US Climate Alliance Grant Program for NWL Research 2020

Quantifying Carbon Sequestration in Nevada's Rangelands

Methods to Map Non-native Annual Species of Nevada, West Desert of Utah, Southeastern Oregon, Southern Idaho, and Eastern California

Deliverable No.1 Report

Credits: L. Provencher/TNC, 2014, Non-native annual species grasslands and forblands of central Nevada

Sarah Byer and Louis Provencher

The Nature Conservancy, Reno, NV

December 15th, 2021

INTRODUCTION/PURPOSE

TNC is working on a model to estimate carbon sequestration by rangelands throughout the state of Nevada and the Basin and Range region. Exotic annual species affect the timing and quantity of carbon in the regional carbon cycle. To incorporate the contributions of annual species, we wanted a more up-to-date map of annual species at a higher resolution than is currently available through the USGS (Landsat-based map). We also wanted to use more locally acquired data from Nevada and the Great Basin to create this map. This map and model are intended to inform how much carbon might be sequestered if perennial species were restored in the areas where exotic annual species have invaded.

The project area focused on rangelands in the Great Basin writ large and included the Great Basin ecoregion of TNC and EPA. Also captured in the analysis were areas of northern Nevada and the southern portions of Oregon and Idaho in the Columbia Plateau ecoregion, and the Mojave Desert in southern Nevada (Figure 1). The Great Basin and Columbia Plateau ecoregions extended into California, east of the Sierra Nevada range, and into western Utah. Being such a large project area, the climate and ecology varied appreciably latitudinally. Annual species evaluated in the Mojave Desert could not be considered in the second part of this study because the growth of native perennial grass species is less than 5% successful in this area. The Mojave Desert was included as the Nevada Division of Natural Heritage (NDNH) required a revised map of non-native annual species for all of Nevada (Peterson 2005, Peterson 2006). Mapping non-native annual species in the Mojave Desert created some problems since the seasonal green-up of native annual grass species will be confounded with the green-up of non-native annual species in south (earlier) than the north (later). The phenological patterns used to distinguish non-native annual grass species from native plants in the northern portion of the project area are less useful in the Mojave Desert, where native plants exhibit a different phenological pattern.

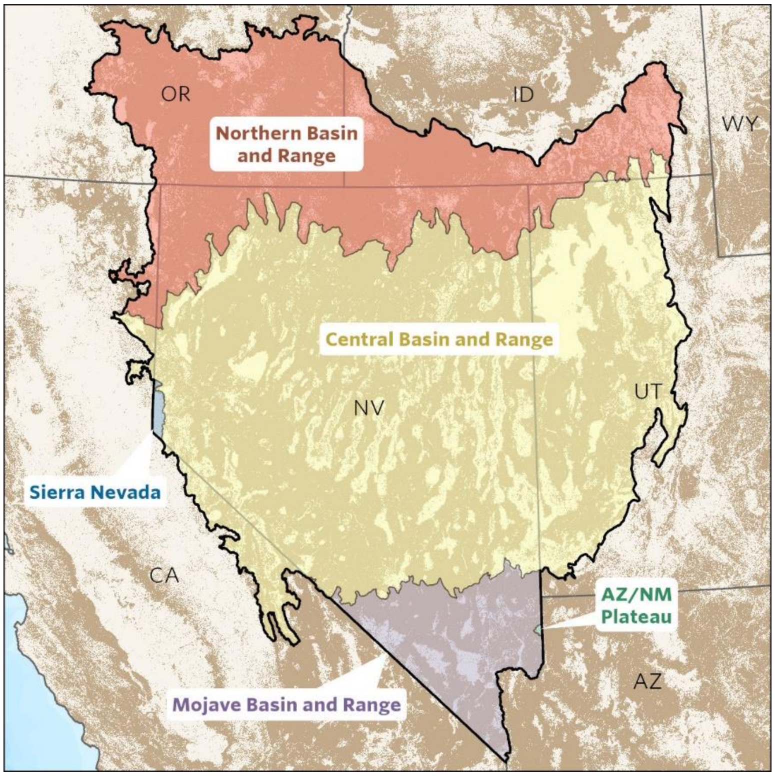

Figure 1. Project area shown to include all EPA Level 3 ecoregions within Nevada as well as the Northern and Central Basin and Range regions. Rangelands are shaded darker than the surrounding landscapes.

Other datasets map non-native annual species within the project area. The U.S. Geologic Survey (USGS) helps produce a near real-time estimate map of annual exotic herbaceous cover that extends throughout most of our project area but does not map southern Nevada (Pastick et al 2020). These maps are available at 30m resolution starting in 2015 (https://data.usgs.gov/datacatalog/data/USGS:5f0e030782ce21d4c4053ec2). The Rangeland Analysis Platform (RAP) is a website developed by the Natural Resources Conservation Service (NRCS), the Bureau of Land Management (BLM), and the University of Montana. RAP hosts map products of plant functional group cover including annual forbs and grasses throughout the western United States (https://rangelands.app/). These maps are available annually from 1984 to 2020 at the 30m resolution across our entire project area (Allred et al 2021).

Overall, we assembled a suite of remote sensing, meteorological, and abiotic data to capture the unique phenological signal of annual species and to map the percent cover of non-native annual species throughout Nevada and the Basin and Range region. The final product was a wall-to-wall map of annual grass cover as a proportion of each pixel at ~10m resolution for calendar year 2020.

METHODS

The sample data used to train the model came from TNC projects throughout the study area and the BLM's Assessment and Inventory Monitoring (AIM) program. Methods described in the project application have changed significantly from those used to build this model. TNC intended to apply similar methods to those used to estimate cheatgrass (*Bromus tectorum*) cover by the Nevada Natural Heritage Program (now NDNH; Peterson 2005, Peterson 2006). With the increased availability of satellite imagery and image processing tools, TNC updated their approach to mapping non-native annual species cover rather than just cheatgrass. This included using more up-to-date training data and finer-resolution satellite imagery resulting in a model that was more sensitive to areas with lower percent-cover of annual species (< 10%) and a map with a higher resolution (10 m) than previously discussed (30 m) thanks to the availability of Sentinel-2 imagery through Google Earth Engine.

Sentinel-2 imagery is captured by twin satellites with 13 spectral bands at 10, 20, or 60m resolutions (https://sentinel.esa.int/web/sentinel/user-guides/sentinel-2-msi). The Sentinel-2 mission began producing images in summer of 2017. Images from Sentinel-2 are available through Google Earth Engine, including bands with data quality information produced with each image. Sentinel-2 images contain bands that can be combined into metrics that represent vegetation productivity over time. Normalized Difference Vegetation Index (NDVI) is a combination of the reflected red and near-infrared (NIR) light from the Earth's surface. Healthy, productive vegetation reflects more NIR light and absorbs more red light, so pixels with a high NDVI value indicate highly productive vegetation. It's essentially a measure of 'greenness' or photosynthetic activity. Sentinel-2 bands can be combined in several ways to represent various characteristics of the land surface, including vegetation phenology, moisture, or soil reflectance.

In the Great Basin where vegetation production is low and slow, it's unusual to see large seasonal bursts of productivity. Annual species have a distinct signature here since they experience quick growth in the early spring when moisture is available and while native plants are still dormant, then quickly senesce in summer (Boyte et al 2016). By the time summer arrives and moisture rapidly becomes less available, native herbaceous species are greener and more productive than their non-native counterparts. We used seasonal remote sensing metrics of vegetation productivity to identify locations that exhibited this behavior.

A common method of identifying annual species in dry regions was to compare NDVI from the spring and summer (Kokaly et al 2011, Boyte et al 2016, Peterson 2006). In a pixel with annual species, the NDVI should be much higher in the spring than in summer. A pixel primarily containing moisture-resilient sagebrush or perennial species should not change in NDVI as much between seasons. Therefore, the large difference of NDVI between spring and summer at a pixel represented the dramatic senescence of annual species that typically occurs at the end of spring and early summer (May/June, Figure 2).

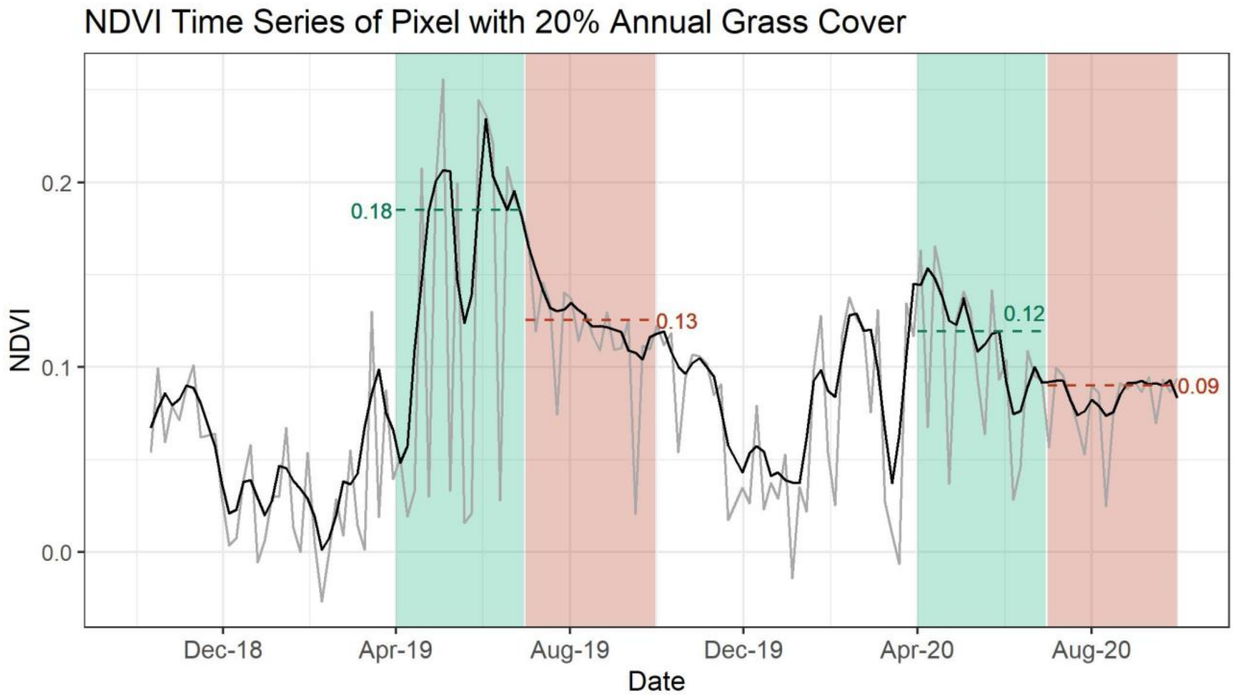

Figure 2. Two years of NDVI values at a location with 20% median annual grass cover. The raw NDVI data are shown in light grey. A smoothed time series is shown in black. The shaded areas illustrate the difference between spring growth (blue) and summer senescence (red) represented by NDVI to identify annual species in high-desert regions. Located in Central Nevada, from the Cortez project area, median spring NDVI at this location is greater than median summer NDVI in both 2019 and 2020 as indicated by the dashed lines.

As previously mentioned, the climate and ecology varied appreciably latitudinally within the large project area. As such, phenological differences are expected from non-native annual species between the southern and northern portions of the project area. Creating a seasonal median from multiple images provides a buffer for these seasonal latitudinal differences (Figure 2). Compared to northern areas, non-native annual grass species in southern areas may begin their growing season earlier (April or even March), because the Mojave warms more rapidly in the spring. Consequently, these areas will likely exhibit senescence earlier as the temperature rise rapidly, and moisture become less available. The seasonal median metrics capture this variation in phenology throughout the project area.

Other vegetation metrics derived from one or more spectral bands were included in the model. A full list of metrics created and used in the Random Forest model are available in Table 1. Seasonal differences of these metrics were also calculated as these represent phenological or ecological processes that help identify areas where annual species are present. Climate data from the Idaho GRIDMET climate products (ultimately derived from 4km PRISM data: https://developers.google.com/earth-engine/datasets/catalog/IDAHO_EPSCOR_GRIDMET#description) were used to produce precipitation metrics as potential predictors to the Random Forest model. Temperature data were shown to be unimportant in mapping non-native annual species and were not included in this analysis (Pilliod et al 2017).

SPATIAL VARIABLES	SEASON	SEASONAL DIFFERENCES	RESOLUTION (METERS)
SENTINEL-2 BANDS			
GREEN (BAND 3)	$\bar{x}_{spr}$, $\bar{x}_{sum}$, $\bar{x}_{fal}$	$\bar{x}_{spr} - \bar{x}_{sum}$, $\bar{x}_{sum} - \bar{x}_{fal}$	10
RED (BAND 4)	$\bar{x}_{spr}$, $\bar{x}_{sum}$, $\bar{x}_{fal}$	$\bar{x}_{spr} - \bar{x}_{sum}$, $\bar{x}_{sum} - \bar{x}_{fal}$	10
VEGETATION RED-EDGE (BAND 5)	$\bar{x}_{spr}$, $\bar{x}_{sum}$, $\bar{x}_{fal}$	$\bar{x}_{spr} - \bar{x}_{sum}$, $\bar{x}_{sum} - \bar{x}_{fal}$	20
VEGETATION RED-EDGE (BAND 6)	$\bar{x}_{spr}$, $\bar{x}_{sum}$, $\bar{x}_{fal}$	$\bar{x}_{spr} - \bar{x}_{sum}$, $\bar{x}_{sum} - \bar{x}_{fal}$	20
VEGETATION RED-EDGE (BAND 7)	$\bar{x}_{spr}$, $\bar{x}_{sum}$, $\bar{x}_{fal}$	$\bar{x}_{spr} - \bar{x}_{sum}$, $\bar{x}_{sum} - \bar{x}_{fal}$	20
NIR (BAND 8)	$\bar{x}_{spr}$, $\bar{x}_{sum}$, $\bar{x}_{fal}$	$\bar{x}_{spr} - \bar{x}_{sum}$, $\bar{x}_{sum} - \bar{x}_{fal}$	10
NARROW NIR (BAND 8A)	$\bar{x}_{spr}$, $\bar{x}_{sum}$, $\bar{x}_{fal}$	$\bar{x}_{spr} - \bar{x}_{sum}$, $\bar{x}_{sum} - \bar{x}_{fal}$	20
WATER VAPOR (BAND 9)	$\bar{x}_{spr}$, $\bar{x}_{sum}$, $\bar{x}_{fal}$	$\bar{x}_{spr} - \bar{x}_{sum}$, $\bar{x}_{sum} - \bar{x}_{fal}$	60
SHORTWAVE INFRARED (BAND 10)	$\bar{x}_{spr}$, $\bar{x}_{sum}$, $\bar{x}_{fal}$	$\bar{x}_{spr} - \bar{x}_{sum}$, $\bar{x}_{sum} - \bar{x}_{fal}$	60
SHORTWAVE INFRARED (BAND 11)	$\bar{x}_{spr}$, $\bar{x}_{sum}$, $\bar{x}_{fal}$	$\bar{x}_{spr} - \bar{x}_{sum}$, $\bar{x}_{sum} - \bar{x}_{fal}$	20
SHORTWAVE INFRARED (BAND 12)	$\bar{x}_{spr}$, $\bar{x}_{sum}$, $\bar{x}_{fal}$	$\bar{x}_{spr} - \bar{x}_{sum}$, $\bar{x}_{sum} - \bar{x}_{fal}$	20
VEGETATION INDICES			
NDVI	$\bar{x}_{spr}$, $\bar{x}_{sum}$, $\bar{x}_{fal}$	$\bar{x}_{spr} - \bar{x}_{sum}$, $\bar{x}_{sum} - \bar{x}_{fal}$	10
EVI	$\bar{x}_{spr}$, $\bar{x}_{sum}$, $\bar{x}_{fal}$	$\bar{x}_{spr} - \bar{x}_{sum}$, $\bar{x}_{sum} - \bar{x}_{fal}$	10
SAVI	$\bar{x}_{spr}$, $\bar{x}_{sum}$, $\bar{x}_{fal}$	$\bar{x}_{spr} - \bar{x}_{sum}$, $\bar{x}_{sum} - \bar{x}_{fal}$	10
MSAVI	$\bar{x}_{spr}$, $\bar{x}_{sum}$, $\bar{x}_{fal}$	$\bar{x}_{spr} - \bar{x}_{sum}$, $\bar{x}_{sum} - \bar{x}_{fal}$	10
TCG	$\bar{x}_{spr}$, $\bar{x}_{sum}$, $\bar{x}_{fal}$	$\bar{x}_{spr} - \bar{x}_{sum}$, $\bar{x}_{sum} - \bar{x}_{fal}$	10
TOPOGRAPHY/SOILS			
ELEVATION	**NA**	**NA**	10
CHILI	**NA**	**NA**	10
LITHOLOGY	**NA**	**NA**	90
PRECIPITATION	$\bar{x}_{spr}$, $\bar{x}_{sum}$, $\bar{x}_{falpy}$, $\bar{x}_{win}$	$\bar{x}_{spr} - \bar{x}_{falpy}$	4000

Table 1. All input variables to the regression Random Forest Model. '$\bar{x}$' refers to median value rather than mean in this model.

TNC primarily used remote sensing metrics that represent the timing and magnitude of vegetation productivity. Metrics included in this model were also chosen based on variable importance identified by Jones et al. (2018) for mapping annual species. Not all metrics used by Jones et al. (2018) were computed for this analysis, just the ones that were identified as more important and possible to create from Sentinel-2 products.

Similar to NDVI, the Enhanced Vegetation Index (EVI) represents vegetation productivity, but it is more sensitive to areas with dense vegetation and reduces background noise, atmospheric noise and saturation thanks to the inclusion of the blue band (https://www.indexdatabase.de/). The Soil Adjusted Vegetation Index (SAVI) uses the ratio between the red and NIR bands like NDVI but includes a brightness correction factor to account for soil brightness where vegetation is sparse. The Modified SAVI (MSAVI) also uses the red and NIR bands to estimate vegetation productivity but uses a different formula that minimizes influence from bare soil effects. Tasseled-cap greenness (TCg) measures how green the reflected pixel is based on the tasseled-cap transformation function on all reflectance bands (Nedkov 2017).

Seasonal metrics of precipitation were created as model inputs because variations in the timing and amount of precipitation have a strong effect on annual grass phenology and composition (Pilliod et al 2017). Non-native annual species are particularly more reactive to precipitation dynamics than native vegetation (Boyte et al 2015). More precipitation in the winter and early growing season (spring) benefits the non-native annual species and increases their cover in the growing season (Pilliod et al 2017). The sooner that precipitation events stop in the late spring/summer, the quicker that annuals will senesce. Precipitation in the fall before the growing season may initiate germination of non-native annual species before native species for the following growing season (Pilliod et al 2017, Horn et al 2017). Seasonal differences in precipitation were also created (spring minus summer, summer minus previous fall) as in Jones et al 2018.

Elevation, aspect, and slope are known to control vegetation composition, and thus, annual grass distribution and cover (Chambers et al 2014, Boyte et al 2015). The Continuous Heat-Insolation Load Index (CHILI) is a 10m dataset derived from USGS digital elevation models available through Google Earth Engine. The CHILI product combines slope, aspect, and latitude into a measure of heat load, a strong predictor of evapotranspiration and, consequently, vegetation distributions (Theobald et al 2015). According to Chambers et al. (2014), resistance to disturbance and subsequent invasion by cheatgrass can be determined by these topographic variables. In the case of aspect, plant communities on north aspects are more resilient to disturbance than southern aspects. Higher-elevation communities (colder/wetter) are also typically more resistant to cheatgrass invasion than lower elevation communities (warmer/dryer; Chambers et al 2014).

Lithology, or soil parent class, data were used due to the strong relationship between soil texture and chemistry of the mapped classes and ecological response (Theobald et al 2014). Certain soil characteristics increase the likelihood of invasion by non-native annual species; resistance to invasion is generally lowest on coarse, dry soils (Chambers et al 2014). The lithology dataset is not as fine-scaled as other national soil products such as the SSURGO and STATSGO databases, but the 20 soil classes in this dataset capture the necessary soil information for this coarse analysis (https://developers.google.com/earth-engine/datasets/catalog/CSP_ERGo_1_0_US_lithology).

TRAINING DATA

TNC DATA

TNC training data were obtained from two landscape conservation forecasting (LCF) projects; one in central Nevada (hereafter, Cortez) and the other from southwest Utah (hereafter, Pine Valley-Mountain Home or PVMH; Figure 3). Descriptions of LCF methods and remote sensing are found in Provencher et al. (2021), whereas reports for each site are found in Provencher et al. (2017) for Cortez and Provencher et al. (2019) for PVMH. An important aspect of TNC's training data was that vegetation classes were in categories defined by percent cover *ranges* for native or non-native species group, shrubs, and trees. Using the vegetation description for each class, ranges of cover (e.g., 5%-15% cover of non-native annual species) were converted to median values, and open-ended cover values (e.g., >5% cover of non-native annual species) were assigned a most likely value that was frequently observed in the field (15% cover of non-native annual species). All TNC data were assigned median percent-cover values of annual grass based on their vegetation system and class. In addition to considering training data with detectable annual grass cover, we included some vegetation classes without annual grass cover from both landscapes in the training data as it was judged just as important to identify locations without annual grass as it is to estimate cover in areas with annual species.

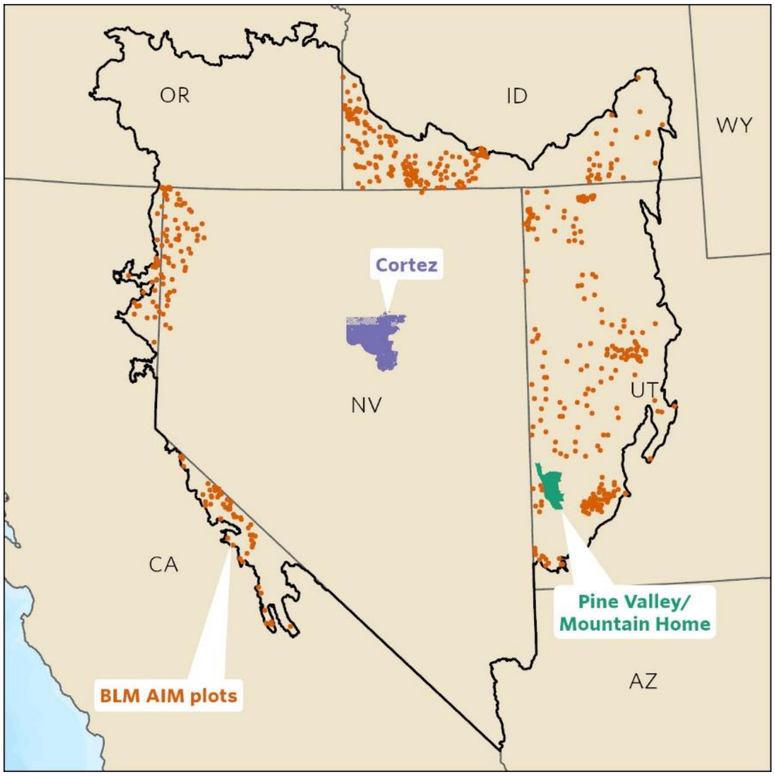

Figure 3. Map of annual grass cover data collected in 2020 used to train the Random Forest model.

The Cortez area was approximately situated off Highway 278 to the east and the Roberts Mountains to the south in Elko, Eureka, and Lander Counties and the Shoshone Range to the West (Figure 4). The area is bordered to the north by the Dry Hills and encompasses to the south the northern tip of the Toiyabe Range, Red Mountains, and the northern part of Carico Valley. The project area spans about 828,894 ac (335,442 ha). Each study area contains typical rangelands; however, the valley floor on the Crescent valley half of the area is substantially lower than the PVMH area to the east. The Cortez Range, Simpson Park Range, Shoshone Range, Sulphur Spring Range, and Dry Hills are primarily volcanic and north-south trending, whereas the Roberts Mountains are dominated by carbonate rocks and have a more circular shape than classic north-south trending basin and range formations.

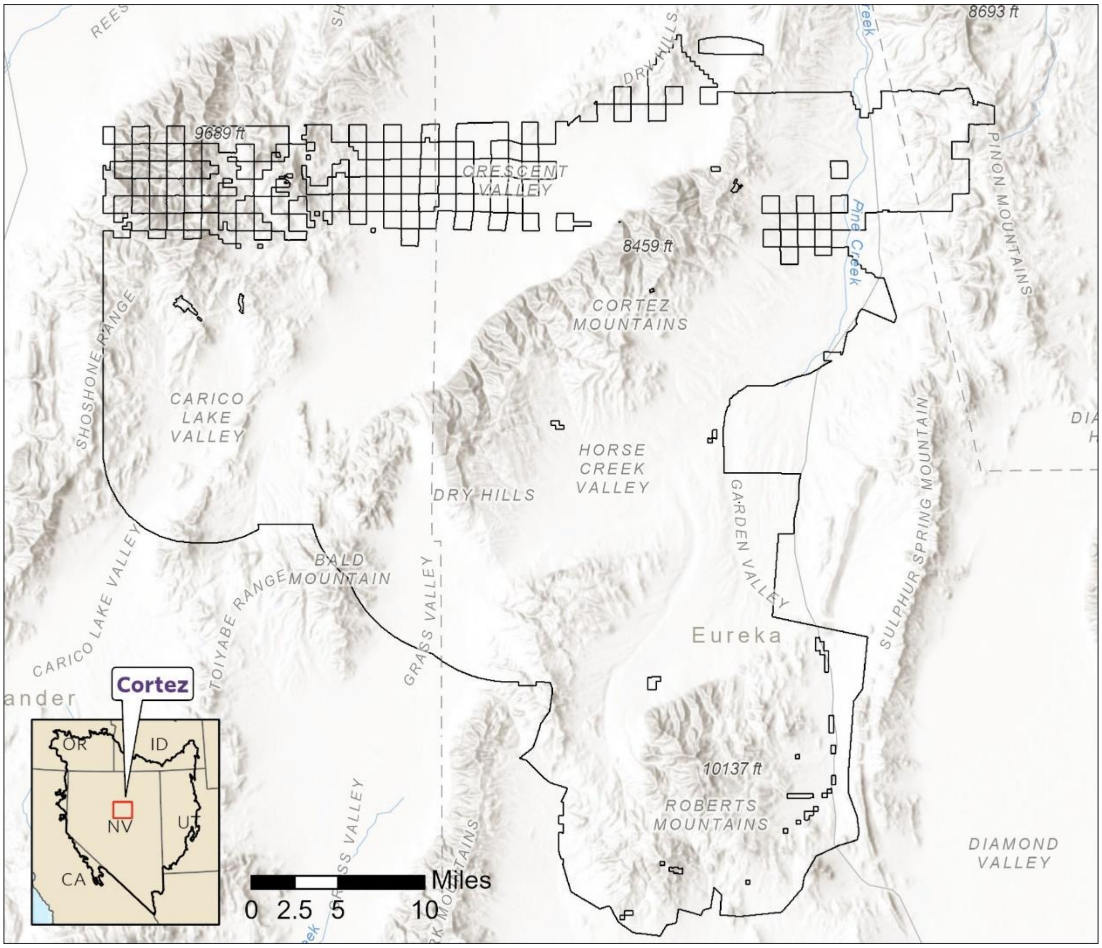

Figure 4. Detailed map of the Cortez area mapped in July 2020.

The PVMH landscape was comprised of the areas known as Pine Valley, the Mountain Home Range, Indian Peak Range, and the western flank of the southern half of the Wah Wah Range in southwest Utah, 30 miles southeast of Great Basin National Park, covering an area of about 319,000 acres (Figure 5). The vegetation is typical of the southeastern Great Basin ecoregion, dominated by sagebrush shrublands and pinyon-juniper woodlands but containing monsoonal dependent communities with such species as ponderosa pine and Stanbury's cliffrose.

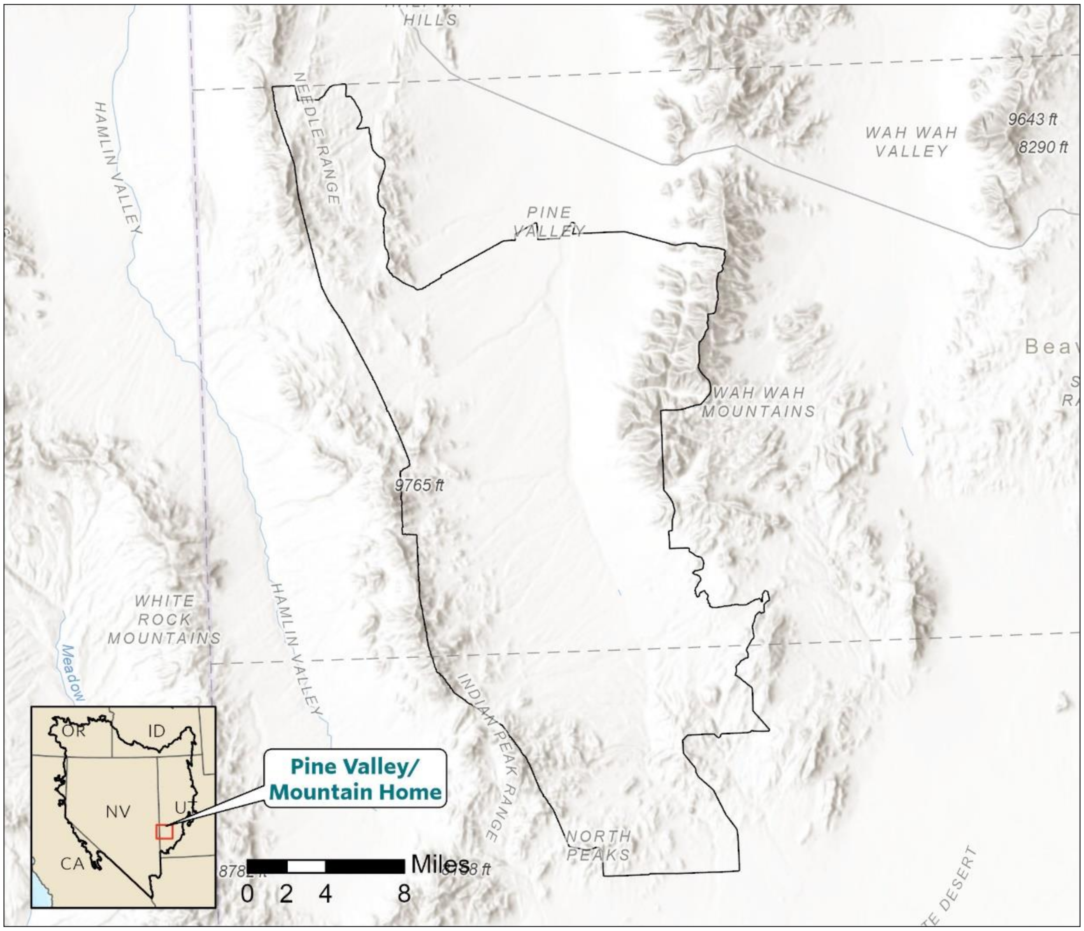

Figure 5. Detailed map of the Pine Valley/Mountain Home area mapped in July 2020.

Rather than using each pixel as a training point from the vegetation rasters, we identified large areas of continuous annual grass cover to retain a series of “large patches” as training plots. The vegetation system and class rasters were converted to polygons. Adjacent polygons with the same vegetation system and class were dissolved into an individual feature. Any feature with a total area < 1000m^2 were removed to ensure that the training data were using large, contiguous patches. Even after filtering for large patches we still had far too many training sites to process in Earth Engine, so we randomly selected 5% of the patches to use as training data. Arcpy’s Feature to Point tool was then used to convert the polygons to points and assigned the points their patch’s median annual grass percent cover values.

Raw NDVI time series were assessed to determine whether the early-season phenology of annual species was detectable at locations with confirmed annual grass presence. Figure 2 shows the rapid increase in productivity in April 2020 followed by a decline in productivity throughout the summer 2020 at this location with observed 20% median cover of annual grass. This location is the center of a large patch of Big sagebrush-semidesert vegetation with annual species present (location: 39.33°N 116.63°W, SYSXCLA Code: 10802100; Provencher et al 2017). This plot is in the southeastern portion of Crescent Valley and has experienced past disturbances that give rise to annual grass invasions.

BLM AIM DATA

Point data with associated estimated cover of non-native annual species were used in addition to TNC data to train and validate the Random Forest model. The BLM AIM TerrADat dataset was filtered to observations made in 2020 and limited to the extent of the project area. The TerrADat data were primarily collected outside the state of Nevada in 2020 with an exception in the northwest portion of the state (Figure 3). Plot locations within scheduled areas are determined randomly – crews go to determined locations and perform a line-point-intercept protocol along transects to record the presence of plants, rock material, or bare ground (Toevs et al 2010). Estimates of functional plant group cover, including annual species, are derived from these observations (Allred et al 2021, Jones et al 2018).

More information about the TerrADat dataset can be found at https://aim.landscapetoolbox.org/wp-content/uploads/2015/08/Monitoring-Manual-Volume-II.pdf. The AH_AnnualGrassCover field was used to represent median cover in the training data. The BLM dataset was merged with TNC datasets and loaded into Google Earth Engine as training data.

A total of 5,080 training points were available, although these points were not evenly distributed across the project area (Figure 3). The Random Forest model was trained with 70% of the data (3,595) and 30% were held out for validation (1,485). The distribution of annual grass cover values ranges from 0% to 91% with a median value of 1% (skewed by large number of 0% cover training points, particularly from the TNC data; Figure 6).

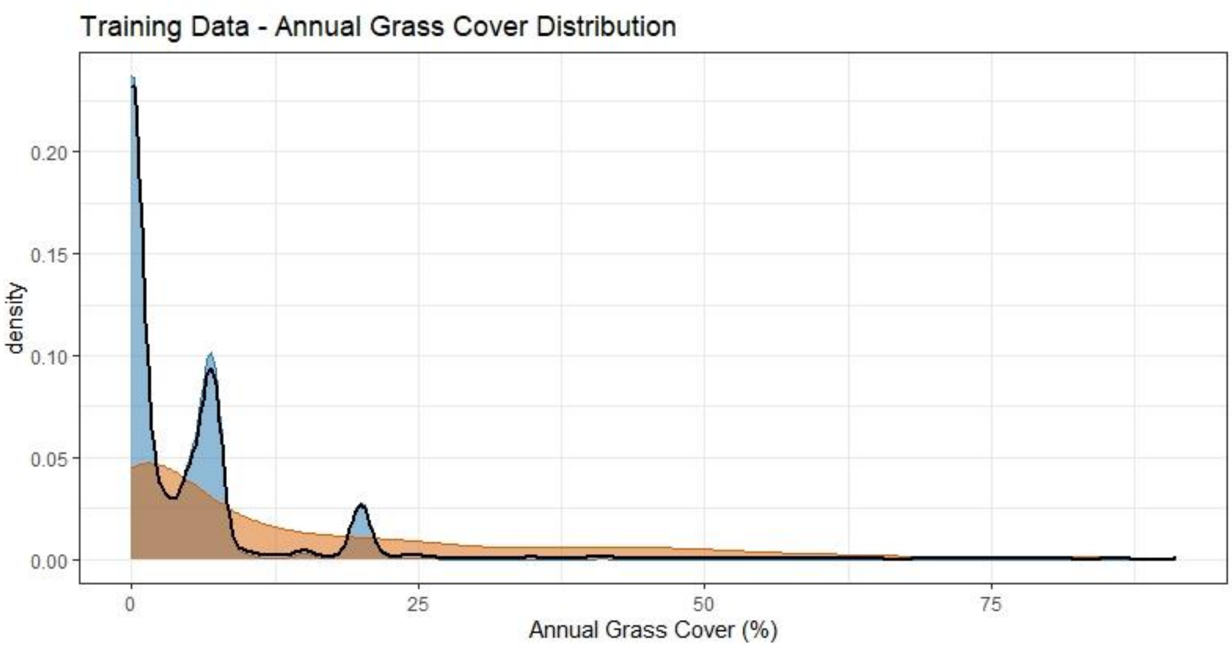

Figure 6. Distribution of median annual grass cover values (%) from TNC-collected data (blue) and BLM AIM data (orange). The density curve of all combined training data is shown by the black line.

RESULTS

MAP DESCRIPTION

The map was produced by applying the Random Forest model to the available Sentinel-2 imagery. It is a $10m^2$ resolution raster with continuous values that range from 0% to 61.1% annual grass cover with a mean of 12.6%. The map was masked using the Coterminous US Rangelands dataset to remove urban/developed areas, open water, forests, and agricultural land (Reeves and Mitchell 2011). In general, the map of estimated annual grass cover looks reasonable; regions with known high concentrations of non-native annual species were modeled to have high cover. The root mean squared error (RMSE) of the available validation data (n = 1240) was 9.29% and the mean absolute error (MAE) was 5.83% (Figure 7). Some validation data points (n = 245) were removed from the accuracy assessment after being masked by the rangeland dataset.

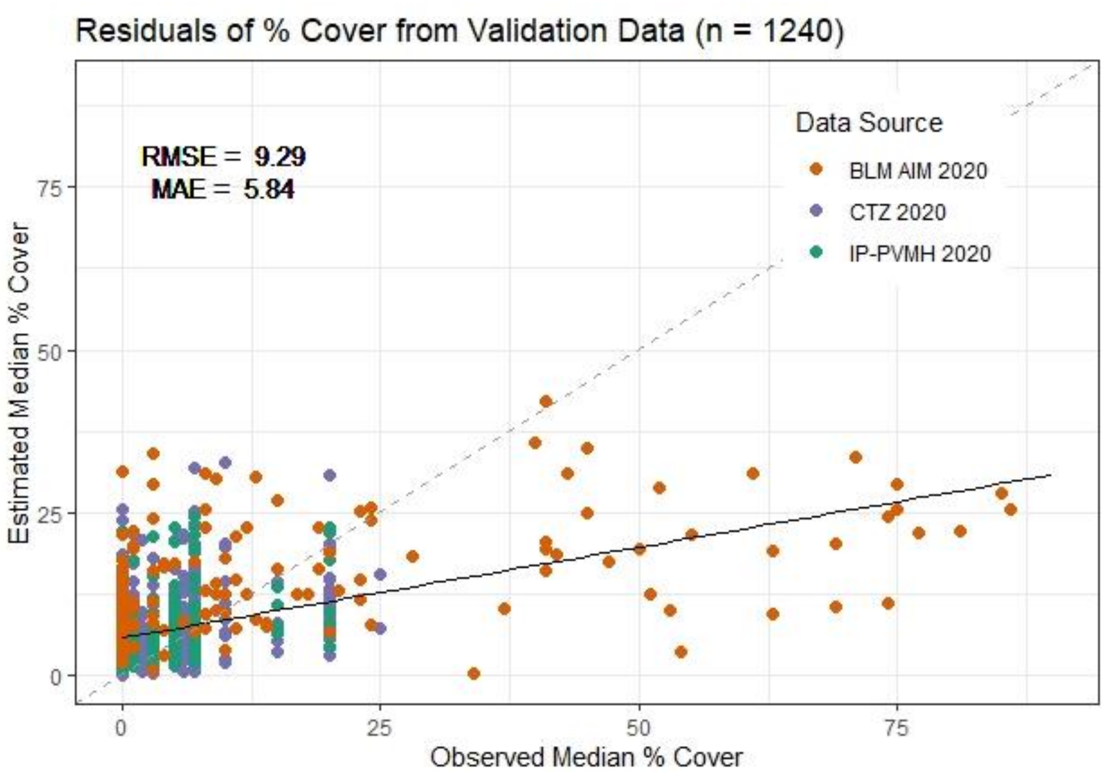

Figure 7. Residuals of the available validation data. Residuals show that the TNC RF model is more likely to underestimate annual grass cover where it is high (> 30%).

Annual species cover was mapped either using original continuous percent cover values or classified into bins of cover range (Figure 8). Overall, higher percent cover values were observed in the northern basin and range towards the Snake River plains, around the Great Salt Lake, and in the Mohave desert northeast of Las Vegas, NV. Relatively higher percent cover values were found inside recently burned areas compared to the surrounding unburned areas, which was expected (Figure 9). Higher-elevation areas were mapped as having less cover than low elevation areas, a consistent observation from other studies (Chambers et al 2014). Another common pattern was high cover of annual species around towns, major roads, and agricultural areas. These spaces are more likely to experience disturbance, leading to greater presence of non-native annual species (Chambers et al 2014).

The model and map produced from this method should not be used as definite proof of the presence or concentration of specific non-native annuals, such as cheatgrass, western tansymustard (*Descurainia pinnata*), or redstem filaree (*Erodium cicutarium*). The model effectively uses imagery and metrics to determine where vegetation phenology is like that of non-native annual species in Nevada and the Great Basin. We acknowledge that the model may be picking up on similar phenological patterns from other plants such as *Poa secunda*, a native perennial grass. Some variants of *P. secunda* may have a matching phenology to non-native annual species – a short growing season that begins in the spring and ends in the early summer as the species senesces (Peterson 2005). A large presence of *P. secunda* may lead to overestimates of the non-native annual species we seek to map. Without site visits, it is difficult to say where these errors may occur or how severe they might be.

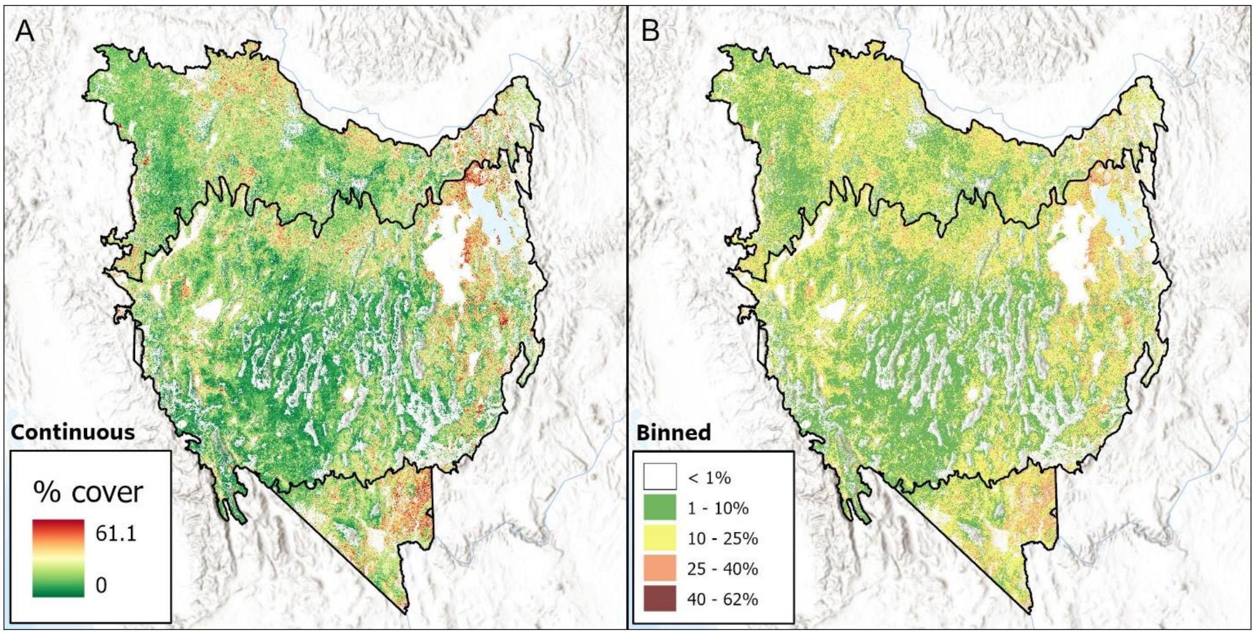

Figure 8. Estimated continuous percent cover (A) and binned cover (B) of non-native annual species.

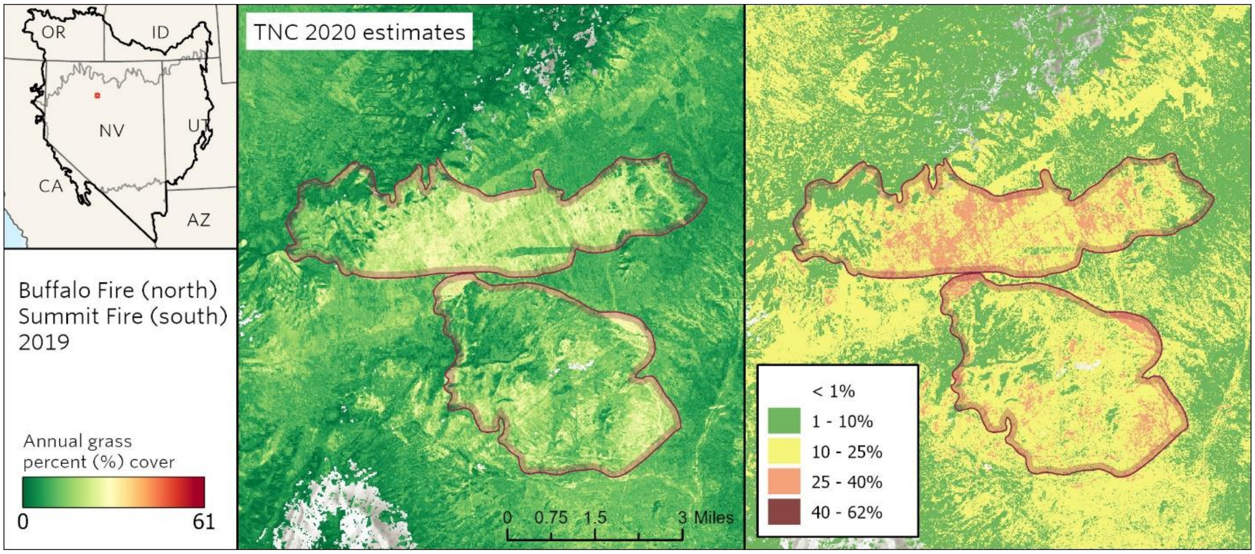

Figure 9. 2020 estimates of annual grass cover in continuous (left) and binned (right) displays are shown to be higher within recently burned areas than the surrounding landscape. The Buffalo (north) and Summit (south) fires burned on BLM land approximately 27 miles southeast of Winnemucca, NV in 2019.

COMPARISON TO SIMILAR DATASETS

Compared to the RAP and USGS maps of annual grass cover, the TNC map has higher overall estimates of cover, despite the differences in values of the training data used to build each model – TNC training data were skewed lower to better estimate lower-density annual grass cover where data are available (Figure 6). Across the project area, mean and median percent-cover of annual species from the TNC 2020 map estimates were 12.6% and 11.3%, respectively. Mean and median for the 2020 USGS near real-time (NRT) map were 11.9% and 10%, respectively. And mean and median for the 2020 RAP map were 11.35% and 7%, respectively. Comparing the maps visually reveals how each model estimates annual grass cover in different parts of the project area (Figure 10).

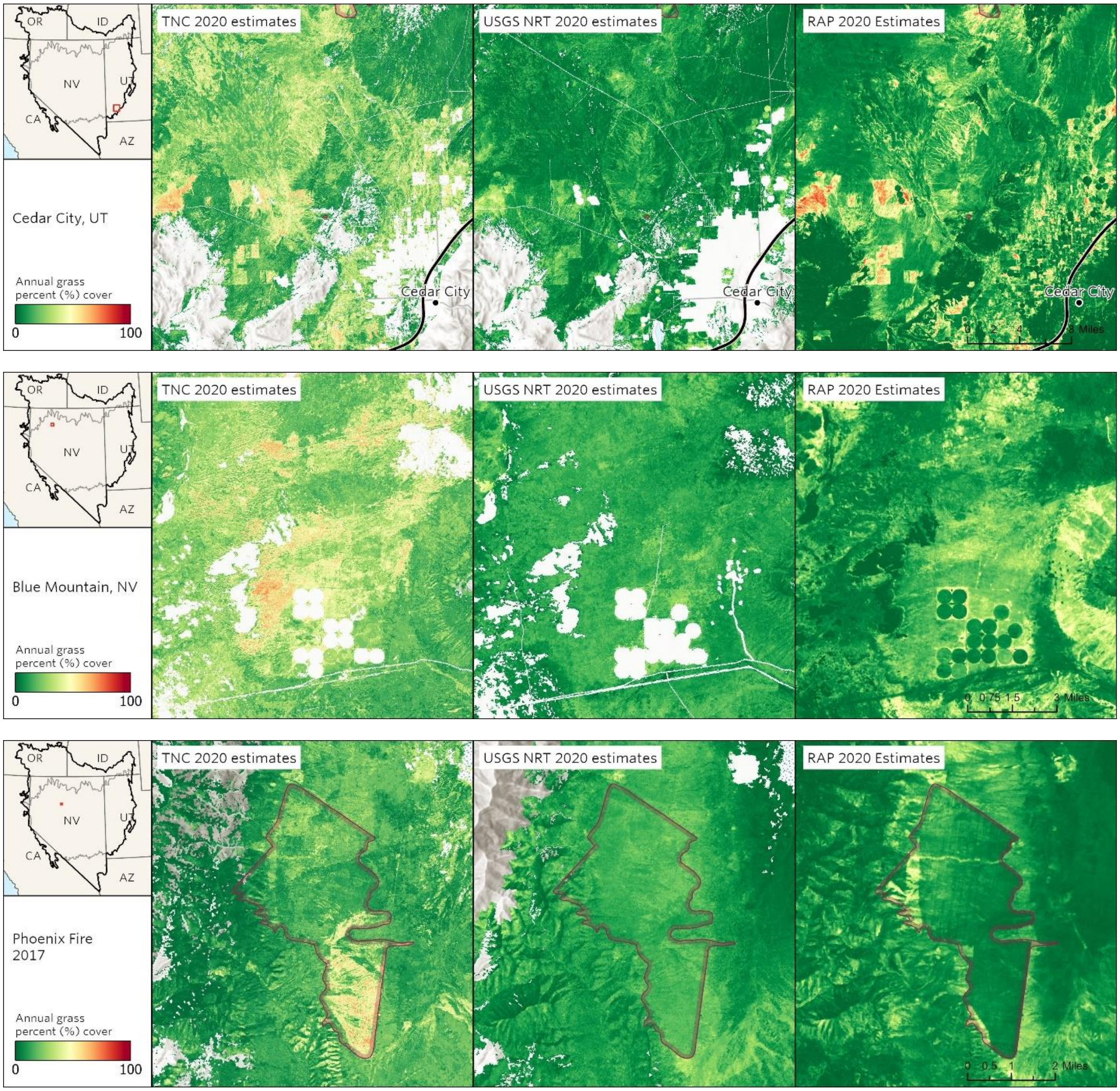

Figure 10. Comparing 2020 annual grass cover estimates across products in different areas. Top – Northwest of Cedar City, Utah. Middle – West of Blue Mountain, NV in a low desert surrounding an agricultural area. Bottom – Burn area from the 2017 Phoenix fire south of Winnemucca, NV.

VARIABLE IMPORTANCE

The Random Forest regression model computed variable importance for each input variable as an output. This value was relative within the input variables such that the relative impact among variables on results could be ranked. The top 20 variables by importance values are shown in Figure 11, but remaining variables are found in Table 1. By far the variable with the most explanatory power was elevation (Figure 11). Figure 11 displays the SHapley Additive exPlanations (SHAP) value for each metric. SHAP values can be calculated for any tree-based model and describe each metric's relative contribution to the modeled independent variable (Lundberg and Lee 2017). Elevation was a very important predictor in the model, likely because of the large elevation range throughout the project area. Boyte et al. (2015) found elevation to have a less important role in their model than other variables, but they attribute this to their model being restricted to areas below 2000m. Our project area ranges in elevation from 145m to 4306m and training data ranged in elevation from 1220m to 3045m.

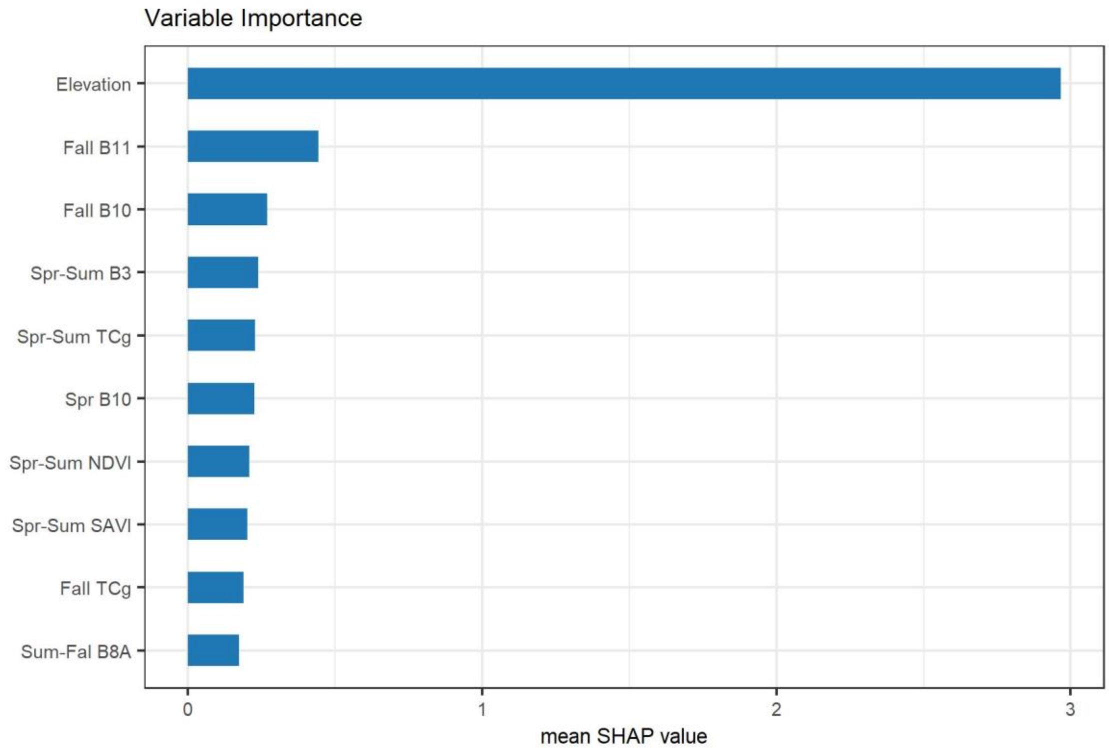

Figure 11. Top 10 variables with most impact on model outputs.

Shortwave infrared (SWIR) bands 10 and 11 from Fall and Spring Sentinel-2 turned out to be relatively important variables (Figure 11). More study would be needed to determine why these might be important variables. It's possible that the SWIR bands, which can be used to display vegetation density or bare soil, have picked up the presence or absence of annual species on the ground. Not surprisingly, metrics that measured the difference between spring and summer vegetation productivity or greenness had a greater impact on model results (Spr-Sum B3, Spr-Sum TCg, Spr-Sum NDVI, etc.).

FUTURE APPLICATIONS

The model allows us to create an annual map of annual grass cover using this method. The map product will be used to determine the acres of treatable land in the Great Basin and Columbia Plateau with annual species and thus, inform management actions. Additionally, we can retain the RF model made using the 2020 inputs and training data, then apply it to future years with concurrent inputs as Sentinel-2 continues to capture imagery. As of writing, inputs for 2021 only available through summer 2021. This model can be used to estimate annual species in future years, though further study into this model's applications and limits should be pursued.

REFERENCES

Allred, BW, Bestelmeyer, BT, Boyd, CS, et al. Improving Landsat predictions of rangeland fractional cover with multitask learning and uncertainty. Methods Ecol Evol. 2021; 12: 841– 849. https://doi.org/10.1111/2041-210X.13564

E. B. Peterson 2005. Estimating cover of an invasive grass (Bromus tectorum) using tobit regression and phenology derived from two dates of Landsat ETM+ data, International Journal of Remote Sensing, 26:12, 2491-2507, DOI: 10.1080/01431160500127815

Peterson, E. B. 2006. A map of invasive annual grasses in Nevada derived from multitemporal Landsat 5 TM imagery. Report for the U.S.D.I. Bureau of Land Management, Nevada State Office, Reno, by the Nevada Natural Heritage Program, Carson City, Nevada.

Provencher L, Badik K, Anderson T, Munn L, Cameron M. 2017. Sage-Grouse conservation forecasting for Barrick's Bank Study Area and Deep South Expansion Projects Plan of Operations Study Area. Report by The Nature Conservancy in Nevada to Barrick Gold Corp., Elko, NV, Version 1.0. The Nature Conservancy, Reno, NV

Provencher L., K. Badik, T. Anderson, J. Tuhy, and E. York. 2019. Landscape Conservation Forecasting™ Pine Valley and Mountain Home Range. Report to Bureau of Land Management, Cedar City Field Office in partial fulfillment of Cooperative Agreement No. L16AC00162. The Nature Conservancy, Nevada and Utah Field Offices. 231 p.

Provencher, L., K. Badik, T. Anderson, J. Tuhy, D. Fletcher, E. York, and S. Byer. 2021 Landscape conservation forecasting for data-poor at-risk species on western public lands. *Climate* 9, 79. https://doi.org/10.3390/cli9050079

Theobald, D. M., Harrison-Atlas, D., Monahan, W. B., & Albano, C. M. (2015). Ecologically-relevant maps of landforms and physiographic diversity for climate adaptation planning. PloS one, 10(12), e0143619

Kokaly, R.F., 2011, Detecting cheatgrass on the Colorado Plateau using Landsat data: A tutorial for the DESI software: U.S. Geological Survey Open-File Report 2010–1327, 88 p.

Jones, M. O., Allred, B. W., Naugle, D. E., Maestas, J. D., Donnelly, P., Metz, L. J., Karl, J., Smith, R., Bestelmeyer, B., Boyd, C., Kerby, J. D., and McIver, J. D.. 2018. Innovation in rangeland monitoring: annual, 30 m, plant functional type percent cover maps for U.S. rangelands, 1984–2017. Ecosphere 9(9):e02430. 10.1002/ecs2.2430

Pastick NJ, Dahal D, Wylie BK, Parajuli S, Boyte SP, Wu Z. Characterizing Land Surface Phenology and Exotic Annual Grasses in Dryland Ecosystems Using Landsat and Sentinel-2 Data in Harmony. Remote Sensing. 2020; 12(4):725. https://doi.org/10.3390/rs12040725

Matthew Clark Reeves, John E. Mitchell, Extent of Coterminous US Rangelands: Quantifying Implications of Differing Agency Perspectives, Rangeland Ecology & Management, Volume 64, Issue 6, 2011, Pages 585-597, ISSN 1550-7424, https://doi.org/10.2111/REM-D-11-00035.1.

Jeanne C. Chambers, Richard F. Miller, David I. Board, David A. Pyke, Bruce A. Roundy, James B. Grace, Eugene W. Schupp, Robin J. Tausch, Resilience and Resistance of Sagebrush Ecosystems: Implications for State and Transition Models and Management Treatments, Rangeland Ecology & Management, Volume 67, Issue 5, 2014, Pages 440-454, ISSN 1550-7424, https://doi.org/10.2111/REM-D-13-00074.1.

Toevs, Gordon & Karl, Jason & Taylor, Jason & Spurrier, Carol & Karl, Michael & Bobo, Matthew & Herrick, Jeffrey. (2010). Consistent Indicators and Methods and a Scalable Sample Design to Meet Assessment, Inventory, and Monitoring Information Needs Across Scales. Rangelands. 33. 10.2458/azu_rangelands_v33i4_toevs.

Stephen P. Boyte, Bruce K. Wylie, Donald J. Major, Cheatgrass Percent Cover Change: Comparing Recent Estimates to Climate Change−Driven Predictions in the Northern Great Basin, Rangeland Ecology & Management, Volume 69, Issue 4, 2016, Pages 265-279, ISSN 1550-7424, https://doi.org/10.1016/j.rama.2016.03.002.

U.S. Environmental Protection Agency, 2003, Level III ecoregions of the continental United States (revision of Omernik, 1987): Corvallis, Oregon, USEPA – National Health and Environmental Effects Research Laboratory, Map M-1, various scales.

Horn, K.J., Bishop, T.B.B. & St. Clair, S.B. Precipitation timing and soil heterogeneity regulate the growth and seed production of the invasive grass red brome. Biol Invasions 19, 1339–1350 (2017). https://doi.org/10.1007/s10530-016-1348-2

Lundberg, S. M., & Lee, S. I. (2017, December). A unified approach to interpreting model predictions. In Proceedings of the 31st international conference on neural information processing systems (pp. 4768-4777).