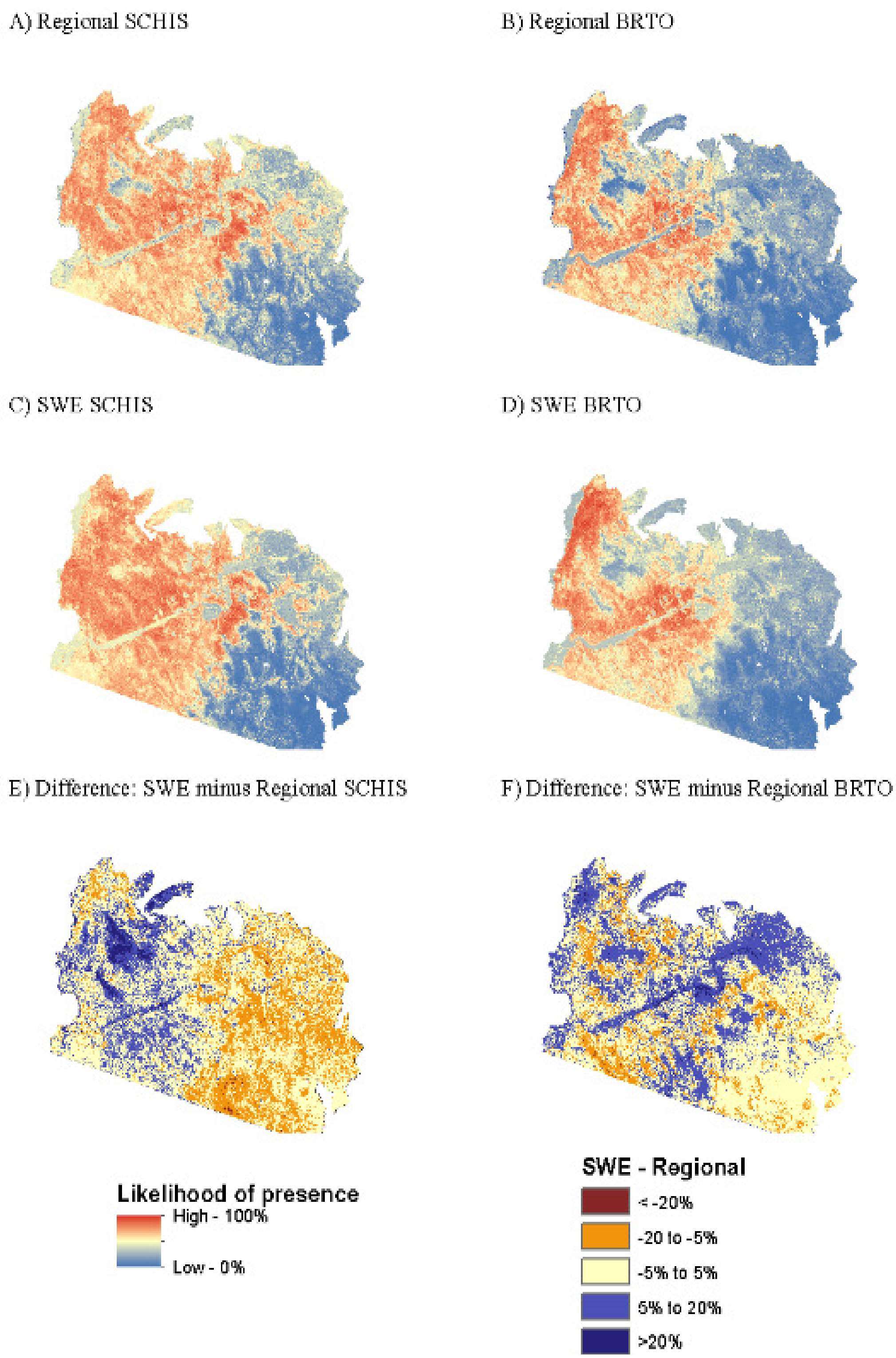


Figure 10. Model outputs from the A) SWE *Schismus* spp. (SCHIS) model, B) SWE *B. tournefortii* (BRTO) model, C) regional SCHIS model, and D) regional BRTO model. Differences between SCHIS and BRTO model outputs are shown in E) and F) respectively.

Table 3. Features used to predict the occurrence and cover of the invasive targets using Google Earth Engine. The total number of features in each category is indicated parenthetically in the group column.

Predictors	Dataset	Bands/variables	Filters[1]	Reduction(s)[2]	Citation/source
Meteorological (9 features)	The Gridded Surface Meteorological (GRIDMET) dataset (daily)	Precipitation, minimum and maximum temperature, and potential evapotranspiration	1983-2012 (the 30-year window leading up to and through the sampling effort) AND the 1st day of the week AND winter season	Mean and variance	(Abatzoglou 2013) https://earthengine.google.org/#detail/IDAHO_EPSCOR%2FGRIDMET
	The Palmer Drought Severity Index (PDSI) dataset	Not applicable	1983-2012 AND winter season	Anomaly[3]	(Abatzoglou et al. 2014) https://earthengine.google.org/#detail/IDAHO_EPSCOR%2FPDSI
Geomorphological (10 features)	The MODerate-resolution Imaging Spectroradiometer (MODIS) Albedo product	Visible, near-infrared, and shortwave white-sky albedo	Winter season	Mean and variance	(USGS LP DAAC) https://earthengine.google.org/#detail/MODIS%2FMCD43B3
	Shuttle Radar Topography Mission (SRTM, see Farr et al. 2007) digital elevation data	Elevation, slope, aspect (i.e., northness), and multi-scale TPI (sensu Theobald et al. *In review*)	Not applicable	Not applicable	https://earthengine.google.org/#detail/USGS%2FSRTMGL1_003
Vegetation indices and surface reflectance (96 features)	MODIS Vegetation Indices products (16-day composite)	NDVI and EVI. Blue, red, near-infrared, and shortwave reflectances.	Sampling year (for anomalies calculations)	- Mean and variance - Anomalies[4]	(USGS LP DAAC) https://earthengine.google.org/#detail/MODIS%2FMOD13A1
			- The month preceeding data collection - The two months bounding the data collection event (before and after) - The 8-month window leading up to the data collection event	- Max (for the first two filters) - Mean, min, max, and variance, as well as slope and intercept (for the final filter)	

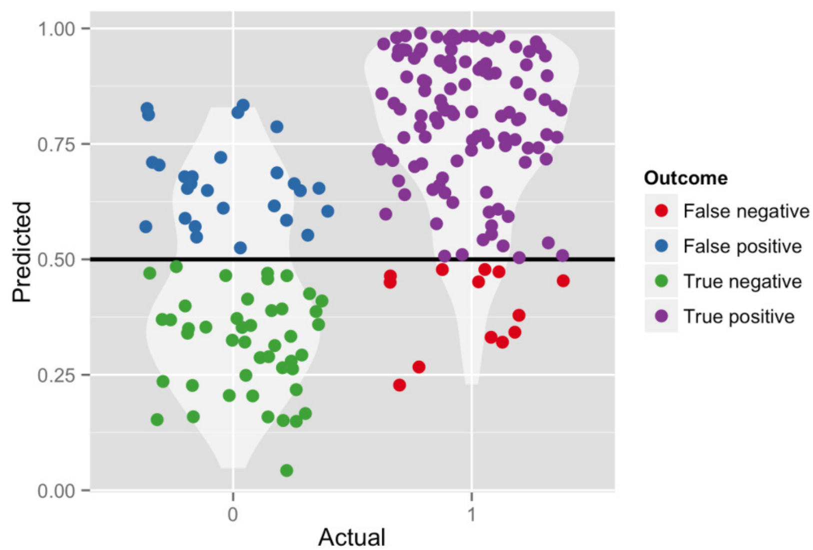
[1]The winter season was defined as December to March. Summer was defined as July to mid-September.
[2]All temporal reductions of image collections were followed with spatial reductions using the footprint of each plot.
[3] The 30-year mean PDSI subtracted from PDSI at the time of sampling.
[4]The mean and variance of selected bands in the year in which sampling occurred, divided by the mean for the entire series (15 years).

For this approach, we compared performance of Random Forest and Support Vector Machine (SVM; Cortes and Vapnik 1995) classifiers to select the algorithm a superior method. Models were tuned and trained using the caret package in R (Kuhn 2008). Each model was tuned to a training partition (70%) of the full dataset using repeated 10-fold cross-validation. Final models were applied to the testing data partition (30%) to generate more accurate estimates of out-of-bag sample error rates for model evaluation. We selected the best model using the *H* measure as part of model training and development (Hand 2009). The best model was re-fit using the full dataset in and the best hyperparameter values identified during the tuning process. This GEE classifier was then used to generate spatially-explicit predictions of the occurrence for *Schismus spp.* and *B. tournefortii*.

Occurrence probabilities were reclassified as present or absent if predictions greater or lower than a specified threshold as described below. We used the false positive rate balanced against false negatives by emphasizing the consequence of either error type. We used the Receiver Operating Characteristic (ROC) curve to visualizes and quantify the impact of the choice of threshold on the false-positive rate (FPR) and false-negative rate (TPR) tradeoff. In the context of plant invasions, false negatives are more consequential than false positives (Smith et al. 1999). Therefore, we created a cost function for each occurrence model by assuming a cost of 1 for false-positive cases and a cost of 2 for false-negative cases. An optimal ROC curve would go through the point (FPR, TPR) = (0, 1).

We used the Area Under the Curve (AUC) to assess the likelihood that the classifier will rank a randomly chosen positive instance higher than a randomly chose negative instance (Fawcett 2006). Conventionally, AUC values of 0.5 indicate that the modeled occurrence values are no better than randomly selected values. AUC scores of 0.6 - 0.7 indicate a poor fit of the model to the data, whereas values of 0.7 - 0.8, 0.8 - 0.9, and 0.9 - 1.0 indicate a fair, good, and excellent fit, respectively. We used these breaks as a rough guide to evaluate occurrence model performance. If presence is considered a positive (1) and absence as a negative (0) result, then **Figure 11** illustrates the tradeoff encountered upon specifying a reasonable threshold. If the threshold is increased, the number of false positives decreases, while the number of false negatives increases.

Figure 11. Jitter plot showing the distribution of absence and presence records (0 and 1 along the *x*-axis) for *Schismus* spp. on the predicted occurrence probabilities. An arbitrary threshold (horizontal black line) of 0.5 is displayed for illustration purposes only.



Random Forest models outperformed SVM models and were used to predict the occurrence of each target species. The AUC for the SCHIS model was 0.877, while the AUC for the BRTO occurrence model was 0.855. Note that the cost associated with the arbitrary threshold of 0.5 shown in **Figures 12** and **Figure 13** is not minimized. The final threshold selected for *Schismus*, based on the cost function and the optimization criteria described above was 0.43. The threshold selected for *Brassica* was 0.38. These can be identified by the inflection point and greenest circles in their respective cost function curves (**Figure 12b, 13b**).

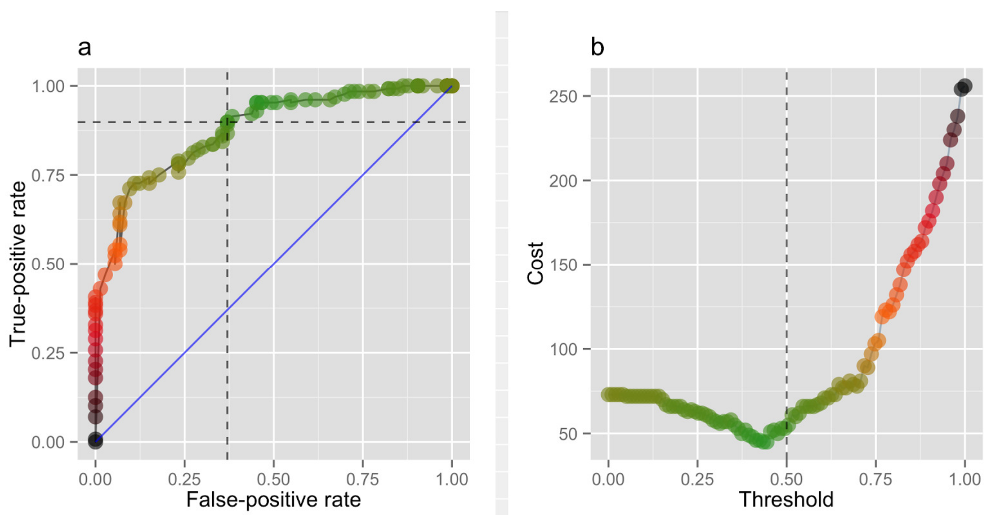


Figure 12. a) Receiver Operating Characteristic curve and b) cost function for the *Schismus* spp. occurrence model. An arbitrary threshold of 0.5 was used here for illustration purposes only. The 1:1 line in blue indicates a hypothetical ROC curve in which a model would perform no better than chance.

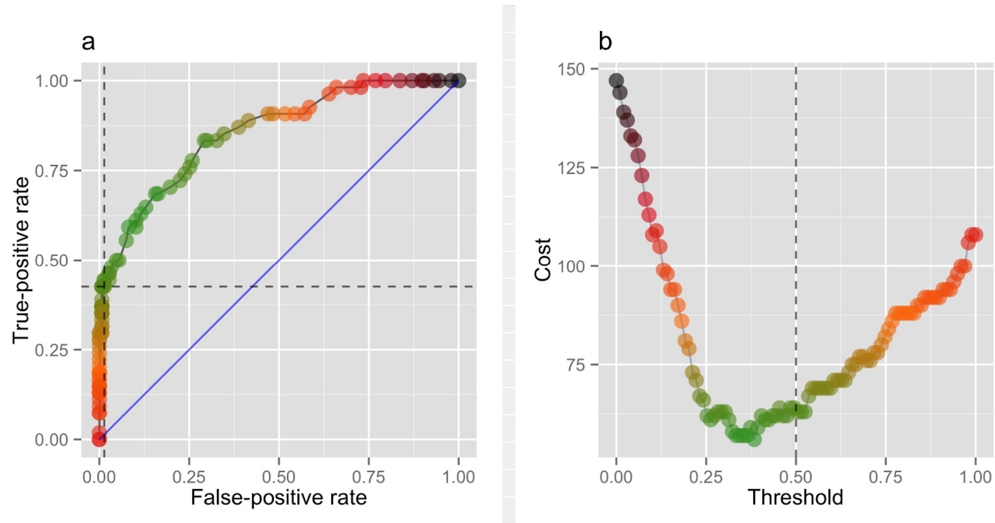


Figure 13. a) Receiver Operating Characteristic curve and b) cost function for the *B. tournefortii* occurrence model. An arbitrary threshold of 0.5 was used here for illustration purposes only. The 1:1 line in blue indicates a hypothetical ROC curve in which a model would perform no better than chance.

We considered models derived for *Shismus* spp. and *B. tournefortii* as falling within the 'good' range according to conventions on AUC-related performance measures. The thresholds derived from the cost functions for each species were both < 0.5, which reflects the relative costs assigned to false-positive vs. false-negative cases *a priori*. We considered that false-negative cases were twice as costly as false-positive cases because the ecological consequences of *Schismus* spp. and *B. tournefortii* going undetected outweigh concern for overestimating their occurrence. The spatial distribution of predicted occurrence probabilities in the bottom row of **Figure 14** and **Figure 15** reflect these optimized cost parameter settings.

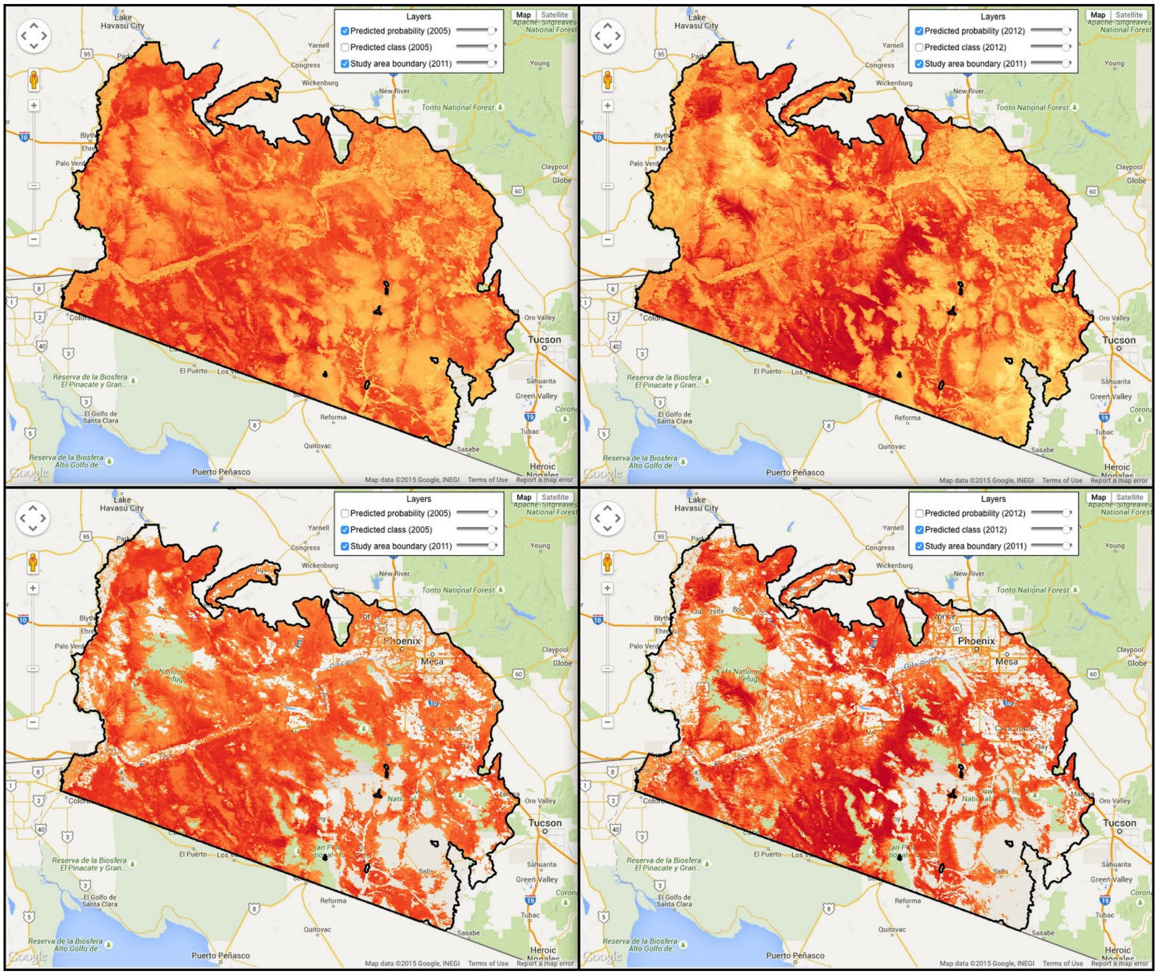


Figure 14. Predicted occurrence probability for *Schismus spp.* in 2005 and 2012 (left and right columns, respectively). Results shown in the maps in the bottom row of the figure have been masked using the threshold identified during the model evaluation step (i.e. 0.43).

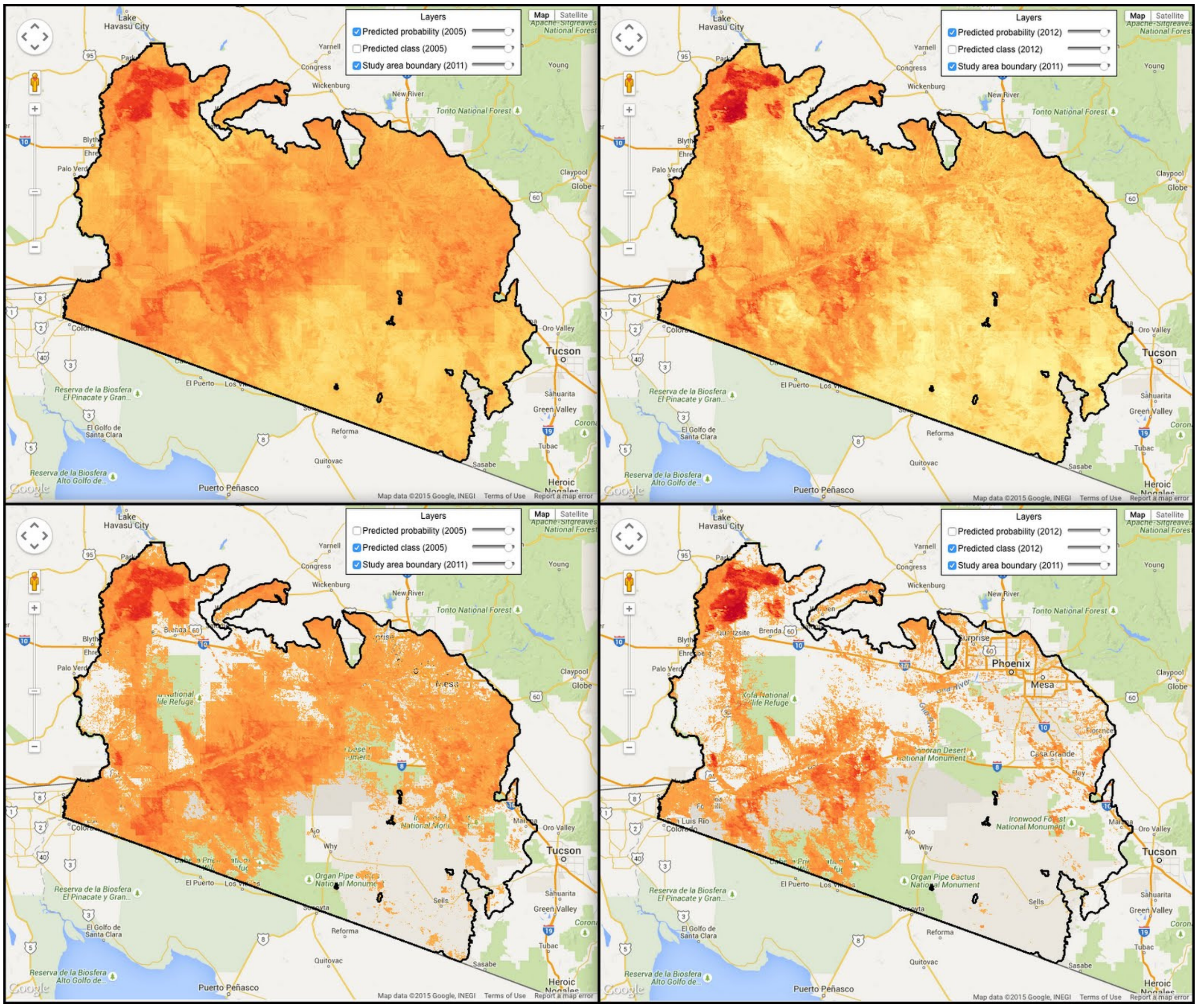


Figure 15. Predicted occurrence probability for *B. tournefortii* in 2005 and 2012 (left and right columns, respectively). Results shown in the maps in the bottom row of the figure have been masked using the threshold identified during the model evaluation step (i.e. 0.38).

The difference in the magnitude of predicted occurrence probabilities between the 2005 high productivity period and 2012 period of below average rainfall was notable for both target invasive species (**Figure 16, 17**). Specifically, the predicted occurrence probability for *Schismus* spp. is not uniformly higher in the wetter, more productive year as it is (with very few exceptions) for *B. tournefortii*. Wetter, more productive conditions appeared to favor *Schismus* spp. southeast of Kofa National Wildlife Refuge while dry, unproductive conditions may slightly favor *Schismus* spp. across much of the south-central portion of the study area. Overall, *Schismus* spp. maintains a relatively stable and pervasive presence across the landscape and across years.

Figure 16. Difference between the predicted occurrence probabilities in 2005 and 2012 for *Schismus* spp. Blue regions indicate higher predicted occurrence probabilities in 2005 while red regions indicate higher predicted occurrence probabilities in 2012.

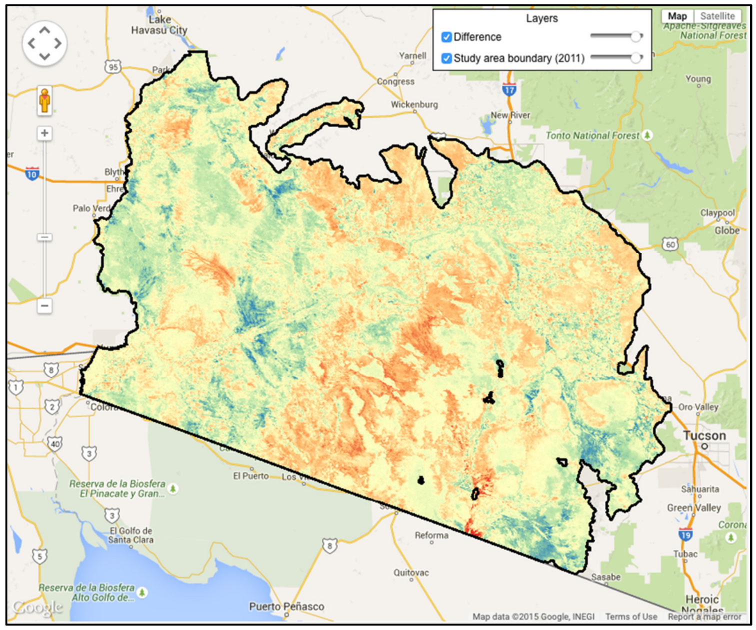
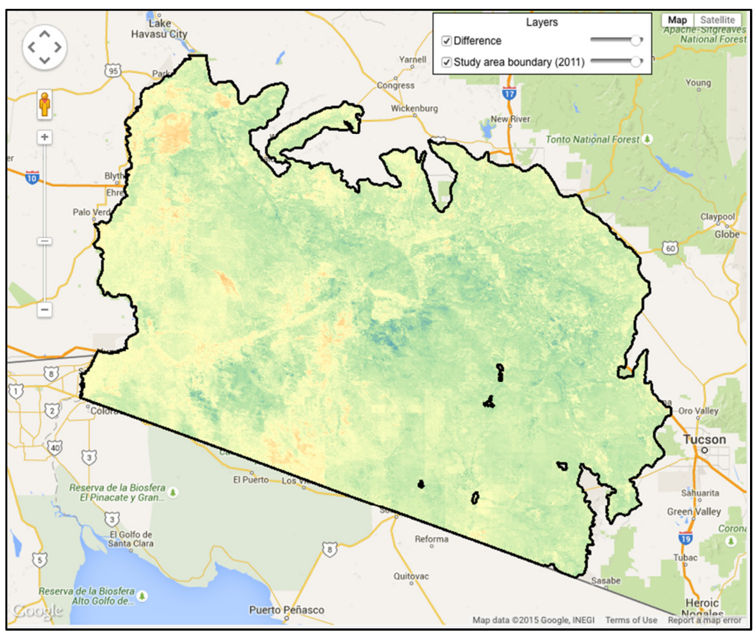


Figure 17: Difference between the predicted occurrence probabilities in 2005 and 2012 for *B. tournefortii*. Blue regions indicate higher predicted occurrence probabilities in 2005 while red regions indicate higher predicted occurrence probabilities in 2012.



Overall, we obtained strong predictive models for the two species that we had sufficiently large sample sizes (**Table 1**). While we did not have the sample sizes needed to create models for the other target species (i.e., *B. madritensis*, *E. vesicaria*, and *C. ciliaris*) the GEE modeling approach showed the most promise for creating accurate occurrence predictions. We highly recommend this approach if extending sampling efforts to overlap with more suitable sites for these species is undertaken in the future.

Management Implications

Management implications from this study are that fine fuel production from both native and non-native invasive plants can vary dramatically from year to year in the study area. Fuel models such as those from LANDFIRE program that are less frequently updated may greatly underestimate or overestimate the potential for large fires in a given year. For example, year 2005 fire burned several large areas that likely surpassed GS1 and GS2 fuel models (Scott and Burgan 2015) typical for fire prone locations in the study area (Gray et al. 2014). Gray et al. (2014) found that maximum NDVI from the preceding growing season along with human infrastructure and biophysical variables were strong predictors of large fires. Therefore, accurate models of fine fuel biomass may not always needed for making valid estimates of fire hazard and risk in these environments. Contiguous areas of maximum NDVI reaching or exceeding 0.40 in this environment are potential candidates for large fires according to findings by Gray et al. (2014) and Gray et al. (2015).

Our ability to map fine fuels was mixed because of poor sampling conditions and low biomass production during this study. However, efforts to map non-native invasive plant distributions were successful for monitoring changing conditions over time. Previous to and during this study we observed a dramatic increases and decreases in fuel bed continuity and composition that were associated with annual increases and decreases in fire hazard (Gray et al. 2014). From our plots, we observed greater fine fuel accumulations on sites with invasive plants suggesting that mapping their distribution or risk of invasion is coupled with the risk of large fires (**Figure 18**). Google Earth Engine provided an open-source and high-performance data processing platform that quickly integrated our field data to develop robust models of invasive plant distributions. We believe that this approach can be applied to accurately map invasive plant distributions and fine fuels in other desert and arid land locations when sufficiently parameterized with stratified and well distributed field data from an area of interest.

Additional field monitoring techniques are also greatly needed to further evaluate fine fuels and invasive plants into the future. Our study period covered extremely low productivity conditions for hot Sonoran desert. Future sampling efforts should consider sampling intervals that may better capture higher productivity patterns where the principal fuel-bed layer is comprised of annual grasses and forbs. We are currently developing new sampling techniques for plots in semidesert grasslands that we anticipate will greatly add to this study's findings.

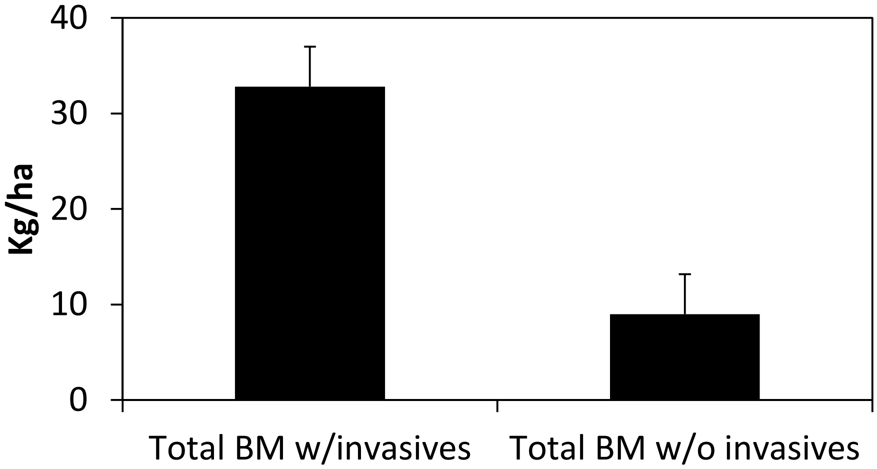


Figure 18. Comparison of mean 2012 subplot biomass on sites with and without target invasive plants (*n* = 2530).

Ongoing Work

Ongoing projects have extended this research which are the DoD SERDP (Project RC-1277) funded project, JFSP funded fire effects monitoring project on Buenos Aires National Wildlife Refuge (BANWR; Project 13-1-06-13), and other graduate student research in the Northern Arizona University Lab of Landscape Ecology and Conservation Biology. Follow-on studies from the SERDP project conducted by Gray et al. (2014, 2015) have added new modeling techniques to predict the risk and spread of large fires in the study area that are valuable decision making tools for fire managers.

A few of the unsuccessful efforts in this study have been revised and successfully developed for the JFSP project in semidesert grasslands at BANWR. We have developed new biomass field sampling, measurement and modeling techniques using a Decagon AccuPAR LP-80 ceptometer that is rapid and accurate for estimating desert fine fuels accumulation on sites. Leaf Area Index (LAI) simultaneously is calculated from above and below fuel-bed measurements of photosynthetically active radiation (PAR) explain 75% of the variation of dry biomass weight from destructive sampling (Sesnie, unpublished data). Models calibrated from destructive sampling are being applied non-destructive samples being collected in the field. These measurements were also validated with separate canopy cover estimates from point intercept data showing a strong correlation between total plot herbaceous biomass and cover (*r* =

0.77). New high spatial and spectral resolution satellite imager collected with the Worldview 3 sensor in September of 2015 (peak growing season) and future airborne laser altimetry data (LiDAR; acquisition planned for 2015 – 2016) will be used to assess fine and tree canopy fuels on BANWR in combination with semidesert grassland plots collected in 2014 and 2015.

New and rapid methods are being developed to combine high-resolution (350 to 2500 nm, 1.4 to 10 nm bands) field spectroscopy measurements with Worldview 2 and 3 image spectra to map invasive plants in the study area (Sankey et al. 2014). These efforts are aimed at reducing field sampling time and detecting invasive plant populations that may cover small areas, but can potentially spread to new areas and increase fire hazard. Mapping and monitoring incipient invasive plant populations, such as recently established *C. ciliaris* on BANWR is greatly needed to avoid larger-scale invasions and expensive mitigation and control efforts in the future.

Future Work Needed

Field sampling efforts for our study were undertaken during below average rain fall and low annual plant production years. Despite challenges such as the ephemeral nature of fine fuels in hot desert environments, further work is needed to quantify fuel bed characteristics conducive to large fires. Alternative methods were developed to assess these conditions using satellite data, NDVI and large fire perimeters (Gray et al. 2014), however assessing hazardous fuel conditions on the ground and relating them to satellite data is still a pressing need. This may require coordinated vegetation monitoring efforts by land management agencies to sample changing conditions as they occur. Multijurisdictional and coordinated field sampling at 2 to 3 year intervals may help to improve on techniques developed with this study. Targeting likely El Niño events (e.g. 2015-2016) and peak growing season for annual plants during January to March in this study area study area will be important as invasive plant control and mitigation is a shared goal among land management agencies.

In addition, the Landsat TM sensor experienced a mechanical failure during this study and was replaced by Landsat 8. The launch of Landsat 8 creates greater opportunities to develop satellite-based estimates of fuel parameters for desert environments with greater bit depth (16-bit pixel values) and a better signal to noise ratio. Some preliminary tests with this remote sensing platform suggest that is has a spatial, spectral, and temporal resolution that is well suited to mapping and monitoring fine fuels in semidesert grasslands.

Deliverables

Manager Workshops

1. Western Wildland Environmental Threat Assessment Center (WWETAC) ArcFuels and fire modeling. Flagstaff, AZ September 27th – 29th, 2010. Attended by BLM, NPS, USFWS fire managers.
2. Tool transfer, training, and presentations. Stakeholder meeting to present data and analyses contribute invasive plant and fire mitigation decision support to SERDP and JFSP project collaborators. Gila Bend Air Force Auxiliary Field, AZ, November 15, 2013.

Publications

1. Bradley, B.A., Olsson, A.D., Wang, O., Dickson, B.G., Sesnie, S.E. (2012). Species detection vs. suitability: Are we biasing habitat suitability models with remotely sensed data? *Ecological Modelling* 244:57-64
2. Gray, M.E., and Dickson, B.G. (2015). A new model of landscape-scale fire connectivity applied to resource and fire management in the Sonoran Desert, USA. Ecological Applications.
3. Gray, M.E., Dickson, B.G., and Zackmann, L.J. (2014). Modelling and mapping dynamic variability in large fire probability in the lower Sonoran Desert of south-western Arizona. International Journal of Wildland Fire 23: 11180-1118.
4. Olsson, A.D., Morisette, J. (2013). Comparison of HyspIRI with two multispectral sensors for invasive species mapping. *Photogrammetric Engineering and Remote Sensing*
5. Olsson, A.D., Sesnie, S.E., Dickson, B.G., Bradley, B., Zachmann, L., Wang, O., Rundall, J. (*In revision*) A spatially weighted ensemble and MODIS phenology-based approach for mapping a Sonoran Desert invasive annual plant *Brassica tournefortii* Remote Sensing of Environment.
6. Sankey, T., Dickson, B., Sesnie, S., Wang O., Olsson ,A., and Zachmann, L. (2014). WorldView-2 high spatial resolution improves desert invasive plant detection. ASPRS – Photogrammetric Engineering and Remote Sensing. 80: 885-893.
7. Wang, O., Zachmann, L.J., Sesnie, S.E., Olsson, A.D., and Dickson, B.G. (2014). An iterative and targeted sampling design informed by habitat suitability models for detecting focal plant species over extensive areas. PlosOne 9: 1-14.

Presentations

1. Sesnie, S.E., L.J. Zachmann, B.G. Dickson, E. Yurchich, J.M. Rundall, and L. Johnson. 2015. Multiscaled approaches to southwestern arid lands vegetation monitoring, modeling, and management. Biennial Conference of the Colorado Plateau and Southwest Region. Flagstaff, AZ October 5-8, 2015.
2. Sesnie, S.E., A.D. Olsson, B.A. Bradley, L.J. Zachmann, B.G. Dickson, and O. Wang. 2012. Phenology as a predictor of non-native species invasion in the Sonoran Desert: a spatially weighted ensemble approach. ASPRS Rio Grande Chapter Annual Spring Meeting, April 12, 2012.
3. Olsson, A.D., Dickson, B., Zachmann, L., Sesnie, S., Wang, O. Remote Sensing Phenology for Invasions: A Challenge and an Opportunity. *4th Phenological Research and Observations of Southwest Ecosystems* (Tucson, AZ). October 2011.
4. Olsson, A.D., S.E. Sesnie, B.A. Bradley, L.J. Zachmann, B.G. Dickson, and O. Wang. 2012. Phenology as a predictor of non-native species invasion in the Sonoran Desert: a spatially weighted ensemble approach. American Society of Photogrammetric Engineering and Remote Sensing (ASPRS) Rio Grande Chapter Annual Spring Meeting, April 12, 2012. (La Cruces, NM)
5. Olsson, A.D., Sesnie, S.E., Dickson, B.G., Zachmann, L., Wang, O., Bradley, B., Rundall, J. Phenology as a predictor of non-native invasive species invasion in the Sonoran Desert: a spatially-weighted ensemble approach. *Invited seminar, National Taiwan University Department of Geography* (Taipei, Taiwan). April 2012.
6. Olsson, A.D. Spatiotemporal modeling of buffelgrass invasion, ecosystem transformation, and adaptive management in the Sonoran Desert. *Invited talk, International Symposium on Invasive Plants and Global Change* (Urumqi, China). June 2012.
7. Dickson, B., A. Olsson, O. Wang, S. Sesnie, L. Zachmann, B. Bradley, J. Rundall, and T. Sisk. 2012. Regional-scale models of non-native plant phenology and invasion to support conservation on military and adjacent lands in the Sonoran Desert. Society for Conservation Biology North America Section Meeting. (Oakland, California).
8. Wang, O., A. Olsson, L. Zachmann, B. Dickson, and S. Sesnie. 2012. Ensemble of habitat suitability and remote sensing models for sampling design: a new approach to

detect invasive plant species in the Sonoran Desert. Society for Conservation Biology North America Section Meeting. (Oakland, California)

Posters

1. Dickson, B., Olsson, A.D,, Wang, O., Zachmann, L., Sesnie, S., Bradley, B., Rundall, J., Sisk, T. Landscape models of non-native plant phenology and invasion to support conservation of military and adjacent lands in the Sonoran Desert. *Annual Partners in Environmental Technology Technical Symposium & Workshop of the Strategic Environmental Research and Development Program (SERDP)*. December 2011.
2. Olsson, A.D., Dickson, B., Wang, O., Zachmann, L., Sesnie, S., Bradley, B., Rundall, J., Sisk, T. Landscape models of non-native plant phenology and invasion to support conservation of military and adjacent lands in the Sonoran Desert. *8th Annual RISE Symposium (Research Insights into Semi-arid Ecosystems).* October 2011.
3. Wang, O., Olsson, A.D., Zachmann, L., Sesnie, S., and Dickson, B. African buffelgrass infestation in the Sonoran Desert of Arizona: a preliminary plant community assessment. *Annual meeting of the Ecological Society of America* (TX). August 2011.
4. Wang, O., Olsson, A.D., Zachmann, L., Sesnie, S., and Dickson, B. Maximizing invasive plant detectability in the field using integrated habitat suitability models, GIS, and remote sensing data. *Annual meeting of the Association of American Geographers* (WA). April 2011.
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Acknowledgments

We would like to thank Erica Stewart and Wade Reaves with the Bureau of Land Management for their willingness to collaborate with us on this project. Thanks are also due to Richard Whittle from the Barry M. Goldwater Air Force Range and Laura Merrill from the U.S. Army Yuma Proving Ground for the generous contributions of their time and commitment to the success of our project. Special thanks are due to Karen Howe from Tohono O'odham Nation for support during training and field work, to Sue Rutman at Organ Pipe Cactus National Monument, and to Steve Rosenstock (project cooperator) and John Romero with the Arizona Game and Fish Department for providing invaluable technical guidance and for safety training in the Sonoran Desert and US-Mexico border region, respectively. Multiple staff with the Bureau of Land Management and US Fish and Wildlife Service, namely and Susanna Henry, John Hervert, John Morgart, and Lindsey Smythe were helpful in the scoping and data collection phases of our project. John Arnett and Chris Black from the Barry M. Goldwater Air Force Range also were kind collaborators throughout the course of our research. Field data was collected by a small 'army' of biological technicians during the spring of 2011 and 2012. Their endurance, enthusiasm, and professionalism were invaluable. Numerous members of the Lab of Landscape Ecology and Conservation Biology contributed to the success of our project, namely Miranda Gray, Cerissa Hoglander, Valerie Horncastle, Karl Jarvis, Aaryn Olsson, Jill Rundall, Teki Sankey, Sasha Stortz, and Ophelia Wang. Clare Aslan graciously assisted with the assembly of this final report. The administrative efforts of Kimberly Cotter, Winnie Ennenga, and Cindy Judge allowed us to stay focused on doing strong science. Similarly, we thank Lori Pelech and Caroline Curtis at the University of Massachusetts, Amherst. Truly, this project 'took a village!'

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