University of Nevada, Reno

Utilizing Remote Sensing to Generate Disturbance Response Group Extent and Vegetative State Maps in MLRA 25

A thesis submitted in partial fulfillment of the requirements for the degree of Master of Science in Animal and Rangeland Science

By

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May, 2019

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THE GRADUATE SCHOOL

We recommend that the thesis
prepared under our supervision by

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Utilizing Remote Sensing to Generate Disturbance Response Group Extent and Vegetative State Maps in MLRA 25

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Abstract:

Disturbance and management decisions on western landscapes occur at a scale far larger than ecological site mapping. Disturbance response groups aggregate ecological sites based upon disturbance ecology, and allow for common state and transition models to be utilized across landscapes. Soil and plant community information was gathered from northern Nevada, where dominant ecological site and related soil differs from minor components in a binary fashion. Loamy and Claypan ecological sites, respectively, vary along an elevation and precipitation gradient through 8”-10”, 10”-12” and 12”-14” precipitation zones. Spatial statistics and water deficit modeling from areas identified during field surveys are utilized to model soil component extent. State and Transition models appropriate to soil component are applied to continuous vegetation mapping derived through remote sensing. Vegetation sampling methods will also be compared to provide a locally accurate relationship between point line intercept, continuous line intercept (for shrub species), Daubenmire and ground based vertical imagery (GBVI) as provided by Open Range Consulting (ORC). ORC has successfully utilized GBVI as training datasets to create land cover maps at a landscape scale. If a relationship is established between traditional plot scale vegetation metrics and GBVI, then existing plot scale vegetation quantification datasets would be able to inform landscape scale cover maps significantly enhancing utility to land managers. This combined with enhanced ecological site maps and appropriate state and transition models as described above could provide a powerful landscape scale management tool.

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A very special thank you is due to ALL who helped this research project come to fruition, a much longer list than is provided here. The Great Basin for its cold beautiful sunrises, stunning vastness, deep mid-day and mid-night quiet, tired sunsets, endless empty dirt roads and all the lessons you learn along them. My wife Dr. Leah Linder for her endless support and encouragement, all my family and friends along the way that make it all worthwhile and provide purpose to my work. Dr. Tamzen Stringham for encouraging me to pursue this study, endlessly providing mentoring and materials at every turn, and sympathy and patience along the way given my good and bad days and occasional late night breakthrough excitement emails. Devon Snyder for a wealth of ecology knowledge, and thoroughness and thoughtfulness which makes science truly valuable, which helped immeasurably along the way. Dr. Peter Weisberg for his guidance and support in learning some of the landscape ecology tools available which helped make this project much more robust. Dr. Paul Verburg for his instruction and guidance in my understanding of how these vegetation communities came to exist in spatial patterns across landscapes and ways to think about soil genesis and its importance to ecology. My field technicians, Alyssa Badertscher, Emily Harmon, and of course Scout and Opal for needed laughs and pets along the way. Ben Stringham for all the logistics support. Annie Overlin for getting me into this 'mess' in the first place.

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Thesis Introduction:

Assessment of rangeland conditions have changed and improved with advancements in ecological understanding (Briske et al., 2008; Dyksterhuis E J, 1949a; Stringham et al., 2003; Westoby et al., 1989). Innovations within our understanding of vegetative cover assessment techniques, as well as plant community dynamics, have aided in overcoming increasingly complex concerns in land management. Many resources exist to help guide land managers through vegetation management issues, though synthesizing all the information for efficient planning can be challenging. The goal of this research effort is to bridge the gap between traditional methods of quantitative rangeland assessment and advancements in remote sensing of vegetative condition. Disturbance Response Groups are used to scale up ecological sites by grouping ecological sites based upon their response to disturbances(T. K. Stringham et al., 2016). State-and-Transition models describe vegetation dynamics within Ecological Sites or Disturbance Response Groups. By merging Disturbance Response Groups and State-and-Transition Modeling, (Stringham et al., 2003; Westoby et al., 1989) with spatially explicit vegetative cover data, we create a novel process that generates state-and-transition model mapping. This working methodology provides a new generation of land health monitoring tools as described within the state-and-transition models. To achieve this, several other concepts must be well understood first, and this manuscript seeks to illuminate those issues.

Comparing common methodologies of vegetative cover estimation has been undertaken previously (Floyd and Anderson, 1987b; Steven S Seefeldt and Booth, 2006; Amy J. Symstad et al., 2008; E. Thacker, 2010) and this study seeks to add to this body of knowledge and include classified imagery. Utilizing all available observations of vegetative cover increases our ability to consider and manage vegetative communities. The Monitoring Manual for Grassland, Shrub land, and Savannah Ecosystems (Herrick et al., 2005) describes the process of “defining the relationship(s) between the field based indicators and remote-sensing indicators (as) challenging. It can even, at times, be impossible.”(Herrick et al., 2005) However, it has been documented that classified ground based vertical imagery (GBVI) could be accurately related to landscape scale IKONOS and LANDSAT imagery (Sant et al., 2014). If a classified image and remotely sensed cover trained with the classified images describing proportional biotic components of a landscape, can be related to remote sensing images, then ground based transect data representing the same factors should be relatable using methods described by Sant et al. (2014). Chapter one of this thesis explores this question utilizing four different ground-based cover assessment techniques, as well as a remote sensing dataset, to determine correlation between datasets and to identify areas or metrics which cannot be related when combining existing data. Understanding relationships between datasets, as well as areas of potential conflict between datasets, are key to utilizing these metrics together in order to enhance our understanding of the landscape.

The stewardship of landscapes based upon categories of vegetative potential, and response to management, is a well-established practice by land mangers across the globe. Disturbance response groups (DRG’s) (T. K. Stringham et al., 2016) simplify landscapes into soil and plant communities, which respond similarly to disturbance and management based on species specific ecological knowledge and relationships to abiotic factors including precipitation, available water capacity, and evapotranspiration given solar gain on a specific site. Remotely sensed data modeling the aforementioned abiotic factors has not previously been used to map the extent of DRG's. If the physical parameters of landscape position and relative soil forming processes, which dictate plant community and ecological sites can be accurately assessed and teased apart, then it should be possible to map these features at landscape scale utilizing existing GIS data of the site characteristics. The ability to accurately map plant communities into DRG's would provide an advancement in the ability to manage and monitor land at large landscape scales, as well as help guide disturbance response efforts such as post fire stabilization and revegetation.

Finally, combining ground-based vegetation data with DRG mapping may allow determination of plant community condition and trend. If we can accurately predict plant functional group proportions from remotely sensed vegetative cover, then we have the necessary information to generate a state-and-transition model map. This type of management-oriented map could be very useful in planning wildfire rehabilitation and grazing management practices, as well as investment to maintain or enhance ecological condition of vegetative communities' at large scale.

This manuscript has been compiled such that steps required to generate state-and-transition model maps is completed within three separate chapters. Chapter three describes the process of making a state-and-transition model map, as well as cautions and areas of improvements needed prior to recommendation for use as a monitoring tool. The map provided in this manuscript displays vegetative states, but not phases within states.

Chapter 1

Comparison of rangeland vegetation cover assessment techniques.

Introduction:

Quantitative assessment of vegetative cover is central to rangeland monitoring, trend assessment, management objectives and wildlife habitat descriptions and guidelines (Friedel, 1991; Pilliod and Arkle, 2013a). Many of the problems that land managers currently face involve attainment of cover values necessary to their management goals or legally mandated habitat objectives required for public land grazing permit renewal (Connelly et al., 2004). Assessment of cover however is not standardized, with numerous methods utilized by land managers and researchers. Measuring vegetative cover utilizing different methods produces different cover values for the same plant communities, even when sample numbers and statistical confidence are similar (Floyd and Anderson, 1987b; Steven S Seefeldt and Booth, 2006; Thacker et al., 2015). Findings on this however have been inconsistent.

Emerging technologies have recently allowed the generation of relationships between remote sensing images and vegetative cover (Duniway et al., 2012; Xian et al., 2015), inferring proportional amounts of various cover on the ground as opposed to classified 'land cover'. The proportional cover values generally cover major functional plant community groups, including Annual vegetation, Perennial herbaceous vegetation, Bare-ground and shrub cover. Sant, Simonds, Ramsey, & Larsen (2014) describe a method for the generation of cover assessment at large scale, which has been utilized by private and public land managers. In their research they have presented very impressive accuracy assessments and convincing arguments, leaving public and private industries curious as to the utility of these products to help aid in their decision making. A comparison of this technique alongside traditional ground-based sampling techniques was completed within this study. Open Range Consulting (ORC) (http://openrangeconsulting.com/) collects Ground Based Vertical Imagery (GBVI) from plots throughout the area of analysis and generates cover maps of vegetation attributes as trained by the classified GBVI images (Sant et al., 2014). This provides an opportunity to examine the classified GBVI relationship to other cover assessments, as well as the ability of the cover values generated from the ORC remote sensing vegetative cover product to relate to traditional ground based sampling methods.

The intention for the study completed here was to compare five cover assessment techniques to determine if these can be related to each other reliably. Ground based methods include: Line-Point-Intercept (LPI), Continuous-Line-Intercept (CLI), Daubenmire frame visual estimation (Daubenmire) (Herrick et al., 2005), Ground Based Vertical Imagery (GBVI) as generated by ORC and remotely sensed vegetative cover data generated by ORC. This effort creates an improvement in our ability to monitor vegetation by increasing our ability to determine if various data sources can be utilized for monitoring. This effort also tries to relate numerous covr metrics to GBVI and ORC raster based fractional vegetative cover, which has not been completed before.

Methods:

Site characteristics:

The study area is located approximately 90 km northeast of Golconda, Nevada, USA. The site is within the public and private grazing lands utilized by the Humboldt River Ranch (previously known as Squaw Valley Ranch). The study area was selected as an acceptably sized portion of land under single management that allowed for capturing remote sensing images. The study area is also representative of vegetative communities throughout Major Land Resource Area (MLRA) 25 (United States. Dept. of Agriculture., 2006) with elevations ranging from 1518 to 2612 meters above mean sea level. Precipitation on site varies from 8-24” per year according to the POLARIS climate model (Daly et al., 2007). Most common vegetative communities found throughout MLRA 25 are represented within the study area. A history of wildfire and restoration attempts exist in the study area, with numerous fire scars of varying ages present on the landscape. The current day landscape into a plant community dominated by Wyoming sagebrush (*Artemisia tridentata* Nutt. ssp. *wyomingensis* Beetle & Young) and a mix of native and non-native bunchgrasses.

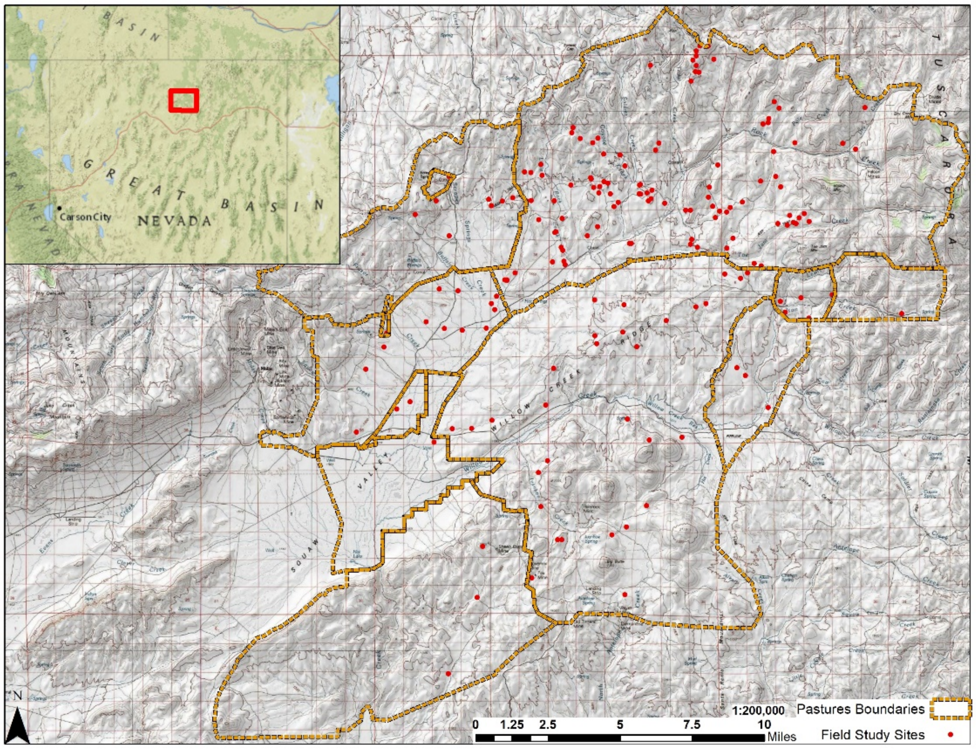


Figure 1-1: Map of the study area, and sample location within the analysis area. The Study area extent was approximately 230,000 acres, managed under the grazing allotments belonging to Humboldt Valley Ranch.

Field Methods:

Transect locations were generated randomly across the project area. Vegetation cover was quantified utilizing data captured by five methods; point line intercept, line intercept (shrubs only), Daubenmire frame (herbaceous plants only, ORC's Ground Based Vertical Imagery (GBVI) classified into vegetative classes and ORC's remote-sensing product utilizing NAIP imagery and ORC Earth Sense Technology. The GBVI and remote sensing data were obtained by ORC.

To facilitate generation of vegetative cover relationships including the GBVI, cover estimation techniques were completed within an 6m x 7m area approximately equivalent to the boundary of GBVI imagery for plots that were analyzed by ORC. Due to contractor constraints, only 38 of the total 172 observations included the GBVI imagery. Vegetation captured in the image was processed by ORC using the Visual Learning Systems Feature Analyst Software (http://www.vls-inc.com) utilizing the methodology described in (Sant et al., 2014), and produced percent vegetative cover within the image of Annual vegetation, Perennial vegetation, Sandberg's Bluegrass, Sagebrush, and Bare ground. Each GBVI plot was oriented to the magnetic North, with the long axis running East-West. Three parallel 6m transects were established running East-West in the study plot, 1.5 meters apart, and were permanently marked in place using steel rebar covered with PVC pipe, marked with flagging tape. Line-Point-Intercept vegetative cover was assessed every 20 cm along the 6m transects, resulting in 90 samples per plot as described by the Monitoring Manual for Grassland, Shrubland and Savannah Ecosystems (Herrick et al., 2005). Continuous-Line-Intercept was recorded for lengths of transect with greater than 50% total shrub cover, and stopped at canopy gaps of greater than 5 cm. Cover increments of less than 2 cm was not recorded. Daubenmire frames were recorded in 5% cover classes, captured at 1-1.5m and 5-5.5m along each transect, for a total of 6 frames per plot location to reduce vegetation trampling within the image capture area.

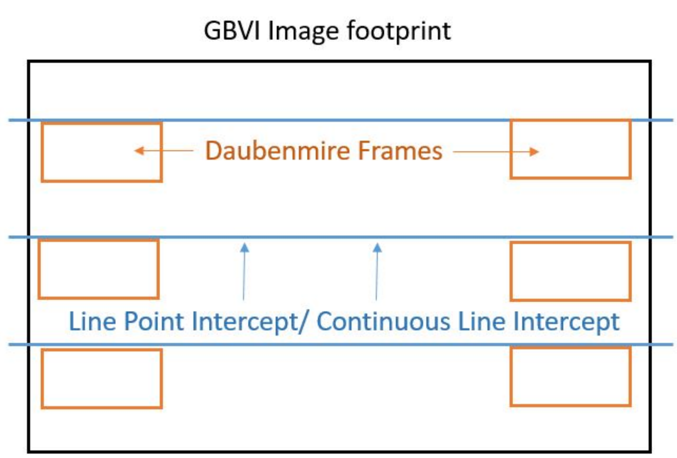


Figure 1-2: Sample design within the GBVI footprint. All five cover metric were completed within this boundary, including Line-Point-Intercept, Continuous-Line-Intercept, Daubenmire visual estimation, Ground Based Vertical Imagery (GBVI) and fractional vegetation cover derived from NAIP imagery at 1m scale as produced by ORC.

The 134 additional sampling locations, not associated with the GBVI images, were quantified using the same protocols along a single transect 18m in length. Six Daubenmire plots were collected along similar intervals at 1-1.5m, 5-5.5m, 7-7.5m, 11-11.5m, 13-13.5m and 16-16.5m. All vegetative data was collected in early summer in the smallest timeframe allowable to reduce impact of seasonal change and plant senescence. Plot location was confirmed with Global Positioning System (GPS) to be accessed for extraction of cover values from 1m remotely sensed fractional vegetative cover data products generated by ORC. Extraction of ORC cover data was completed at three scales: 1m point extraction, 5m buffer, and 25m buffer. A GPS was used to locate the plot with 3-5m assumed accuracy which is coarser than the cover data resolution (1m raster grid). Due to this fact, all data at "point" locations was extracted using bi-linear interpolation, averaging values from adjacent cells sharing a complete edge with the raster cell at the GPS point. Five cells were utilized to interpolate the value at the GPS 'point' location. At the 5m and 25m buffers, data was extracted and averaged for all cells within the buffer around the GPS point, averaging 79 and 1,964 pixels respectively.

Data collected for LPI, CL, and Daubenmire was entered into the program 'Database for Inventory, Monitoring, and Assessment' (DIMA, 2018 The Jornada Institute); and grouped into cover classifications from species level data. LPI data was extracted using "All Hit" methodology, in which all interception of the point is counted for total foliar cover. 'All-Hit' extraction method was utilized as it has been shown to relate more closely to Daubenmire cover as well as classified Rapid Eye satellite imagery (Karl et al., 2017) which is recorded at similar resolution to

NAIP. As cover can be counted twice utilizing this method, it is possible for cover greater than 100% to be achieved if multiple hits are recorded in the understory of a dense plant community. Due to this, some plots did have greater than 100% coverage in this study, and were included in the analysis.

Data Management and Statistical Analysis:

Summary statistics were compiled for cover values assessed at 172 study locations. Of these, 37 plots were imaged utilizing GBVI, and therefore the statistics involving GBVI relationships have a maximum N=37. Vegetation data was compiled and analyzed within functional vegetative groups given growth form and life history. Annual herbaceous vegetation, Perennial herbaceous vegetation, Sagebrush, shrubs and bare-ground categories were compiled utilizing information provided by the USDA plants database. Within these functional groups, plots were analyzed as an entire group for discussion of monitoring values with the maximum number of observations. Summary statistics, linear regressions, boxplots, and Wilcoxon signed rank tests were generated for each measurement type utilizing R statistical software (R Core Team, 2017).

Results:

Comparison of cover values at specific sites:

Line-Point-Intercept and Continuous-Line-Intercept

Line-point-intercept and continuous-line-intercept cover assessments has the strongest positive association within this study (Figure 3; $R2=0.92$ and $p< 0.001$ for sagebrush and $R2 = 0.93$ and $p<0.001$ for total shrub cover).

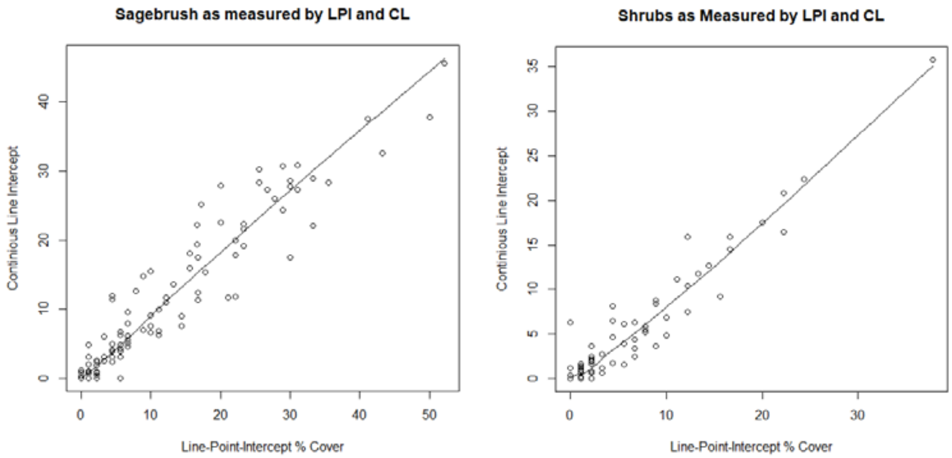


Figure 1-3: Sagebrush and Shrub cover as assessed by LPI and CL measurements across 172 observations within the project area.

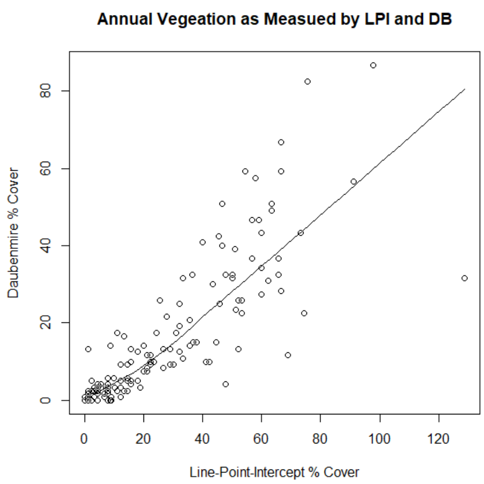
'Shrub cover' included all shrubs excepting sage brush. Although shrub cover was generally low across the project area, the two cover values correlated tightly with low standard errors and a regression slope near 1. Error, however, increased between cover metrics as the percent cover of sagebrush or total shrubs neared zero.

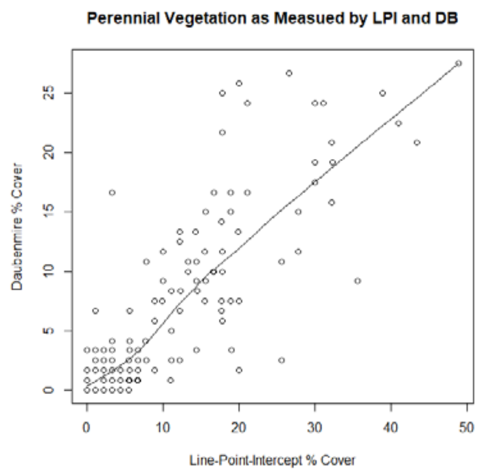
Table 1*:* Regression, LPI & LC***:*** Linear regression statistics for LPI and CL measurements at all observations. Dataset mean values provided in addition. Sagebrush category includes all species and observations of sagebrush. Shrubs includes all plants categorized as Shrub or sub-shrub according to the USDA plants database.

Linear Regression, LPI and CL:	**Sagebrush**	**Shrubs**
Mean Cover Values, LPI/CL	7.49/6.84	2.54/2.09
Residual Standard Error:	3.024	1.32
Adjusted R^2:	0.9267	0.935
P-Value:	<0.0001	<0.0001

Line-Point-Intercept and Daubenmire Frame Visual Estimation:

Daubenmire cover was generally lower than LPI cover. Cover value relationships were closest at low values, and the differences between the cover assessment techniques appeared to increase as cover increased.





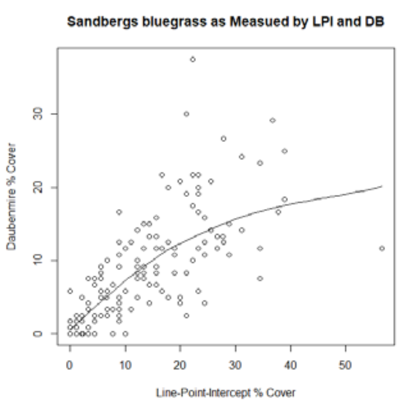


Figure 1-4: Annual herbaceous vegetation, Perennial herbaceous vegetation, and Sandberg Bluegrass cover as assessed by LPI and Daubenmire visual estimates measurements across 172 observations within the project area.

Regression fit was closest with annual and perennial herbaceous vegetation cover. Sandberg bluegrass (POSE) had a less reliable relationship as cover values increased as well as evidenced by a flattening linear regression line in the figure below. Overall mean value of annual herbaceous cover was 57% of the cover generated by LPI, displaying that *although the regression shows a fairly decent relationship between the two variables, the relationship is not 1:1 and conversion between the values would need to be applied to use the values congruently.*

Table 2*: Regression statistics and relationships between the LPI and Daubenmire frame visual estimation. Dataset mean values provided in addition.*

Linear Models, LPI and DB:	**Annual**	**Perennial**	**Sandberg's bluegrass**
Mean Cover Values, LPI/DB	25.8/14.8	18.1/13.7	13.5/8.9
Residual Standard Error:	13.42	5.83	7.53
Adjusted R^2:	0.71	0.68	0.49
P-Value:	<0.001	<0.001	<0.001

Line-Point-Intercept (LPI) and Ground Based Vertical Imagery (GBVI):

LPI and GBVI were closely related throughout this dataset. Sagebrush and Annual herbaceous cover presented the highest coefficient of determination (displayed below as R^2) or closest fit to the regression line at 0.82 and 0.79 respectively. The slope of all lines were significant (P-value of <0.001). However, there was a low R^2 value (0.37, 0.46) and high standard error (5.9, 7.8) for the relationship between LPI and GBVI for the functional groups of Perennial vegetation and Sandberg bluegrass respectively (Table 3).

Table 3: Regression with fitted line statistics and relationships between the LPI and GBVI classified imagery. Dataset mean values provided in addition. Functional vegetative groups are as follows; 'Annual' refers to all annual herbaceous vegetation, 'Perennial' refers to all perennial herbaceous vegetation and 'POSE' refers to Sandberg's bluegrass *(Poa secunda)* specifically, not counted with Annual or Perennial vegetation. Sagebrush refers to all Sagebrush species present.

Linear Models, LPI and GBVI:	**Annual**	**Perennial**	**Sandberg's Bluegrass**	**Sagebrush**

Mean Cover Values, LPI/ORC	25.81/25.89	18.06/11.73	13.47/11.43	7.49/7.40
Residual Standard Error:	13.8	5.868	7.815	4.644
Adjusted R2:	0.7997	0.3746	0.4614	0.8255
P-Value:	<0.001	<0.001	<0.001	<0.001

Similarities as well as differences in mean values in the measurement types reflect the quality of the coefficient of determination in this analysis, where plant functional groups with similar mean values tend to have higher R^2 values (Table 3). Residual standard error is also related to the potential range of values input into the model. For example, Annual grass tends to create near monocultures in some sites, which can lead to cover values exceeding 100% as the grass can be counted in multiple layers using this LPI protocol and analysis method.

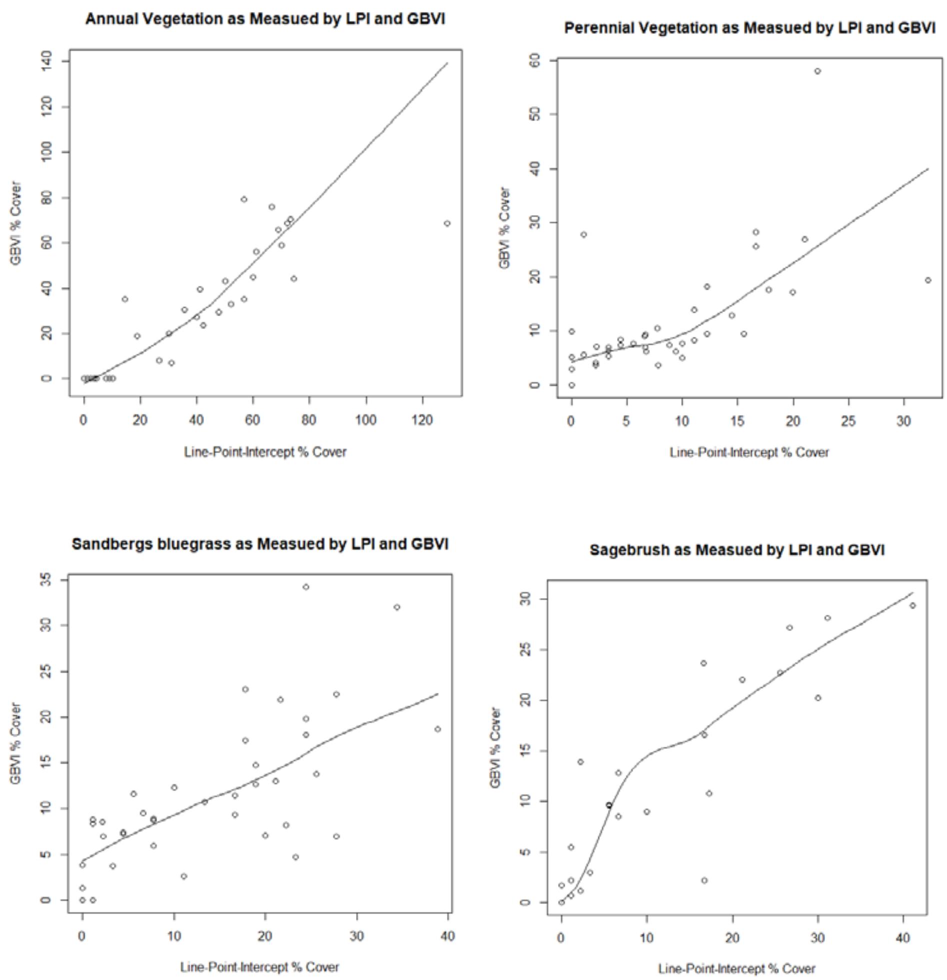


Figure 5: Annual herbaceous vegetation, Perennial herbaceous vegetation, Sandberg's Bluegrass and Sagebrush cover as assessed by LPI and GBVI classified imagery measurements across 38 observations within the project area.

Daubenmire Visual Estimates and Continuous-Line-Intercept related to GBVI

Daubenmire estimates of Annual grass, Perennial grass and Sandberg bluegrass were compared to GBVI estimates of the same functional groups. In addition, Continuous-Line-Intercept measurement of sagebrush cover was also compared to GBVI estimates. Annual vegetation as measured by Daubenmire and GBVI had a strong relationship between the two datasets at low cover values, becoming less obvious at higher cover values.

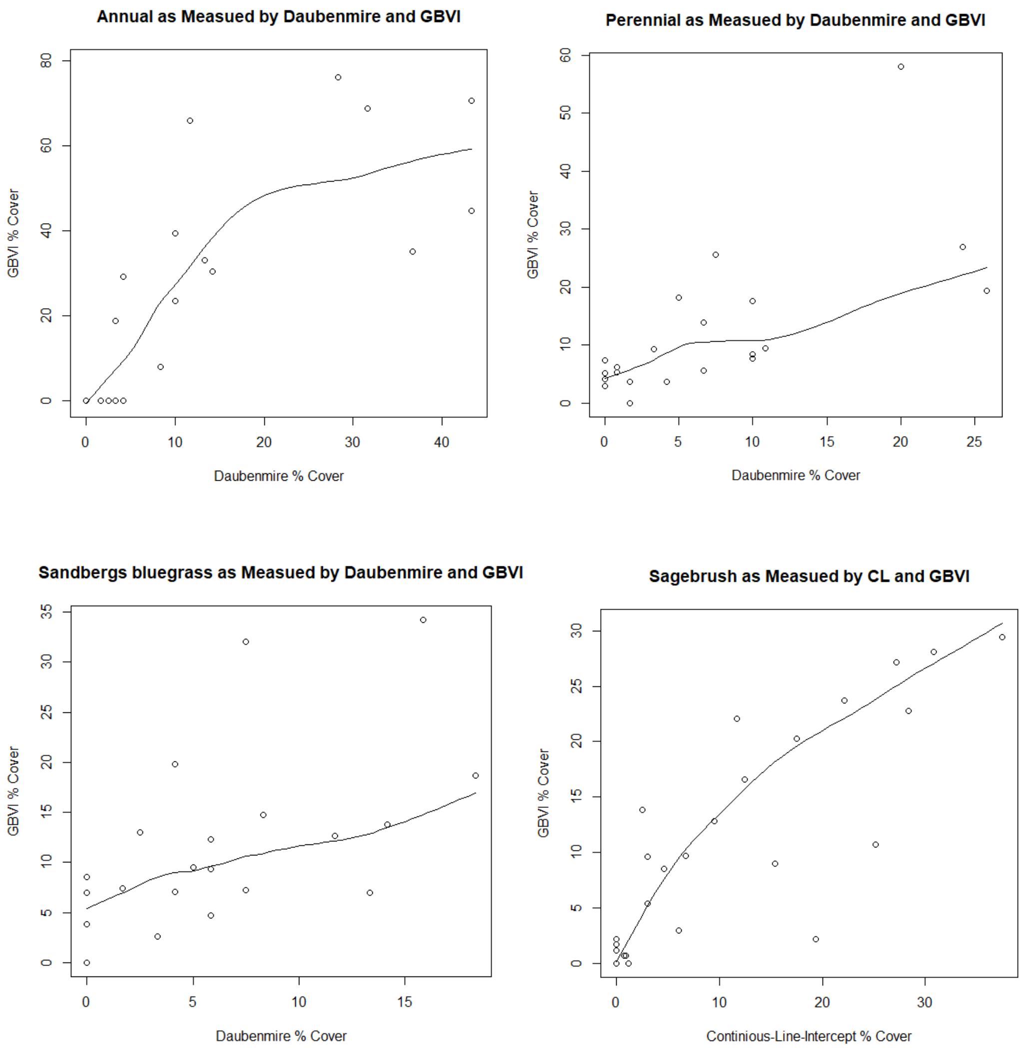


Figure 6: Annual herbaceous vegetation, Perennial herbaceous vegetation, Sandberg's bluegrass and Sagebrush cover as assessed by LPI and GBVI classified imagery measurements across 38 observations within the project area.

Although the regression fit was generally poor, all regression lines showed some relationship between the data as the P<0.01 level. The magnitude of the residual standard error compared to the mean value for the dataset indicates that either many more observations would be needed in order to define a relationship which was consistent enough to be utilized in monitoring and observing change, or a consistent relationship cannot be established. Perennial grass shows a close relationship between values at low cover, and sagebrush measurements appear to be more closely related at higher cover measurements around 30% sagebrush cover.

Table 4: Regression between the Daubenmire frame visual estimation and Open Range Consulting's (ORC) Ground Based Vertical Imagery (GBVI). Dataset mean values are provided in addition. Functional vegetative groups are as follows; 'Annual' refers to all annual herbaceous vegetation, 'Perennial' refers to all perennial herbaceous vegetation and Sandberg's bluegrass *(Poa secunda)* specifically, not counted with Annual or Perennial vegetation.

Linear Models, DB, CL, and GBVI:	**Annual**	**Perennial**	**Sandberg's bluegrass**	**Sagebrush**	**Shrubs**
Mean Cover Values, DB/GBVI	12.86/25.8	7.103/11.73	6.428/11.48	7.52/7.40	1.85/1.2
Residual Standard Error:	9.345	5.771	4.665	5.313	2.331
Adjusted R^2:	0.5923	0.4519	0.2711	0.7576	0.6358
P-Value:	<0.0001	0.0005	0.009	<0.0001	<0.0001

ORC Continuous Raster Datasets

Scale of Assessment:

ORC fractional vegetative cover datasets of Annual, Perennial, Sandberg's bluegrass, Sagebrush, Shrub and bare ground were assessed at 3 scales due to the image and resultant dataset pixel size being smaller than typical field GPS accuracy. Few rangeland field data collection efforts utilize sub-meter GPS, therefore it was important to determine the appropriate scale for accurate data assessment as this study involves matching 'typical' ground based data collection. Median vegetative cover values were generated from Box-and-whisker plots and compare vegetative cover values generated at the three scales of assessment;

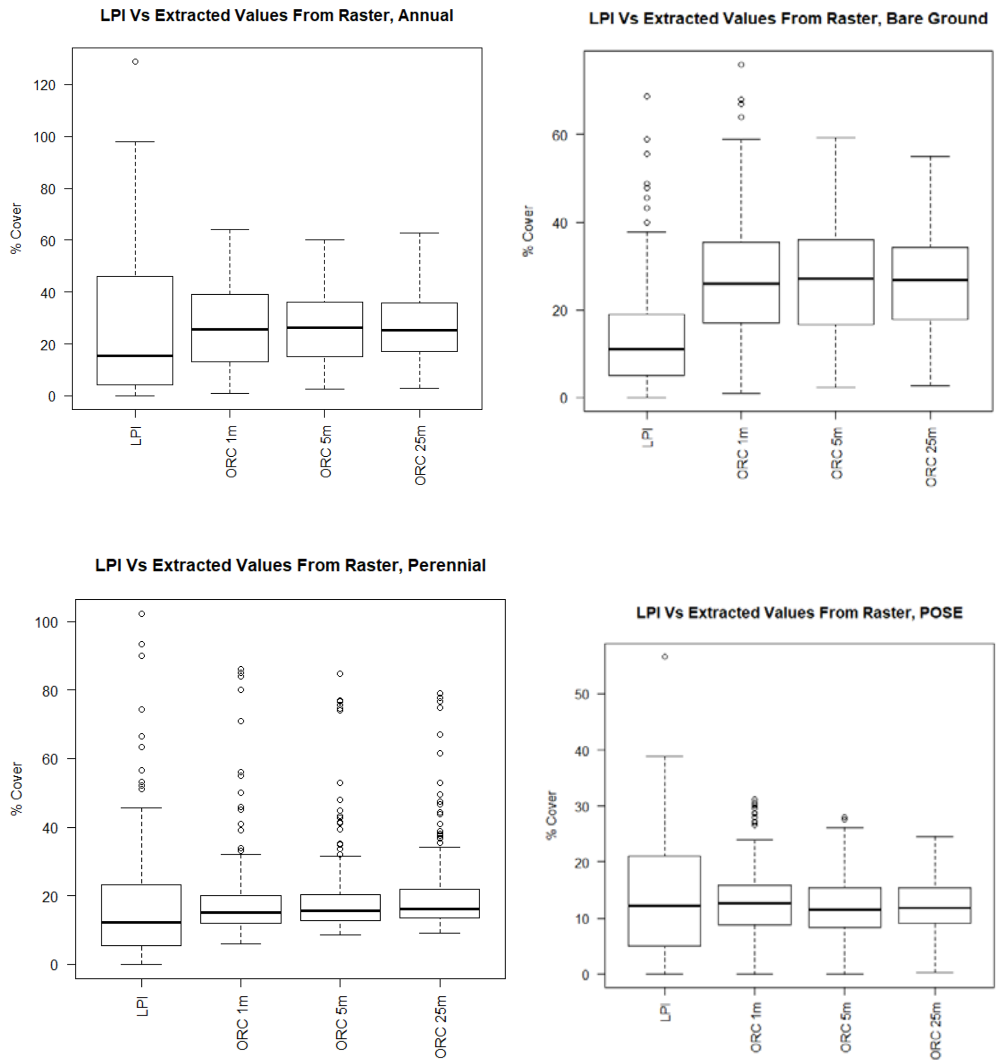


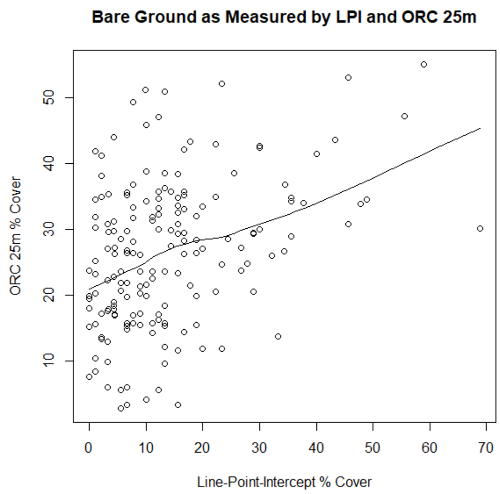
Figure 7: Box-and-Whisker plots of Line-Point-Intercept (LPI) cover and cover values extracted from the ORC 1m raster dataset assessed at 3 different scales. Median values of annual herbaceous vegetation, bare ground, perennial herbaceous vegetation and Sandberg's bluegrass are presented

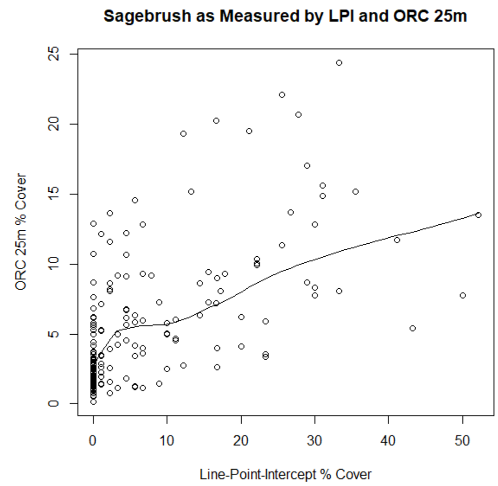
Median values are generally consistent across extraction buffer sizes. The 25m buffer however, with 1963 cells averaged, more completely covered the sampled area leading to reduced variance in this extraction without a significant change in median value. For this reason, the 25m buffer scale was utilized as the area of comparison to LPI data. Mean and median values for each cover assessment method and vegetative cover is provided below in table 6.

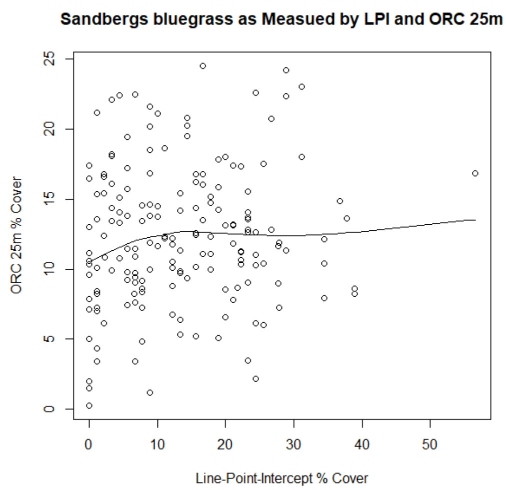
Table 5: Regression statistics and relationships between the LPI and ORC Vegetative cover raster dataset. Dataset mean values provided in addition.

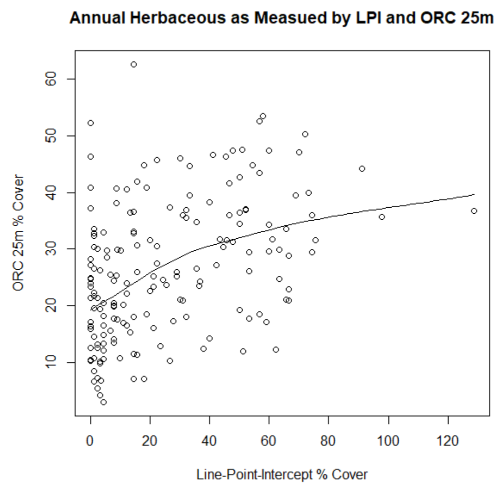
Linear Models, LPI and ORC 25m:	**Annual**	**Perennial**	**Sandberg's bluegrass**	**Sagebrush**	**Bare ground**
Mean Cover Values, LPI/ORC	25.81/26.59	18.06/20.38	13.47/12.30	7.49/5.84	14.19/26.44
Residual Standard Error:	23.01	13.38	10.42	9.088	11.67
Adjusted R2:	0.1679	0.4889	0.0104	0.3344	0.1384
F-Statistic:	86.89	164.6	2.804	86.89	28.47

Linear models between LPI cover and ORC's continuous raster cover were not correlated at the 1m and 5m scale and weakly correlated at the 25m scale (Figure 8). Perennial herbaceous vegetation had the strongest relationship with an R^2 value of 0.48. whereas, Sandberg bluegrass had the lowest level of correlation with an R^2 at 0.010. The density plots appear normally distributed at 25m. Shapiro-Wilk normality tests generate a p-value of 0.3654 for the 25m extraction buffer.


Bare Ground as Measured by LPI and ORC 25m
ORC 25m % Cover
Line-Point-Intercept % Cover


Sagebrush as Measured by LPI and ORC 25m
ORC 25m % Cover
Line-Point-Intercept % Cover


Sandbergs bluegrass as Measued by LPI and ORC 25m
ORC 25m % Cover
Line-Point-Intercept % Cover


Annual Herbaceous as Measued by LPI and ORC 25m
ORC 25m % Cover
Line-Point-Intercept % Cover

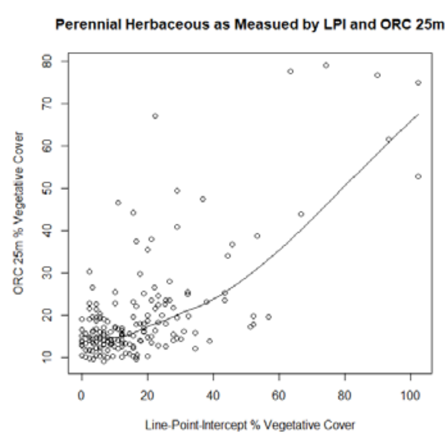

Perennial Herbaceous as Measued by LPI and ORC 25m
ORC 25m % Vegetative Cover
Line-Point-Intercept % Vegetative Cover

Figure 8: Cover values of bare ground, sagebrush, annual herbaceous vegetation, perennial herbaceous vegetation and Sandberg's bluegrass as measured by Line-Point-Intercept and ORC Raster datasets extracted within a 25m buffer around the ground based sampling. The residual standard error was 10.42 on 170 degrees of freedom. The adjusted R^2 was 0.01.

Central Tendency of the Dataset Averaged across all observations:

Plot vegetative cover was assessed at 172 locations throughout the study area. Mean cover between methods was most similar within the functional group of Annual herbaceous and Sandberg Bluegrass and Sagebrush cover as measured by Line-Point-Intercept and ORC raster values. Mean values of the Daubenmire frame visual estimation differed significantly more than the of the ORC fractional vegetative cover at the 3 scales of extracted raster data. Results for a Wilcoxon Signed Rank Test are given below. Due to the fact that the plots were measuring the same vegetative cover, paired observations were assumed at each site. Rows (Table 6) with P values less than <0.05 are typically considered to be significantly different from one another. Annual Vegetation, Sandberg bluegrass, and Sagebrush cover as assessed by LPI and ORC fractional vegetative cover were not significantly different.

Table 6: Mean and median cover of quantified by line-point-intercept (LPI), Daubenmire, continuous line and 25m scale ORC fractional vegetative cover. The Wilcoxon signed-rank test was utilized to determine if the central tendency of the compared cover values were significantly different. "CA" in the table stands for "Cover Assessment".

Wilcoxon signed rank test with continuity correction, Paired Observations								
Vegetation	**CA 1**	**Mean Cover**	**Median Cover**	**CA 2**	**Mean Cover**	**Median Cover**	**V=**	**P-Value=**
Annual	LPI	25.81	15.56	Daubenmire	14.83	8.33	9198	<0.00001
Perennial	LPI	18.06	12.2	Daubenmire	13.7	9.17	9698	<0.00001
Sandberg Bluegrass	LPI	13.47	12.2	Daubenmire	8.92	7.5	9010	<0.00001

Sagebrush	LPI	7.43	2.2	Continuous Line	6.84	0.89	3652	0.0013
Shrubs	LPI	2.54	0	Continuous Line	2.099	0	1763	<0.00001
Perennial	LPI	18.06	12.2	ORC 25m	20.38	16.12	5260	0.00087
Bare ground	LPI	14.19	11.1	ORC 25m	26.44	26.7	1417	<0.00001
Annual	LPI	25.81	15.56	ORC 25m	26.59	25.4	6559	0.1789
Sandberg Bluegrass	LPI	13.47	12.2	ORC 25m	5.84	4.32	7910	0.4714
Sagebrush	LPI	7.43	2.2	ORC 25m	12.3	11.89	7212	0.291

Discussion:

Relation to existing literature:

Our research results confirm existing literature surrounding cover assessment comparisons, and add another technique to the analysis; Open Range Consulting's (ORC's) Ground Based Vertical Imagery (GBVI) and their continuous cover raster datasets. Cover assessed by differing methods are measuring slightly different things to sample vegetation across the landscape. This difference creates dissimilarity with many of the analysis techniques. ORC's raster datasets have been published with excellent accuracy determinations (Danvir et al., 2018; Sant et al., 2014), and land managers are curious as to the utility of this product for monitoring and managing landscapes. Supporting management decisions with this product utilizing ground based cover assessment collected in numerous ways is also a question asked here. Can we relate data from numerous sources (LPI, CL, Daubenmire) frame to help inform managers of vegetative conditions across the landscape and use this to support or refute remote sensing data.

Floyd and Anderson (1987), compared Continuous-Line-Intercept, Line-Point-Intercept, and Daubenmire canopy cover and determined that LPI was more accurate and more time efficient than Daubenmire. It was also concluded that of the metrics, LPI generated the most precise estimates. Dethier M.N. et al., (1993) concluded as well that visual estimates increased in accuracy as the size of the area of estimation decreased, resulting in a 4 x 5 cm ideal frame size which is not appropriate for determining landscape scale plant community composition. Thacker (2010) in his PhD dissertation, also found higher overall cover provided by LPI inventory versus Daubenmire frame canopy cover, even while using Braun and Blanquet cover classes typical to this type of vegetation monitoring (Wikum and Shanholtzer, 1978). He similarly found that as cover increases, mean values between the cover estimates grew apart. Thacker et al., (2015)had very similar results to this study as well in which their data showed that LPI cover estimates were generally higher than Daubenmire estimates, and that differences between the two methods increased as total vegetative cover increased. Karl et al., (2016) pointed out that the two methodologies conducted by Thacker in 2015, in that assessment were potentially not comparable utilizing the specific survey methodology they used. This is due to the fact that Daubenmire was measuring foliar cover and not total vegetative cover. They conclude that without a thorough methods section detailing how the data were analyzed, that it is possible that one method (LPI) was actually measuring total canopy cover versus Daubenmire would be analyzing total foliar cover.

In 2017, Karl et al. published another paper on validating remote sensing with ground based measurements. In this publication, they found that utilizing the “All Hit” analysis method of LPI reduced the root mean square error of vegetative cover estimates utilizing 5m-resolution RapidEye imagery. Hulvey et al., (2018) analyzed Daubenmire frame ocular assessment against another method of image classification in which a grid of points (utilizing “SamplePoint” software) was used to assess cover within the image boundary. Daubenmire was found to provide a higher cover estimate due to the fact that it gathered information about under canopy vegetation that investigators identified on-site but was not quantifiable in the image. The Hulvey study would indicate that utilizing only 'top hit' of LPI data would likely correspond to image analysis better. Godínez-Alvarez et al., (2009) had a similar result as this study comparing similar metrics as Hulvey et al., (2018) showing that LPI generates generally higher cover values than does ocular estimates such as Daubenmire frames. Their study also indicated that precision of cover estimates was generally higher with LPI data than ocular estimates. Pilliod and Arkle, (2013b) also assessed cover accuracy of classified imagery using Grid Point intercept, LPI, and Point-Quarter methodology in the Great Basin. They found an alternative result where variance increased as vegetative cover decreased. Their research confirmed the precision of cover estimates as provided by LPI, though found significant utility for the image based quantification from a time and accuracy standpoint for capturing major functional groups.

Lawley et al., (2016) sought to integrate site-based sampling to validate remote sensing, much as we have done here. They note that often the ground based sampling methodology should be designed to integrate easily into the remote sensing product. Sampling within homogeneous vegetation to avoid pixel mixing was suggested to avoid issues between the datasets. They note that this does not confirm the accuracy of the dataset in mixed vegetation areas. Seefeldt and Booth (2006) assessed visual estimation, laser-point frame, 2m above-ground level (AGL) imagery and 100m AGL imagery. In a similar result to this research, they also found so significant difference in mean values of the digital imagery, yet also found this result with visual observation as well. Their study finds that the 2m and 100m imagery was most efficient with similar standard deviation, and had the advantage that the imagery could be re-analyzed through time. Symstad et al., (2008) compared point frequency and visual estimate methodologies. They found similar variance between the methods, and similar to this study, higher cover values for graminoids and total cover. Their study also showed an increase in the total number of species captured using visual estimation within a Daubenmire frame.

Results and Implications for Management:

Understanding relationships between vegetative cover assessment techniques is critical to interpreting scientific studies and management goals interpreted through vegetation survey data. Numerous cover assessment techniques are available and can all adequately sample vegetation given appropriate sample size and stratification of sample units, yet most methods yield differing mean cover values which is often used in habitat management (e.g. NVCA Approved BLM RMP 2015 Sec 2.2). Stakeholders working together to meet vegetative cover goals need to utilize similar assessment techniques, or have a thorough understanding of the relationships between the two sampling techniques and the potential for interrelation.

Field survey data and capture of traditional ground based survey methodology provided additional information important to understanding the ecology of the systems surveyed. Areas which were annual dominant according to the ORC raster dataset, but were not annual on the ground, were found to exhibit numerous other conditions which could easily be interpreted through imagery as being annual grass. These conditions include but are not limited to: Perennial forbs which senesce late season; plots with increased soil exposure of a light color; and plots with increased levels of herbaceous litter. For this reason, specific plant community information needs to be gathered at ground level in order to provide needed background on the data provided by the datasets, which is not possible to do at this time without ground based data. Our study indicates that additional utility is provided in utilizing both ground based datasets and raster datasets to get additional species specific information about a study area, unavailable through remotely sensed datasets.

Relationships between Datasets:

Line-Point-Intercept, Continuous-Line-Intercept and Daubenmire

Line Point intercept and Continuous Line Intercept were very closely related in measures of total sagebrush cover and total shrub cover. The linear model statistics of the two measurement techniques indicates that these two types of cover assessment can be utilized alongside one another at most cover values, with a decrease in relatability at higher cover values. As existing literature (Floyd and Anderson, 1987a) indicates that LPI is a more rapid technique yielding similarly accurate data, LPI appears to be a more efficient cover assessment method in this area. This same phenomenon was observed between Line-Point-Intercept metrics and Daubenmire Frame assessment, in which a close relationship is established at lower cover values, becoming less reliable at higher cover values. The result is logical for a visual estimation technique, where a similar percentage of cover estimation difference applied to greater cover values creates a larger divergence in values. For this reason, many vegetation studies record cover 'classes' such as the Braun-Blanquet Cover-Abundance Scale (Wikum and Shanholtzer, 1978) which are not equally sized. Our study attempted to capture cover as estimated to the smallest increment allowable on typical 'Daubenmire' style frames. Daubenmire frame cover was generally lower than LPI cover, with differences between cover types. Perennial grass as quantified in a Daubenmire frame was shown to be around 25% less than LPI overall, and annual grass around 44% less using the same method. These differences would impact management significantly.

Depending on management goals, it should also be noted that Daubenmire frames are likely to capture greater numbers of species than would LPI

GBVI and Ground Based Cover Assessment:

Ground based vertical imagery was related to the ground based cover assessments, and most strongly related to LPI. Sagebrush LPI cover showed the closest relationship to the GBVI assessments. Continuous-Line intercept (CL) had a slightly poorer fit ($R^2 = 0.75$), and slightly higher residual standard error. Annual cover provided by the GBVI also fit LPI cover fairly well. LPI generally fit GBVI cover best, and even there the linear regression fit was poor for perennial cover and Sandberg's bluegrass (*Poa secunda).* Daubenmire and CL generally had worse linear regression fits. Other research groups as mentioned above have experience better results on classified near ground imagery utilizing grid-point-imagery and other image sampling techniques(Godínez-Alvarez et al., 2009; Hulvey et al., 2018; Pilliod and Arkle, 2013b). It is worth noting that classification of these images occurs through supervised classification, and manual identification of image components to fit these spectral traits. Shadow, identification in small stature plants which senesce early (Sandberg's bluegrass), as well as non-vegetative features including gravel and litter are known to be difficult to identify spectrally.

ORC Raster Based Fractional Cover and Ground Based sampling:

Scale of assessment is an important consideration in assessing cover measurements utilizing the ORC vegetative cover 1m gridded imagery. The 1m pixel image is georeferenced to sit nearly as possible to the ground that it represents, however this practice is known to be imperfect. The 'flat' image sits across terrain of various slopes, with increased amounts of land laying within the flat 1m grid as a function of slope. Geo-referencing this type of image is notoriously difficult, and some level of error is always associated with this practice. Although sub-meter GPS accuracy is possible with post-processing, typically this level of accuracy is not utilized due the expense, weight, and additional effort required for sub-meter GPS. Typically, vegetation sampling occurs with 3-5m accuracy typical of GARMIN type GPS handheld units. As this study was not trying to validate the accuracy of 1m resolution cover, but rather determine relationships and relatability to ground based sampling, this type of GPS was utilized to capture the ground-based vegetation sampling data used to compare the ORC 1m fractional vegetative cover here. Data was extracted from the 1m raster at multiple scales in order to figure out which scale was most accurate for relating vegetation cover. Vegetative cover extracted at all scales had similar mean values, with variance decreasing as extraction area increased. For this reason, the 25m buffer averaged cover data was utilized in this analysis. It should be noted that mean cover values between ORC raster products and LPI were very close, with ORC raster datasets and LPI being the only datasets which could not be assumed to be drawn from separate populations as determined by a Wilcoxon signed-rank test. If mean vegetative cover as assessed across an entire study area is the goal of a study, this product appears to produce similar results to LPI.

Linear regression fit between LPI and ORC raster datasets however was overall very low. Perennial herbaceous vegetation had the best regression fit with an R^2 of 0.49, however this is drawn from a small sample size. The majority of the data occurred at very low cover values, where almost no regression relationship existed between the datasets. Sandberg's bluegrass had the lowest relationship with an R^2 of 0.01. The utility in management however should be cautioned. If no strong relationship between ground-based vegetation assessment and ORC raster at any cover level or with any functional cover group, mean cover values which have similar mean values appears to be a spurious result. As the source imagery (NAIP) is difficult to normalize between years, use of this tool to measure change should be questioned as well. Reference locations to measure change in a pasture would be un-relatable utilizing these methods, removing the ability to utilize this data alongside existing data which exists for a site. The residuals or standard error between the ORC raster and any of the other cover metrics is near the mean value, indicating that vegetation as observed in the ground could vary from the ORC raster dataset by nearly 100%.

Conclusion:

Consistent relationships between any of the ground based vegetative cover assessments nad the remotely sensed vegetative cover were not established in this study. Cover metrics which yield differing cover values can yield important information so long as the relationship between the two assessment techniques is appropriately understood and consistent. There is an increasing demand for remote sensing based vegetative cover datasets to reduce ground survey time, and a thorough understanding of strengths and weaknesses of a given remote sensing dataset must be held by managers in order to fully utilize these products. The research presented above implies that vegetative cover assessed by numerous metrics can be related and utilized for management purposes. Relation of remote sensing products to important ecological indicators of a given ecosystem is of primary importance, and without the ability to sense the important indicators of the systems or find a relatable variable, the effort cannot be a useful management tool. Field based knowledge can and should be utilized to inform remote sensing datasets, and can also help remote sensors stratify a landscape given ecological knowledge of an area to provide better, more informed products about a management area. While it is unlikely that the need for quality ground based vegetation survey information will be supplanted by remote sensing in the near future, the ability for land managers to utilize remote sensing datasets to add to their understanding of a site and aid in spatial problem solving is increasing all the time and should be cautiously incorporated into vegetation management strategies.

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Chapter 2:

Disturbance ecology and abiotic variables improve modeling of Great Basin sagebrush landscapes into ecologically similar units

Abstract

Disturbance Response groups (DRG's) are a method of stratifying landscapes into ecological units by grouping ecological sites, based on their responses to natural or human-induced disturbances. DRG's are an important management concept, of which the spatial extent has been developed utilizing 3rd order soil mapping. In an effort to improve the resolution of DRG mapping, distrobution of DRG's was modeled utilizing machine learning techniques and available remote sensing data. Four DRG's, characterized by Wyoming big sagebrush (*Artemisia tridentata* Nutt. ssp. *wyomingensis* Beetle & Young) and Thurbers needlegrass (*Achnatherum thurberianum* (Piper) Barkworth), low sagebrush (*Artemisia arbuscula* Nutt.) and bluebunch wheatgrass (*Pseudoroegneria spicata* (Pursh) Á. Löve), low sagebrush and Idaho fescue (*Festuca idahoensis* Elmer), mountain big sagebrush (*Artemisia tridentata* Nutt. ssp. *vaseyana* (Rydb.) Beetle) and Idaho fescue, occur along an elevation and precipitation gradient within the study area. Spatial information from physical parameters as well as water balance bioclimatic variables were identified at points which had field verified association with DRG, and the values were used as predictor variables to classify DRG's in the project area. Mean annual temperature,

mean annual precipitation, the difference between actual evapotranspiration summer low and fall peak, and cumulative annual climatic water deficit proved to be the most influential of the variables tested. The resultant Random Forest classification map of the four disturbance response groups was 14% more accurate than the existing DRG mapping.

Introduction

Assessment of rangeland condition has changed and improved with advancements in ecological understanding (Briske et al., 2008; Dyksterhuis E. J., 1949a; T. K. Stringham et al., 2003; Westoby et al., 1989) and spatial quantification of rangeland plant communities is of increasing importance for assessment and management. In the United States, the Natural Resource Conservation Service (NRCS) is the agency responsible for mapping the nation's soils and for correlating landform, soils and climate with a 'distinctive kind and amount of vegetation' known as Ecological Sites (Butler et al., 2003). In rangeland settings, soils are typically mapped at 1:20,000-1:63,360 scale. This creates soil map units which are typically comprised of associations or multiple components which may be correlated to more than one ecological site. Due to the fact the soils are mapped in associations, the ability to map the location of individual ecological sites is limited to the dominant component or dominant ecological site of the soil map unit. Mapping ecological sites based on the dominant soil component has allowed land managers to segment and conceptualize vegetative community potential and associated disturbance response spatially through ecological sites assigned to soil map units. Aggregation of ecological sites into Disturbance Response Groups reduces spatial error, allowing for simpler restoration and management plans at landscape scales, however, loss of potentially important information remains an issue (T. K. Stringham et al., 2016). At the same time, technological advancement in computing and remote sensing has seen significant usage in rangeland assessment due to scale and cost benefits (Hardin and Jackson, 2005; Homer et al., 2012; Moran et al., 1997; Sant et al., 2014; Washington-Allen et al., 2006). Elevation, precipitation, bioclimatic variables and vegetative cover can be mapped at increasingly fine detail (Hijmans et al., 2005), and its utility to land managers is becoming increasingly apparent.

If the physical and bioclimatic parameters associated with the vegetative potential of the landscape can be accurately identified, then improvement to DRG mapping utilizing remotely sensed data should be possible through modeling and machine learning techniques. Classification and regression tree models are frequently utilized by ecologists for quantifying the relationship between a response variable and the other variables that help approximate a given phenomenon. Random Forest analysis combines a large number of classification trees, learning from each previous tree generated to create a more accurate classification tree model for assessment. This process models complex relationships between numerous variables, providing insight into complex relationships (Elith et al., 2008). Random Forest modeling (Prasad et al., 2006) has been shown to be a very powerful tool in predicting spatial distribution of ecological phenomenon.

The modeling process outlined in this paper should be accurate to the extent that scale and accuracy of data sources and interrelatedness of physical processes allow. The ability to accurately map DRGs provides an advancement in the ability to monitor, assess, and manage land at large scale, and help guide rehabilitation efforts such as post-fire emergency stabilization planning. Advancement in this area provides tools for the management of resources, and could increase a land managers ability to utilize available resources more efficiently.

We developed a knowledge base of the relationships between remotely sensed bioclimatic and abiotic variables important for predicting the vegetative potential of northern Great Basin rangelands. In addition, we improved Disturbance Response Group mapping and provided a process for future mapping efforts.

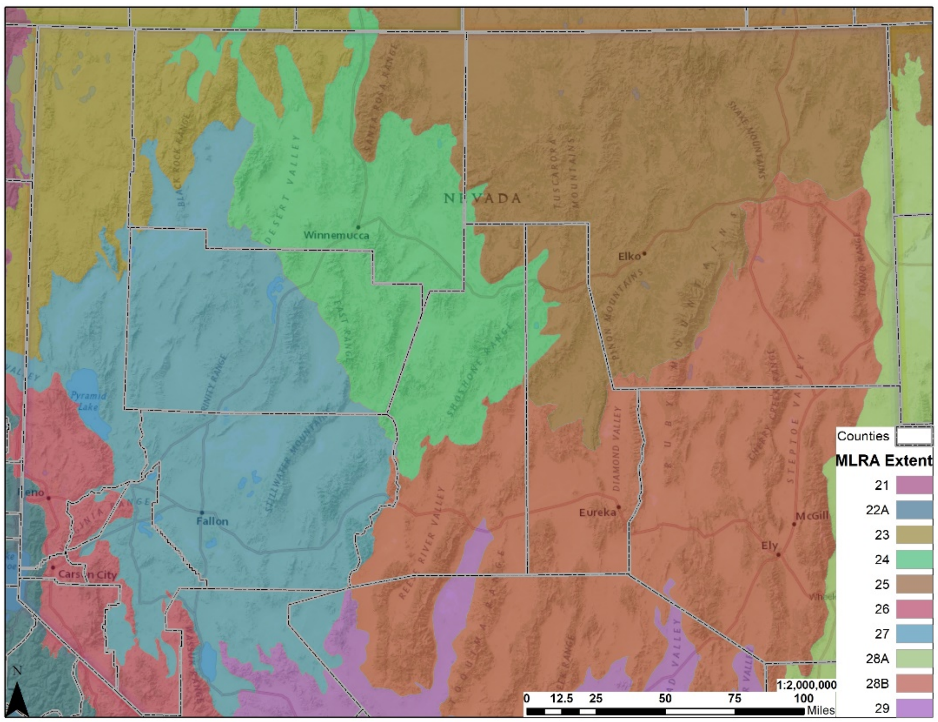

Figure 1: Major Land Resource Areas in the Great Basin, western United States. The extent and scale of MLRA boundaries is evident in this map, as well as the subsequent challenges of managing and modeling vegetation community extent at this scale.

Methods/Approach:

Project Area

The study area is located in north-central Nevada, approximately 40 miles north of the town of Golconda. The project exists within the framework of a larger effort investigating Disturbance Response groups within Humboldt (Squaw) Valley Ranch. The Tuscarora moutains frame the northwestern portion of the project area, with Humboldt (Squaw) Valley running to the southeast. The study was completed within the boundaries of the ranch where a record of recent fire and restoration efforts exists.

Available plant nutrients at a given site dictate potential vegetation communities. Sites with shallow soils and limited potential rooting depth support vegetation suited to shallow rooting lifeforms. In this project area, plant communities dominated by low sagebrush (*Artemisia arbuscula*) are found on soils with a fine textured, moderately to strongly structured subsoil at a depth of 2 to 10 inches or shallow depth to lithic contact. The low sagebrush community is further differentiated by understory plant community differences with the lower elevation, low sagebrush associating with bluebunch wheatgrass (*Pseudoroegneria spicata*) and the higher elevation type with Idaho fescue (*Festuca idahoensis*). Disturbance response grouping places the low sagebrush – bluebunch wheatgrass ecological sites into DRG 1 and the low sagebrush – Idaho Fescue sites into DRG 2 (Stringham et al. 2017). Larger, deep rooted shrubs (e.g. *Artemisia tridentata* Nutt. ssp. *wyomingensis* Beetle & Young; Wyoming sagebrush) or mountain sagebrush (*Artemisia tridentata* Nutt. ssp. *vaseyana* (Rydb.) Beetle) grow in areas of moderately deep to deep and well drained soils which facilitates the plant's growth form and deep taproots. The Wyoming sagebrush group occurs in the 200-300 mm precipitation range and is dominated by an understory of Thurber's needlegrass (*Achnatherum thurberianum*) and bluebunch wheatgrass whereas the mountain sagebrush group occurs above 12" of precipitation with Idaho fescue as the dominant understory grass. The Wyoming sagebrush types have been placed in DRG 4 and the mountain sagebrush ecological sites in DRG 6 (Stringham et al. 2017).

Soil development and nutrient availability in areas of deep or shallow soils have been physically differentiated to create the vegetation and DRG mosaic observed in the project area today. Precipitation and evapotranspiration vary across the mountainous landscape given aspect, slope, solar gain and numerous potential other parameters. These parameters can be quantified and modeled through space within GIS.

The project area was stratified into four Disturbance Response Groups (DRG's) based upon existing ecological site areas described by the NRCS soil survey:

DRG	Modal Ecological Site	Modal Vegetation
1	Claypan 10-12" P.Z.	ARAR8/PSSPS-ACTH7
2	Claypan 12-16" P.Z.	ARAR8/FEID-PSSPS
4	Loamy 8-10" P.Z.	ARTRW/ACTH7-PSSPS
6	Loamy Slope 12-16" P.Z.	ARTRV/FEID-PSSPS

Table 1: Disturbance Response Groups (DRG) being modeled in the study area. Modal Vegetation described using species codes as utilized by the USDA plants database. Codes present are: ARAR8 (*Artemisia arbuscula* Nutt.), PSSPS (*Pseudoroegneria spicata* (Pursh) Á. Löve ssp. *Spicate),* ACTH (*Achnatherum thurberianum* (Piper) Barkworth). FEID *(Festuca idahoensis* Elmer), ARTRW (*Artemisia tridentata* Nutt. ssp. *wyomingensis* Beetle & Young) and ARTRV (*Artemisia tridentata* Nutt. ssp. *vaseyana* (Rydb.) Beetle). Additional information on Disturbance Response Group creation and theory can be found in (B. T. K. Stringham et al., 2016). Information about specific Disturbance response

group mapped in Nevada can be found at: http://naes.unr.edu/resources/mlra.aspx. Numbers given after Modal ecological site names are associated with soil type and precipitation amounts in inches.

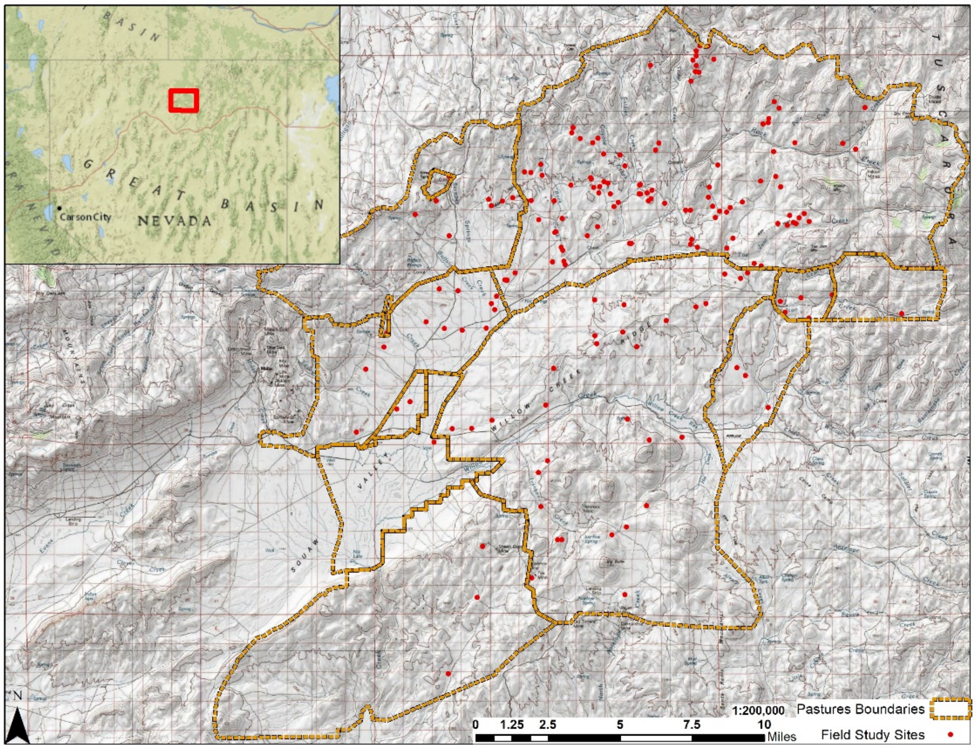

Figure 2: Map of the study area, and sample location within the analysis area. The study area extent was approximately 230,000 acres, managed under the grazing allotments belonging to Humboldt (Squaw) Valley Ranch.

Sample Design and Field Methods

A total of 172 sample locations were randomly located across the research area (Figure 2). At each study plot, an 18" soil pit was dug and identifiable horizons as well as soil texture were recorded. Vegetative cover was collected utilizing Line-Point-Intercept (LPI) methodology (Herrick et al., 2005). Through vegetation and soil pit characteristics, the plots were assigned a

DRG. All field analysis occurred in the spring and early summer of 2017 and 2018 before senescence had completed. Sampling locations which appeared to be in transitional vegetation areas where ecological site or DRG could not be identified were excluded from the study. Study sites were constrained to slopes less than 20 degrees, within 1 miles of an existing road and in areas of visually consistent vegetation cover for 50 m^2 around the plot. In all 172 sites were sampled, 49 sites in DRG 1 (low sagebrush – bluebunch), 36 sites in DRG 2 (low sagebrush – Idaho fescue), and 63 Sites in DRG 4 (Wyoming sagebrush), and 24 Sites in DRG 6 (mountain sagebrush).

Statistical Modeling of Disturbance Response Groups

Physical characteristics of each study site were extracted to point locations in GIS (ESRI ArcMap 10.4.1 2018) through 30m resolution raster grids derived from a digital elevation model. Variables thought to impact the soil texture, Claypan presence, and plant community development were derived from the digital elevation model and included elevation, slope, curvature and solar radiation and annual precipitation as derived from the PRISM dataset (PRISM Climate Group, 2017). Solar radiation (ESRI ArcGIS 10.4.1 2018) was also utilized as a measure of relative temperature and evaporation given slope and aspect. Solar radiation parameters were set at the center of the project area to be captured on June 1st, 2017, a date generally equivalent to the height of growing season.

Functionally relevant climate variables generated by (Dilts et al. 2015) were also utilized in the random forest Model as extracted point values. Variables which were shown to be most predictive of shrub species presence across Nevada were similarly utilized in this model. Variables utilized in the model include temperature range, cumulative annual climatic water deficit (CumlCWD), steepest rate of decline of actual evapotranspiration (DeclAET), difference between actual evapotranspiration summer low and fall peak (FallAET), difference between water supply and AET during the spring (WsAETSpr). These variables were generated using the Thornthwaite method (Lutz et al., 2010) as applied to the PRISM (PRISM Climate Group, 2017) dataset, and have been shown to be influential in predicting plant community composition in the Great Basin (Dilts et al., 2015).

The PRISM dataset was utilized as the climactic predictor, from which mean annual precipitation (30 year average) and mean annual temperature were extracted (Daly, 2006; Daly et al., 2007). The POLARIS dataset was used to extract soil property information including soil texture and percent sand/silt/clay at depths of 5-15 cm and 15-30 cm. Saturated soil water content (Theta_s) was also extracted at 5-25 cm depths and 15-30 cm depths (Chaney et al., 2016).

Random forest (randomForest package) technique utilized in R program (**R** Core Team, 2013) and ArcGIS (ESRI ArcMap 10.3.1, 2017) allows detailed exploration of physical parameter relationships to the extent of DRG’s. Random forest completed 1,000 iterations, randomly sampling variables and training data, and averaging from within the dataset allowing greater predictive ability and detection of in-obvious data structures,. This also avoids overfitting of the model to the data provided (Prasad et al., 2006).

Site variables were loaded into a Random Forest (randomForest R package) environment and computed using R software (R core development team, 2018) through ArcGIS (ESRI ArcGIS 10.4.1, 2018). The random forest method utilized was a classification as DRG was set as a factor response variable. The analysis was completed with 1000 trees. Random forest analysis are known to perform optimally with >500 trees (Elith et al., 2008). The model was set to test four variables at each split. Each variable is measured for accuracy and importance by random point permutation within the model.

The Random Forest model generated from sampled locations was utilized to create relationships between training data and predictor variables across a surface for the extent of project area. Raster grids for each variable were resampled to a 100m grid size through a cubic convolution, with modified size and location cell values fitted to the nearest 16 input cell centers. Cell sizes for elevation based variables were increased from 10m to match climatic variables at 100m grid size and projected to match exact extent for DRG prediction.

Results

The final Random Forest model had an estimate of error rate of 46.8 given data withheld by the model in each interation. By DRG, classes had the following error rate; DRG 1 (Low sagebrush – bluebunch): 51.0%, DRG 2 (Low sagebrush – Idaho fescue): 41.7%, DRG 4 (Wyoming sagebrush): 37.5% and DRG 6 (mountain sagebrush): 70.8% (Table 2).

Confusion Matrix					
DRG	**DRG 1**	**DRG 2**	**DRG 4**	**DRG 6**	**Class Error:**
DRG 1	24	5	19	1	**0.510**
DRG 2	6	21	0	**9**	**0.417**

DRG 4	22	1	40	**1**	**0.375**
DRG 6	3	12	2	**7**	**0.708**
Total:					**0.468**

Table 2: Random Forest Confusion matrix. Highlighted values represent accuracies in proportion to errors (non-highlighted columns). Numbers represent classification of points into surface generated by the random forest prediction of input variable raster's. E.g. the first column shows DRG 1, with 24 points placed correctly, 5 points placed in DRG 2, 19 points placed in DRG 4, and 1 point placed in DRG 6, providing a 51.0% error rate for DRG 1.

The accuracy matrix shows important points of model agreement and disagreement. The relatively large numbers in column and rows of DRG 4, show that the Wyoming sagebrush DRG was predicted fairly well given the information provided to the random forest analysis. Most frequently, the low elevation DRG's 1 & 4 were mistaken, displaying that these conditions were very similar and not easily split by any of the variables utilized in the model. It also shows similar confusion between the higher elevation DRG's 2 and DRG 6. DRG 4 and 2 are rarely confused in the model due to elevation and precipitation discrepancies evident in the plant communities. The accuracy of the map expected by random chance is 29%, and the observed accuracy is 53%. This provides a Kappa statistic for this map of 0.334.

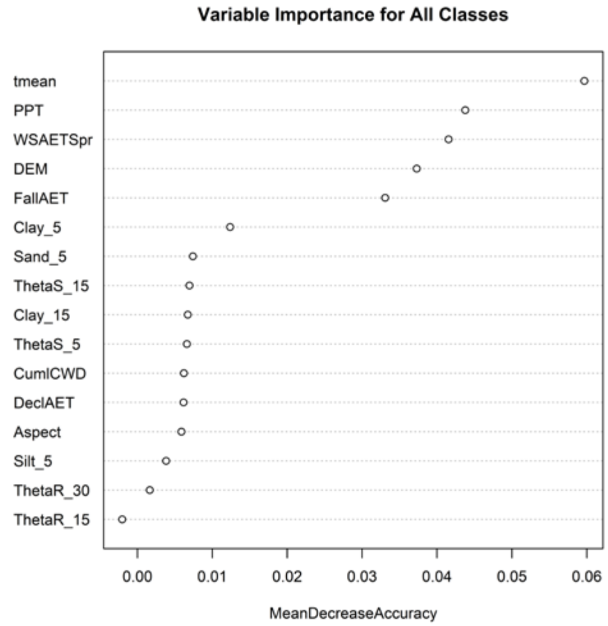

Figure 3. Variable importance of each variable as a predictor of DRG, expressed as a total. Variables in order from top to bottom: Mean annual temperature (tmean), Precipitation (PPT), the difference between water supply and AET during the spring (WSAETSpr), Elevation (DEM), Clay % at 5-15cm (Clay_5), Sand % at 5-15cm (Sand_5), Saturated Soil Water content (ThetaS_5), the cumulative annual climactic water deficit (CumlCWD), the steepest rate of decline of soil water balance (DeclAET), Aspect as derived from the DEM, continuous values (Aspect), Silt % at 5-15cm depth(Silt_5), the saturated soil water content at 30-45cm (ThetaR_30), and the saturated soil water content at 15-30cm depth (ThetaR_15). Order of variables is listed in declining level of importance.

Disturbance Response Group's showed very different levels of importance for several variables utilized in the model. Annual mean temperature and precipitation consistently predicted DRG best, indicating that much of what is observed here is an elevation gradient. Further work and refinement of predictor variables needs to be completed to separate out soil/vegetation relationships. This result is important for mapping DRG extent, due to the fact that disturbance response in plant communities and resilience is often associated with elevation and increased available moisture (Mueggler, 1975). Elevation derived datasets including curvature and watershed were inserted in the model to predict important soil genesis variables such as water runoff and areas of sufficient water input to generate additional clay illuviation which could lead to the development of a claypan. These elevation derived variables did not perform as well as the elevation or climactic water deficit variables and were removed from the final analysis.

Disturbance Response Groups 1 and 4 responded to very similar variables. This is a logical result given that the two disturbance response groups are interwoven on the landscape and exist in similar position and elevation zones. The identification of variables which are important to predict this phenomenon will aid in further refinement of predicting these two ecologically different areas. As shown in Table 3, Clay percentage from 15-30cm and the Steepest Rate of Decline in AET were very important predictor for DRG 1, but ranked very near the bottom for DRG 4. DRG 2 which dominates the higher elevation was also more accurately predicted by mean annual temperature, FallAET and WSAET. This displays the importance of climactic variables, as well as the accuracy of these variables in predicting climactic phenomenon in a basin and range geography (Strachan and Daly, 2017a).

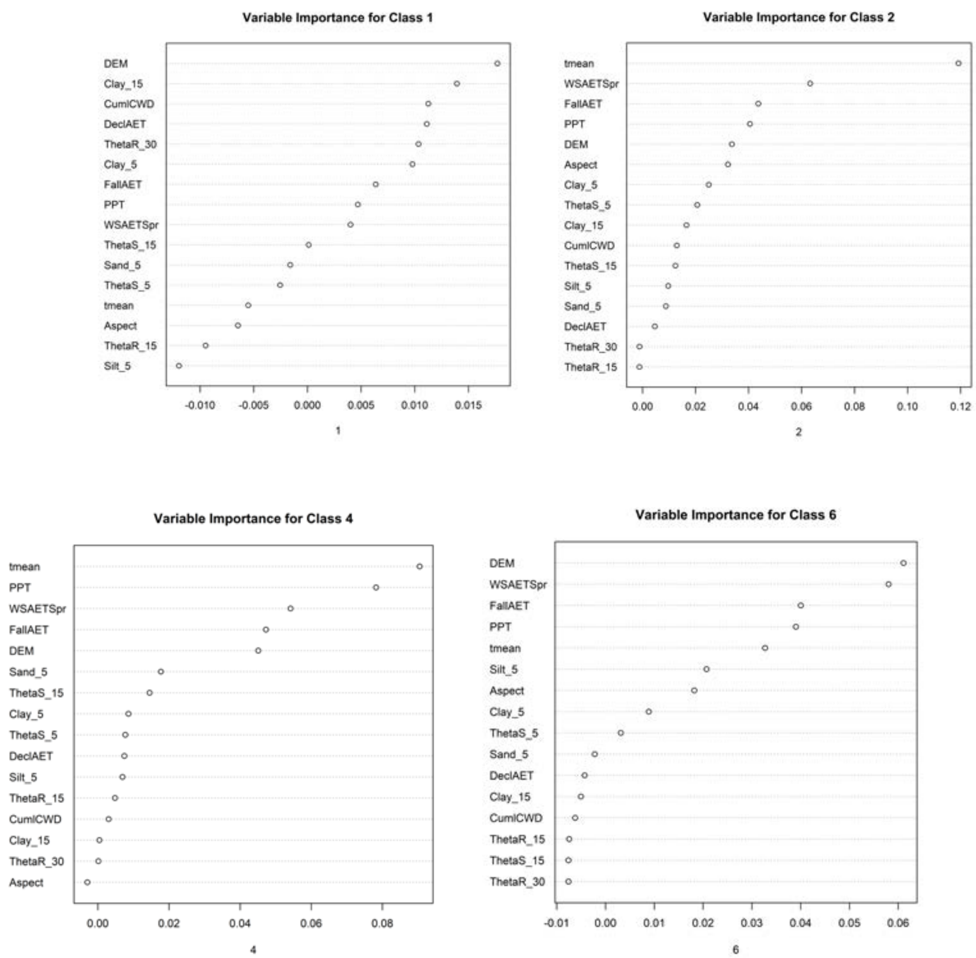

Figure 4. Variable importance of each variable as a predictor of DRG, expressed per DRG. In the output diagram "Class" is used to describe the DRG numbered. Order of variables is listed in declining level of importance. Each DRG's classification solution utilizes different variables in different amounts.

The Gini impurity index derived through the Random Forest model is highly instructive in that it shows how often a randomly chosen data point would be labeled incorrectly given random assignment to groups. This can help show which types of predictor variables are adding the most accurate information to the modeled area. This is another way of seeing which datasets reduce error in classification most often. This Random Forest model has undergone numerous changes and refinements, each subsequent iteration adding additional variables and removing those which had poor performance in this study area. Inserting additional ground based observations which were collected based upon the distribution of existing model errors, and utilizing those train future models will help make this more accurate and applicable to larger areas.

Mean Decrease Gini Impurity Index	
tmean	9.57
PPT	7.2
WSAETSpr	7.04
DEM	7.24
FallAET	7.04
Clay_5	3.81
Sand_5	3.16
ThetaS_15	3.23
Clay_15	3.63
ThetaS_5	3.13
CumlCWD	3.9
DeclAET	4.12
Aspect	5.34
Silt_5	4.27

ThetaR_30	3.17
ThetaR_15	3.14

Table 3: Mean decrease in Gini impurity index. The Gini index is very consistent with the permutation importance measure. Note that overall values differ from those in Figure 3 split amongst the predictor variable DRG. Similarly, Annual precipitation (PRISM) and difference between actual evapotranspiration summer low and fall peak (FallAET) are the greatest contributors to the model.

Ecological implications are evident throughout examination of Tables 2,3 & 4. In the lower elevation DRGs, a distinction between DRG 1 (low sagebrush) and DRG 4 (Wyoming sagebrush) is difficult and problematic, in that they occur in a gentle mosaic across the landscape. In this case, it is possible to see that Clay percentage from 15-25 cm depth as derived from POLARIS gridded soil data (Chaney et al., 2016), a variable that is negatively correlated with the higher elevation plots, is more important at the lower elevations (Table 3, Class 1). Within DRG 1 (Low sagebrush), Clay percentage from 15-25cm is the second most important predictor variable. DRG 4 (Wyoming sagebrush) occurs within the same elevation band, and Clay percentage at 15-25cm depth is the 14^{th} most important predictor. This matched known soil information relating to these separate DRG's. Slope and solar radiation performed poorly for each Disturbance Response Group and were removed from analysis.

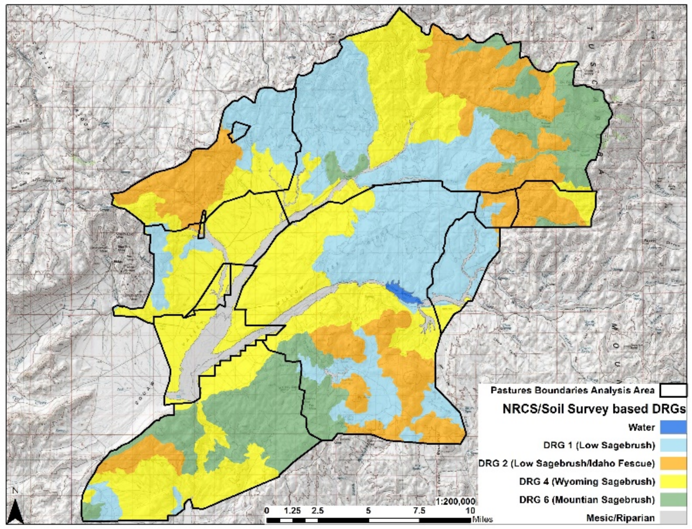

Figure 5: NRCS Soil map unit/Ecological Site association map of DRGs within of the study area. Many of the soil polygons in this map contain sub-dominant components.

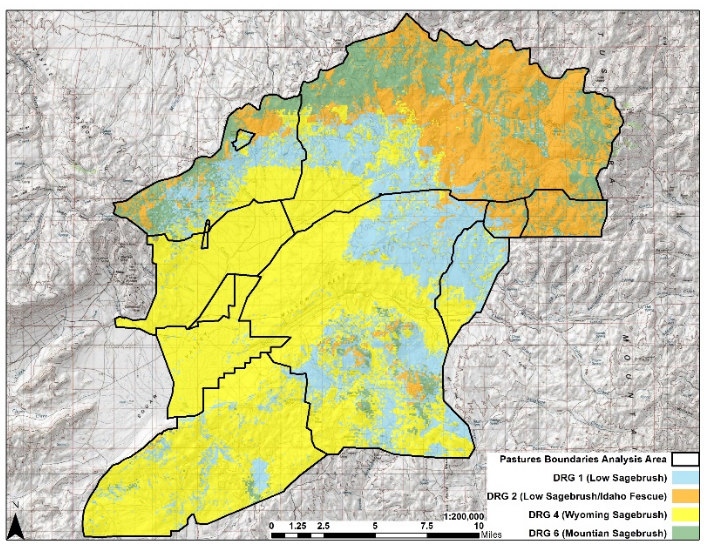

Figure 6: Predicted surface of Random Forest analysis of the study area.

The effort described in this chapter should be compared to the existing DRG mapping method (T. K. Stringham et al., 2016) for this area utilizing NRCS generated soil map unit polygons, grouped based upon ecological site and DRG associations. The soil mapping method is currently 39% accurate within this project area as observed by relation to 172 points visited on ground as derived through an accuracy matrix. The mapping technique presented here improved the accuracy of the Disturbance Response Groups to 53.2%, 14% more accurate than the current method of Disturbance Response Group polygons.

Discussion

Disturbance Response Groups simplify the landscape into ecologically significant units derived from soil mapping data, published literature on soils, plant ecology, plant response to various disturbances, and disturbance history of the area. DRGs are valuable landscape scale tools utilized by public land management agencies. Mapping of DRGs has been limited by the scale of soil mapping data available for rangelands necessitating the need to utilize emerging technologies such as remote sensing products to enhance mapping efforts. The random forest method utilizing bioclimatic variable described in this paper shows increased accuracy in DRG mapping within the study area, and provides a knowledge base from which to map DRG's at landscape scale. As Disturbance Response Grouping is a new theory, little work has been done to improve mapping of this product. Ecological sites have been mapped previously using GIS processes (Creque et al., 1999), however this process only utilized soil texture and slope to predict ecological site extent across a study area in central Utah. The method utilized here evaluates numerous predictors, and relative importance will certainly vary if the process is applied to other DRG's. Ecosystem resilience has been analyzed through soil survey information by Maestas et al., (2016). This current effort is aimed at helping tie numerous efforts together into a more cohesive process, utilizing DRG's to make the process simpler and more applicable to larger swaths of land. DRG's are very useful in that they help conceptualization of plant communities and potential restoration or degradation pathways. Through aggregation of ecological sites however, there is a large amount of variability contained within a given DRG, including annual production and cover estimates, land form or position, and vegetative potential in terms of cover and abundance of key species. The large scale nature of DRG's make it a better tool for landscape scale management, as opposed to pasture or smaller rehabilitation projects where the increased resolution and precision of information provided by Ecological Sites would be of importance and practical to implement due to the smaller scope of analysis.

The model appears particularly useful in identifying areas of mosaic between DRG's 1 and 4. In these areas, the model appears to have done an excellent job of identifying subtle landform features and gentle undulations in terrain which would indicate presence of one species or another. It has also done an excellent job of identifying DRG 2 and 6 amongst the higher elevation conditions even at lower elevations when aspect has created areas with soil moisture retention high enough to behave as a DRG 2 or 6 community. This was assumed to be a very difficult task in this undertaking, as steep northerly aspects were known to be influential in plant community on these sites, and aspect and slope variables performed poorly by themselves in this as well as previous iterations of this modeling exercise. Water deficit and bioclimatic variables did an exceptionally good job of identifying these areas, as they incorporate aspect and slope along with other important factors, including available water content of the soil, precipitation, solar gain and evapotranspiration.

Climactic water deficit variables were very important in our analysis and have proven very useful in numerous studies looking at the distribution of vegetative communities across a landscape (Dilts et al., 2015; Keim, 2010; Stephenson, 1990). Current research into the generation of increasingly precise climate variables, which could be used to improve the predictive power of the variables further is being undertaken currently. Recent research into the efficacy of PRISM demonstrated reduced accuracy from originally published model accuracy when applied to the Walker basin, in similar basin and range topography to this study area (Daly, 2006; Strachan and Daly, 2017b). The generation of climactic models at higher accuracy and resolution, when combined with large input datasets could provide additional insight and mapping capabilities for land manager and ecologists. Additionally, the generation of other climate water variables as proxies for plant available water may yield additional predictive power as well.

The map generated in this study accurately depicts the near complete extent of the big sagebrush plant community in the valley bottoms, as well as the predominance of DRG 2 and DRG 6 at higher elevations. The study area has experienced 32 wildfires in the last 34 years, and much of the higher elevation DRG has retained its characteristic species through numerous disturbances including wildfire and legacy grazing effects. In the lower elevations, post fire ecological sites and DRG’s can be difficult to distinguish due to conversion to cheatgrass monoculture. The extent of cheatgrass monoculture across the research site precludes utilizing vegetative cover as a predictor variable as cheatgrass monocultures can exist within any of these DRG’s given sufficient ecological degradation. Soil pit information dug on site along with landform and elevation are the only way of determining disturbance response group in today’s landscape.

DRG extent and plant community response to disturbance is shown to be very closely related to elevation. However, the Great Basin presents a difficult situation in which to predict these values. The larger orographic effect and resultant precipitation in the Sierra Nevada mountains reduces the effect observed on the numerous smaller ranges east. This phenomenon is notoriously difficult to model as noted by Strachan and Daly, (2017) in further studies on the PRISM climactic variables in Nevada. However, even at this coarse level of predictive power, variables modeling this phenomenon generally outperformed any of the input variables utilized independently. The difference between the higher elevations of the Tuscarora mountains and the valleys below is clearly displayed in this predicted surface. This is a result of the ability of the precipitation and related climate variables to predict phenomenon well at a landscape scale.

Further Study:

Areas of further investigation for this analysis are numerous. Increased field validation sites across larger portions of the landscape and quality of predictor variables are chief amongst them. Expansion of the project into different portions of the state and subsequent field efforts will be completed in the coming field seasons to add to areas in which existing data is scarce. Increased predictor variable resolution is also thought to be able to enhance the accuracy and utility of the model as well. Wetness index, Integrated Moisture index and image band combinations known to relate soil and plant community information can also be calculated for the project site.

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Chapter 3:

Remotely sensed vegetative cover datasets: Application to state-and-transition model mapping

Introduction:

Remote sensing can provide accurate estimates of vegetative cover (Homer and Bobo, 2011; Homer et al., 2012; Moran et al., 1997; Sant et al., 2014). Ecological interpretation of remote sensed data requires knowledge of the relationships between vegetation, soils, climate and recent disturbance events such as wildfire. One method for classifying landscapes into meaningful ecological units, known as ecological sites (ES), is described by the United States Department of Agriculture(USDA), Natural Resource Conservation Service (NRCS)(2013). In large landscapes, such as the Great Basin, USA the utility of the ES concept loses utility due to the intensity and complexity of ES mapping, therefore, Stringham et al., (2016) developed a process based on disturbance ecology that allows for upscaling of ecological sites by combining ES together into groups based on the dominant vegetation response to similar disturbances. These groups are referred to as disturbance response groups (DRGs). State-and-transition models (STMs) describe the expected ecological dynamics of the DRG in response to various management actions or natural disturbances (Briske et al., 2008; Groffman et al., 2006; Stringham et al., 2003, 2001).

In addition, ecological information synthesized by DRG (Stringham et al., 2016, 2015a) and the associated STM provides rich insight into the resilience and species specific indicators of the plant communities as well as risks of transition to alternative vegetative states after disturbance such as wildfire. Linking remotely sensed data with DRG extent mapping (Phipps, 2019) provides a mechanism for describing the ecological consequences of vegetation community change, as described in STMs, allowing managers to make spatially informed decisions based on the resilience and restoration potential of the specific location.

Ground based survey data for the plant community within a DRG should be utilized to inform our understanding of landscape condition. GIS tools allow remotely sensed vegetative cover data to be applied in such a way that decisions about management can be made with the specific vegetative potential of the DRG in mind. Vegetative potential is determined by the soil, nutrient and climate inputs on a given piece of land which will dictate the amount of and type of plants which are likely to exist there. Random forest (Breiman, 2001; Elith et al., 2008) modeling provides a machine learning technique to relate numerous predictor variables to known study locations on the ground utilizing a decision tree method (Breiman, 2001; Prasad et al., 2006). Ground based sample sites belonging to a single DRG can be assigned to a vegetative 'state' through a grouping method utilizing vegetative cover of the sample site. This has the advantage that it removes observer bias concerning the ecological condition of the site. The ground-based points assigned to a vegetative state, can then be utilized to generate a random forest model to relate the continuous vegetative cover raster datasets to predict vegetative state within a DRG. This process would need to be completed for each DRG as the relationship between raster based vegetative cover and vegetative state observed on ground would be unique to each DRG.

When exercise is constrained to areas predominantly belonging to one DRG, the possibility to relate the remotely sensed cover values to the appropriate vegetative state exists. This is due to the fact that vegetation dynamics on each different DRG are known to be different. This has implications for the use of the remotely sensed any fractional vegetative cover data as a management tool. If this process is completed without regard to DRG extent, the utility of the tool is diminished as vegetation dynamics and remotely sensed cover values are potentially lost in the diversity of site potential across the landscape. The ability to analyze within a DRG creates the ability to spatially and quantitatively assess vegetative trends already described for that plant community. Visualization of condition or vegetative state spatially provides managers with an easier way to understand resource concerns that may not be apparent from the ground and measure change in areas which have not been assessed on the ground. The application of STMs to remote sensing data provides ecological knowledge at the dominant species level vs. functional group and provides information on restoration techniques at the plant community level. Knowledge of dominant species information from DRGs can be applied to the landscape if we know what the dominant plant groups there are. Land managers have utilized (STM's) for management decisions since the early 2000's (Briske et al., 2008; Stringham et al., 2003). Visualization of spatially explicit STM maps in order to implement management changes across a landscape has been desired.

The logic model developed for this project is presented in Figure 1. Details of each step are presented sequentially in the methods section.

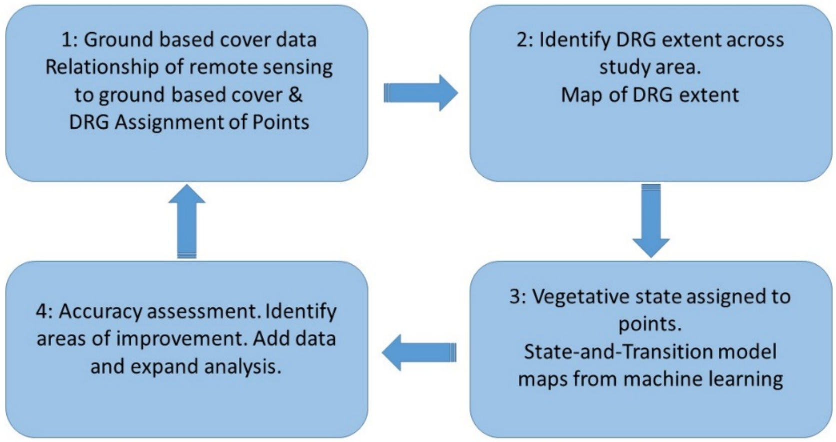


Figure 1**:** Flow chart of State-and-Transition model map generation process. Left upper quadrant is covered in chapter 1, Right upper quadrant is chapter 2, Lower right quadrant is Chapter 3 (This chapter), and the lower left quadrant incorporates future advancements and iterative refinement of the process.

The generation of state-and-transition model maps becomes increasingly more accurate as our ability to remotely sense fractional vegetative cover and identify DRG extent increases (Phipps, 2019; Sant et al., 2014; West et al., 2005; Xian et al., 2015). This study provides a novel method to generate state-and-transition model maps when exact relationships between remotely sensed vegetative cover and ground based vegetative cover are poorly understood. The application of machine learning techniques to relate remotely sensed cover to state-and-transition model maps provides an advancement in the ability to monitor and manage plant communities at landscape scale.

Methods:

1: Ground Based Sample Points and Relationship to Remote Sensing:

Ground based vegetative cover was sampled from 172 locations within a 230,490 acre area of public and private lands within the grazing lease of Humboldt River Ranch near Midas, NV. Sample locations were generated randomly in GIS. At each sampling location, soil profile information was collected to a depth of 20”. Vegetative cover was measured using line-point-intercept (LPI) (Herrick et al., 2005). Soil and vegetation information was utilized to assign the plot to a DRG given published soil and plant associations within that DRG (Stringham et al., 2015a). Four distinct DRGs were identified and sampled (Table 1).

***Table 1*:** Sampled ‘Disturbance Response Groups’ (DRG’s) (Stringham et al. 2016), within the study area as described in the MLRA 25 Report (Stringham et al., 2015a). DRG’s listed include group number, dominant sagebrush, and USDA plants database Symbol descriptions for dominant plant community. Symbols used include: Low sagebrush (*Artemisia arbuscula* Nutt.), symbol ARAR8. Thurbur’s needlegrass (*Achnatherum thurberianum* (Piper) Barkworth), symbol ACTH7. Bluebunch wheatgrass (*Pseudoroegneria spicata* (Pursh) Á. Löve), symbol PSPP6. Idaho fescue (*Festuca idahoensis* Elmer), symbol FEID. Wyoming big sagebrush (*Artemisia tridentata* Nutt. ssp. *wyomingensis* Beetle & Young), symbol ARTRW8. Mountain big sagebrush (*Artemisia tridentata* Nutt. ssp. *vaseyana* (Rydb.) Beetle), symbol ARTRV.

Observations Per DRG	
DRG	**Observations**
Group 1: Low sagebrush; ARAR8/ ACTH7-PSSP6	49
Group 2: Low sagebrush, Idaho fescue; ARAR8/FEID-PSSP6	35
Group 4: Wyoming big sagebrush; ARTRW8/ ACTH7-PSSP6	63

Group 6: Mountain sagebrush; ARTRV/FEID-PSSP6	25

Remotely sensed continuous vegetative cover value predictions of the area were provided by Open Range Consulting (ORC) for the following classifications: Perennial Vegetation, Annual Vegetation, Sandberg Bluegrass (*Poa secinda* J. Presl), Sagebrush Cover, and Bare ground. ORC photographs Ground- based Vertical Images (GBVI) at high resolution, which are subsequently classified onto the same vegetative categories as the fractional vegetative cover provided by ORC (Sant et al., 2014). The GBVI cover values were utilized to train 1m NAIP imagery captured September 3 2018, and June 8 2015. The ORC process has been updated since publication (Sant et al. 2014) with the inclusion of 'randomForest' and 'Boosted Regression Tree' (BRT) in R as opposed to 'tree' (R Core Development Team, 2018; Eric Sant, Personal Communication 2018). The generation of Sandberg bluegrass cover is an additional cover class not included in the Sant et al. (2014) publication.

Vegetation from the LPI cover data was categorized into functional groups as follows: Annual grass, Annual Forbs, Perennial Bunch Grasses, Sandberg Bluegrass, Sagebrush and Bare Ground. The Annual Forb and Annual grass functional groups were subsequently combined as were Perennial Forbs and Perennial grasses in order to align LPI vegetation groups to the remote sensing products. Due to the fact that the resolution of the provided vegetative cover grids was smaller than the assumed accuracy of the GPS utilized to collect the LPI cover data, the ORC vegetative cover datasets were extracted within a 25m buffer around the GPS point, averaging 1963 points. This was completed within a 5m buffer as well as utilizing point based extraction and bilinear interpolation to determine the best scale for analysis. The 25m had a very similar central tendency as the other datasets with reduced variance and were therefore utilized for this analysis.

In order to examine relationships between LPI and the spatial dataset generated by ORC, we evaluated pairwise comparisons between mean values of the functional groups, indicating that the remotely sensed cover closely approximated mean values of LPI cover data (Table 2). ORC vegetative cover which have a similar mean to LPI include Annual Vegetation, Sandberg Bluegrass, and Sagebrush cover (Table 2).

Table 2: Regression relationships between ground based LPI values and ORC raster values extracted and averaged within a 25m buffer around the start pf the LPI line.

Linear Models, LPI and ORC 25m:	**Annual**	**Perennial**	**Sandberg's Bluegrass**	**Sagebrush**	**Bare Ground**
Mean Cover Values, LPI/ORC	25.81/26.59	18.06/20.38	13.47/12.30	7.49/5.84	14.19/26.44
Residual Standard Error:	23.01	13.38	10.42	9.088	11.67
Adjusted R^2:	0.1679	0.4889	0.0104	0.3344	0.1384
F-Statistic:	86.89	164.6	2.804	86.89	28.47

Linear regressions were completed to examine how the LPI data relates to the 25m extracted ORC raster based cover values. The resultant R2 values are very low, indicating that the remotely sensed cover datasets do not show a close relationship to the LPI cover. Residual standard error is also important in considering the utility and relatability of the relationship between LPI and ORC cover data.

Table 3: Wilcoxon Signed Rank test using pairwise observations. Populations which receive a P-value of less than <0.05 are assumed to have a central tendency or mean value significantly different from the alternative cover measurement technique.

Wilcoxon signed-rank test with continuity correction, Paired Observations				
Cover Assessment 1	**Cover Assessment 2**	**Vegetation**	**V=**	**P-Value=**
LPI	ORC 25m	Perennial	5906	0.01912
LPI	ORC 25m	Bare ground	1753	<0.00001
LPI	ORC 25m	Annual	6450	0.1309
LPI	ORC 25m	Sandberg Bluegrass	7485	0.5399
LPI	ORC 25m	Sagebrush	6137	0.7604

Scatter plots display this showing measurments of each point given the two separate metrics. Sagebrush and Perennial herbacious vegetation at levels of cover >20% had the closest relationships to each other (Figure 2).

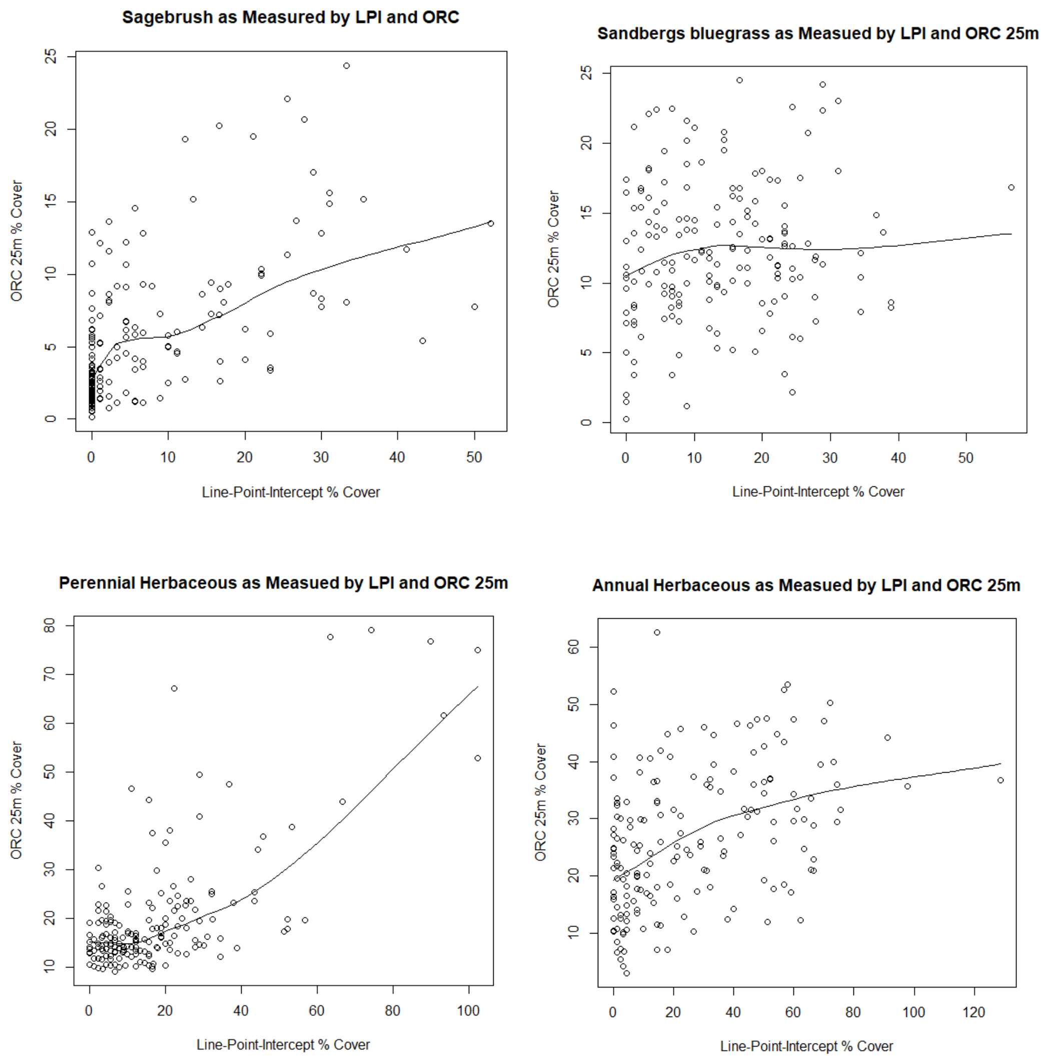
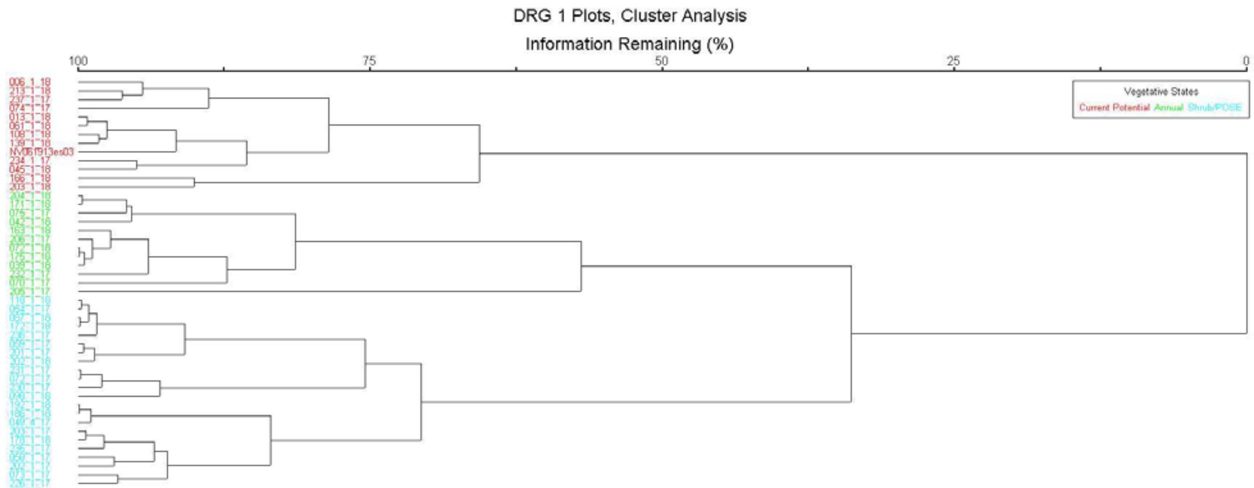
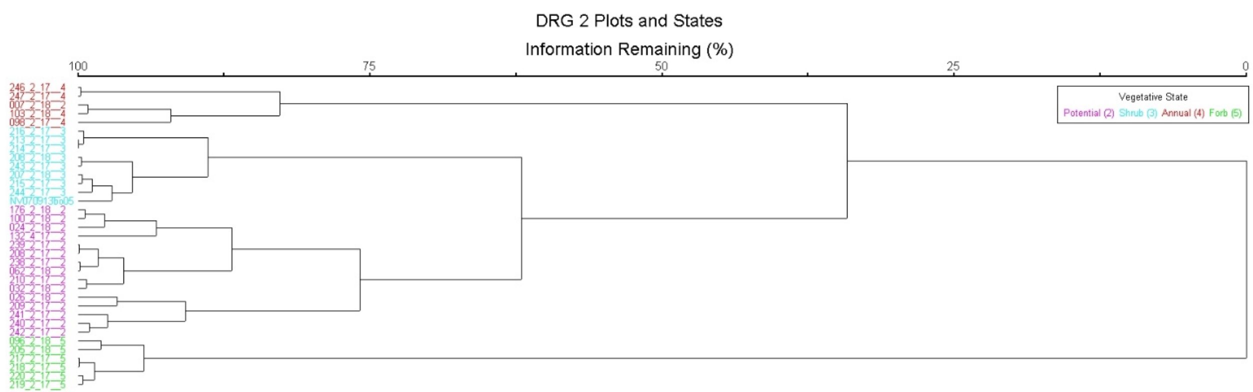


Figure 2: Scatter plots and fitted lines between ground based data and the remotely sensed vegetative cover. A regression line moving at a direct 45-degree angle from the origin represents a direct relationship between variables. A flat line horizontally across the plot indicated that no relationship exists between the datasets.

Principle component analysis was utilized to discern vegetative state groupings among the ground based plots given vegetative cover value of plant functional groups built to resemble the remotely sensed cover groups (e.g. Annual, Perennial, Sandberg Bluegrass). Raw data was normalized utilizing the proportion of functional group total cover to total cover prior to cluster

NMS analysis. A cluster analysis was completed utilizing the Sorenson -Bray-Curtis method as the distance measure and the Ward's group linkage method. Three clusters were determined for DRG 4 and 1 and four clusters for DRG's 2 and 6 (figure 3).





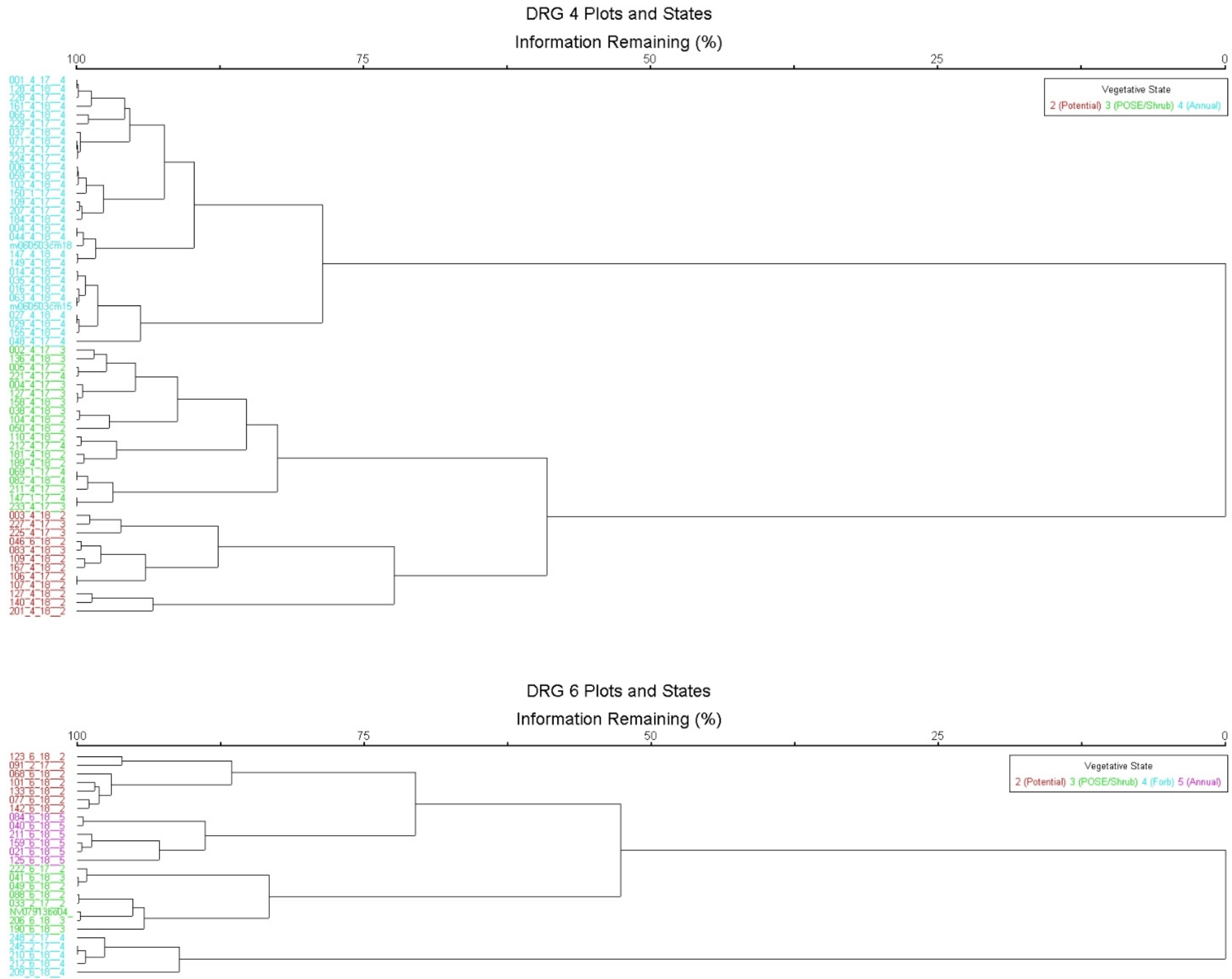


Figure 3**:** Cluster analysis completed by DRG utilizing PC-ORD 7. Groups were assigned a vegetative state after the grouping had been completed and was verified utilizing NMS to be cluster along axis which depicted known ecological dynamics of the vegetative state.

Non-metric multi-dimensional scaling (NMS) analysis using the Sorenson Bray-Curtis distance measure was completed to evaluate stability with a stability criterion of 0.000001 (Zimmermann and Guisan, 2000).

Once DRG and state were assigned to each plot, each state proportional group population was tested for normality using a Shapiro-Wilk test (P<0.05) (R Core Team, 2017). The vegetative state of the ground based plots was generated and utilized to train and test DRG models.

2. Identify DRG extent across the landscape

Disturbance response group (DRG) extent across the landscape was generated utilizing random forest in ArcGIS predicting spatial extent across a variety of raster datasets including climate, Thornwaith water deficit variables, and soil data generated by POLARIS soil mapping project (Phipps 2019,, Chaney et al., 2016). DRG spatial extent as derived by Phipps (2019), was extracted to define individual DRG's. DRG specific areas were utilized to extract vegetative functional group cover values as generated within the ORC fractional vegetative cover dataset (figure 4).

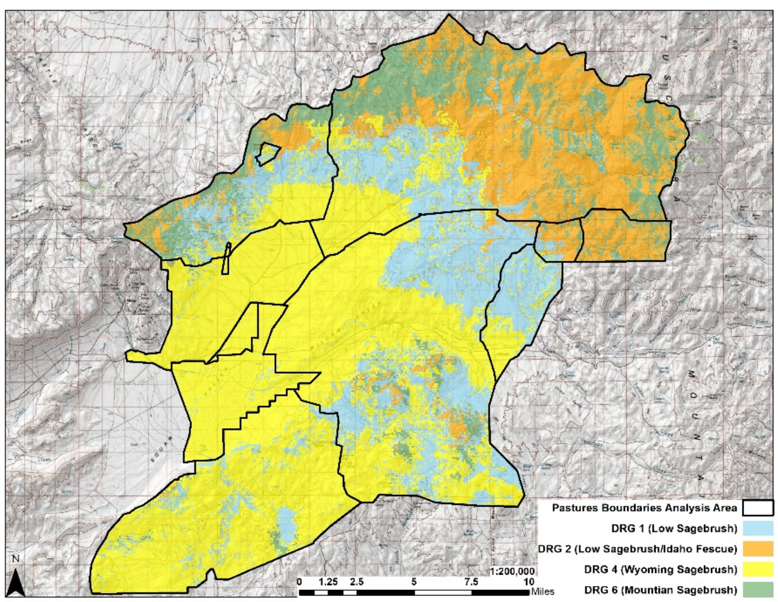


Figure 4**:** DRG extent predicted across the project area. Physical parameters, climate and bioclimatic variables were used to generate DRG extent through randomForest predicting across raster based grids.

3. State-and-Transition Model Mapping Using Vegetative State Assigned Points

Perennial, Annual, Sagebrush, Other Shrub, Sandberg bluegrass and Bare Ground cover raster datasets of the individual DRGs were utilized to develop a random forest model using the vegetative state assigned to the sample plots. The random forest algorithm modeled a relationship between assigned vegetative state of the plots and cover values of the ORC raster-based vegetation datasets at each observation location. Iterative random forest modeling allows generation of specific relationships within each DRG to be created between the cover values associated with the ORC functional cover groups and the vegetative states within the mapped extent of the DRG. Cover values appropriate for determining vegetative state in one DRG were not the same as in another DRG, and each cell of the state-and-transition raster was evaluated given the random forest modeled dynamics specific to the DRG.

Results

The state-and-transition model map (Figure 5) displays the vegetative state of a given pixel across the study area and relates each 1m pixel of the map to the knowledge contained within the state-and-transition model described for each DRG. This allows inference of the spatial extent of vegetation communities’ current condition, resilience, and vulnerabilities or risk.

Due to the fact that the DRG extent needed to be modeled at 100m scale, some pixel change effects are observed where differing vegetation dynamics are modeled into a different DRG. The basis for the mapping product is the DRG extent mapping provided in Figure 4.

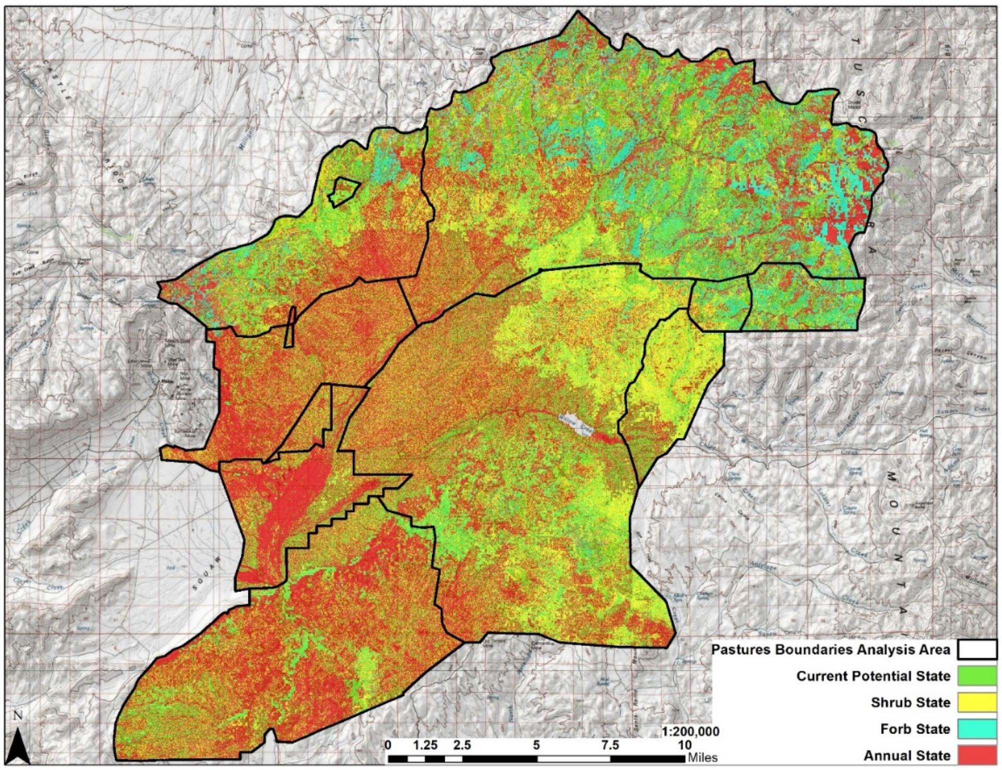


Figure 5**:** State-and-Transition Model map of the project area. Separate random forest models were generated for the modeled extent of each DRG, allowing for separate models of vegetation dynamics to be modeled within the extent of each DRG.

This mapping effort generated differing error terms for each state within each DRG, presented below (Table 4). Changes in DRG are visible in the STM map, due to the need to separate the plant communities for mapping. This is not representative of the landscape as changes in plant community composition and separation of DRG on the actual landscape are non-discreet and gradual. Due to predictor variable grid size and computing restrictions, modeling the subtle transition is not possible at present, yet the process outlined in this paper represents an advance in our ability to conceptualize plant community dynamics across a landscape. Advancement in remote sensing ability will increase accuracy of techniques such as this to match vegetative remote sensing datasets with vegetative state as determined through multivariate analysis.

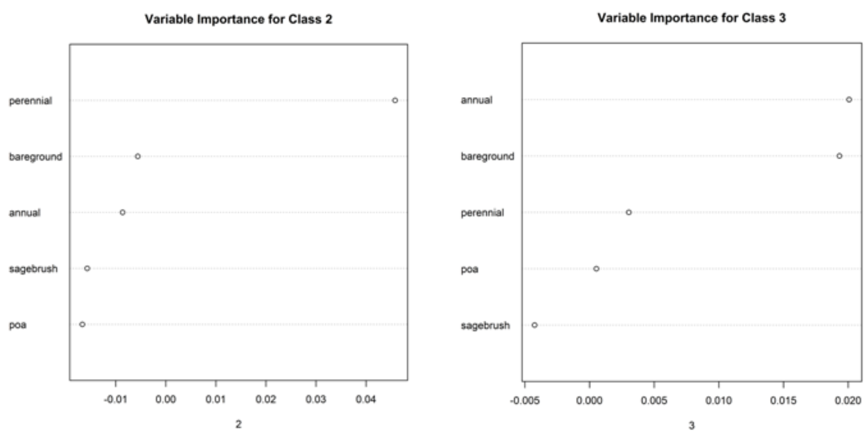
Table 4**:** Estimate of error for each state-and-transition model by DRG. This estimate was computed using withheld 'Out of Box' (OOB) observations not used in the generation of the mapping product. Accuracy in these cases is a product of the ability for predictor variables to match ground based observations.

DRG:	**OOB Estimate of Error Rate:**
DRG 1	63.3%
DRG 2	38.9%
DRG 4	57.1%
DRG 6	66.7%

The STM map also shows areas of increased resilience at higher elevation (DRG 2 and 6) and pulls perennial forb patches out of a dataset, given relationships to other vegetative variables in the analysis (Figure 5). Perennial forbs communities were identified as annual in the remote sensing product, due to their late season senescence. The ORC dataset did not separate perennial forbs however, this machine learning methodology was able to use the annual raster as well as other predictor values within this DRG to generate a map of perennial forb communities which exist in DRG's 2 and 6. This is a benefit of this methodology, in that the machine learning algorithm identifies trends which match the input data, without relying on a consistent relationship between ground based cover and the remotely sensed products.

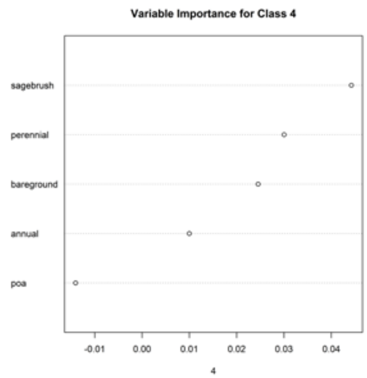
DRG 1 Low sagebrush / Thurbers needlegrass: Accuracy and importance classes:

The overall error rate associated with on ground locations as predicted by relationships of vegetative cover datasets is 63.3%. The greatest level of error is associated with the Current Potential state 2, as predicted predominantly by perennial vegetation. The Shrub state 3 had the least error in prediction, at 45.5%. Annual and bare ground were the strongest predictors of this state within the random forest model. Annual state 4 has a 66% accuracy rate and was predicted most strongly by sagebrush, perennial grass and bare ground, but not annual vegetation as would seem necessary (Figure 6).



DRG 1 Accuracy Matrix:

Predicted	
State	**Class Error**



Field State

	2	3	4	
2	2	9	2	0.846
3	4	12	5	0.455
4	2	6	4	0.667

Figure 6: Variable importance and accuracy matrix for the state-and-transition model mapping which occurred within the modeled DRG1 extent. Variable "Classes" are interchangeable for variable "State". The accuracy matrix is also referred to as a confusion matrix, showing vegetative states and how often classifications are correct or if confused, with which other vegetative state. Areas of greater confusion can be very instructive in model and predictor variable improvements. DRG 1 has three vegetative states; State 2 is a 'Current Potential' state, State 3 is a 'Shrub' state and State 4 an 'Annual' state. Note that the numbering differs from DRG 2 and 6 in which Sate 4 is an 'Annual' state.

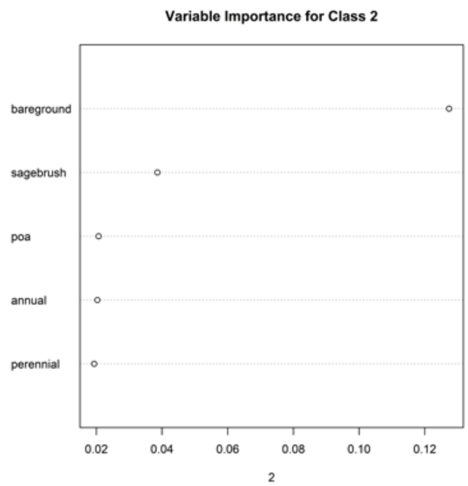
DRG 2 low sagebrush / Idaho fescue: Accuracy and importance classes:

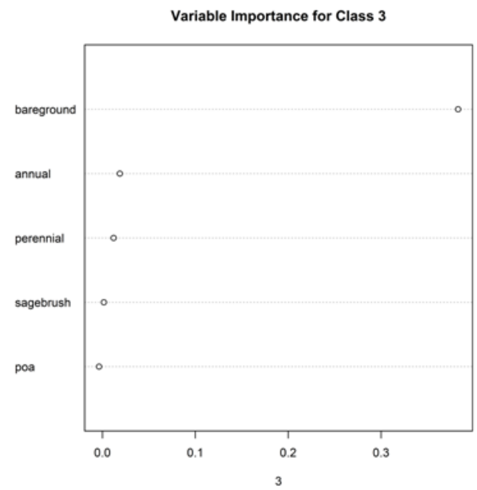
The Current Potential state 2 in this DRG was best predicted in this remote sensing product by bare ground. The low sagebrush / Idaho fescue DRG is comprised of ecological sites described and quantified by NRCS (Stringham et al., 2015) as typically having 20 to 35 percent vegetation cover indicating bare ground and rock comprised a significant component of this DRG. Unfortunately, the Current Potential state 2 vegetation community in this model also has the highest error rate, classifying only 16% of the ground based plots correctly.

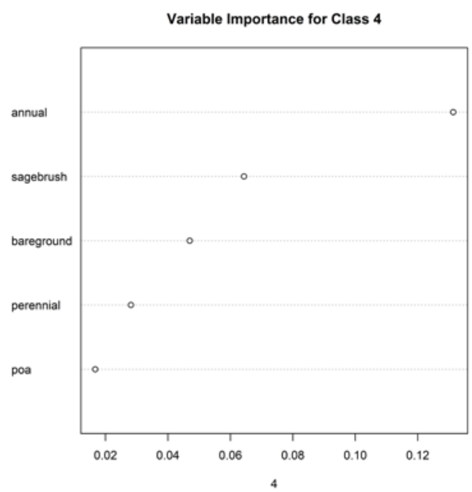
Bare ground was an important predictor of the Shrub state 3 in this DRG, with annual vegetation also serving as a moderate predictor. This state was mapped correctly 78% of the time in this

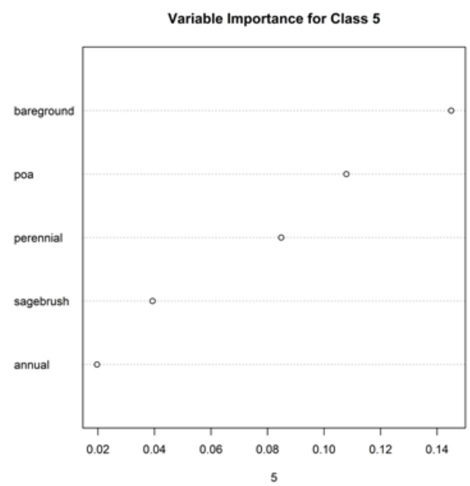
DRG. The Annual state 4 was most accurately predicted by the state-and-transition model map. This is a positive result in that the annual grass raster dataset as provided by ORC did effectively predict annual vegetation in this DRG, a result which was not evident in the linear regression of all plots. Sagebrush was also a decent predictor of the annual state.

The Forb state 5 in this DRG is marked by the dominance of the perennial forb mule-ears (*Wyethia amplexicaulis* (Nutt.) Nutt) This occurs in large mostly homogeneous patches of dense mule-ears. This site was best predicted by bare ground and the Sandberg bluegrass dataset. In the machine learning environment, seemingly unrelated variables can still serve as a predictor of this condition (Figure 7).









DRG 2 Accuracy Matrix:

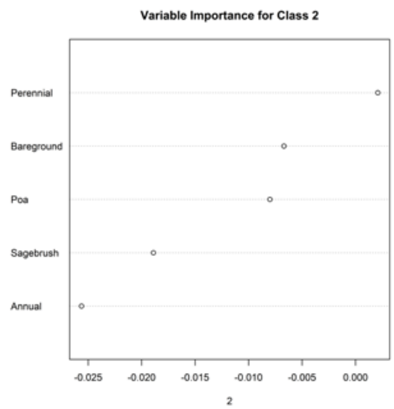
	Predicted State				**Class Error**
Field State	**2**	**3**	**4**	**5**	
2	9	2	3	1	0.400
3	2	7	0	0	0.222
4	2	1	3	1	0.571

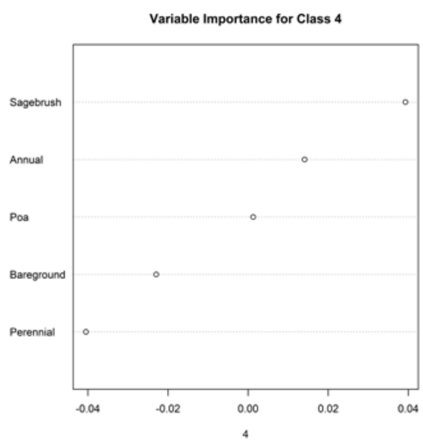
5	1	0	1	3	0.400

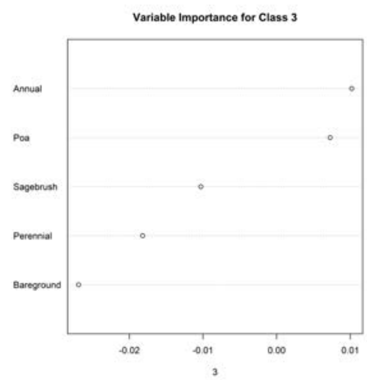
***Figure 7*:** Predictor variable importance plots for DRG 2 State-And-Transition model mapping. DRG 2 has four vegetative states; State 2 is a 'Current Potential' state, Sate 3 is a 'Shrub' state, State 4 is a 'Forb State' and State 5 is an 'Annual' state. Note that the numbering differs from DRG 1 and 4 in which Sate 4 is an 'Annual' state.

DRG 4 Wyoming sagebrush: Accuracy and importance classes

Predictor Variable importance in DRG 4 appears to closely mimic ecological understanding of site processes; Perennial herbaceous raster dataset being a dominant predictor of the Current Potential state 2. Sandberg bluegrass and Annual being a predictor of Shrub State 3. Annual vegetation and sagebrush being a predictor of Annual state 4, as much of the DRG 4 within the study area has been re-seeded successfully with sagebrush although annual vegetation remains dominant in the understory.







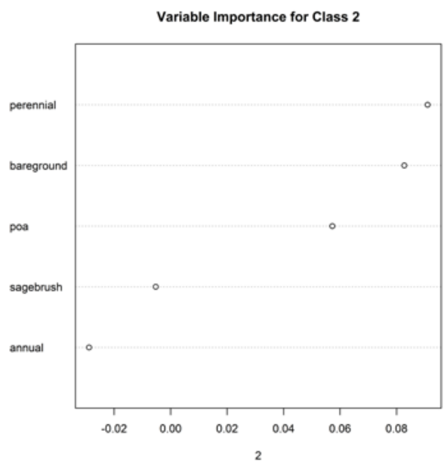
DRG 4 Accuracy Matrix:

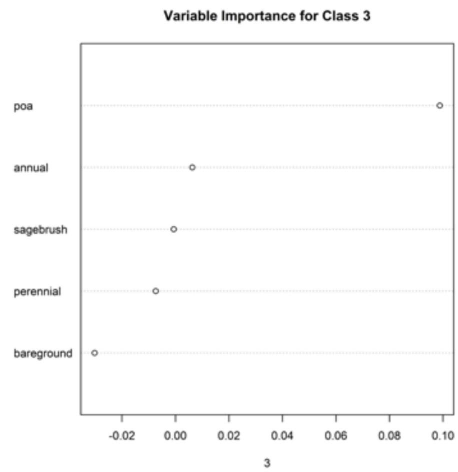
		Predicted State			**Class Error**
Field State		**2**	**3**	**4**	
	2	1	3	8	0.917
	3	3	3	13	0.842
	4	2	10	18	0.419

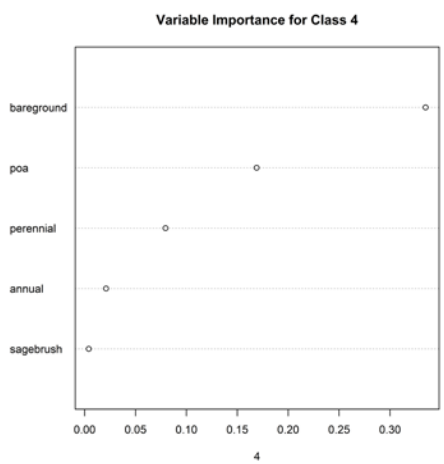
Figure 8**:** Variable importance and accuracy matrix for DRG 4.

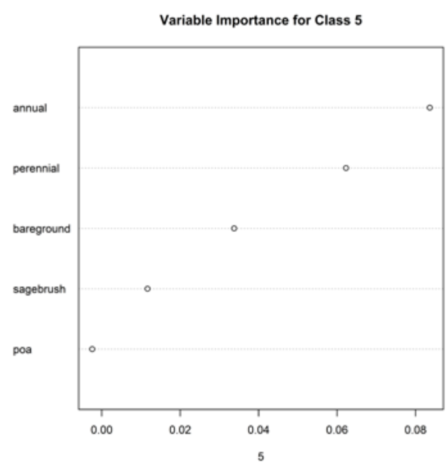
DRG 6: Mountain sagebrush: Accuracy and importance classes

Historically dominated by mountain sagebrush with an Idaho fescue and bluebunch wheatgrass, this DRG occurs above 5800 feet in elevation with moderately to deep soils. These are higher precipitation sites with deeper loamy soils. Current potential State 2 of this DRG was best predicted by perennial vegetation and bare ground raster datasets. Sandberg bluegrass was a strong predictor of the Shrub State 3 which was also characterized in the NMS and ordination analysis of this DRG. Annual vegetation and Sagebrush were also strong predictors of this state, which aligns with ground based knowledge of the state. State 4 of DRG 6 is a Perennial forb site, which was best predicted by bare ground. These sites tend to have very little bare ground exposed during flowering or vegetative portions of the year. It is possible that the dataset is gathering post-senescence imagery and projecting increased bare ground in these areas. Accuracy for this state was high. The Annual State 5 was strongly predicted by the annual cover dataset (Figure 9).









DRG 6 Accuracy Matrix:

Predicted State **Class Error**

Field State

	2	**3**	**4**	**5**	
2	2	4	0	1	**0.714**
3	3	2	1	2	**0.750**

4	0	0	2	1	**0.333**
5	1	2	1	2	**0.667**

Figure 9**:** Predictor variable importance by State ('Class' in this figure), given ORC vegetative cover datasets. Accuracy matrix is presented at the bottom of the figure indicating the tested accuracy of each state prediction. Perennial Forb State 4 was most accurately predicted in this study with just over 33% error. Annual State 5 was the next most accurate, with over 66% error.

Discussion:

State-and-Transition model mapping provides an advancement in our ability to visualize and communicate plant community dynamics at landscape scale. The results presented above are displayed as examples of analyzing models such as are presented here, and utilizing predictor variable importance to elucidate important ecological trends existent within the plant community. The inaccuracies of the vegetative cover dataset make the utility of the map impractical, and ideally datasets which more closely represent on ground conditions will be utilized in future iterations of this product. The map as presented does provide utility however, displaying the potential for this type of analysis to create a process for the generation of State-and-Transition model maps in future analysis.

The STM narrative provides information on potential methods for maintenance as well as restoration pathways (Briske et al. 2008, Stringham et al. 2003, 2015a). This can be extremely useful due to the ease of interpretation by a wide audience, as both public and private land mangers utilize the state-and-transition model framework to understand plant communities on the landscape. Examples of utility include determination of areas most vulnerable to annual grass invasion after wildfire for informing restoration efforts, wildlife habitat assessment for risk of weed invasion or loss of sagebrush cover, fuel-continuity, or restoration opportunities and methods which are proven to succeed on a specific soil and precipitation regime (DRGs). State-and-transition maps can be utilized to communicate an enhanced understanding of plant communities and management strategies at landscape scale.

A relatively small amount of work has been published on this issue, though none utilizing this method. Daniel et al., (2016) created a State-and-Transition simulation model (ST-sim), and the model has seen a significant amount of use in the state of Nevada (Provencher et al., 2013). Jensen et al., (2001) used GIS modeling to map potential vegetation describing 5 different shrubland 'types', which can be considered similar to vegetative states as described here, but do not include the level of species specific information that Nevada State-and-Transition models do. Zald et al., (2014) studied forest composition in the central Cascade mountains including disturbance history and response in their analysis utilizing LIDAR to generate vegetation indices. This method differs from Disturbance Response Groups (DRG's) in that the landscape was not stratified by soil and physical process parameters as described in chapter 2 (Phipps 2019).

The conceptualization of generating STM maps in a robust manner and considerations therein is of greater importance in this manuscript than is the utility of the map or datasets analyzed here. A significant error term inherent to all cover assessment techniques requires land managers to make final decisions with knowledge of a specific plant community cover across a portion of their management area, rather than averages from individual points. Raster datasets are no different in that they can and should be utilized to help inform decisions about management of vegetation communities, with the recognition that what is being measured is actually slight changes in pixel reflectance values as observed by sensors of various resolution and altitude, not vegetation. The relationship to vegetative cover is interpreted, with numerous confounding factors. Additional ways of generating and utilizing remote sensing data emerge regularly, with improvements each time.

Increased sample size of ground based data and enhanced relationship understandings between known ground based cover data and remotely sensed cover values will reduce error terms as well as allow researchers to gain additional insight about the vegetation interactions with the DRG's as told by the remote sensing relationships. As ground based data and remote sensing are both point in time observations, detecting change over time can be very expensive and time consuming. Remote sensing has the potential to reduce this, which would significantly help land managers understand trend of relationships.

As the analysis presented here was conducted in four parts, a separate analysis completed for each DRG, a brief discussion of trends within each DRG model is presented below.

DRG 1

DRG 1 was predicted moderately well, however the predictor variables were counterintuitive in some cases. Multivariate ordination helped separate states based on similar predictors as are presented here, generated by ORC. While much of the model appeared to function as much would be expected, Annual state 4 was most strongly predicted by perennial vegetation and bare ground. Herein lies a problem with both the vegetative cover datasets predicting these states as well as un-restrained machine learning techniques. The annual state in this DRG separated from other plots using ground based data and proportion of total plot cover. In order to most accurately predict the STM map so that annual states overlapped points which were in an annual state, alternative predictor variables were utilized, in this case variables which ecologically don't make sense, displaying error in predictor variables as well as our ability to predict state and transition modeling across these.

DRG 2

Current Potential state 2 was accurately predicted by bare ground, a result which coincides with knowledge of the site. Due to the increased level of precipitation and reduced evaporation, these sites tend to be less water limited and have increased resilience to invasive annual vegetation as well as severe reductions of deep rooted perennial grasses from excess herbivory over time. A reduced percentage of these areas have transitioned away from the current potential or historic plant community. The site is effectively resource limited by the existent plants and the bare ground present tends not to provide sufficient resources for the establishment of novel plant species, maintaining much of the historic plant community composition.

Shrub state 3 was accurately predicted by the Sandberg bluegrass dataset. This result also makes ecological sense in that much of the state is typically dominated by Sandberg bluegrass (*Poa secunda* J. Presl) which senesces at much the same time as the Annual grass and vegetation in the project area, and is notoriously difficult to separate from annual grass using imagery. It is likely that some image confusion created this effect.

DRG 4

Annual state 4 was best predicted by annual grass as well as sagebrush. These sites are at very high risk of wildfire as fuel continuity and flame length in these sites are both very large, and rehabilitation projects in this state have often added sagebrush into the landscape, yet failed grass seeding's tends to become resource limited and stress the sagebrush into an unhealthy and increasingly flammable situation.

DRG 6

Perennial forb state 5: One obvious state change which does not occur in the lower elevation DRG 1 is the conversion to perennial forbs, predominantly mule-ears (*Wyethia amplexicaulis* (Nutt.) Nutt.). This vegetation transition typically occurs where historic sheep bedding grounds reduced vegetation as well as organic topsoil in places, creating a site which favors deep tap rooted forbs (Stringham et al., 2015b). Forb: This community is very resilient and challenging to restore to its historic plant community of bunch grasses and sagebrush. It is likely a relic of overuse in sheep bedding grounds historically, where all deep rooted vegetation was removed from these sites (Mueggler and Blaisdell, 1951). These sites may be an excellent opportunity for remote sensing groups to hone classification schemes using this vegetative community which has very little bare ground, almost no other species within it, and senesces in mid-summer much like the annual grass or Sandberg bluegrass.

Conclusion

NAIP imagery is much less standardized in its capture as well as our ability to apply radiometric normalization between scenes. Due to contractor constraints, imagery captured in different dates, as well as imagery captured on the same date in a separate exposure often has very different pixel brightness values for the same vegetation between scenes. Landscape scale management will require multiple image scenes, and normalization between them is a must if machine learning is to predict consistently across them. While this may not create an issue for images captured at a very similar time, repeating the process over time would be much less accurate using NAIP. LANDSAT has been utilized to create shrub-land cover for the Great Basin through the entire Landsat library back to 1984 (Colin Homer, personal communication) which should be published in the near future. This presents an opportunity to test the information within the State-and-Transition models as well as the ability for the mapping product to accurately predict and map the changes we observe on a landscape.

The sagebrush biome is known to have very subtle changes in reflectance values which represent significant changes in management opportunity on the ground (Shi et al., 2017; Xian et al., 2013), making this a very challenging environment for remote sensing. The geologically diverse landscape of Nevada creates a myriad of soil colors which influence image classification, and several species of sagebrush have very similar spectral characteristics. An added challenge in this environment is that important ecological drivers of plant community function are every difficult to identify utilizing remote sensing methodologies. Sandberg Bluegrass (*Poa secunda* J. Presl) is a shallow rooted perennial bunchgrass, that senesces at much the same time as the annual grasses (Primarily Cheatgrass, *Bromus tectorum* L.*)* yet functions very differently from annual grass and will hold annual grass invasions at bay. Beyond being spectrally very similar to annual grass, the Sandberg bluegrass often grows beneath shrubs on site, making observation particularly difficult from above. Future studies will ideally incorporate other metrics or predictor variables in place of this to get around this problem.

Hazards exist in remotely determining plant community condition and it is strongly urged that mapping efforts such as this are used strictly for planning purposes, and that on ground conditions are verified before any management decisions are enacted. While we collectively stand to gain in conservation of these landscapes though enhanced planning tools, we stand to lose habitat if lands are mismanaged through misidentification of on-site conditions and issues. On-ground managers with a thorough understanding of plant community dynamics and knowledge of conditions on ground should remain the final decision maker. If spatial planning and issue identification can be targeted with State-And-Transition model mapping and the map can be verified for accuracy, the map can help managers visualize management challenge extent and pattern. This would allow them to better use their livestock and stockmanship to manage issues on the landscape such as fine fuel build-up or target seeding of undesirable plants to enhance forage and habitat onsite.

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Thesis Conclusion

The generation of State-and-Transition model maps requires an understanding of all components required to use State-And-Transition models. With this understanding it can serve as an accurate and useful planning tool, applied in a spatial context. Plant community dynamics need to be well understood at a landscape scale, and utilized to generate State-And-Transition models which can be used as a framework from which to better understand plant community succession. Understanding correlations between vegetation measurement types can allow us to use numerous data sources in order to gain the most complete understanding of vegetative cover, as well as for classifying the vegetation into vegetative state in a robust manner removing observer bias. This understanding of vegetation is also critical to knowing the strengths and weaknesses of remote sensing products, and verification of the remote sensing data's information with what is known about vegetation in ground. The spatial extent of DRG's or plant communities for which the State-and-Transition models can be applied must also be understood. Once these components are well understood, then vegetation dynamics of a particular DRG and vegetative state can be assessed, completed independently for each disturbance response groups to capture the differences in potential and risk of a particular DRG. Once compiled, DRG specific DRG maps can be combined to make a contiguous DRG map at landscape scale.

It has been demonstrated here that although mean cover values across all sites show no significant difference between line point intercept (LPI) data and the ORC remotely sensed cover values, very little relationship exists between the datasets on a point to point basis. A strong relationship between LPI and continuous line intercept measurement of sagebrush does exist, and both measurements are strongly related in mean values as well as spatially through linear regression. LPI and Daubenmire frames also showed a close relationship between points in regression, with Daubenmire typically providing lower cover values than LPI. The absence of a tight regression between ground based data and the remotely sensed data means that the maps generated using remote sensing dataset suitable for proof of concept exercises, and are not recommended for use as a management tool.

The DRG concept's utility is proven utilizing the ground based data collected, and transects are placed within vegetative states utilizing ordination and relative cover percentages to normalize for varying production of individual ecological sites which comprise the DRG. Specific strengths and weaknesses of relating ground based cover with remotely sensed cover are discussed; Within DRG 4, the most dominant DRG within the study area, Annual grass cover is very similar between LPI and ORC Continuous cover remote sensing datasets. This is not the same for Perennial grass, which although shows similarity across the study area, when constrained to DRG 4 displays greater differences in cover values. This implies that perennial grass sites identified with the remotely sensed dataset are likely to be more perennial and more extensive than was observed on-ground. This also implies that the annual state is likely more recognizable in DRG 4, as much of the most significant known sources of error with annual vegetation in the remote sensing dataset occurs in other higher elevation DRGs.

The development of a DRGs map as outlined in this thesis is completed with 20% greater accuracy than the existing method utilizing soil map unit polygons created. In the process of searching for strong predictor variables to aid in mapping DRG's across the landscape, additional ecological knowledge was gained about the abiotic drivers of site function and plant community needs. Elevation, precipitation, evapotranspiration and water deficit of soils on site were the strongest predictors of DRG location on the landscape.

Vegetation observations classified into vegetative states utilizing ordination practices were then utilized to create a predictive model of remotely sensed vegetative cover to vegetative state across the project area. Random Forest was utilized to create the relationship between remotely sensed values at the ground based transect locations with a vegetative state assignment. ,These relationships were subsequently applied across all cells in the dataset, generating a State-And-Transition model map within the extent of the DRG. Once this process was completed within each DRG, the maps were merged together, creating a State and transition model map that crosses multiple DRGs, yet utilizes vegetation dynamics specific to each DRG to guide the mapping effort. Although the error associated with this specific map precludes its use in vegetation management, the process is thought to be robust and paves a path forward to advancement as understandings in DRG location prediction and remotely sensed vegetation cover improve.

Contributions: The ability to generate State-and-Transition model maps is an

advancement in providing tools to land managers which are easily interpretable, inclusive of ecological knowledge of the various plant communities which exist in the great basin, and allows for spatial planning of management areas. In order to get making State-and-Transition model maps however, several advancements were made as described above. The concepts of utilizing DRG's as a stratification method for analyzing landscapes is further proven here, and vegetative trends, relative resilience to invasion from annual grass, and differences between DRGs is shown in this manuscript. Relationships between cover metrics will allow other data sources to be added to future analysis similar to this as well as for land managers to be able to add to their knowledge of a vegetation community if given access to data collected by a different organization or protocol. Enhanced knowledge of plant community extent across a landscape would be extremely useful to post fire rehabilitation and other restoration projects across the landscape. This would aid in placing seed for re-vegetation in places which have a better chance of success, potentially saving millions of dollars in re-seeding efforts placed into soils which will not support those species. State-and-Transition model maps will help land managers target weed infestations, treat gently land which is in delicate equilibrium, and utilize more completely land which has already undergone transition to a degraded state and which reduced herbivory on allows the growth of excess fuel continuity, creating additional devastation in the case of a wildfire.

Limitations: The study is limited in geographic extent, as well as observation numbers. For

this reason, conclusions made surrounding DRG vegetation dynamics should be verified with additional data before application across the entirety of the Major Land Resource Area (MLRA).

As all Daubenmire visual observations were made by the author, potential bias exists within the relationships between the LPI data and the Daubenmire data caused by unintentional observer bias. There are known issues in the accuracy of the predictor variables utilized in the prediction of DRG extent across the landscape, so while the process elucidates important ecological knowledge not previously incorporated in the DRG reports, the absolute values of the predictor variables should not be utilized. The relative importance of variables in this case is much more important than the actual modeled value at these locations. The State-and-Transition model map unfortunately had a much higher error term than should be utilized to manage plant communities. Thus, the processes presented in this paper should be considered important steps and methods for the generation of State-and-Transition model maps, but utilized with a more re-producible and longer term vegetative cover model and training data which covers a geographically broader area. The process of State-And-Transition model mapping is a balance of organizing large amounts of ecological information and predictive modeling to generate maps which are management friendly and useful to a wide audience, without sacrificing management integrity or our greatest understanding of ecological process of rangeland vegetation communities and management recommendations.

Future Direction

We plan to continue this assessment and progress on greater scale with greater background and proof of concept. Utilizing the National Land Cover Database (NLCD) generated by the USGS, fractional vegetative cover is modeled for the Great Basin shrubland in similar functional group categories as the vegetative cover product analyzed here, with the added utility of having the same process applied to the entire Landsat library back to 1984. This longer term vegetative cover library will be utilized to test model accuracy and utility as past vegetation treatments and disturbances (including wildfire) will be utilized to tune the model and test the hypothesis and steady state thresholds presented by the model. It will also be possible to utilize management information from private and public land managers across the Great Basin to search for effect or stability generated through their management of the land and vegetation communities.