Project Title: Development of the Rangeland Vegetation Simulator: A module of the Forest Vegetation Simulator

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Abstract

The escalating awareness of non-forested landscapes and realization that more emphasis is needed for an all lands approach to management increasingly requires timely information to improve management effectiveness. The Forest Vegetation Simulator (FVS) has been used in a large number of studies to project future vegetation conditions and is often used in conjunction with the richly populated Forest Inventory and Analysis (FIA) database. The FVS lacks the routines and algorithms for dealing with non-forest landscapes and is therefore only applicable on a limited number of landscapes. This obviates the need for simulation capabilities in non-forested environments, in addition to improved characterization of understory conditions (herbaceous and shrub species) in the FVS. In response to this need, we developed the Rangeland Vegetation Simulator (RVS) and new models for estimating understory conditions in forested landscapes. The RVS is calibrated on 112 unique sites and enables simulation of ecological dynamics, production and fuels in either a spatially explicit manner or as a processor of inventory data much like the FVS. Validation of the RVS, in this inaugural development, suggests significant promise for its use to describe vegetation and fuel data when the structure and composition are given, but its ability to describe succession is limited and in some cases unrealistic. The premier outputs of the vegetation simulator are:

1) Standing biomass, carbon, and annual production of herbs and shrubs (including standing dead herbaceous material).
2) Vegetation structure, composition, and seral stage
3) Fuelbed properties (1, 10, 100, 1000 hr fuel) and fire behavior fuel models
4) Response of these attributes to herbivory and fire

The Ecological dynamics underlying the RVS are LANDFIRE's Biophysical Settings (BPS) models. These models do not account for invasive species and other contemporary ecological theory. As a result, in this project, a prototype application using Ecological Sites and their associated state-transition models were merged with the RVS fuel, growth and biomass algorithms to test the efficacy for describing fuel bed properties. This was funded as a separate project but is really part of this larger effort to improve non-forest simulation and management Results indicate significant promise for Ecological Sites replacing the BPS models of succession for a national strategy involving rangeland ecological simulation in support of rangeland management and administration.

A final component of this project was development of equations to predict understory response to overstory and site factors in forested environments, especially focused on herbaceous and shrub structure. The understory equations were developed for 4 major forest types covering approximately 44 million of acres in the U.S. including: lodgepole pine, Douglas fir, grand fir, and ponderosa pine. McFadden statistics range from 0.22 for herb height to 0.87 for tally tree cover of the Pacific Northwest FIA Region. Predictions of shrub cover and height are relatively more accurate than those of herbaceous species.

Background and Purpose

This final report describes results from three intertwined projects, "Development of the Rangeland Vegetation Simulator: A module for FVS", Development of the Rangeland

Vegetation Simulator, and Incorporating Ecological Sites into the Rangeland Vegetation Simulator which were funded to address the following project task identified in the RFP: "Non-Forest and Understory Fuels Growth, Response and Succession". We include all three reports weaved into a single larger report because of the synergies between these three, very closely related, projects.

Non-forest landscapes occupy roughly 662 million acres in the coterminous U.S. and account for many of the wildland fires observed through time (Reeves and Mitchell 2011). Non-forest vegetation responds much more quickly and with greater relative growth rates and variability than forested environments. Despite these factors the ecological and fire communities lack a system that enables quantification of successional dynamics and associated structure, composition or fuelbed characteristics. Therefore a system is needed which enables quantification of vegetation composition and structure in response to management or disturbance with an emphasis on providing data and information on fuelbed characteristics in sufficient detail to permit estimations of fire behavior and effects in support of improving the Forest Vegetation Simulator. Such a system is needed because succession, growth and fuels of non-forest vegetation are not estimated in the FVS although current decision support systems such as Interagency Fuels Treatment Decision Support System (IFT-DSS) require this information.

This situation inspired our project to develop a comprehensive system for simulating succession, productivity, and fuels in non-forest environments. This system is called the Rangeland Vegetation Simulator (RVS). The RVS provides information on an annual time step and can be used to evaluate plot level data or be used in a spatially explicit mode. The system was designed to be relatively simple to execute in comparison to more sophisticated ecosystem simulation models such as the Century model (Parton et al., 1993) and Biome-BGC (Running et al., 1993). Although it lacks the sophistication of these classic ecological models, the RVS takes advantage of remote sensing data as a primary input and, importantly, it is calibrated to quantify the vegetation response to wildfire and grazing. Grazing effects the fuelbed profile, vegetation cover and height but does not necessarily affect the successional dynamics since the BPS succession models do not account for modern grazing regimes used with domestic herbivores. Presently, capacity exists for operating on 112 distinct biophysical sites and yields up to 20 parameters describing ecological processes or quantities for each year in a simulation.

A critical element for readers to recognize is the tight linkage between the Biophysical Settings (BPS) geospatial data product, its associated successional models, and the RVS. The BPS controls several key processes. First and most significantly, the BPS controls the estimated successional development of each stand which inherently depicts vegetation prior to settlement by Euro-American's. Second, the BPS creates a spatial context within which various processes and parameters are controlled. For example, for climate, growing conditions and growth rates are constrained for each BPS. Using BPS to control estimated growth rates and annual production prevents illogical combinations of stand properties to be simulated. For example, a shortgrass prairie will not reach annual production of 6000 lbs ac^{-1} since the climate and growth rates are informed and calibrated for each BPS individually. These concepts and others are discussed at length below including algorithmic development. Hopefully, this inaugural program development portends years of model use and improvement to come.

This system provides two overarching benefits:

1) A research tool enabling projections of future vegetation conditions improving our ability to estimate the effects of management actions on future vegetative states.
2) A decision support tool enabling land management agencies to more accurately describe post-disturbance successional dynamics, and most importantly, estimate wildland fire behavior and effects from a rich suite of fuelbed characteristics that the RVS offers.

This project also tested use of Ecological Sites in a state-transition simulation modeling context in concert with the ST-SIM software platform. This was tested on the Loamy Plains of North Central Colorado across a continuum of grazing intensities. Bias and mean absolute error of annual production were -58 and 177 lbs ac^{-1} respectively. In addition to prototyping use of Ecological Sites for coupling with the RVS, the relationships between Ecological Sites and LANDFIRES's BPS data were evaluated. All Ecological Sites with vetted descriptions were mapped for the western U.S. and overlain with the BPS data. Data summaries were developed to describe the number and complexity of Ecological Sites with respect to the various BPS categories. This combined database was used to answer a series of questions to ultimately determine the level of effort required to develop a national strategy for consistent and comprehensive ecological simulation in support of rangeland management and administration. For complex areas, as many as 264 Ecological Sites are required for full coverage, however, usually only a few Ecological Sites are required to simulate a majority of the area. In some cases Ecological Sites cover greater than 7 million acres enabling good economies of scale.

The third phase of this project developed predictive equations for estimating understory vegetation structure in response as a function of overstory conditions and site characteristics. As with the development of the RVS, these equations enable new modeling in support of fire behavior and effects in the understory (shrubs, and herbaceous species). These new equations, developed by analysis of over 6,500 FIA plots, are available for use in the FVS program to enabling more accurate predictions of herbaceous and shrub structure. McFadden statistics range from 0.22 for herb height to 0.87 for tally tree cover of the Pacific Northwest FIA Region.

In this report we provide a detailed assessment of these three project objectives of:

1) Development of the RVS for quantifying biophysical elements and estimating successional trajectories of non-forest lands with distinct application to fuelbed properties.
2) Evaluating use of Ecological Sites with the RVS via ST-SIM
3) Develop predictive equations for selected forest types of the western U.S. for estimating understory structure

In the first half of the report we discuss the development of the RVS while in the second and third we discuss merging Ecological Sites and the development of the understory equations respectively. This project is obviously different than more traditional research projects where the problem is identified, data are collected, statistical analysis is performed and results are presented. We will be publishing results of the models *use* and development in the future, and we have spent a great deal of time warehousing and cataloging the computer code developed over 4 years.

1.0 OBJECTIVE 1: Creating the Rangeland Vegetation Simulator

1.0.1 Methods

1.0.1.1 The Code

RVS is an open source C++ library written for multi-platform deployment. The code is hosted on Github at https://github.com/rlank/RVS. Current development is focused on Windows, but a makefile has been written and tested for Linux. C++ was chosen for compatibility with the Forest Vegetation Simulator (FVS), which is written primarily in FORTRAN, but also in C and C++. Each module exists in its own namespace, and the program can be used and imported into other code projects if technical users want to access certain features of RVS externally. Data for RVS is held in a single SQLite database. SQLite was chosen because of its simplicity and compatibility with FVS. SQLite is free and open source, and RVS generally backwards supports old versions of SQLite (but is shipped with the latest version). Since RVS is highly dynamic, this means each simulation requires numerous database queries. These are very slow. Also, again because of RVS' dynamic nature, not all of the input database is needed for every simulation. Nor should it be loaded, because it would be a waste of memory, so, RVS holds a dictionary of active queries. Each time a query is requested, the backend observer (a subroutine) checks to see if this data has been requested before. If it hasn't been queried before, it does actually go to the disk and get the data. Then, however, it adds it to an in-memory SQLite database. This database is created when RVS starts and is deleted when RVS is done. As the simulation continues, if the data is requested again the observer can pull it out of the in-memory database rather than the disk. This improved RVS performance over 1000% and RVS can now run 1500 plots for 50 years each on a mid-range desktop in about 30 seconds.

1.0.1.2 User Input

The purpose of this section is to highlight how the RVS works and what is generally required to enable simulation. While contemplating the methods presented here the reader should remember that this system was designed to estimate fuelbed parameters at the expense of other system properties. It is not possible to give priority to all elements within the simulation system but we attempt to clearly identify assumptions and point out weaknesses in the system schema. It is also important to consider that, for the purposes of estimating elements of fire behavior, there is little difference between a site exhibiting 500 lbs ac^{-1} annual production of herbaceous fuels and a site exhibiting 850 lbs ac^{-1}if a standard fire behavior processor such as Behave (Andrews and Bevins 2003), NEXUS (Scott 1999) or FARSITE (Finney 2004) is used since both stands would likely be classified using the same stylized fuel model (likely a GR1 from the Scott and Burgan (2005) set). So, a high level of accuracy may not be required in many model elements when estimating fire behavior is a priority (the situation may be different where fire effects such as consumption is an issue). In addition, from a composition perspective it may not be necessary to, for example, differentiate *Artemisia tridentata subsp. wyomingensis* (Wyoming big sagebrush) from (basin big sagebrush) (*Artemisia tridentata subsp. tridentata*) since both will produce very similar fire behavior, and effects. Nor might it be necessary to differentiate *Bromus inermus* (smooth brome) from *Agropyron cristatum* (crested wheatgrass) on a given site since both will produce similar fire behavior and effects such as emissions and fuel consumed. So, when evaluating model assumptions and potential usefulness and limitations consider the *efficacy* of the system as much as the *accuracy*.

To invoke the RVS program, a user needs to supply a latitude, longitude and simulation design criteria. It is also strongly recommended that users supply vegetation inventory information including vegetation cover, height and composition, but this is not totally necessary. Without user interaction, a simulation can be performed but should not be considered reliable and these types of simulations are considered "blind simulations" (Table 1). Prior to simulation, for each plot in the users' database, a series of geospatial data sources must be sampled to "pre-load" extra information to assist the simulation. This process is called the RVS data loader and for now will require interaction with the RVS team (Matt Reeves and Rob Lankston, contractor). Users can do it themselves but they should have some help from a GIS analyst to sample the data and could also request the data from the RVS team directly.

Table 1. The level of user input influences the number of assumptions necessary to conduct a simulation. This table applies to any situation except when the invasive species listed in "XYZ table" are found. To answer the question of whether or not shrubs or herbs are present or expected in the future, the user would indicate either a value of 0% cover (indicating none was measured) or a blank value (nothing is entered) for cover indicating the desire to have the successional model decide when and if herbs or shrubs should be present.

User Situation	Succession Class	Herb structure	Shrub structure	Are shrubs present or expected in the near future?[1]	Are herbs present or expected in the near future[2]
User supplies nothing "Blind Simulation"	Mapped Succession Class	Function of estimated annual net primary production and relative proportion of shrubs	Function of time since disturbance and BPS (succession stage and BPS determine growth rates	Succession models describing estimated species assemblages (relative proportion of lifeforms)	Succession models describing estimated species assemblages (relative proportion of lifeforms)
User supplies height and cover for both herbs and shrubs[3]	If shrub and herb structure and composition are known, the succession class can be estimated	Supplied by user	Supplied by user	Known from input	Known from input
User supplies height and cover for herbs only	If herb structure and composition is known, the succession class can be estimated	Supplied by user	None estimated in present succession stage. Might come into the community in a later stage.	Supplied by user	Known from input
User supplies height and cover for shrubs only	If shrub structure and composition are known, the succession class can be estimated	Supplied by user	Supplied by user	Known from input	None estimated in present succession stage. Might come into the community in a later stage.

[1]This is part of the plot-level input. If the user leaves this blank, the RVS will estimate, based on the succession models for each BPS whether or not shrubs should be present in future years of the simulation. [2]Users should

supply an estimate of whether or not herbaceous lifeforms (grasses and forbs) are present or should normally be expected at the site. For example, some sights could exhibit shrub cover and height well beyond expected conditions (such is the case with many sites exhibiting dense stands of decadent sagebrush. Often these sites would have historically exhibited reasonable production of herbaceous species but this may no longer be the case. So to assist the RVS in recognizing this condition, the user should consider simply supplying this information in the input database and indicate that "herbs are NOT present or expected in the near future". [3]If user-supplied height and cover of shrubs exceeds the appropriate structure suggested by each succession model in each BPS, shrubs will not be grown in the future. This generally applies, however, to shrub height but not necessarily cover.

In the early stages of the dissemination of the RVS, while use is in its infancy, users may request assistance until appropriate server architecture is constructed. The data sampled during the RVS data loader process, and their use in the simulation is depicted in Table 2.

Table 2. Geospatial data elements that are sampled to provide guidance for a simulation and to provide "backup values" in case a simulation is blind.

Simulation parameter	Usage	Source
Biophysical Settings (BPS)	Controls NDVI, Precipitation, and growth rates of shrubs and linkages between herbaceous cover and biomass.	LANDFIRE (Rollins 2009)
Succession Class	Provides an estimate of where the stand is in terms of successional status (early, mid, or late). Succession class also controls growth rates of shrubs within a given BPS (e.g. shrub growth rates are often higher earlier stages). Controls species cohorts and estimated dominance of lifeforms. For a given succession class, up to four species are estimated. This information is reported at the lifeform level	LANDFIRE (Rollins 2009)
Precipitation	Controls annual production in concert with NDVI and BPS.	PRISM (Daly et al., 2009)
Normalized Difference Vegetation Index (NDVI)	Controls annual production in concert with precipitation and BPS.	LANDFIRE (Rollins 2009)
Existing Vegetation Height (EVH)	Provides a general estimate of vegetation height for a starting point in the simulation (only if the simulation is blind).	LANDFIRE (Rollins 2009)
Existing Vegetation Height (EVC)	Provides a general estimate of vegetation cover for a starting point in the simulation (only if the simulation is blind).	LANDFIRE (Rollins 2009)
Existing Vegetation Type (EVT)	Provides an estimate of the vegetation class (Ecological System; Comer et al., 2003). In the RVS, it is used to provide a general estimate of the presence of invasive and exotic species. The succession class product indicates that a particular site may have "uncharacteristic" vegetation qualities but it does not indicate a likely species assemblage and therefore, the EVT is needed to further diagnose the situation.	LANDFIRE (Rollins 2009)

Data retrieved by the data loader process is meant to provide a starting point, a suggested set of plot characteristics, and the hope is that the user will review the first set of inputs and update them to reflect what is known at the site. In this manner it is very important that a user be aware of the sampled BPS underlying the plots available for simulation. This is because, as described in detail below, the BPS controls many critical processes during the simulation. In many cases it is possible that due to mapping errors, thematic accuracy, plot placement etc., the BPS will not be representative of the system desired for simulation. As a result, the original data retrieved should be reviewed with a significant amount scrutiny since sampling a set of 30-m^2 map products is not a substitute for plot inventory. If a user does interact provide details regarding vegetation structure and composition the simulation are considered an "informed simulation". Informed simulations are overall better than blind simulations. Either way, the RVS will not care whether the simulation is blind or informed and will merely read the plot inventory (either from the data loader process or from a user's field sampled database) regardless of accuracy or origins of the dataset. To provide clarity regarding the differences between informed and blind situations the potential situations that may be encountered are expanded in Table 1.

The dominant system flow components described in the remainder of this report are:

1) Succession
    a. Dealing with invasive species
2) Growth
    a. Growing Season Index
    b. Annual Production and Biomass
        i. Herbaceous component
        ii. Shrubs
3) Management Actions
    a. Fire
    b. Herbivory
4) Fuelbed components
    a. Individual fuelbed components
    b. Fuel classifications
5) Integration with FVS
6) Model Output
7) Next Steps

1.0.1.3 Succession

The first step in understanding the successional status of stand is to understand the age or time since disturbance. To determine the approximate age of the stand, cover and height information is needed so that a point within the succession class can be chosen to initialize the simulation. With the BPS, succession class, cover and height and exotic/invasive information (Table 2) the RVS can estimate what point in a succession stage a stand is presently in. One point of potential confusion is the sampling of the Existing Vegetation Type (EVT) to inform the succession modeling. The only components from the EVT geospatial product used in the RVS modeling process are the estimated presence of invasive or exotic species. The reason for this is that each succession already has a set of species cohorts and rates of growth so that the EVT information is not needed to represent an estimate of relative abundance of various life-forms. However, the succession class product does include two categories to describe uncharacteristic conditions owed to exotics or native species including "Uncharacteristic Native" and "Uncharacteristic Exotic".

1.0.1.4 Dealing With Invasive Species

The Clementsian viewpoint implied in the BPS succession models has the significant shortcoming of linear assumptions of succession and stand growth and inability to describe effects of invasive species. Considering the significant area of non-forested lands occupied by invasive species such as cheatgrass (*Bromus tectorum*), some method for estimating the successional trajectories and more importantly (for this project) the response of fuelbed properties. So, since there are no available models in the BPS concept to deal with the critical issue of invasive species, we suggest dealing with them outside of the BPS framework. This acknowledgement of the weakness in the BPS modeling framework is what prompted us to prototype Ecological Sites (https://esis.sc.egov.usda.gov/) as a backdrop to evaluate vegetation dynamics of alternative states in a state-transition simulation modeling system. This is discussed in a separate report.

1.0.1.5 Estimating Stand Age

Estimating the approximate age of the stand is one of the most critical aspects in the succession sub-routine because it influences growth rates and the general proportion of lifeforms in the stand. Consider the data and BPS model in Table 3. Assume the sampled succession class at a plot location on the Inter-Mountain Basins Montane Sagebrush Steppe - Mountain Big Sagebrush BPS (Table 3) is “Mid” and the estimated shrub cover was 25% while heights were estimated at 0.9 meters. Based on the implied growth rates (derived from the succession class characteristics; discussed later) the estimated age of the stand is 31 years. Therefore, the growth rates of a 31 year old stand will be used to simulate height and cover growth through time. The order of species listings from left to right indicate expected relative abundance in (Table 3). In this case “ARTRV; mountain big sagebrush” is expected to be significantly more abundant than “AMAL; serviceberry”. Serviceberry can often exceed 3 meters but since the heights listed here are considered cover weighted heights, the expected height of mountain sage and three-tip sage (ARTR4) get greater weighting in the estimated average maximum stand height of 1.5 meters. In addition, the canopy cover values represent the characteristics of the dominant vegetation. This is done to be consistent with the LANDFIRE succession models the dominance is determined by height. Thus, if shrubs are present in any abundance in the assumed species assemblage they will be considered to be dominant. In the example from above, the mid-successional stage is dominated by shrubs which are also indicated by the fact that a shrub species is listed first in the order of species. The cover and height of herbaceous species is dealt with later in the report.

Table 3. The Inter-Mountain Basins Montane Sagebrush Steppe - Mountain Big Sagebrush and associated succession class characteristics. The order of species listings from left to right indicate expected relative abundance. In this case "ARTRV; mountain big sagebrush" is expected to be significantly more abundant than "AMAL; serviceberry". Serviceberry can often exceed 3 meters but since the heights listed here are considered cover weighted heights, the expected height of mountain sage and three-tip sage (ARTR4) get greater weighting in the estimated average maximum stand height of 1.5 meters.

Stage/cohort	Start	End	Min	Max	Min	Max	Species 1	Species 2	Species 3	Species 4
	years[A]		Canopy cover (%)[B]		height (m)					
Early	0	11	0	5	0	0.6	*FEID*	*PSSP6*	*ACNE9*	*LUSE*
Mid	12	49	10	30	0.6	1.1	*CHRYS9*	*SYOR2*	*FEID*	*ARTRV*
Late	50	110[B]	31	80	1.1	1.5	*ARTRV*	*ARTR4*	*SYOR2*	*AMAL*

[A] – The maximum age of 110 years in this example simply indicates the endpoint at which the woody vegetation at this BPS will cease to grow taller or increase in cover and has therefore reached an "equilibrium" with the site.
[B] – Each cohort of dominant species within a successional stage is assumed to reach maximum stature at the midpoint of time within the class. For example, in the "Early" class in this BPS, both cover and height are assumed to reach a maximum by 2.5 (3) years.

Once the height, cover, and age can be estimated, the RVS will simulate the progression of succession in a stand according to each BPS model. This is done by allowing cohorts of vegetation (Table 3) to "enter" the stand based on time since disturbance. In this manner, cohort number one is gradually replaced by cohort number two and cohort number two is gradually replaced by number three etc. Stand level cover and height is a function of growth rates, time since disturbance, and the proportion of each cohort estimated to be present on the landscape. Note that when cover and height of a cohort reaches its maximum potential, the height of the stand does not decrease appreciably but as a stand average it might be somewhat less since the height is a cover weighted average and if short species have significantly greater foliar cover than taller species, the stand average will be weighted towards the shorter species (**EQ. 1**).

EQ. 1 $Stand_{avght} = ((((Cohort1_{cov} * Cohort1_{prop}) * Cohort1_{ht}) + ((Cohort2_{cov} * Cohort2_{prop}) * Cohort2_{ht})) / 2)$,

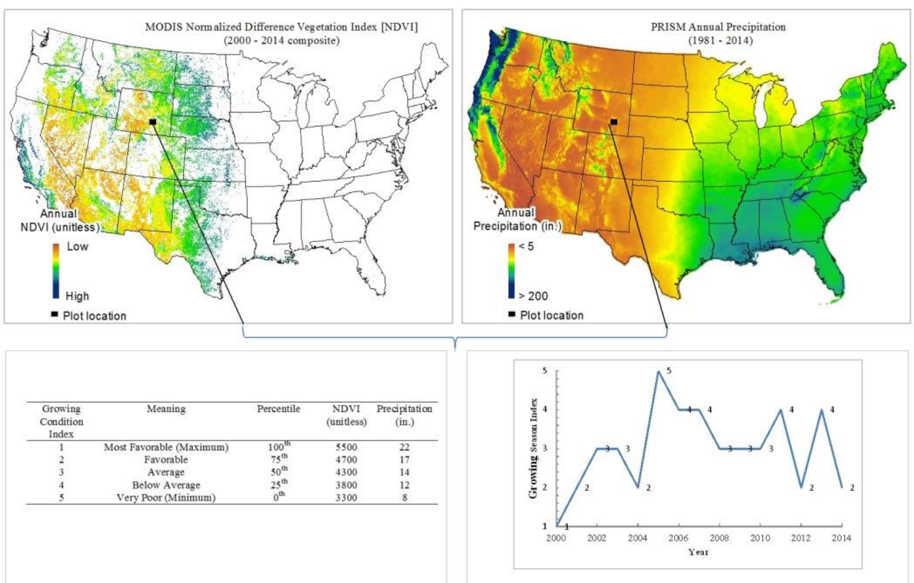
Where $Stand_{avght}$ is the cover weighted stand level height estimate, $Cohort1_{cov}$ is the estimated cover of cohort 1. $Cohort1_{prop}$ is the estimated proportion of the community that cohort 1 occupies, etc.

1.0.1.6 Growth

1.0.1.6.1 Growing Condition Index

Since the system described here runs on an annual time step, annual growing conditions must be specified. To accommodate ecological simulation, the system is designed to accept generalized growing conditions which are effectively combinations of remote sensing inputs and estimates of annual precipitation. The user, however, does not need to generate their own classes of annual precipitation and remote sensing inputs because this has already been accomplished and simplified in a spatially explicit database and made available during the RVS data loader process. Users need to request this database. The only decision the user has to make is the kind of climate scenario under which effects of management actions will be analyzed. Thus, the annual sequence of growing conditions can be dictated by the user or it can be completely stochastic. For example, sometimes managers want to estimate what the effects of inappropriate stocking rates occurring under drought like conditions will be. It is important to realize, however, that since both the remote sensing and precipitation data are spatially explicit so the growing conditions for a region are appropriately constrained to values that have actually been observed for a given site. So as the user overlays the X, Y locations within the RVS data loader process the appropriate data ranges of vegetation abundance and climate are retrieved. From this range, the user must specify the climate scenarios (growing condition index) desire to be evaluated.

The precipitation data used for formulating the growing conditions come from the Parameter-elevation Relationships on Independent Slopes Model (PRISM) Project (Daly et al., 2001). Data between 1981 and 2014 are used to quantify the range of annual precipitation estimated over the coterminous U.S (Fig. 1). In addition to precipitation, the growing condition index also involves the commonly used normalized difference vegetation index (NDVI) which is a remotely sensed ratio of red and near-infrared electromagnetic radiation.



Growing Condition Index	Meaning	Percentile	NDVI (unitless)	Precipitation (in.)
1	Most Favorable (Maximum)	100^{th}	5500	22
2	Favorable	75^{th}	4700	17
3	Average	50^{th}	4300	14
4	Below Average	25^{th}	3800	12
5	Very Poor (Minimum)	0^{th}	3300	8

Figure 1. Both climate data from PRISM and NDVI data from MODIS are used to describe growing conditions and formulate the growing condition index. The index represents the following percentiles for both datasets; 0^{th}, 25^{th}, 50^{th}, 75^{th}, 100^{th}.

The details of NDVI are not germane to this report but the manager (or user) of the RVS needs to understand that the NDVI increases as vegetation abundance (or biomass) increases. The rationale for including the NDVI in the growing conditions index is so that present vegetation conditions can be estimated. For example, as demonstrated in Fig. 2, areas within the same Biophysical Setting can have significant differences in productivity due to different management schemes or other reasons. Thus, by including NDVI in the growing condition index, given the same precipitation, the system can “see” the differences across the landscape and estimate production and fuels accordingly.

Figure 2. Management schemes can effect vegetation assemblages and structure even if the potential productivity is identical. This figure shows demonstrates this point by identifying an area where a fence line has created different management strategies and subsequent rangeland production.

The combination of annual precipitation from 1981 to 2014 and vegetation abundance and vigor information (NDVI) from 2000 to 2014 to define growing conditions enables spatially explicit simulation capabilities constrained by observed conditions. This is an important point for the manager to understand. Thus for any given rangeland site in the coterminous U.S., the range of observed growing conditions, as expressed by NDVI and precipitation and represented as 5 index values is known. In this manner, to supply growing conditions for the simulation the user only needs to specify the point locations of the sites being analyzed and the index (3 - average, 5 - very poor etc) to represent the expected growing conditions for each year in the simulation (Fig. 1). This simplified approach to describing climate conditions was developed so that users need not know anything about NDVI or what it means but instead only need to indicate the general sort of climate conditions desired for the simulation.

1.0.1.6.2 Modeling Herbaceous Annual Production

Herbaceous annual production is estimated in two steps, the first of which uses a statistical modeling approach relating NDVI and precipitation and site specific parameters with annual production. The NDVI has long been used to describe both net primary production (An 2009; Paruelo et al., 1997; Paruelo et al., 1998; Senay and Elliot, 2000; Wang et al., 2005) and biomass (Al-Bakri and Taylor 2003; Kogan et al., 2004; Reeves et al., 2001). Annual production is thus estimated as $Prod_{ann}$= (intercept) + (PPT * X1) + (NDVI * X2) + (SiteID [coeff.]) + (PPT * SiteID * X3) + (NDVI * SiteID * X4) where $Prod_{ann}$ is the estimated annual above-ground production, PPT is annual precipitation, NDVI is the annual maximum NDVI at the site, SiteID is a unique site specific coefficient for each BPS (e.g. a site representing the Intermountain Basins Big Sagebrush BPS, has a different coefficient than a semi-desert grassland site). In addition, precipitation has also been used extensively to estimate biomass (Le Houérou et al., 1988 ;Yang et al., 2008;Polley et al., 2010; Zhu and Southworth 2013). Models using only precipitation, however, will not perform well in areas where differences in management schemes produce differing vegetation assemblages and vigor. That is why the NDVI is used in concert with precipitation and site specific characteristics to estimate annual production. The annual values for precipitation and NDVI are derived from the growing conditions index defined above. The details of how these statistical models were created are beyond the scope of this report but the cross validation results are shown in Fig. 3.

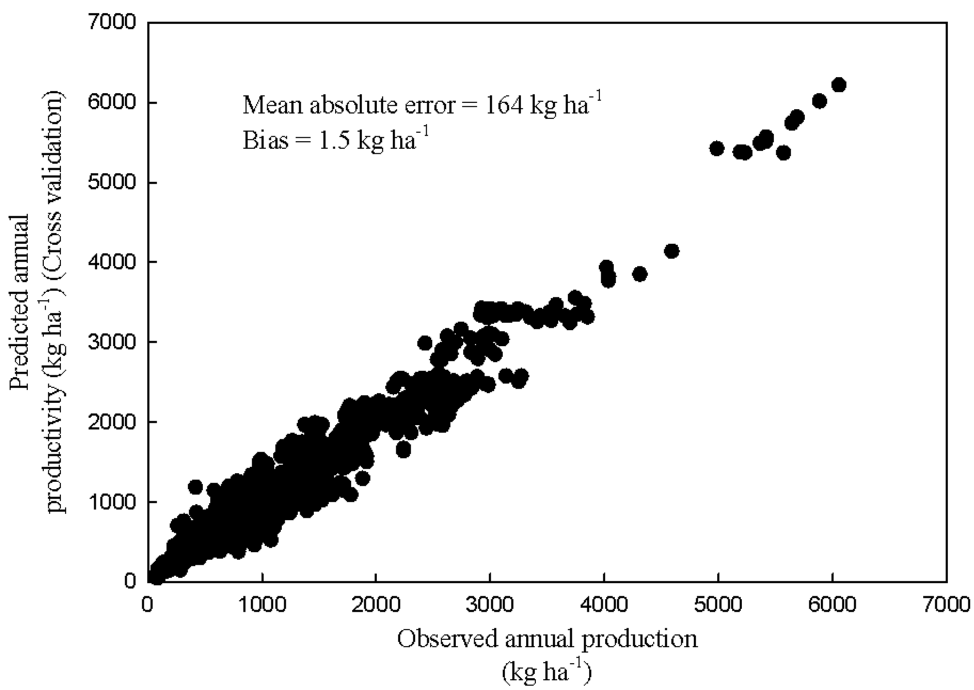


Figure 3. Cross validation of annual productivity model. The observed values are derived from the Soil Survey Geographic Database (SSURGO) dataset. The predicted values are derived from the biomass model relying on precipitation, NDVI, and BPS.

A general description of how the statistical models were built is as follows:

1) For each BPS compute low production, normal production and high annual production values in each Soil Survey Geographic (SSURGO) (http://www.nrcs.usda.gov/wps/portal/nrcs/detail/soils/survey/geo/?cid=nrcs142p2_053627) polygon. In the SSURGO database the low, normal and high annual

production values for each soil type are usually and represent the production "observations".

2) For each BPS calculate average annual precipitation and maximum NDVI.
3) These factors and their interactions form the basis for the statistical model describing annual production for each BPS.

The model of annual production, while theoretically representing total site production (shrub leaves and herbaceous response), is skewed towards representing the herbaceous response. This is because over the decades when field personnel collected clip and weigh annual production information in support of SSURGO development, generally speaking, preference was given to sites with dominated by herbaceous vegetation given the interest in utilizable livestock forage. Therefore, the production models are more reliable in habitats often dominated by herbaceous lifeforms, such as grasslands or shrub steppe.

However, the estimated annual production is total aboveground ecosystem production and is proportionally allocated to herbaceous lifeforms based upon the relative abundance of herbs versus shrubs. The relative abundance of herbs and shrubs is calculated as the proportion of cover by herbs or shrubs relative to total vegetation cover. For example, assume cover of herbaceous vegetation is 35 percent while cover of shrubs 15 percent cover. As a proportion of the total, the herbaceous component occupies 70 percent of the relative abundance (35 / (35 + 15) * 100). This simplified process is used due to a lack of suitable data describing the relationship between shrubs and herbs and annual production across diverse communities. The dominant assumption implied in this procedure is that there is a linear relationship between the relative abundance of herbs with estimated annual production.

1.0.1.6.3 Modeling Woody Annual Production

Modeling woody annual production requires estimates of growth rates which, in turn, depend on the succession class and BPS. Presently allometric equations are available for 39 shrub species. These equations were obtained from the H.J. Andrews Experimental Forest (http://andrewsforest.oregonstate.edu/data/abstract.cfm?dbcode=TP072&topnav=97). Though many equations have been formulated, the pool of possible allometric equations (Means et al., 1994) here (Table 4) is limited to those requiring only height and cover. For example, many shrub allometric equations linking stem attributes to other traits such as above ground biomass require parameters such as diameter at root collar (DRC) or number of stems (if the species typically manifests as multiple stems such as greasewood (*Sarcobatus vermiculatus*). If a species is recorded in the supplied plot inventory but is not represented by an equation in Table 4 then a crosswalk to a known species must be performed by the user. For example, presently there is no equation representing creosote bush (*Larrea tridentata*) so a crosswalk to another species' equation must be made for creosote bush. To accommodate this selection process, the RVS has an option whereby each shrub in each plot record is processed using every biomass equation available for the desired trait to calculate (e.g. above ground biomass) (Table 5).

Table 4. List of species and dependent variables for which allometric equations are available in the system.

Species	Allometric result
Alnus sinuata	Total foliage biomass
Amelanchier alnifolia	Total foliage biomass
Arctostaphylos columbiana	Total aboveground biomass
Arctostaphylos patula	Total aboveground biomass
Artemisia tridentata	Projected area, crown, horizontal surface
Ceanothus cordulatus	Total aboveground biomass
Ceanothus sanguineus	Total aboveground biomass
Ceanothus velutinus	Total aboveground biomass
Chimaphila umbellata	Total aboveground biomass
Chrysothamnus nauseosus	Total aboveground biomass
Cornus stolonifera	Total foliage biomass
Holodiscus discolor	Total foliage biomass
Juniperus communis	Total foliage biomass
Lonicera utahensis	Total foliage biomass
Pachistima myrsinites	Total aboveground biomass
Philadelphus lewisii	Total foliage biomass
Physocarpus malvaceus	Total foliage biomass
Prunus virginiana	Total foliage biomass
Purshia tridentata	Total aboveground biomass
Quercus kelloggii	Total aboveground biomass
Rhododendron macrophyllum	Total aboveground biomass
Ribes spp.	Total foliage biomass
Rosa spp.	Total aboveground biomass
Rubus idaeus	Total foliage biomass
Rubus leucodermis	Total aboveground biomass
Rubus parviflorus	Total aboveground biomass
Rubus ursinus	Total aboveground biomass
Salix spp.	Total foliage biomass
Sambucus cerulea	Total aboveground biomass
Sheperdia canadensis	Total foliage biomass
Sorbus scopulina	Total foliage biomass
Spirea betulifolia	Total foliage biomass
Symphoricarpos albus	Total aboveground biomass
Symphoricarpos albus	Total foliage biomass
Vaccinium globulare	Total foliage biomass
Vaccinium scoparium	Total aboveground biomass

Table 5. The RVS offers the ability to process every plot with every biomass equation so the user can see the different results of estimated per stem biomass for shrubs. Each number is a different equation and the units are pounds per acre. The mean and standard deviation yield information about the uncertainty surrounding each biomass calculation. Users can elect this function to process all of their plot data to understand spatial variability in fuels.

Plots	**165**	**166**	**167**	**168**	**201**	**202**	**620**	**622**	**623**	**624**	**626**	**627**	**628**	**629**	**630**	**631**	**Mean**	**STD**
EOSG 02	2	2	3.5	4	4	3.5	3	3.5	4	3.5	3	3	4	3	3.29	0.67	3.3	0.7
EOSG 04	2.5	1.5	3	2	5	1.5	1	3.5	1	1.5	2	5	4.5	4.5	2.75	1.49	2.8	1.5
EOSG 05	2	3.5	3	4	3	2	1	4.5	4	4	1.5	4	1	3.5	2.93	1.21	2.9	1.2
EOSG 06	1.5	3	3	3	4.5	5	5	5	1.5	4.5	2	1	2.5	1	3.04	1.52	3	1.5
EOSG 07	2	4.5	5	2	2	3.5	2.5	5	1.5	2.5	1.5	4	2	4	3	1.29	3	1.3
EOSG 09	1.5	3	3.5	4	4	5	4.5	5	3	2.5	2.5	4.5	3.5	3	3.54	1.03	3.5	1
EOSG 10	2	2.5	4.5	2	3	3	4.5	1	1.5	2.5	2	5	1.5	1	2.57	1.3	2.6	1.3
EOSG 11	5	2	3.5	5	3	3.5	4	4	4.5	5	3.5	3.5	2	4.5	3.79	0.99	3.8	1
EOSG 12	6	14	13.5	8.5	5.5	5.5	10.5	8.5	6	8	15	12	5.5	7	8.96	3.43	9	3.4
EOSJ 01	5	15	8	7.5	13	5.5	7	15	5.5	10.5	15	6	8	13.5	9.61	3.91	9.6	3.9
EOSJ 02	13.5	10	11	7.5	7.5	9	12	8.5	13.5	11.5	9	12.5	14	7.5	10.5	2.38	10.5	2.4
EOSJ 03	11.5	7	14	10.5	9.5	12	13	12.5	6.5	15	11.5	6.5	10	9	10.61	2.7	10.6	2.7
EOSP 01	10	12	7	12.5	5	8.5	13.5	15	15	9.5	13.5	5	12	15	10.96	3.53	11	3.5
EOSP 02	8.5	14	13	6.5	7.5	6	5.5	11	14	5	7.5	10.5	14	12.5	9.68	3.41	9.7	3.4
EOSP 03	7.5	15	7.5	7	13.5	15	7.5	6.5	7	8	7	6	8	5	8.61	3.31	8.6	3.3
EOSP 04	6.5	11.5	14	7.5	6.5	11	7.5	9.5	6.5	7.5	6	5	6	10.5	8.25	2.62	8.3	2.6

As indicated in Table 5, a distribution of estimated per stem biomass values can be generated for each shrub record in the input database. Once the plot level inventory of structure and composition is known, the annual production of shrubs is estimated using the following steps.

1) Calculate the inter-annual growth rates of shrubs
2) For each year in the simulation estimate the incremental change in stature as changes in cover and height.
3) Apply stand level allometric equations describing biomass of shrubs for each year of the simulation.
4) Changes in estimated biomass are subsequently used to represent annual production of shrubs in a year. These estimates, however, do not include an accounting for "annual increment" of woody stems.
5) Expand estimates of "per stem" annual growth to an area (acre) basis

1.0.1.6.3.1 Step 1 - Shrub Growth Rates

Stand level shrub growth rates are modeled as a potential growth rate (controlled by site and successional stage) which is attenuated by the climate index discussed above. Growth rates, however, can increase or decrease based on growth conditions, depending on the site. The sites referred to here are, again, determined by the BPS estimated at each plot. This is a very critical point for users of RVS to understand. If a site is coded with an incorrect BPS, the simulation will be very unreliable because the BPS controls growth rates.

An example of how this is computed is found in Table 6. As can be seen in Table 6, if an incorrect BPS is chosen for a plot then shrubs will grow too fast or too slow. Likewise, transitions between succession classes will be too fast or too slow so a user must do everything they can to ensure that the correct BPS is chosen.

Table 6. Example of how growth rates for shrubs are calculated for a Biophysical Setting (BPS). This Biophysical Setting is the Inter-Mountain Basins Montane Sagebrush Steppe - Mountain Big Sagebrush. These growth rates only represent shrubs in the system.

Stage	Start	End	Min	Max	Min	Max	Height growth rate (m yr^{-1})	Cover growth rate (% yr^{-1})
	years[A]		canopy cover (%)[B]		height (m)			
Early	0	11	0	5	0	0.6	0.2	0.83
Mid	12	49	10	30	0.6	3.1	0.160	1.58
Late	50	110[B]	31	80	0.6	10	0.167	1.33

[A] – The maximum age of 110 years in this example simply indicates the endpoint at which the woody vegetation at this BPS will cease to grow taller or with greater cover and has therefore reached an "equilibrium" with the site.
[B] – Each cohort of dominant species within a successional stage is assumed to reach maximum stature at the midpoint of time within the class. For example, in the Early class in this BPS, both cover and height are assumed to reach a maximum by 2.5 (3) years.

A good rule of thumb is that if a user cannot determine the BPS, then a series of BPS's should be evaluated for that site to determine whether or not the growth rates seem correct. The BPS product has been structured to reflect the fact that much of the pre-Euro American vegetation has been converted to various land uses such as agriculture and residential land Fig. 4. There are 112 BPS types for which growth rates and ecological succession (albeit crudely) can be simulated, of which, 21 are never dominated by shrubs in any succession stage (according to the LANDFIRE BPS succession models) and are therefore represented by herbaceous or succulent species.

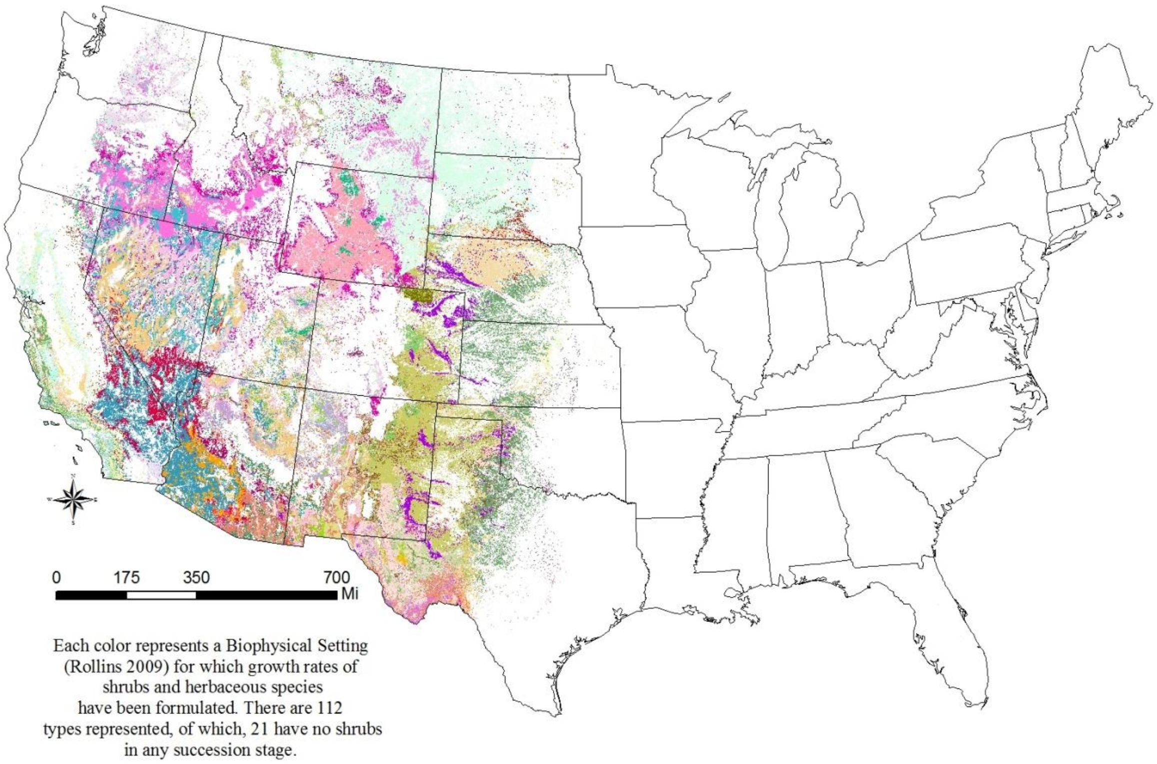


Figure 4. The spatial extent of Biophysical Settings (areas that are now converted to alternate land cover or land use classes, such as agriculture, are represented as a white color) that can be potentially evaluated in the system discussed in this report combining the Rangeland Vegetation Simulator and the ST-SIM program.

The spatial arrangement of the 112 BPS's available in the system is presented in Fig. 4. Table 6 provides an example of how growth rates are generally estimated using the succession models in the LANDFIRE database. There are details omitted on this topic because it is beyond the scope of this report but the table gives a general idea of shrub growth rates implied in the system. The growth rate estimates derived from this process represent a kind of potential growth rate.

1.0.1.6.3.2 Steps 2 and 3 and 4: Estimate Incremental Change, Biomass, and Annual Production

For each year in the simulation, the annual change in cover and height is estimated using the growth rate which is attenuated by the growing conditions. After estimating the growth of shrubs, allometric relationships are applied so that a new estimate of incremental above ground biomass is produced. An example allometric relationship of *Artemisia tridentata* (big sagebrush) and *Arctostaphylous patula* (greenleaf manzanita) to canopy dimensions is shown in Fig. 5. An equation from (Frandsen 1983) was used in this example for the sagebrush while one from (Ross and Walstad 1986) was used in the greenleaf manzanita example. By subtracting the previous year's biomass from the present, an estimate of production (above ground production) can be generated (**EQ. 2**).

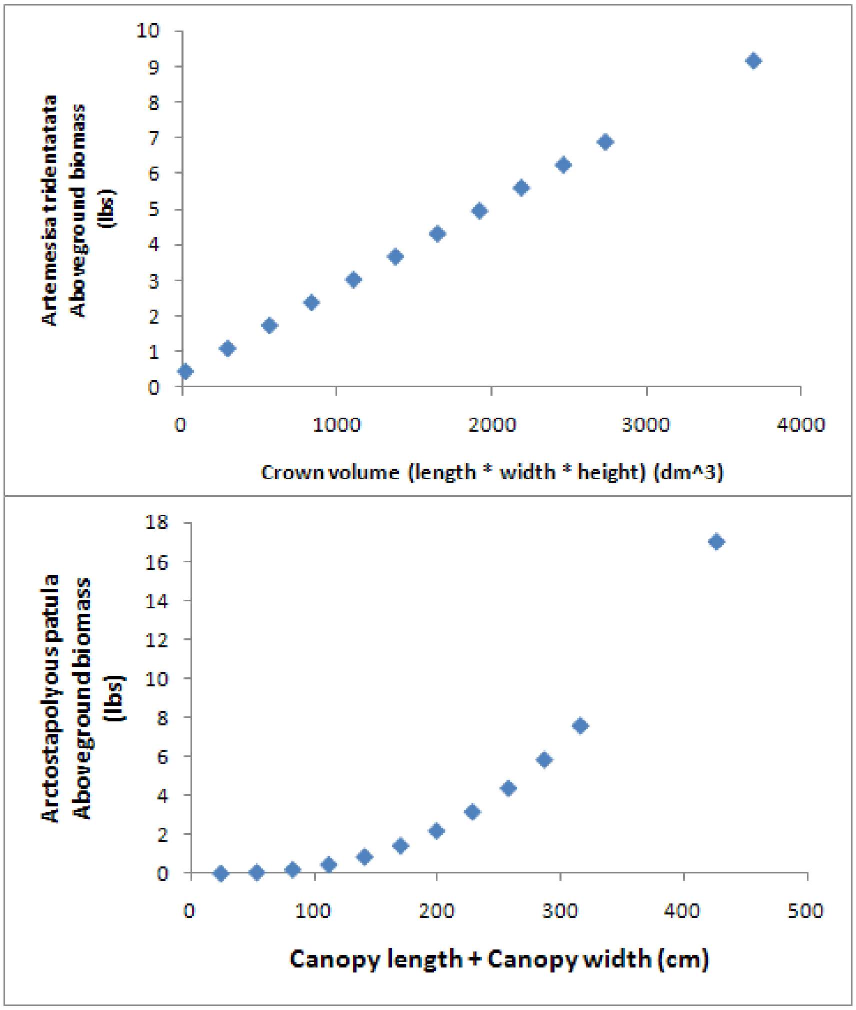


Figure 5. Relationships between shrub physiognomic characteristics and above ground biomass for *Artemisia tridentata* (big sagebrush) and *Arctostaphylos patula* (greenleaf manzanita). The equations used to produce the above ground biomass for sagebrush and greenleaf manzanita are BAT = 201.4062 + 1.162 * VOL and BAT = exp(-7.3531 + 2.6925 * ln(LEN+WID), respectively where BAT is total above ground biomass, VOL is canopy volume, LEN is the length of the canopy measured perpendicularly do the width (WID).

EQ 2. $\mathbf{Shrub_{annprod} = Shrubbio_{T} - Shrubbio_{T\text{-}1}}$

where $Shrub_{annprod}$ is the estimated annual production of shrubs, $Shrubbio_{T-1}$ is the estimated shrub biomass at 1 year prior and $Shrubbio_{T}$ is the estimated shrub biomass in the present year.

1.0.1.6.3.3 Steps 5 – Expand estimates of “per stem” annual growth to an area (acre) basis

All biomass, production and fuel data are first generated on a per stem, per species basis. To scale these estimates to an area an expansion factor is needed. Therefore, an estimate of stems per acre is needed. For each plot, for each shrub species encountered in the plot database, the stems per acre is calculated in three steps

1) Compute the projected crown area on a horizontal surface

2) Quantify the number of times this area can be divided into an acre
3) Scale the value from point 2 above by the absolute canopy cover that each species represents in the stand.

The projected crown area (PCH) is estimated using the following equation:

EQ. 3. log10 (PCH) = -0.8471 + 2.2953*log10(HT),

where PCH is the projected horizontal crown area in cm^2 and HT is the height of each shrub in cm (Fig. 6). In the example given in Fig. 6, the shrub species given is 1 meter tall occupying 20% canopy cover (Fig. 7). With these dimensions the estimated stems per acre is 1,461. Assume that the per stem total aboveground biomass estimate per stem is 6 lbs (dry weight basis). This would be tantamount to 6 lbs per stem * 1461 stems per acre = 8,766 lbs ac^{-1}.

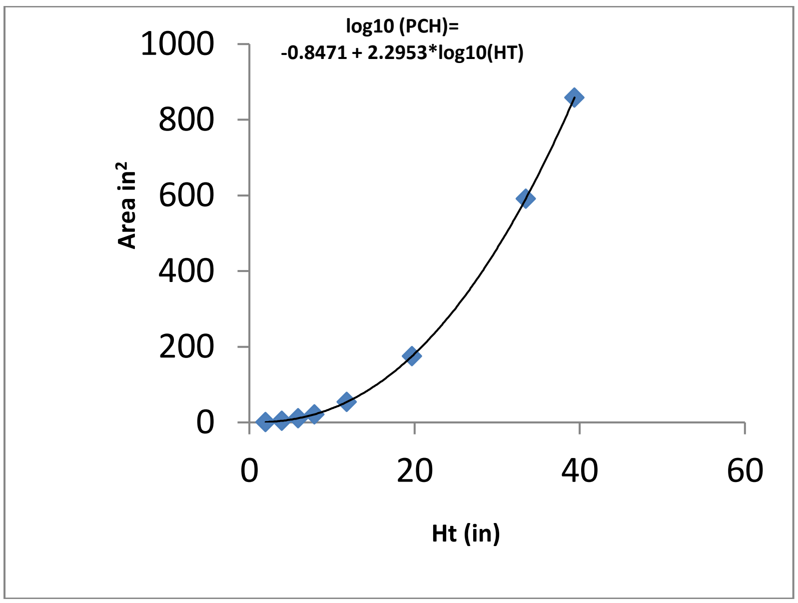


Figure 6. First step in calculating stems per acre is to claculate the projected crown surface area (in this case in^2). In this example, the cm have been converted to inches.

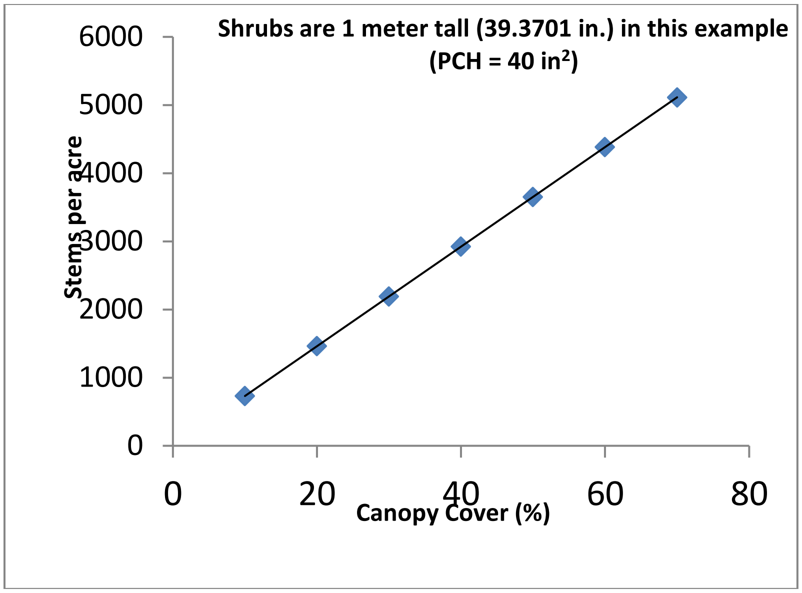


Figure 7. Scaling potential stems per acre by the canopy cover estimate for each shrub species in a plot data list. In this instance, the shrubs were estimated at near 1 meter tall. This results in 859 in^2 (5.96 ft^2) of projected crown area. If this species was estimated at 100% canopy cover the number of stems per acre would be 43,560 ft2 (the numebr of square feet per acre) / 5.96 ft2 = 7,305. However, as canopy cover is reduced, the number of stems per acre is reduced commensurately. For example, at 20% canopy cover the shrub which is 1 m tall in the example would yield an estimated stems per acre at 1461. This was calculated by taking the total possible stems per acre at 100% canopy cover and reducing it by 80% because the estmate canopy cover. Therefore 7,305 * 0.2 = 1,461.

1.0.1.7 Linking Herbaceous Canopy Cover and Height with Biomass

At this stage in the modeling process, production estimates have been derived for both the herbaceous and shrub components of the site being analyzed. In addition, shrub cover is known given the growth rates for each BPS and the inventory data supplied in the initiation of the simulation. However, an estimate of herbaceous cover and height is still needed to sufficiently describe fuelbed properties for each year in the simulation. The LANDFIRE BPS succession models do provide estimates of herbaceous growth, and we decided to use a combination of methods for estimating cover and height of the herbaceous components of each vegetation type. The reason for this is that the annual production of herbs is more variable than that of shrubs so an explicit linkage between canopy cover (foliar cover not basal) and height and biomass is needed.

Linkages between canopy cover or height and herbaceous biomass have not been established across the breadth of non-forested ecosystems available for simulation in the system. In addition, data describing these relationships often only apply to individual sites or are recorded on very small experimental areas rendering them less reliable across sites. Recent work demonstrates, however, that linear relationships between canopy cover and biomass *within* a given system are reasonable to expect (Röttgermann et al., 2000) but in areas of high biomass actual predictions of biomass from remotely sensed data (such as the NDVI reported here) are more difficult due to the well-known "saturation" feature (Tian et al., 2015). Fig. 8 clearly shows the saturation feature which, in this dataset, begins to occur at about 2,500 lbs ac^{-1} of annual production. Recognizing the 1) lack of suitable published data describing cover/height and biomass relations; 2) the overall linearity of the relationship within a single system (i.e. within a single vegetation type such as shortgrass steppe, the relationship between canopy cover and biomass is more or less linear), we used linear functions within each BPS to quantify the relationship between biomass, canopy cover and vegetation height.

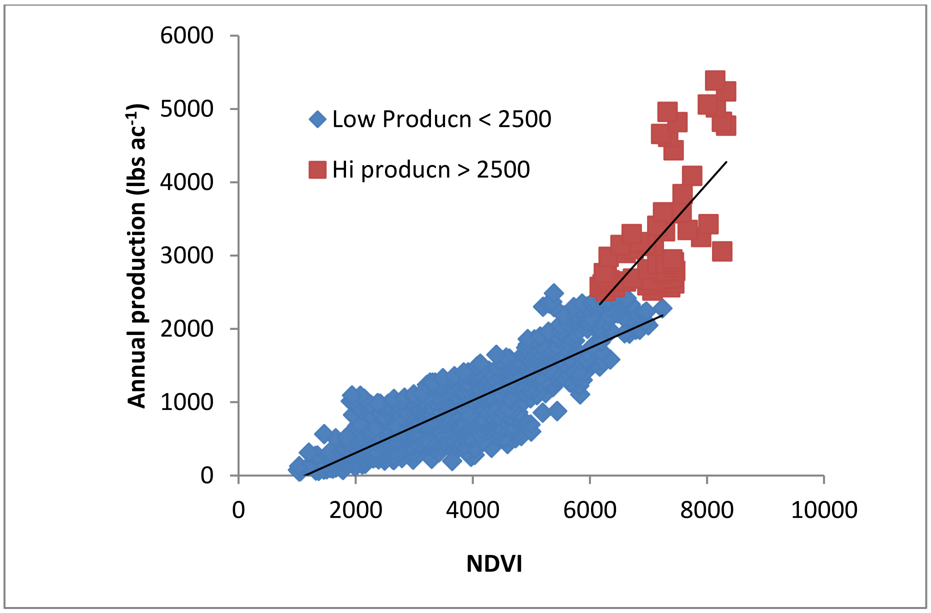


Figure 8. The NDVI demonstrates a saturation feature whereby increases in biomass do not produce commensurate increases in NDVI. This threshold appears to be 2,500 lbs ac^{-1}, and therefore, the relationship between NDVI and production is relatively linear from 0 to 2,500 lbs ac^{-1}.

For each of the 112 BPS types available in the system we quantified the maximum, minimum and mean expected production by applying the statistical model to estimate annual production described above. The low values represented in Table 7 represent a mean "low" predicted biomass value across many sites represented by a given BPS. To illustrate, review the spatial distribution of BPS units. Each color represents a single BPS across the landscape. Obviously, within such broad geographic ranges, high variability in NDVI, precipitation and therefore annual production is observed. As a result, the values present in Table 7 represent averages across the spatial extent of each BPS and production class (low, average, high). The production values do not suggest upper or lower limits for a given site, but instead represent the generally expected ranges of production. It is against these values of production that expected ranges of canopy cover and vegetation height are regressed. The canopy cover and height "observations" used for this purpose are retrieved from each BPS succession model. This is meant to yield a general idea of the usual range of canopy cover and height for each BPS.

Table 7. Estimated relationships between annual production and canopy cover and stand height. The slope and intercept represent the relationship where annual productivity is the independent variable. Only 7 Biophysical Settings (BPS) out of 112 possible are depicted here.

BPS	Annual Production (lbs ac-1)			Foliar canopy cover (%)			Canopy height (m)			Canopy cover slope	Canopy height slope
	Low	Average	High	9	19	29	0.1	0.56	1.01	0.023	0.0003
Apacherian-Chihuahuan Semi-Desert Grassland and Steppe	500	828	1218	21	43	64	0.19	0.69	1.2	0.024	0.0002
Central Mixedgrass Prairie	1912	2623	3346	24	46	67	0.27	1	1.73	0.019	0.0002
Central Tallgrass Prairie	3718	4715	5559	6	24	41	0.19	1.3	2.42	0.0297	0.0006
Inter-Mountain Basins Big Sagebrush Shrubland	692	1065	1511	10	21	32	0.2	0.9	1.6	0.0208	0.0005
Inter-Mountain Basins Big Sagebrush Steppe	652	1022	1457	51	76	100	0.1	1.6	3.1	0.0211	0.0001
South Texas Lomas	2699	3620	4519	6	24	42	0.1	0.3	0.5	0.0222	0.0002
Wyoming Basins Dwarf Sagebrush Shrubland and Steppe	750	1143	1603	9	19	29	0.1	0.56	1.01	0.0233	0.0003

For each BPS the regressions are forced through zero so that if an estimate of 0 pounds per acre of annual production is found, the estimate of canopy cover will also be 0.

In each BPS succession model there are a series of stages (for non-forested systems there are usually 3; early, mid and late). In each successional stage there are ranges of height and cover of dominant life forms estimated. Thus, as depicted in Table 7 the slope resulting from linear regression of annual production upon cover and height can be estimated. We recognize that relating canopy cover and height to biomass across multiple vegetation communities is generally unsupported in the literature. This is good because we hope that skeptics may also be able to offer robust field data that can improve the relationships we established between biomass and cover and height. Further we recognize that within a given functional group or lifeform there can be extensive morphological differences which will skew the relations between biomass and cover and height (Mitchell et al., 1987). The values do not represent upper and lower thresholds of cover and height but, like the estimated production values, represent normally expected values for lower, average and upper cover and height condition. Finally, it is also important to remember that there is usually no significant difference in modeled fire behavior or fuel loads between herbaceous cover of 25% and 35%. So again, the efficacy must we weighed against the accuracy.

1.0.1.8 Management Actions

Two management actions are available during simulation including herbivory and fire. Initially, herbicide application was considered as a management action but, due to a surprising lack of data or (information) describing topkill effects and ecosystem response to herbicide application (either broadleaf types or glyphosate), these effects are not simulated.

There are two aspects of modeled management actions that are important for the user to understand. The first aspect is the effect on the successional dynamics. For example, fire will usually kill most big sagebrush species and potentially create a new successional pathway and change states in coming years. The second aspect is the effects of management actions on productivity, standing biomass, and fuelbed parameters. Using the previous example, if fire consumes big sagebrush individuals, 1, 10 and 100, and 1000 – hr time lag fuels from shrubs are reduced or removed from the site and potentially there may be an increase in 1 – hr fuels from herbaceous species in response to competition release. Since the effects of management actions on successional dynamics (i.e. how vegetation composition responds to management) vary considerably here they are generally described but the effects on biomass and fuelbed parameters are explained in more detail.

1.0.1.8.1 Fire

Presently it is assumed that fire will reduce 1, 10, 100 and 1000 (if present) – hr time lag fuels proportional to the amount of shrubs reduced across the landscape. The amount of shrub kill after a fire is quite variable in practice and depends on many factors and is therefore beyond the scope of the system to provide that information automatically. As a result, the estimated effects of fire should be calibrated by users depending on the vegetation in question. The system does, however, provide a default starting point such that non-sprouting shrubs will be "killed off" or removed from the stand (Fig. 9). In contrast, sprouting species are consumed but re-establishment and growth is simulated more quickly depending on the system. The assumptions present in these subroutines are that:

1) Each species is either a sprouter or non-sprouter
2) If they are sprouters, every individual in the stand will recover

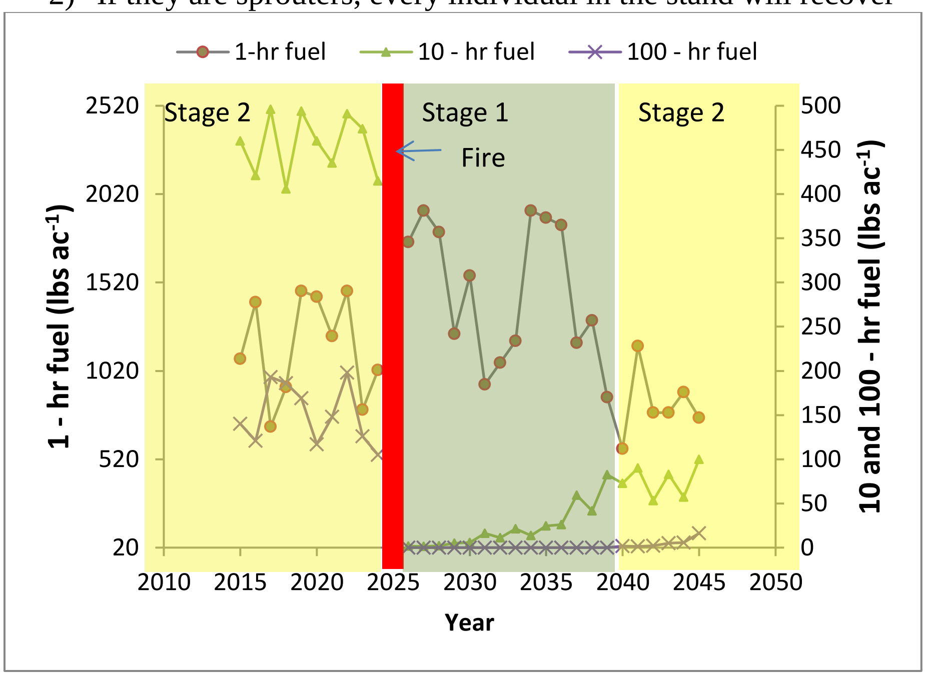


Figure 9. Example of how a fire will reset succession based on the BPS being modeled. This, in some cases is not a good view of ecology but it's the limitaion of the BpS system. For describing successional development and trajectories.

Like other assumptions implicit in this system, these are overly simplistic because some shrubs like *Purshia tridentata* (antelope bitterbrush) will sometimes resprout following fire but not always. For example, it is often killed by summer or fall fire (Blaisdale 1950; et al., 1992), but may sprout after light intensity spring fires (Agee 1994; Blaisdell and Mueggler 1956) but not after multiple fires (Shaw and Monsen 1983) The general effect of fire in the RVS is to reduce fuels (fuel consumption) and to reset successional status.

1.0.1.8.2 Herbivory

In a similar manner to fire, effects of herbivory differ greatly between sites. To simulate the effects of herbivory on stand components the user needs only to supply stocking rate information (how many animals, how long are they present and how big is the landscape being simulated) in addition to the type of herbivore in the simulation.

The reduction in biomass and fuels resulting from herbivory are based on the empirical observation that ruminants generally require roughly 2.6% of their body weight of daily intake of dry matter. For example, a 1000 pound cow will require roughly 26 pounds of dry matter intake per day. If this animal is present on the site being simulated for 1 month this is tantamount to 780 (26 pounds times 30 days) pounds of dry matter (an animal unit month; AUM). Many factors influence the actual amount of dry matter intake including age, breed, forage quality, supplements, water availability, metabolic state, etc. In an effort to simplify the situation, however, the assumption of 2.6% of body weight is used. In addition to stocking rate information, the type of animal must be supplied as well. This is necessary because different classes of livestock generally prefer different types of forage.

In the system described here, grazers and intermediate classes of livestock are available for simulation. Grazers prefer and consume herbaceous stand components (especially grasses) while intermediate species such as goats will consume browse at nearly an equal rate to grasses but usually only smaller size classes of browse (woody material) such as 1, and 10 – hr time lag fuels. The various species of herbivores and the AUM adjustments for body size are shown in Table 8.

Table 8. Average weights of herbivores and conversion factors for estimating daily forage intake.

Animal	Average weight (lbs)	AUM Conversion	Herbivore Class[1]
Cow	1,000	1	Grazer
Horse	1,100	0.9	Grazer
Elk	600	1.5	Grazer
Mule Deer	125	4.5	Intermediate
Sheep	120	5	Grazer
Goat	120	5	Intermediate
Pronghorn Antelope	90	6	Intermediate

[1]These classes are assigned for the present decision support system described in this report. In reality, the classification may not be this simplistic with only two classes.

As an example, 1 cow is roughly equal to 5 sheep in terms of body weight and expected daily intake requirement. So if 1 sheep is present the calculation of daily forage intake is 26 pounds

*1/5 = 5.2 pounds of dry matter intake per day. In addition to conversion assumptions, the general class of livestock is also shown. This is a difficult and incorrect (albeit necessary) assumption because any class of livestock can switch preferences based on many factors including availability and familiarity. For example, in some situations cows will consume browse such as sagebrush (Peterson et al., 2014; Ngugi et al., 2014; Veblen et al., 2015) if they are trained. Using these assumptions and this information, biomass and therefore fuels, are reduced proportionally to stocking rate and duration and herbivore type (Fig. 10). In Fig. 10, the simulated effect of 5 goats for 30 days on various fuel size classes is demonstrated.

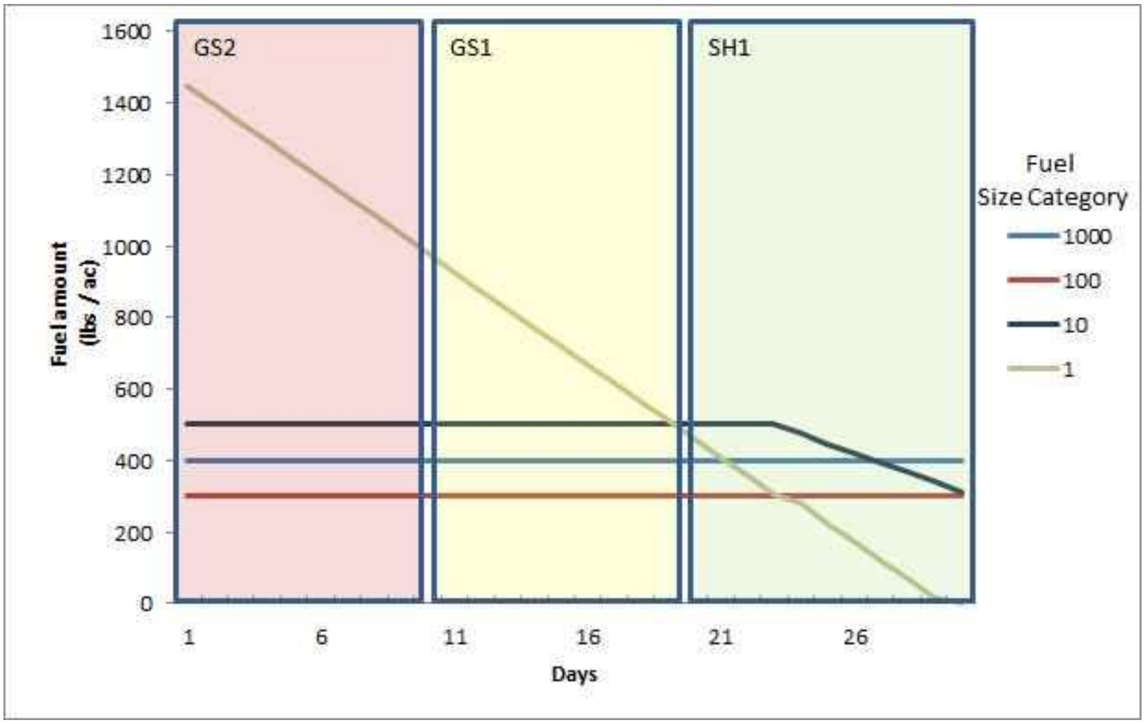


Figure 10. Estimated reduction in biomass, and therefore fuels, in response to herbivory. The shaded colors and text including GS2, GS1, SH1 represent surface Fire Behavior Fuel Models (Scott and Burgan 2005) and, in this order, depict the linear depletion of 1-hr fuel from the stand based on the standardized estimate for forage requirements of a cow represented by the Animal Unit Month (780 lbs of dry matter per month).

These reductions are possible only with one, sometimes incorrect, but necessary assumption. The dominant assumption is that no regrowth occurs after herbivory since the RVS operates on an annual timestep and biomass represents peak greeness. This assumption would be more correct if the herbivory occurs after the peak of the growing season and if the region does not experience a bi-modal growing season.

1.0.1.9 Fuelbed Components

1.0.1.9.1 Individual Components

For each year in the simulation, fuels are estimated for every stand. Estimating fuelbed parameters occurs in three steps. First, the present year's herbaceous production is added to estimated standing dead herbaceous vegetation resulting from previous growth. Estimating the previous year's standing dead or herbaceous litter material is not based upon experimental observation for a couple of reasons. This topic is not widely studied across multiple ecosystems and it is difficult and time consuming to derive experiments that track the fate of herbaceous growth, senescence and decomposition across multiple vegetation types. The paucity of suitable plot data for estimating the amount of standing dead material is therefore based on the authors guess and casual observations of various vegetation stands with significant herbaceous components throughout the western United States. Our colleagues at the Agricultural Research Service (ARS) recently gave us results from 10 years of grassland observations on Shortgrass steppe near Cheyenne, Wyoming and standing dead values averaged 22% across grazing treatments. This means that, on average, in shortgrass steppe, standing crop of the present year includes 22% of the previous year's production plus the present annual production. The function used in the RVS, to estimate the standing dead material is shown in Fig. 11 In this function, on average, the first year value for standing dead remaining is about 30%.

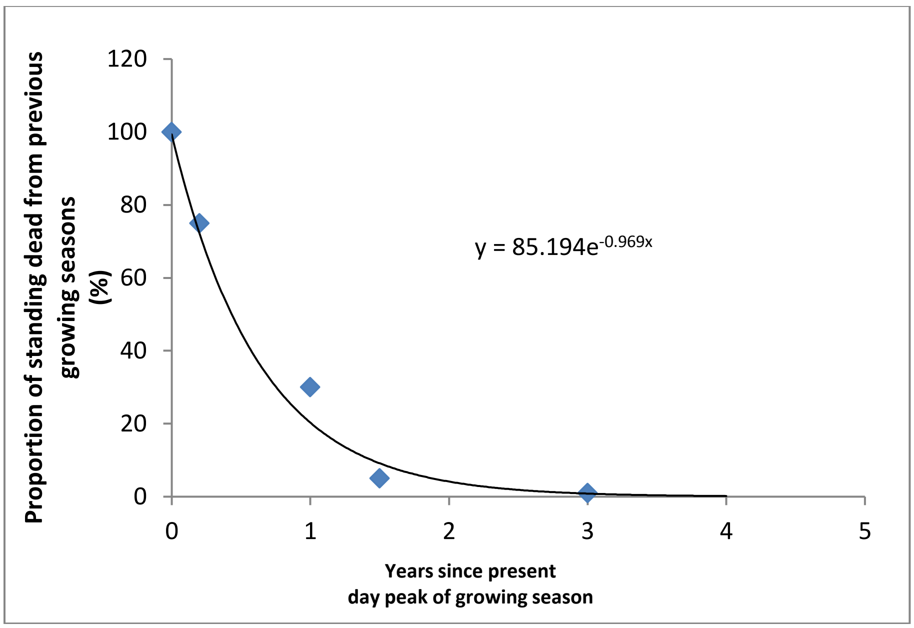


Figure 11. The postulated effect of time on the amount of dead grass in a stand estimated at Standing dead = $85.194e^{-0.969x,}$ where X is number of years past since present day. This relationship is a guess based on personal observations by the author because, to our knowledge, relationships like this have not been quantified by other researchers in a suitable fashion.

To illustrate consider a site producing 1000 lbs ac^{-1} of herbaceous production per year for the present year and the last 3. This is tantamount to approximately 1,330 lbs ac^{-1} of total phytomass at the peak of the present years growing season based on Fig.11. This is important because the herbaceous portion is assumed to be comprised of 1-hr time lag fuel size class (0 to ¼ in. diameter), so accounting for the herbaceous components in the stand is important for characterizing fire effects and behavior.

The second step in estimating fuel bed parameters involves accounting for woody fuels including the annual production of shrubs. The size classes of 1, 10, and 100 hour time lag fuels correspond to diameters of 0-¼", ¼"-1", 1"-3" respectively and are estimated using allometric relationships in much the same way that biomass and production are estimated for shrubs (Fig. 12). The general idea for this process emanated from (Means et al., 1996) and the library of allometric equations were received from obtained from the H.J. Andrews Experimental Forest (http://andrewsforest.oregonstate.edu/data/abstract.cfm?dbcode=TP072&topnav=97).

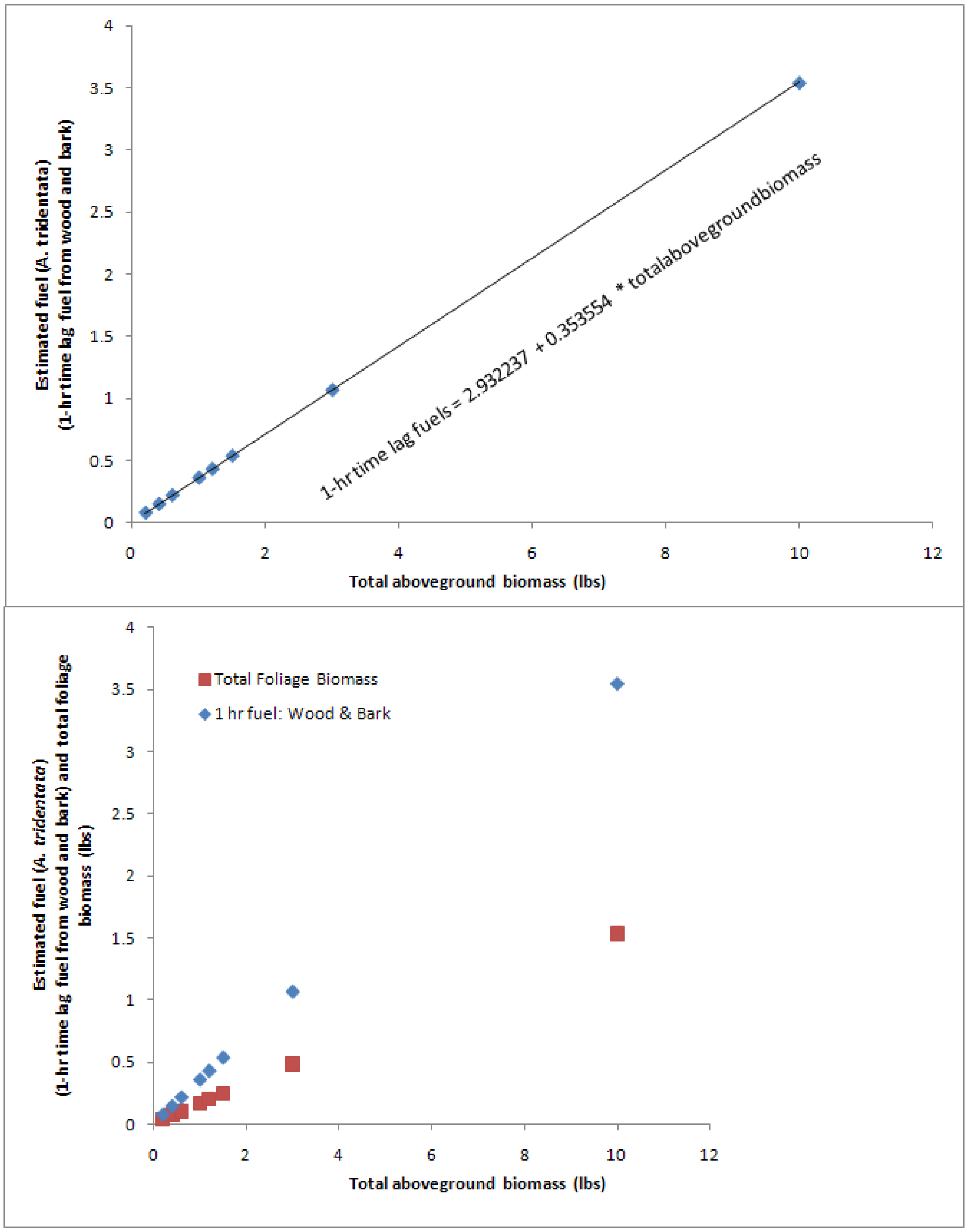


Figure 12. Example allometric equations for estimating 1-hr time lag fuel for wood and bark and total foliage fuel for big sagebrush. These equations for big sagebrush are FWB = 2.932237 + 0.353554 * BIO and ln(BFT) = -1.498408 + 0.955207 * ln(BAT) where FWB is the estimated fuel from wood and bark, BAT is total aboveground biomass, and BFT is the total 1-hr fuel in the shrub canopy from foliage.

Data were provided by the HJ Andrews Experimental Forest research program, funded by the National Science Foundation's Long-Term Ecological Research Program (DEB 1440409), U.S. Forest Service Pacific Northwest Research Station, and Oregon State University. One of the principle differences between estimating fuel size classes versus estimating biomass of shrub is that inputs to biomass are generally limited to parameters associated with canopy cover and height while many fuel equations use, as their primary input, total above ground biomass which is itself estimated from allometric relations. There are 27 species represented in the system but for each species there are multiple equations for various fuel parameters (Table 9).

Table 9. List of all species and associated fuel parameters available in the RVS.

Species	Total foliage biomass	Dead crown			Dead wood & bark			Live Crown			
	TFB	1hr	10hr	100hr	1hr	10hr	100hr	1hr	10hr	100hr	1000hr
Acer glabrum	X				X	X	X				
Alnus sinuata	X				X	X	X				
Amelanchier alnifolia	X				X	X	X				
Arctostaphylos patula	X	X	X	X	X	X	X	X	X	X	X
Artemisia tridentata	X	X	X	X	X	X	X	X	X	X	
Berberis repens	X				X						
Ceanothus velutinus	X	X	X		X	X		X	X		
Cornus stolonifera	X				X	X					
Holodiscus discolor	X				X	X					
Juniperus communis	X				X	X					
Lonicera utahensis	X				X	X					
Menziensia ferruginea	X				X	X					
Philadelphus lewisii	X				X	X					
Physocarpus malvaceus	X				X	X					
Prunus virginiana	X				X	X					
Purshia tridentata	X	X	X	X	X	X	X	X	X	X	
Ribes spp.	X				X	X					
Rosa spp.	X				X	X					
Rubus idaeus	X				X	X					
Rubus parviflorus	X				X	X					
Salix spp.	X				X	X	X				
Shepherdia canadensis	X				X	X					
Sorbus scopulina	X				X	X	X				
Spirea betulifolia	X				X						
Symphoricarpos albus	X				X	X					
Vaccinium globulare	X				X	X					
Vaccinium scoparium	X				X						

There are potentially 11 fuel parameters to estimate using the allometric equations in the system (Table 9). The system reported here makes estimates of 1, 10, and 100-hr, and to a lesser degree 1000-hr, fuel components on shrubs using the equation types listed in Table 9 and incrementally accounts for shrubs in wood and bark and foliage alike.

1.0.1.9.2 Fuel Classifications

The third and final step in estimating fuelbed parameters is to use composition, structure, biomass, and fuel size class loadings to classify a plot at a given point in time during the simulation into surface Fire Behavior Fuel Models (FBFM) (Anderson 1982; Scott and Burgan 2005), Fuel Loading Models (FLMs) (Sikkink and Keane 2009). In addition, many of the attributes produced using the RVS can be used to develop new fuelbeds in the Fuel Characteristic Classification System (FCCS) fuelbeds (Ottmar et al., 2007). Surface FBFM's are classified based on rulesets that account for the above mentioned site and fuel characteristics. An example rule set is shown in Table 10. The actual classification process is somewhat more detailed than suggested by Table 10.

Table 10. Example rulesets between site conditions, fuel parameters and surface Fire Behavior Fuel Models (FBFM). Note that multiple fuel models are possible within the ranges of stand attributes depending on what values each attribute exhibits.

Biophysical Settings	Herb Ht (ft)	Herb Cover (%)	Shrub Ht (ft)	Shrub Cover (%)	Live Herb (lbs ac)	FBFM 40	FBFM 13
Intermountain Basins Big Sagebrush Steppe	0 to 1	0 to 20	0 to 2	0 to 20	0 to 800	GR1/SH1/ GS1	1
Intermountain Basins Big Sagebrush Steppe	2 to 4	20 to 60	2 to 5	20 to 60	800 to 1500	GS2/GR2	2/6
Intermountain Basins Big Sagebrush Steppe	> 4	60 to 100	> 5	60 to 100	> 1500	GS2/SH5	2/5/6/
Western Great Plains Shortgrass Prairie	0 to 1	0 to 20	0 to 2	0 to 20	0 to 1000	GR1	1/8
Western Great Plains Shortgrass Prairie	2 to 3	20 to 60	2 to 5	20 to 60	1000 to 2000	GR2	2/5/6/
Western Great Plains Shortgrass Prairie	> 3	60 to 100	> 5	> 60	> 2000	GR2/GR4 /SH5	2/3/6/

Note that several fuel models can be possible within a given range of stand attributes (Table 10). Rules is meant to give the reader a general understanding of how the process is conducted. For example, in the Western Great Plains Shortgrass Prairie BPS, if herb heights are about 2 - 3 feet but cover is 60% and production is 2,000 lbs ac^{-1}, then a GR2 (Scott and Burgan 2005) may be appropriate, but if herb cover is 80% and production greater than 3,800 lbs ac^{-1}, a GR4 may be more useful for describing potential fire behavior. Similar rulesets are in place for the FLM (Table 11). This suite of fuel classification information enables fire behavior and fire effects in non-forested systems.

Table 11. Fuel Loading model (FLM) classification from Lutes et al (2011). Most stands users will encounter would be classified as an FLM014 (< 12 T ac^{-1}).

Effects Group	System	Total Plot Load: Lower limit (>)	Total Plot Load: Upper limit (<=)
		------- kg m^{-2} (T ac^{-1}) ------	
FLM014	Sagebrush	0.0 (0.0)	2.7 (12.0)
FLM053	Sagebrush	2.7 (12.0)	6.2 (27.5)
FLM065	Sagebrush	6.2 (27.5)	13.0 (58.0)
FLM015	Chaparral and herbaceous	0.0 (0.0)	4.3 (19.0)
FLM054	Chaparral and herbaceous	4.3 (19.0)	9.9 (44.0)
FLM066	Chaparral and herbaceous	9.9 (44.0)	20.6 (92.0)

1.0.1.10 **Dealing With Trees**

The RVS will not simulate vegetation succession on all sites (BPS's). Generally speaking, there are 3 possibilities for any given plot in the input database and ensuing simulations. To determine which of these types a given plot belongs to, the RVS reads the list of input plots prior to any simulation. After reading the BPS, the RVS will determine what to do next, based on the type of BPS present (Appendix 1).

These situations are described below:

1) All processes (succession, growth, biomass, and disturbance) can be simulated "as-is". This situation reflects vegetation types where tree species are not part of the BPS successional modeling framework. Types such as Intermountain Basins Big Sagebrush, and Northern Great Plains Mixed-grass Prairie are examples of this type.
2) No processes will be simulated, including fuel load estimates at time 0 (processing input data and estimating fuel loads without modeling succession. These include all riparian types (found in Appendix 1), missing BPS values or BPS values that are not understood (e.g. due to spelling error in the input table).
3) Succession will be modeled up until the midpoint of the last successional stage prior to trees being introduced into the stand. For example, consider Fig. 13. The Stage 3 cohort is modeled to begin being introduced into the stand by the midpoint of Stage 2 (peak structure and dominance of those species in stage 2). After this time in the simulation, succession will cease and the simulation will be completely unreliable. Likewise, if there are tree species listed in the input table (from an informed simulation), this will classified as past the midpoint of Stage 2 (the beginning of Stage 3). After this time in the simulation, succession will cease and the simulation will be completely unreliable.
4) Fuels will be quantified for Time 0 (the time of inventory), but no succession is modeled. Consider a plot dominated by trees presently, with an understory of shrubs and grasses (broken out by composition, cover, and height). If the user simply wants the shrubs and grasses to be processed to describe fuel loads, ignoring the trees, then this option is available. This will represent the fuel loads for Time 0, but succession will not be simulated.
5) Finally, the user can force succession to be simulated in forested stands. This can be done by choosing a BPS that likely represents the understory response post treatment (fire or grazing). For example, consider the stand in Fig. 14. This stand has an overstory of *Pinus* and *Quercus* species with an understory dominated by *Arctostaphylos patula* (greenleaf manzanita) and various grasses. Let's assume a user is interested in growing the shrubs and estimating herbaceous response that is likely for this type. One way to "force" RVS to simulate the understory succession is to choose a non-forested BPS with similar species composition in the region and substitute. For example, one could consider using a Chaparral BPS such as Northern and Central California Dry-Mesic Chaparral (a type where *Arctostaphylos patula* is very common). This way the simulation will be "fooled" into thinking that the site is a non-forested site and the herb and shrub dynamics can be processed (but the trees will be ignored). This is a useful but quite dangerous operation but it can be used to understand possible succession after a treatment or disturbance. In some stands where tree generation is expected to take a long time, this might not be a bad choice but this method is not recommended without consulting the developers of the system.

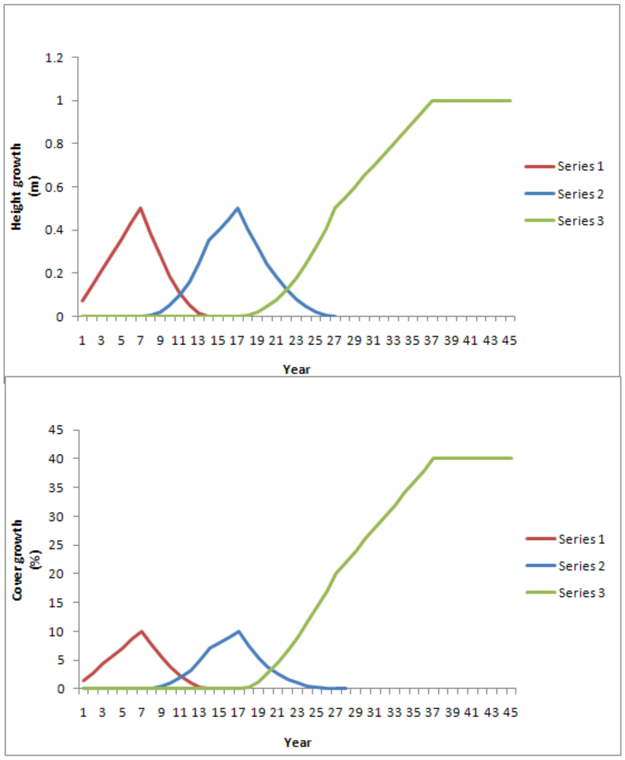


Figure 13. Example growth of canopy cover and height (of shrubs) for 3 cohorts. Each BPS has a unique set of growth estimates for shrubs.

Figure 14. An example of stand where careful selection of a BpS must be made. This is a stand where an "overstory/understory" model might be more appropriate. This image was obtained from the FCCS Digital Photo series (http://depts.washington.edu/nwfire/dps/).

1.0.2 Projects Completed With the RVS

Many results have been generated during the process of developing the RVS. Table 13 shows a general timeline, venue and results for various activities achieved as a result of this work. We address three of these below in more detail including:

1) Supporting R5 Forest Plan revision through new forage and carrying capacity estimates from RVS algorithms
2) Supporting R4 Forest Plan revision by providing standing carbon estimates from RVS algorithms
3) Supporting the Fire Lab and EPA through seamless rangeland fuel data for emissions inventories

All grazing allotments in R5 have been updated with annual production estimates from 2000 to 2015 using RVS algorithms. This enables more careful planning and also supports grazing management decision identified in the NEPA process. Using these data carrying capacity can be estimated by intersection with other important data such as distance form water, slope, fencing etc. Fig. 15 demonstrates the output from the RVS and shows the temporal profile for a given allotment. In Fig. 15, the RVS identified grazing allotments exhibiting steep reductions in carrying capacity. The Piute allotment was one of the worst in California in terms of loss of production through time.

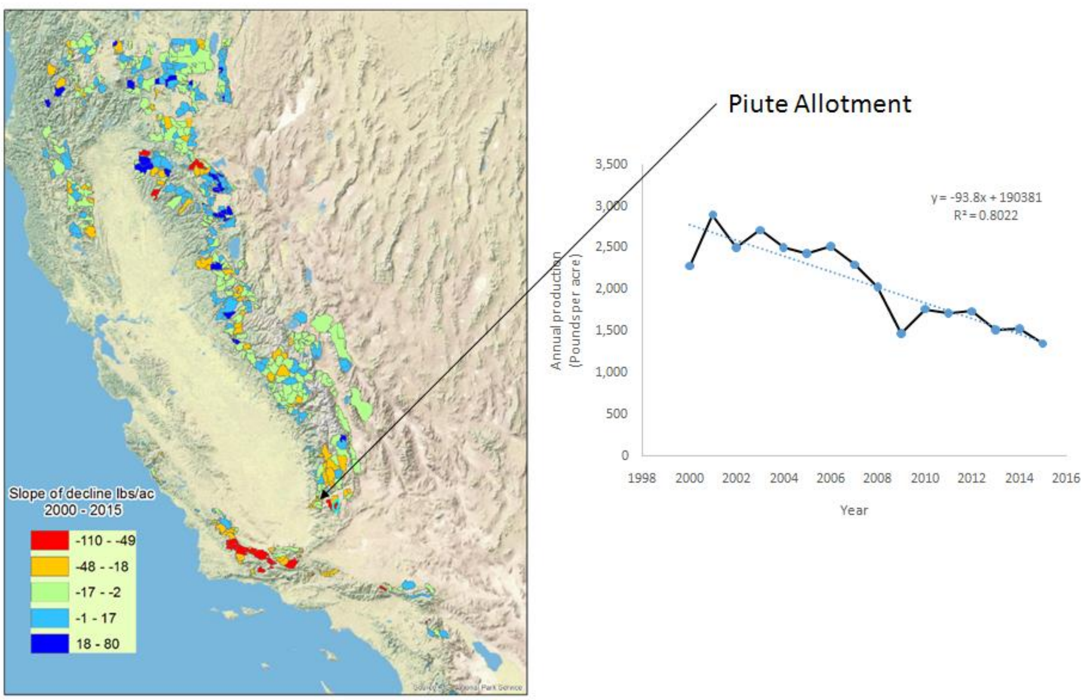


Figure 15. An example of how the RVS can be used to identify anomalous growth trends such as that exhibited in California's grazing allotments administered by the USFS in R5.

Using the RVS, we provided R4 of the USFS with above ground carbon estimates in all shrubs. This was the first time this has been done seamlessly across all National Forests for a region. The resulting database is being used to fulfill the requirement to evaluate carbon stocks (both above- and below-ground) for the planning process. Finally, applying the RVS in a spatially explicit mode enables estimate of non-forest fuel loads across all 662 million acres of U.S. rangelands. These new fuel bed estimates have been used by the Missoula Fire Sciences Lab to produce new carbon emission inventories. These data represent the 1, 10, 100, and 1000 – hr time lag fuels in both shrub and herbaceous species circa 2013.

Table 13. Results of the RVS project to date.

Deliverable Type	Description	Delivery Status
Website	Website for the RVS Code Depository: "https://github.com/rlank/RVS"	Completed (2017)
Symposium	The RVS inspired me to develop a symposium for SRM Annual Meeting: "Remote Sensing and simulation Modeling in Support of Public Rangeland Management and Administration"	Scheduled (2017)
Presentation	Lecture on rangeland simulation with RVS to native American students at Salish Kootenai Tribal College. May 10, 2016. We are examining the potential for including simulation modeling in the new Inter-Tribal rangeland curriculum	Completed (2016)
Presentation	International Rangelands Congress: "A Prototype Application of State and Transition Simulation Modeling in Support of Grassland Management"	Completed (2016)
Presentation	GEIA Conference "Improved Emission Estimates for Large Wildfires in the United States"	Completed (2014)
Poster	International Rangelands Congress: "The Rangeland Vegetation Simulator: A system for quantifying production, succession, disturbance and fuels in non-forest environments	Completed (2016)
Poster	Ecological Society of America: "Simulation modeling improves climate change risk management strategies in grasslands. "	Completed (2016)
Poster	Society for Range Management Annual Meeting: "The Rangeland Vegetation Simulator"	Completed (2014)
Workshop	Set the course for evaluating Ecological Sites and merging ST-Sim with RVS algorithms. Resulted in four prototype areas where ecological processes were simulated on Ecological Sites.	Completed (2014)
RVS Program Version 1.0 Completed	Program is available for integration with FVS: RVS is an open source C++ library written for multi-platform deployment. The code is hosted on Github at https://github.com/rlank/RVS. Current development is focused on Windows, but a makefile has been written and tested for Linux. C++ was chosen for compatibility with the Forest Vegetation Simulator (FVS), which is written primarily in FORTRAN, but also in C and C++.	Completed (2016)

Landfire Collaboration	Working with USGS, NASA and LANDFIRE to implement RVS for updating LANDFIRE landscapes to account for management, climate and disturbance.	Ongoing
Prototype project linking with Ecological Sites via ST-SIM	The ability to use Ecological Sites with ST-SIM and interpreted using the RVS growth, biomass, and fuel subroutines successfully demonstrated. Many presentations have been given to demonstrate this project.	Complete (2016)
Program for extracting and processing SSURGO soil data for coterminous US	This program was developed in support of the RVS effort to include Ecological Sites as a potential succession framework to replace BPS. The tool extracts any SSURGO attribute desired but we have used it for extracting and identifying Ecological Sites.	Complete (2014)
Application of RVS	RVS was used in R4 (NFS) to calculate standing carbon stocks in shrubs to support Forest Plan Revision. Region 4 now has soil organic carbon stocks and aboveground carbon stocks on all non-forest lands. Seamless carbon maps	Complete (2016)
Application of RVS	RVS was used in R5 (NFS) to estimate annual production of all grazing allotments in support Forest Plan Revision. Region 5 now has annual rangeland production maps from 2000 - 2015	Complete (2016)
Published Database	Reeves, M.C. Annual Rangeland Production Estimates for R5 Grazing Allotments. 2016. RMRS Library Digital Database	In press
Published Database	Reeves, M.C. Above Ground Carbon Estimates in R4. 2016. RMRS Library Digital Database	In press
Understory Equations for FVS	We derived understory equations for improving estimates of stand structure in understories of forested stands.	Complete (2015)
Invited Publication	Remote Sensing: Editor Lalit Kumar. Special issue of remote sensing *(Above Ground Biomass)*: Reeves, M.C. M. Krebs. Estimating above ground biomass in rangeland environments	In Prep
Publication	New equations for predicting herbaceous and shrub structure in forested environments. Preparation for publication in Forest Ecology and Management	In Prep

1.0.2 Merging With the Forest Vegetation Simulator and Output List

The Rangeland Vegetation simulator can function as two different use cases: library and simulation. Each major processing module (Biomass, Fuels, Succession, and Disturbance) is completely independent of each other, though they follow a common inherited design. The modules have a functional API and can be called programmatically by another program, allowing technical users to use RVS as a library of functions (e.g. if a user wanted just to use the biomass allometry functions of RVS). In simulation mode, the command module simply uses each of the processing modules in a chain of responsibility pattern, repeating this chain for however many years the user wants to simulate.

The intent of developing the RVS was predicated upon finally fusing its functionality with the Forest Vegetation simulator (FVS). Fusing the RVS is a complicated task, in part, because the RVS is coded in C++ while the FVS was developed mainly in FORTRAN. In addition, since the FVS has never accommodated non-forest vegetation inventory, new databases embedded within the FVS are required. In addition to new databases, the FVS also now requires a new set of keywords from which the RVS can be invoked and parameterized. These keywords include provisions for setting up management actions and reporting options in much the same manner as setting up a forested simulation in SUPPOSE (the interface developed for setting up and conducting FVS simulations).

This process has been one of the bottlenecks of RVS development, especially given the lapses in employment and personnel in both the FVS and RVS teams. Progress is being made however and should be complete by summer 2017. In addition, there has been discussion and movement towards redeveloping the SUPPOSE interface to FVS which could create challenges to successful integration of the RVS as a module. Despite these issues, good progress has been made on this novel system and the RVS team and FVS leadership (Mike VanDyck) have worked quite well together and recognize the importance of timely integration of the RVS.

Going forward, one of the main challenges of using FVS and RVS in concert for full ecosystem simulation is dealing with mixed stands. For example, consider the Jeffrey pine stand in Fig. 16. The inventory associated with this plot includes the trees but also some shrubs (*Arctostaphylos patula, Amelanchier alnifolia, Ceanothus cuneatus*) and herbs (*Festuca idahoensis*). Presently, RVS will ignore the trees since they are dealt with in FVS but fuel loads and production values for the shrubs and grasses will be calculated. We are working to come up with a solution but in the interim, we recommend a couple of temporary solutions until the FVS and RVS teams can consolidate parallel performance of these programs. The suggestions are:

1) Run a simulation with FVS to deal with the trees and then;
2) Run a simulation with the RVS module to deal with the understory and combine these outputs as needed.
3) Work with the FVS team to invoke some of the new understory growth functions that are not yet programmed in FVS but can probably be dealt with on an as needed basis. This process is explained in the final part of this report.

Figure 16. Jeffrey pine stand with understory demonstrating how mixed stands are complicated to simulate ecological processes. This image was obtained from the FCCS Digital Photo series (http://depts.washington.edu/nwfire/dps/).

1.0.4 Concluding Thoughts Regarding the RVS

The RVS represents new simulation capability. It is meant to be a starting point, a beginning architecture that will hopefully improve our understanding of non-forest systems and highlight the need for improvement. However there are significant limitations as one would expect. To be fully transparent and to communicate areas that need future improvement we provide a list of limitations and assumptions below. As a result of these numerous limitations users must carefully check inputs and model outputs. Finally, because of the novelty of the RVS it is obvious that many things could be improved with time and hopefully we are able to do that in the near future.

1) Dealing with mixed systems
2) BPS to control succession and growth (again it is critical to select the correct BPS, or rely on the RVS data loader process and assume it accurate). Also, recognize the limitations dealing in BPS's where trees are found in later successional stages
3) Unknown relations between herbaceous and shrub cover. This has implications for estimates of annual production of herbaceous species where shrubs are present. We are working with the USGS and BLM to obtain more plot level data to improve how allocations of annual production. Small datasets for individual projects may be able to describe these relations but not across types.
4) No accounting for invasive species in successional models (because of the link to BpS). Since invasive species are uncharacteristic, a model simulation cannot be

performed if exotic species are entered in the species list and this is why we advocate use of state-transition models from Ecological Sites in the next objective of this report.

5) Simplistic estimates of fire effects on succession
6) Simplistic estimates of herbivory on vegetation and fuels
7) Limited numbers of allometric equations describing relations between vegetation structure and fuel

OBJECTIVE 2: Evaluating use of Ecological Sites with the RVS via ST-SIM
2.0.1 Introduction

The Great Plains grasslands of North America provide a multitude of ecosystem services including clean water, forage, habitat, recreation, and pollination of native and agricultural plants. A general lack of quantitative information regarding the effects of varied management strategies on spatially heterogeneous landscapes further complicates the issue. In particular, quantifying the interaction of environmental (e.g., drought) influences and managerial strategies such as grazing, and herbicide on fire frequency and seasonality the western Great Plains is problematic given the paucity of studies in this region. This presents unique challenges to managers seeking to understand, explain, and justify desired management strategies. This is especially true given the ever-increasing environment awareness exhibited by the public at large and increasing mounting consumption of goods and services from rangelands.
Key to the development of land management strategies for land managers is the incorporation of drought influences on ecosystem productivity, function and fuel bed properties. Widespread, severe, multi-year droughts are a regular element of the Great Plains system (Woodhouse and Overpeck 1998; Schubert et al., 2004). These drought conditions are projected to increase in frequency, severity, and spatial extent (IPCC 2007). The projected increase in drought conditions will likely alter grassland composition and productivity, disturbance and erosion (et al., 2002) (Finch et al., 2012).

Widespread juniper encroachment has led to the most dramatic changes in the Great Plains biome since the Dust Bowl era (Engle et al., 2008). In addition, woody plant encroachment into southern Great Plains grasslands represents major management challenges. For example, woody encroachment is the primary reason for the decline of the lesser prairie chicken, *Tympanuchus pallidicinctus*, (Fuhlendorf et al., 2002), which is now being considered for listing under the Endangered Species Act (Tidwell et al., 2013). Additionally, in areas of long-term juniper encroachment, fires have shifted from frequent grass-driven surface fires to infrequent, juniper-driven crown fires. Such alterations to the fire regime and fire suppression potential are important contributors to the recent rise in housing losses, suppression costs, and human injuries and deaths resulting from wildfires in the Great Plains (Tidwell et al., 2013).

Given the uncertainty of future climate conditions and lack of decision support tools, managers need to know how management actions over the long-term interact with climate variability. In response to this need we have developed a decision support system which models the impact of climate on fuelbed properties and associated ecological effects of climate on Great Plains grasslands. The system is comprised of two distinct tools which act in concert to produce state-of-the-art ecosystem modeling capabilities. The first tool (Rangeland Vegetation Simulator,

RVS), which is a deterministic model, is still in development. The RVS estimates growth, succession, fuels and effects of fire, herbivory, and herbicide on non-forest systems. The second tool, ST-SIM which enables stochastic modeling of ecological dynamics. In this system, ST-SIM is used for developing and conducting state-transition simulation model for the study area.
The term "state-and-transition model" (STM) was first introduced by Westoby et al., (1989) in reference to conceptual models describing the successional dynamics of rangeland vegetation over time. Through the use of box-and-arrow diagrams, these early models described a series of discrete states in which a parcel of land could find itself at any point in time, along with transitions, both natural and anthropogenic, that could move land between these states.
Conceptual STMs are generally developed with one or more of the following goals (Bestelmeyer et al., 2009, Karl and Herrick 2010):

1. Communicating and interpreting ecological processes. STMs provide a simple, flexible approach for describing vegetation dynamics. They provide a common set of terms for scientists and managers to use when referring to the ecology and management of vegetation across a landscape. The models, in turn, provide a framework for reporting across different agencies; they also provide an excellent visual tool for communicating ecological concepts to a wide range of stakeholders.
2. Identifying poorly understood ecological processes. Through the development of STMs, knowledge gaps in the understanding of the ecology of a system become apparent; this, in turn, can help identify where future research efforts should be directed.
3. Assisting in monitoring design. STMs can indicate which sites are more or less likely to experience changes in vegetation over time, and thus will require greater monitoring intensity.

A second form of STMs exist that extend the conceptual models such that they become quantitative, leading to models that can simulate the states and transitions that might occur over time across a landscape; these are often referred to as "state-and-transition simulation models" (STSMs). The first published example of STSMs being applied to vegetation dynamics was the development of models to predict the combined effects of succession and disturbance, including various land management strategies, on the forest and rangeland vegetation of the Interior Columbia River Basin (Hann et al., 1997); since then STSMs have been applied in a wide range of ecological settings (Forbis et al., 2006, Hemstrom et al., 2007, Carlson and Kurz 2007, Provencher et al., 2007, 2013, Strand et al., 2009, Frid and Wilmshurst 2009, Czembor and Vesk 2009, Klenner and Walton 2009).

STSMs are stochastic models: the models use a combination of probabilistic and deterministic transitions to predict a range of possible future conditions. Because the models are stochastic, the simulations can be run using a Monte Carlo approach: this involves repeating the simulations many times with parameter values selected randomly from specified probability distributions. The result is a range of outcomes for future vegetation that reflect natural variability and uncertainty, rather than a single prediction. In addition STSMs can be run spatially over an entire landscape, in which case the landscape is divided into a series of spatial cells (e.g. pixels or polygons), and the fate of each cell is tracked over time; the output of spatial STSMs is typically a map providing predictions of future vegetation across the landscape. A particular form of spatial simulation, referred to as a spatially-explicit STSM, allows for the transition probabilities and targets of each cell to be influenced over time by the state of the cell's neighbors. This allows for the effects of spreading processes (e.g. invasive plants) to be reflected in the model predictions.

A suite of software tools have been developed allowing users to design and run STSMs (Daniel and Frid 2012). These tools have all been jointly funded by multiple agencies over the years, and as a result they are all available for free. The latest of these is ST-Sim (ApexRMS 2015), a fully integrated framework for creating and running both non-spatial and spatially explicit STSMs. ST-Sim is freely available for download and is being used by ecologists and land managers across North America. Various ST-Sim applications were recently showcased at the Second State-and-Transition Simulation Model conference (Wilson et al., 2014 – see also www.stsm2014.org).

In the system presented here for managers of the Great Plains the two programs communicate with one another such that ST-SIM estimates the structure and composition through time while the RVS is responsible for estimating annual production, biomass, and fuels. The user of the system has control of various elements of ecological succession and must provide a baseline of ecological trajectories. For example, what are the ecological dynamics of the system being studied and what viewpoint of succession is desired? Is the system supposed to modeled as a linear progression (e.g. a Clementsian viewpoint) or is the site more appropriately characterized using state/transition theory?

As a user driven simulation system, this decision support tool enables managers to determine the most appropriate management strategies for reducing fuel loads and fostering ecological resiliency. This novel decision support system represents a multiyear, international effort, and this document describes a prototype application on the Great Plains and estimates ecosystem response by focusing on two important elements including: 1) estimating future fuel bed properties and associated fire behavior and 2) quantifying feedbacks between fire cycle, climate and species assemblages and structure. Model output and algorithms are calibrated and validated using long-term data sets describing vegetation, response to fire treatments, local climate, herbivory, and herbicide through predictive modeling. Properly calibrated application of the system will aid design of land management strategies and demonstrate the means to extrapolate these predictions to landscapes throughout the Great Plains and elsewhere that proper parameterization is conducted. When properly calibrated the system is useful for broadly scoped situations as:

1) Aiding the risk assessment between the no action and proposed action on decision-making and NEPA documentation.
2) Aiding in addressing public concerns when presenting prescribed fire proposed actions.
3) Presenting the long range implications and potential impacts of development in vegetation types or next to public land boundaries.
4) Providing information or education tool to public, elected officials and other agencies.

In addition, more detailed situations can be evaluated such as:

1) Quantifying the impact of fire, and herbivory on successional trajectories and associated fuelbed properties
2) Quantifying stand attributes in the context of wildlife habitat suitability analysis. For example, “what is the impact of proposed management actions on sagebrush structure and composition and what will that mean for sage grouse brooding habitat”

3) Quantifying fuelbed loading and continuity for evaluating fire behavior potential. For example, “What is the reduction is spread rate and flame length resulting from a proposed fuel reduction project and should prescribed fire, and herbivory be used to achieve the desired reduction?”.

To demonstrate use of the system for addressing these questions, we developed a prototype application specifically for managers of the Great Plains. The second largest component of the National Forest System is the national grasslands. The Forest Service currently administers twenty national grasslands consisting of 3,842,278 acres of federal land. National grasslands are located in thirteen states. However, nine national grasslands consisting of 3,161,771 acres of federal land are in the Great Plains states of Colorado, North Dakota, South Dakota, and Wyoming. National grasslands in these four states alone thus contain more than 82% of the total national grassland acreage (Olson, 1997). As a result, the decision support system is applied to the Loamy Plains Ecological Site (ES) on the central Great Plains in north central Colorado (Fig. 17).

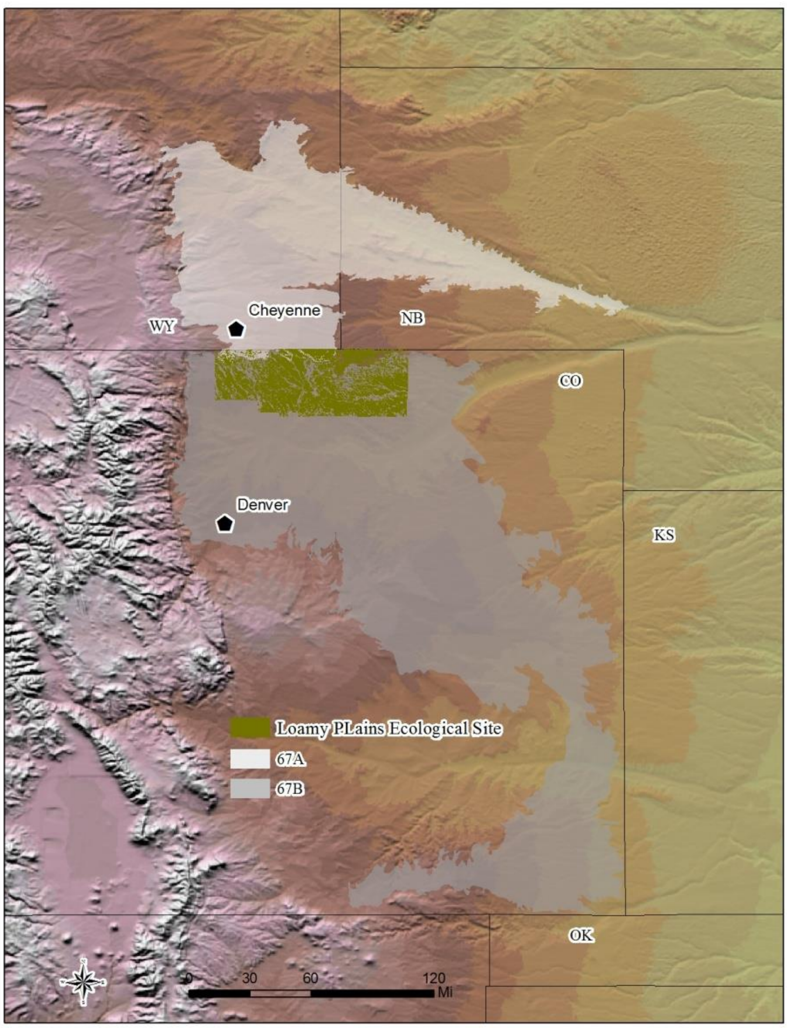


Figure 17. Location of the Loamy Plains Ecological Site for examining the potential for linking State-Transition Simulation Modeling from ST-SIM and the RVS.

The application of the system in this region is meant to accomplish three primary goals:

1) Communicate to managers in the region that this system is available for their use. To this end, we provide enough background and methodological information for managers to use the system directly by correspondence with the development team at the Rocky Mountain Research Station.
2) Demonstrate usefulness and limitations of this newly developed to hopefully incite managers to be become engaged with the tool so as to calibrate it for use in areas of their choosing. In addition, we discuss the results of the prototype application on the central Great Plains which should, themselves, provide guidance to managers about expected effects of management actions on ecological status and vegetation composition and structure through time.
3) Analyzing the relationship between the LANDFIRE BPS data and the ES's that intersect them.

It is the hope and intent of the development team that this report will suitably convey use, calibration and application of the system such that it will form an integral component of planning processes engaged in by managers throughout the extent of U.S. rangelands. This report, however, should not be considered a user's manual but instead represents demonstration of its use as a decision support tool.

2.0.2 Goals 1 and 2: Communicating and Describing a Prototype Application

2.0.2.1 Simulation Flow

The overall system flow is shown in Fig.18. Prior to simulation, the manager must determine the questions or problems that will ultimately be used to design simulation. Three main inputs are required at this stage including estimated growing conditions, management actions, and landscape conditions including stand location (Latitude and Longitude in the NAD83 datum) and vegetation composition and structure. At the least, these data need to describe cover and height of shrubs and herbaceous species. Identification of species is not required for herbs or shrubs but results will be less reliable if species level information is not supplied because it will not be known which allometric equations to use. It is important to recognize that this section of the report describes system processes representing the default (e.g. the dominant system processes and associated assumptions) system or, in other words, the manner in which the system behaves if the user is limited to minimal interaction. Is also important to recognize that this system was built with the potential for significant user interaction, particularly in the realm of vegetation succession and the manner in which vegetative assemblages relate to one another and the mechanisms by which transitions between states are common.

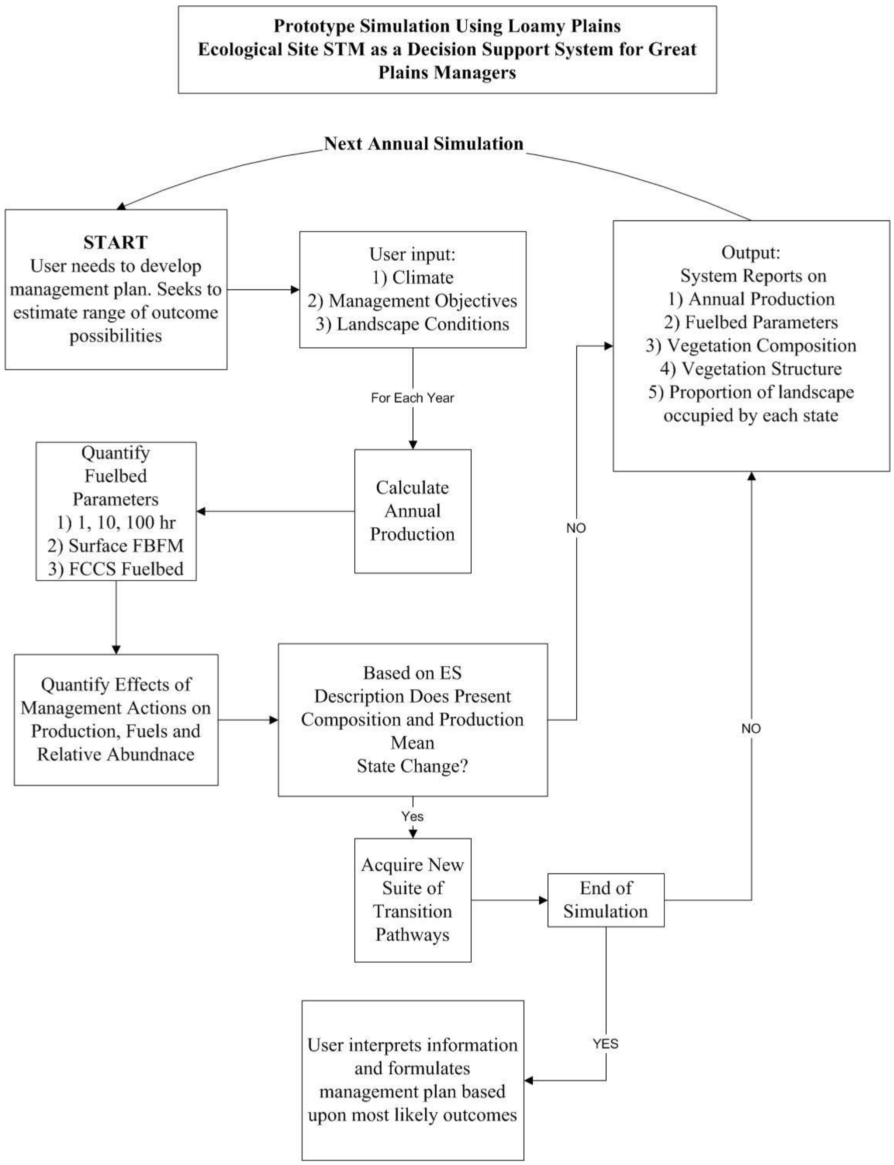


Figure 18. The overall flow for the system linking the Rangeland Vegetation Simulator and ST-Sim. This system begins with a manager formulating a "what if" scenario and adds design criteria (climate, management actions etc.) and spatially explicit plot level information describing vegetation composition and structure.

2.0.2.2 Study Area

A prototype of the system was applied on the Loamy Plains ES (R076BY002CO) found in the Major Land Resource Area (MLRA) 67B consisting of the southern part of the Central High Plains (67B) extends across most of the eastern portion of the state of Colorado, from the border with Wyoming and Nebraska to the border with Oklahoma and New Mexico (Fig. 17). The climate within this region is characterized by a mean average annual precipitation of 305 – 406 mm, with the amount received in any given year varying widely, from less than 200 mm to more than 500 mm. The region also experiences average winds of 9 mph annually, with peak winds in the spring. Average growing season length is 142 days, with the frost-free period extending

from mid-May to late-September. Mean monthly minimum temperatures vary from -11.0 C (Dec) to 13.0 C (July), and mean maximum monthly temperatures vary from 7.3 C (Jan) to 34.4 C (July).
The most common ES within this MLRA is the Loamy Plains ES, which occurs on nearly level to gently sloping plains (0 to 6% slopes) from 3800 to 5600 feet in elevation. This ES is characterized by soil textures consisting of loam, sandy loam, or very fine sandy loam in the surface layer and loam in the subsurface layer. These soils are typically well-drained, moderately to very deep, formed in loamy loess and eolian deposits, and occur on upland plains as well as terraces.

The dominant plant species on this ES (in terms of their basal area and contribution to ANPP) are two C_4 shortgrasses (blue grama, *Bouteloua gracilis* and buffalograss, *B. dactyloides*). Other less abundant but important plant species include C_3 perennial gramminoids (*Pascopyrum smithii*, *Hesperostipa comata*, Elymus elymoides, and *Carex* spp.), a C_3 annual grass (*Vulpia octoflora*), C_4 bunchgrasses (*Aristida longiseta, Sporobolus cryptandrus, Bouteloua curtipendula*), plains pricklypear cactus (*Opuntia polyacantha*), and subshrubs (*Gutierrezia sarothrae, Eriogonum effusum, Artemisia frigida*; Lauenroth and Burke 2008). In some portions of the MLRA, plains pricklypear cactus can be the most abundant species after the C_4 shortgrasses, with basal area of up to 5% (Milchunas et al., 1989). The most widespread forb species is the perennial scarlet globemallow (*Sphaeralcea coccinea*). A diverse community of annual and perennial forbs also occurs on this site, particularly in wet years, with the forb composition highly dependent on annual weather conditions. Variation in plant community composition on this ecological site is primarily characterized by variation in the relative abundance of C4 grasses versus C3 perennial graminoids.

Phase 1 is characterized by nearly complete dominance of C4 short grasses, with western wheatgrass occurring in only trace amounts. The state is often described as having a "sodbound" structure and is associated with heavy grazing pressure throughout the year or the growing season. Dominance of the C4 shortgrasses is associated with their high grazing tolerance, which in *B. gracilis* is associated with high relative allocation of photosynthate to belowground roots and crowns, and in *B. dactyloides* is associated with the production of stolons and prostrate leaves below the grazing height of ruminant herbivores.

Phase 2 is characterized by the dominance of C4 shortgrasses, but with greater abundance of cool-season graminoids compared to Phase 1, particularly western wheatgrass and needle-and-thread grass. This phase is associated with reduced overall grazing intensity, or grazing regimes that involve more pulsed grazing pressure (i.e. characterized by greater variability in space and over time). Other species that may increase in phase 2 relative to phase 1 in portions of the MLRA include winterfat (*Ceratoidies lanata*) and legumes such as American vetch (*Vicia americana*).

Phase 3 is characterized by a substantial increase in C_3 graminoids relative to phase 2, particularly western wheatgrass and needle-and-thread grass. This shift results in a significant increase in aboveground net primary productivity, particularly with wet spring conditions, relative to phase 2. Phase 3 is associated with low to moderate overall grazing intensity, and may be facilitated by more pulsed and variable grazing distribution in space and time.

Phase 4 is associated with the lack of grazing or fire for long periods of time, and is characterized by increased surface litter, increases in C3 perennial grasses, and a concomitant decline in plant basal cover and density.

2.0.2.3 STSM Description for MLRA 67B "Loamy Plains"

The conceptual version of this State/Transition model is described in detailed in the ES's Information System (ESIS) database[1]. A number of modifications were made to this conceptual model in order to incorporate new information gathered by researchers at ARS:

1. The "states" identified as *Blue Grama Buffalograss Sod* and *Red Threeawn Annuals Bare Ground* were represented as "phases" of the reference without the irreversible transitions identified in the original ESD. This modification is based on work done by Augustine et al., (2014) showing a rapid recovery of the system following the extirpation of prairie dog colonies at sites that experienced long term grazing and disturbance.
2. For each phase in the reference plant community except the *Red Threeawn Annuals Bare Ground* phase we added a parallel phase representing a high density of plains pricklypear cactus. This reflects recent work by Augustine et al., (2015) showing that the lack of fire can lead to an increased density of cactus which in turn reduces grass availability for livestock consumption.

Fig.19 shows the overall structure of the State/Transition Simulation Model (STSM) states and the duration of each phase with "age zero" representing those sites that have experienced heavy repeated disturbance by either cattle or prairie dogs. The following are the key processes and associated transitions that are included in the model:

1. "Normal Grazing" by cattle represents a utilization rate of approximately 0.5 AUMs per hectare per year. This type of grazing shifts a site back in the successional trajectory by two years towards age zero.
2. "Heavy Grazing" by cattle represents a utilization rate of approximately 0.9 AUMs per hectare per year. This type of grazing shifts a site back in the successional trajectory by four years towards age zero.
3. "Lack of Fire" for a period of 20 years or more results in a transition to the cactus equivalent of the current phase representing a site with a high density of prickly pear.
4. "Fire" prevents the transition to the cactus phase and if it already has occurred reverses it. It also transitions sites from the excessive litter phase to the historic climax plant community phase.
5. "Drought" results in a backwards shift in the successional trajectory by two years towards age zero.

1 https://esis.sc.egov.usda.gov/ESDReport/fsReport.aspx?id=R067BY002CO&rptLevel=communities&approved=yes&repType=regular&scrns=&comm=

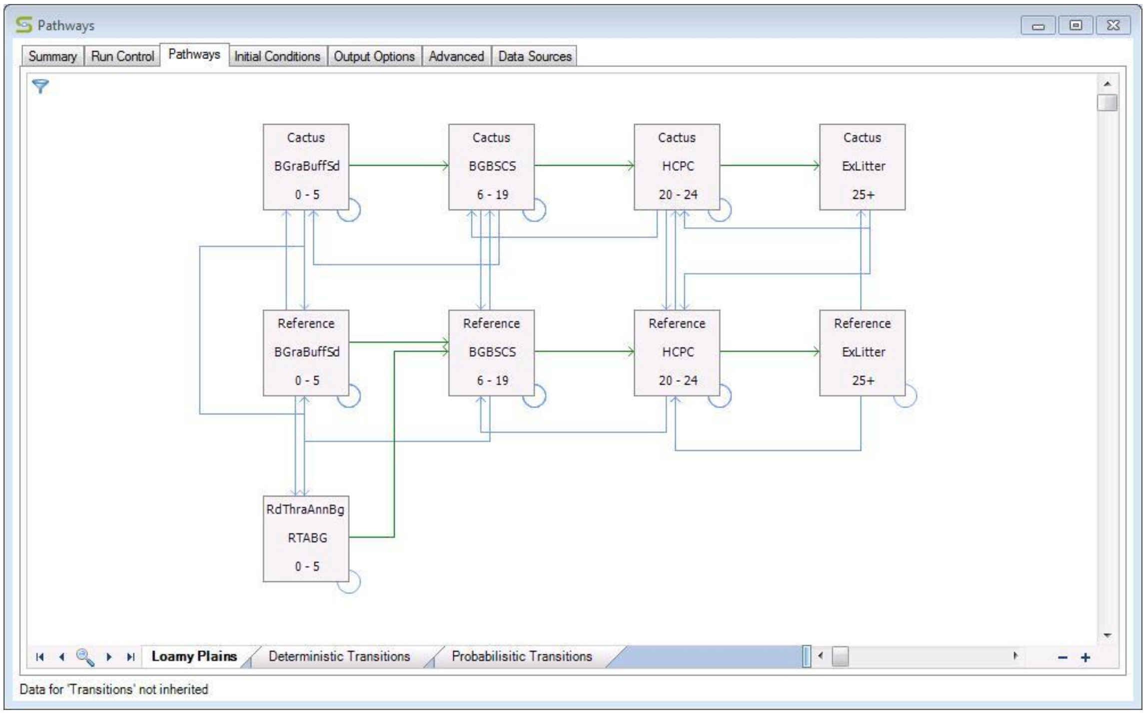


Figure 19. Overall structure of the STSM for the Loamy Plains Ecological Site for MLRA 67B. Abbreviations are as follows: BGraBuffSd – Blue Gramma Buffalograss Sod, BGBSCS – Blue Gramma Buffalograss Sod with Cool Season Remnants, HCPC – Historic Climax Plant Community, ExLitter – Excessive Litter, RedThraAnnBG – Red Threeawn Annuals Bare Ground.

The rate at which these transitions occur in the model can be set in various ways. For example, the rate of grazing is set by specifying the target AUMs applied to the landscape or the plot on each year of the simulation. The model then allocates this target across the simulation cells probabilistically. Fire or the lack of it can be specified probabilistically, using a time varying annual probability, or deterministically by specifying the years during which the plot or a specified area of the landscape will burn.

During the simulation, percent cover and height by functional group (herb, shrub, tree) are accounted for by using the relationship between canopy cover and productivity derived from the Landfire BPS classes as portrayed in Table 7. To demonstrate the use of the model we defined a number of example scenarios for a single plot 1 acre in size. The plot was initialized in the Historic Climax Plant Community phase with 30% herb cover. Each scenario was simulated from 2015 to 2050 and the simulations were repeated 100 times to provide a distribution of outputs. The scenarios simulated involved three components:

1. Grazing intensity (none, 0.5 AUMs per acre per year, 0.9 AUMs per acre per year, none followed by 0.5 AUMs per acre per year after 2030).
2. Drought (none, drought between 2025 and 2029).
3. Fire (none or an annual probability ranging from 0.01 to 0.05 depending on vegetation phase).

In addition to simulating ecological change and corresponding fuelbeds through time, a landscape level simulation representing the Loamy Plains ES was also performed. The processes for performing a landscape level simulation are identical as to a single plot, but the landscape conditions for each area must be specified. This enables the evaluation of fuel conditions across the entire 320 acre pasture.

2.0.2.4 Data Used in the Simulation

Data used for this prototype project are categorized as location, growing conditions, current vegetative states, and proposed management actions (Table 14). The number of potential combinations of proposed management actions is quite large but to demonstrate a range of potential outcomes we chose to emulate the effects of no, moderate, and heavy stocking rates with either no drought or extended drought.

Table 14. List of model initialization parameters. This list represents parameters actually used in this prototype analysis.

Location	Temporal domain	Growing conditions	Current vegetative states	Simulation design criteria
Multiple plot locations in the area of north central Colorado on the Loamy Plains ecological site	50 years	Annual Precipitation (mm) [Parameter-elevation Relationships on Independent Slopes Model; PRISM, (Daly et al., 2001)	Estimated vegetation composition and structure (plot inventory, reconnaissance). Leo, what is our starting condition for the landscapes?	1) No drought, no grazing 2) No drought, 0.5 AUMs ac^{-1} 3) Extended drought, 1.2 AUMs ac^{-1}
		Annual maximum Normalized Difference Vegetation Index (NDVI) Moderate Resolution Imaging Spectroradiometer (MODIS; 250 m^2)		

We wanted to match the periodicity of growing conditions as closely as possible so a historical time series from 1981 to 2012 was used to guide the simulation. In total there were 50 years of simulation (2000 to 2015 for validation and 2015 to 2050 for the projection period). Since the historical period only represents 31 years of observations, the time series was repeated in the simulations (Fig. 20). For example, for 2013, the year 1981 was used. The observed precipitation is shown in relation to the "normal" growing condition index to show the direct relationship between precipitation, NDVI (not shown) and the growing condition index (explained above in this report). In addition to normal conditions, an extended drought was simulated whereby all years in the simulation were estimated to be at 50th percentile (growing index of 3) or below.

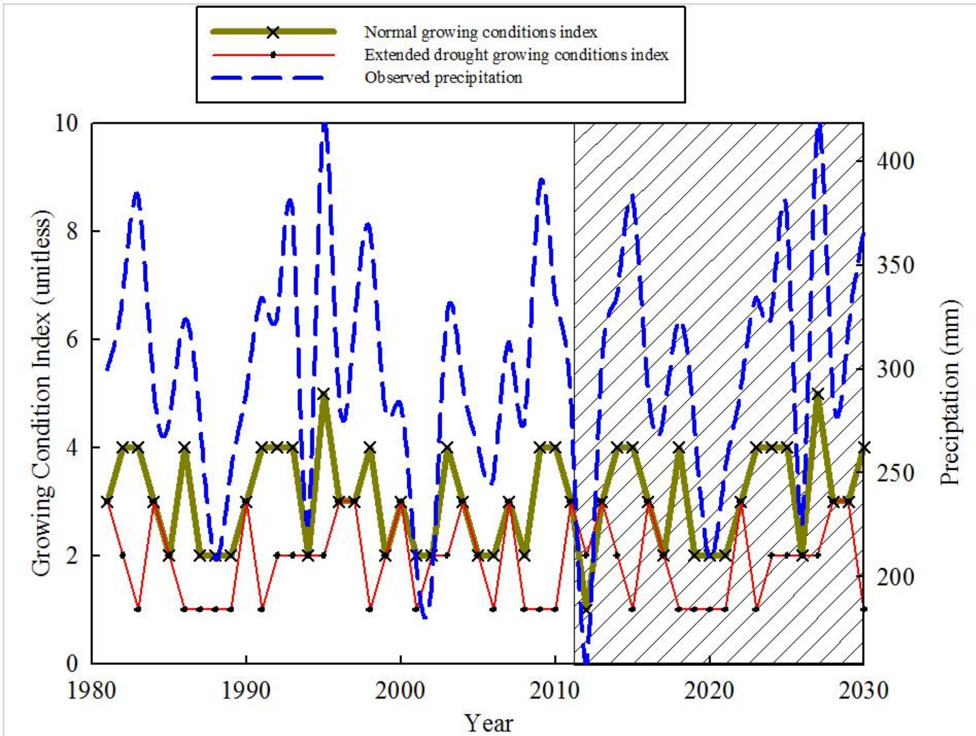


Figure 20. Time series of growing conditions used in the simulations. The shaded area represents where data were duplicated from the beginning of the time series.

There were two time periods for simulation, including one to accommodate the validation period (2000 to 2015), and one for a projection (2015 to 2050). The purpose of the first period was to accommodate the time period during which validation data were collected and also to demonstrate the relationship between annual production and surface FBFM. The purpose of the projection period was to implement the sets of treatments outlined above and observe the estimated long term response of the vegetation. In the projection period, fire was introduced into the system probabilistically, which explains some of the variability between iterations.

2.0.2.5 Validation

The STSM which was digitized from the Loamy Plains ES state-transition diagram was calibrated and validated using long term experimental observations from the Agricultural Research Station. Recall that at each year of the simulation, the model produces annual estimates of production for each state phase. To compare with the observations, all production, across all the state phases in each year was aggregated to derive a single production value representing temporal averaging for each grazing scenario. The data observations of annual production were given to us by the ARS High Plains Experimental Station. For the validation, the ST-SIM model was run from 2000 to 2015 to match the time period for which the observations were recorded. In this simulation, cover, height, annual production, 1- hr herbaceous fuels and surface Fire Behavior Fuel Models were simulated although the only validation data available was the annual production.

2.0.2.6 Results

2.0.2.6.1 Validation and Surface FBFM Results

For the period between 2000 and 2015, the observed production ranged, on average, between about 900 and 1200 lbs ac$^{-1,}$ while predicted values ranged from about 850 to 1100 lbs ac^{-1} (Fig. 21). In all grazing treatments the predicted and observed values aligned well but, with a bias of -60 lbs ac^{-1}, tended to under predict observations. In addition the variability of production values of the observations was much greater since these are collected in very small plots in a 320 acre pasture while the model encapsulates the spatial averaging that occurs over the entire area. Though not part of the official validation part of this project, Fig. 22 shows the sensitivity of this novel system to interannual changes, from 2000 to 2015, in production and, more importantly, what it means for the estimated surface FBFM. Note that the heavy grazing scenario produced, on average, an approximated reduction in annual production of about 70%.

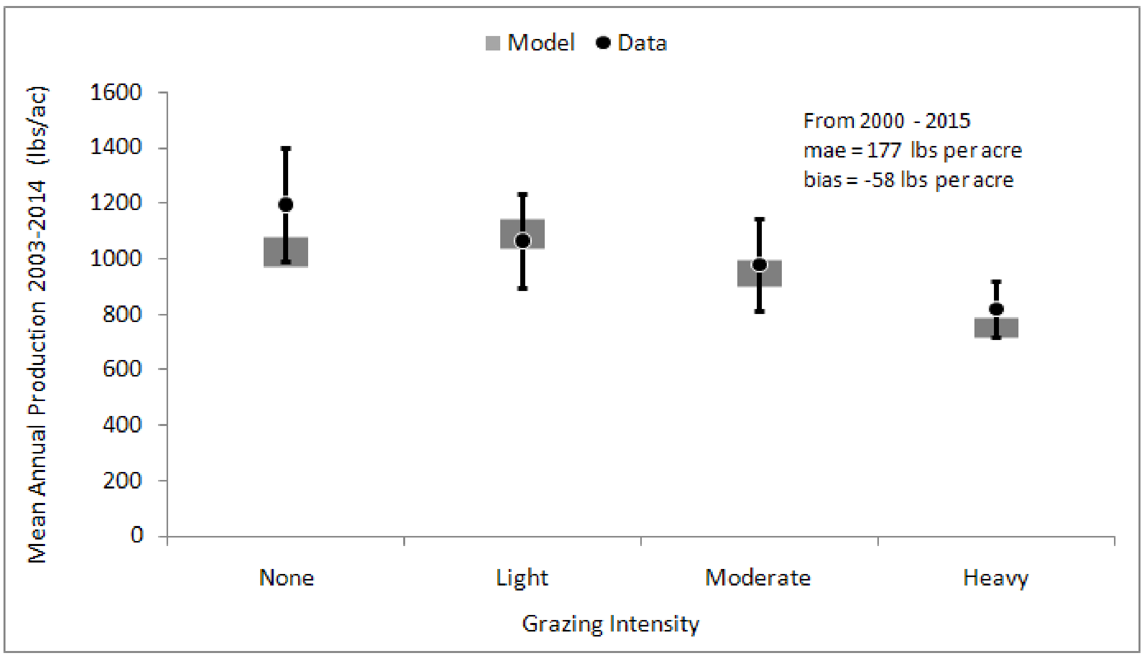


Figure 21. Predicted and observed annual production data collected over the study area by the staff of the ARS High Plains Research Center.

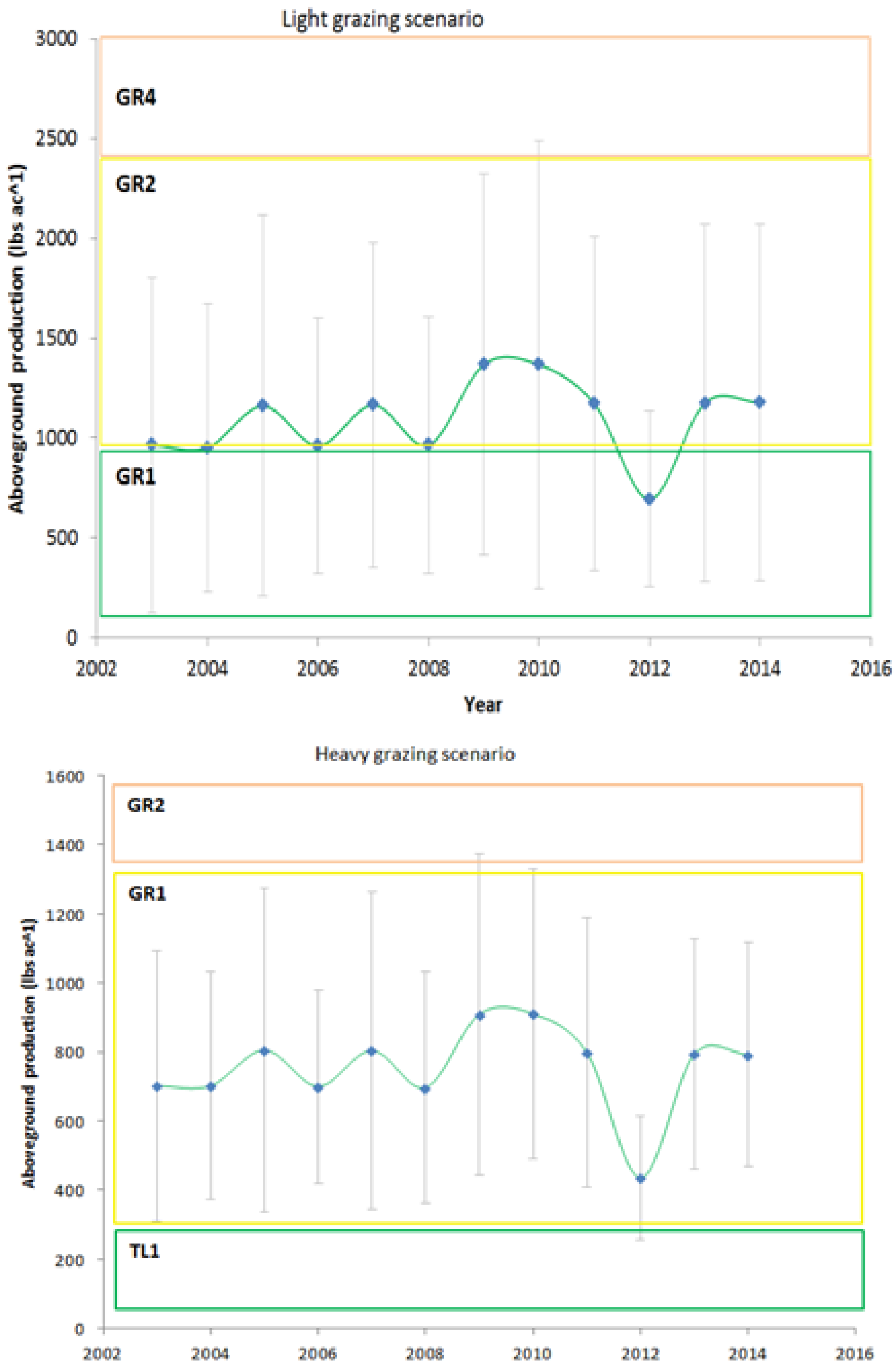


Figure 22. Predicted annual production and surface FBFM for Ecological Site in the study area from 2000 – 2015 across two grazing treatments.

In addition, the RVS fuel subroutine uses this information combined with other data to estimate the surface FBFM which is generally coded as a GR1 (very low expected fire behavior) for the heavy grazing scenario while the light grazing scenario consistently produced a GR2 and, in some areas of the pasture, a GR4. This demonstrates the suitability of this system, using

Ecological Sites, for evaluating the effectiveness of grazing treatments (and fire if desired) with respect to fuels.

2.0.2.6.2 Projection Period Results

Fig.'s 23 and 24 show projected herb cover for the plot (central 50% of iterations) in scenarios with fire and Fig. 25 demonstrates some scenarios without fire. Fig. 26 shows the probability of the plot being in any one ES Phase over time for each of the different scenarios that included fire. The simulation clearly demonstrates the propensity of this ES, as coded in the ST-SIM platform informed by RVS subroutines, that cool season species are replaced by warm season sod-producing species more quickly in the heavy grazing scenario. It is interesting to note, however, that drought, coupled with the moderate grazing regime produced nearly similar results by the end of the simulation period (Fig. 26). However the drought effect was much less apparent with respect to state changes towards the warm season sod-state in the no grazing treatment.

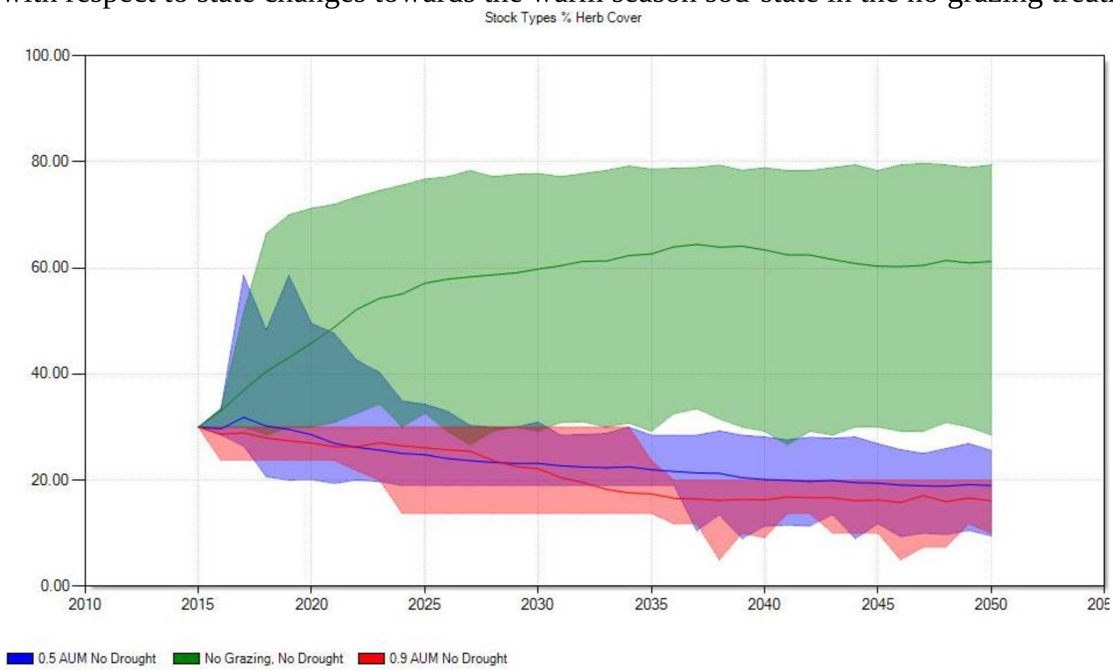


Figure 23. Projected percent herb cover (central 95% of iterations) under different drought and grazing scenarios with fire.

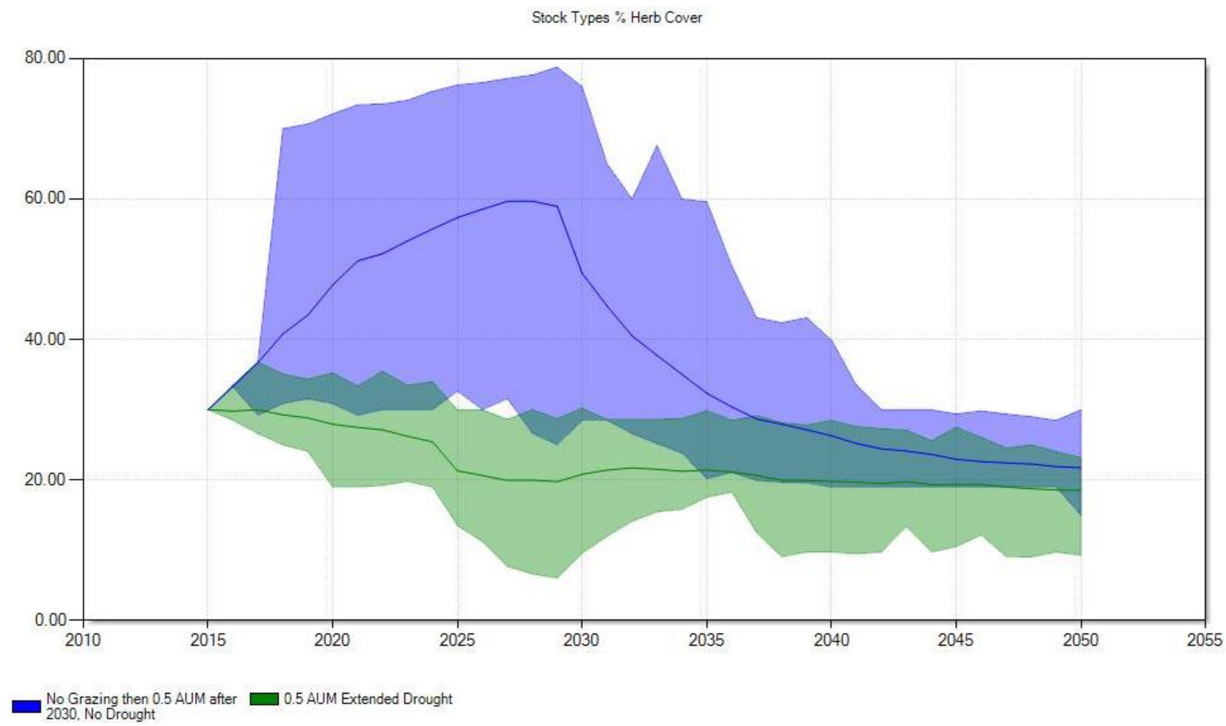


Figure 24. Projected percent herb cover (central 95% of iterations) under different drought and grazing scenarios without fire.

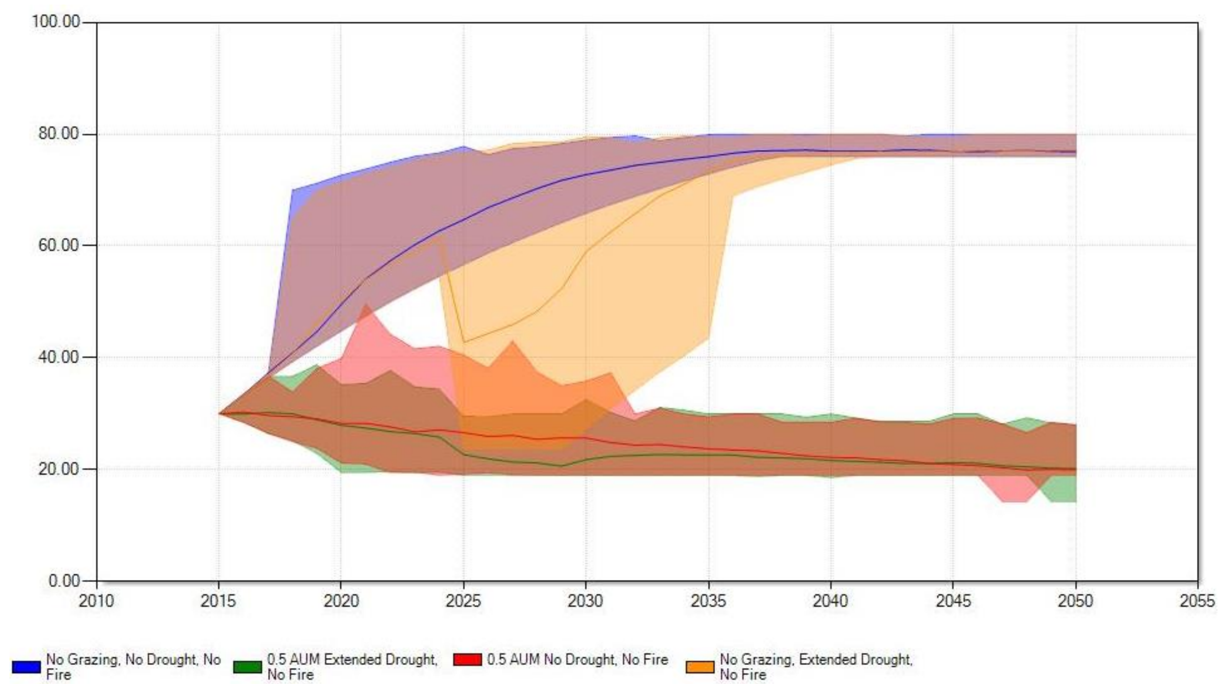


Figure 25. Projected percent herb cover (central 95% of iterations) under different drought and grazing scenarios without fire.

So, in this system, the no grazing scenario delayed the introduction (or probability of introducing) warm season dominance for at least 20 years while the heavy grazing scenario began increasing this probability in as little as 5 years. The no grazing, no drought scenario did not produce noticeable increases in the sod-state but it had the greatest effect on increasing production of the excessive litter state.

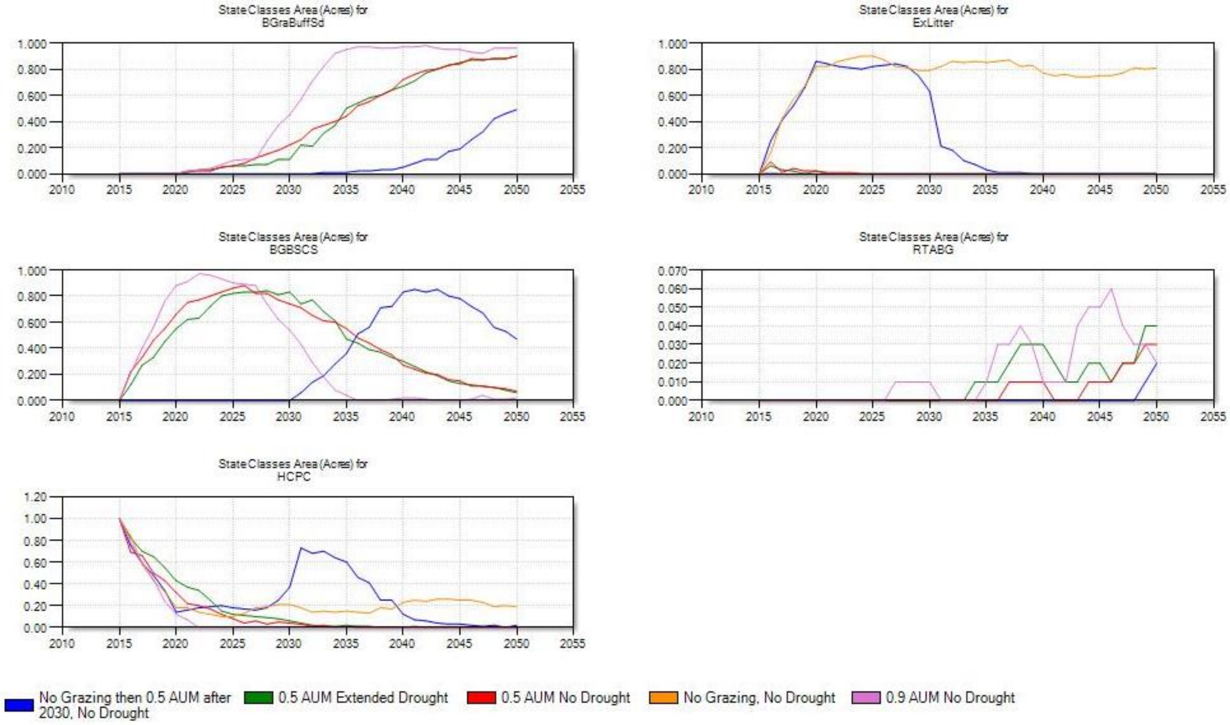


Figure 26. Probability of the plot being in each of the ecological site phases over time. Abbreviations are as follows: BGraBuffSd – Blue Gramma Buffalograss Sod, BGBSCS – Blue Gramma Buffalograss Sod with Cool Season Remnants, HCPC – Historic Climax Plant Community, ExLitter – Excessive Litter, RedThraAnnBG – Red Threeawn Annuals Bare Ground.

This condition has significant ramifications for fuel accumulation and therefore the expected fire behavior. With respect to various management and climate scenario effects on canopy cover, these are best represented in a table format. As a result, three tables are provided for brief overviews of model results including Table 15, Table 16, and Table17.

Table 15. Canopy cover results with respect to the Loamy Plains Ecological Site processed in ST-SIM with RVS subroutines. In this simulation, no drought was imposed but fire is active in a stochastic manner. In addition, different grazing regimes were examined.

GRAZING	NO DROUGHT
NONE	Rising to 60% but with the greatest variation
Normal	Nearly identical to heavy after about 10 years, resulting in average cover of about 20 %. However, by the end of the simulation period the normal grazing scenario produced overall greater cover and higher fuel loads than the heavy grazing scenario.
Heavy	Noticeable immediate reductions in canopy cover relative to the no grazing scenario.

Table 16. Canopy cover results with respect to the Loamy Plains Ecological Site processed in ST-SIM with RVS subroutines. In this simulation, drought and no drought were imposed and fire is active in a stochastic manner. In addition, different grazing regimes were examined.

GRAZING	DROUGHT	NO DROUGHT
NONE- Delayed then moderate after 2035	N/A	Canopy cover climbing from 40 to about 70% after about 15 years, but with high variability. The introduction of moderate grazing at that time (2035 decreased cover through time stabilizing at about 25%
Normal	Canopy cover dropped immediately through time stabilizing near 20% cover after 8 – 10 years.	N/A

Table 17. Canopy cover results with respect to the Loamy Plains Ecological Site processed in ST-SIM with RVS subroutines. In this simulation, drought and no drought were imposed and fire was not permitted. In addition, different grazing regimes were examined.

GRAZING	DROUGHT	NO DROUGHT
NONE	N/A	Canopy cover climbing from 40 to about 70% after about 15 years, and with small variability. The introduction of moderate grazing at that time (2035 decreased cover through time stabilizing at about 25%. Compared with the fire scenario of with no grazing and no drought, this treatment exhibited much less variability in the cover response.
NONE	Somewhat tracks the no drought scenario for about 11 years and then cover drops significantly to about 25% but recovers towards the end of the projection period	N/A
MODERATE	Canopy cover dropped immediately through time stabilizing near 20% cover after 8 – 10 years. This produced the lowest cover of all treatments with little variability indicating the relatively certainty of this effect.	Canopy cover dropped immediately through time stabilizing near 20% cover after 8 – 10 years. The main difference compared with drought is that there is a lot more variation towards increased cover indicating that this treatment, overall, will produce slightly greater residual cover and slightly higher fuel loads than the extended drought scenario.

Overall, the results portrayed here representing ecological simulation with ecological sites, ST-SIM and the RVS demonstrate the potential for seamless, wide area simulation of management effects in rangelands of the western U.S.

2.0.3 Goal 2: Ecological Site Relationships With BPS Across the West

In this second goal the spatial and thematic relations between ES's and BPS were examined. This was done to better understand how these two datasets can be used in concert to develop a national strategy for producing ecological simulation across the western U.S. to support fire management and landscape conservation. This task was accomplished in three steps:

1) Map ES's
2) Intersect ES's with BPS data
3) Examine the relationships between BPS and ES's using seven questions
    a. For each BPS, in each mapping zone, how many unique ES's are there?
    b. For each BPS, in each mapping zone, what is the biggest ES (most coverage)?
    c. For each BPS, in each mapping zone, what proportion of each BPS has no ES?
    d. For each BPS, in each mapping zone, how many ES's does it take to cover 90% of BPS area?

e. For each BPS, in each mapping zone, what are the top 3 (greatest areal coverage) ES's?
f. Without respect to zone, what is the biggest ESD across all BPSs?

In addition to answering these questions we provide an estimate of the process for enabling a seamless solution for mapping ecological dynamics across the western U.S. using the RVS for the fuels, and production and ES's coded in ST-SIM for estimating the proportion of the landscape in various vegetative states. In effect, we estimate the difficulty of implementing the prototype discussed above across the landscape using ES (where they exist) and BPS to fill in the gaps. This process was made possible by the questions and spatial analysis outlined above in the questions we answered.

2.0.3.1 Mapping ES's

To map ES's, the entire SSURGO data depository was obtained on an external hard drive. We had to develop a program for extracting the ES's (EcoClassID) from the SSURGO database. This custom program was developed and is standalone software available from the author. It can be used to extract and aggregate any attribute in the SSURGO database. For each Map Unit in the database there are multiple components (and ES's) in various proportions. The precise location of each component, however, is not possible to know. For example, for a given soil polygon in a given mapping unit, the exact ES is not known unless the entire Map Unit is occupied by a single ES. As a result, a spatially explicit database describing all ES's representing a given map unit with their corresponding proportions was completed. In addition, we also developed a database describing only the most abundant ES's in each Map Unit. Using these data the extent of ES's was quantified across the western U.S.

2.0.3.2 Intersecting ES's with BPS Data

After preparing and mapping all ES's, the next step was to spatially intersect ES's with the BPS data from LANDFIRE. This spatial intersection was constrained by the following criteria:

1) Evaluate predominantly non-forest vegetation
2) Focus on the analysis mask shown in Fig. 27

Figure 27. Extent of the analysis of Ecological Sites with respect to BPS.

Two intersections were performed. One accounted for all possible combinations of ES's and BPS while the second accounted for only the top ES in each BPS. This produced a "noisy dataset" with hundreds of thousands of combinations that were not realistic. For example, if 5 aberrant BPS pixels intersect an ES, that is a new combination. Indeed many combinations represented just a few acres. As a result the following screens were performed prior to answering our main questions outlined above.

1) ES Description classifications were restricted to only vetted ESIS systems representing the most recent, authorized, and nationally sanctioned classification. This is an 11 character alpha-numeric code (e.g. R041XB206AZ). This restriction alone reduced the number of records within our database by over 40%.

2) Extracted SSURGO-ES Description data were queried further to contain contiguous areas of 1000 acres or greater. Based on the 35 m^2 resolution of the resampled SSURGO data, this amounted to a minimum threshold of 3303 pixels (1000 acres = 4,046,856 $m^2/(35*35)$ = 3303 pixels). This reduced our data by another 88%.

3) Soil component percentages within a mapping unit were summed together in instances where there were two (or more) of the same ES's for a given SSURGO sampling unit. This resulted in a complete list of unique ES IDs for a given mapping unit (in descending order of component percent).

4) Lastly, the ES Descriptions with the largest summed component percentages were then selected for inclusion for each mapping unit representing more than 1000 acres, by selecting **MAX** component percent and **First** ES Description, where multiple ESDs exist for a given mapping unit.

The resulting database contained 99,494 records, each representing one ES Description (with the largest component percentage) per mapping unit greater than or equal to 1000 acres. Summarizing and aggregating **unique** ES Descriptions further by BPS and Zone resulted in a database containing 23,030 records. This dataset formed the final database from which our questions were answered.

2.0.3.3 Answering the Questions

1) For each BPS, in each mapping zone, how many unique ES's (ES) are there? Answer: There are a total 1251 BPS and Zones (unique combinations of BPS and Zones) in our dataset. Applying our criteria, we have 891 BPS and Zones which contain ES's. The remaining 360 BPS and Zones were either excluded (i.e. BPSs from eastern U.S.) or did not contain ESDs that met our filter criteria (above). This number ranges from 1 to 264 unique ES's. Fig.28 displays the number of ES's in each BPS. In a sense it determines how "complex" a landscape is for a given BPS.

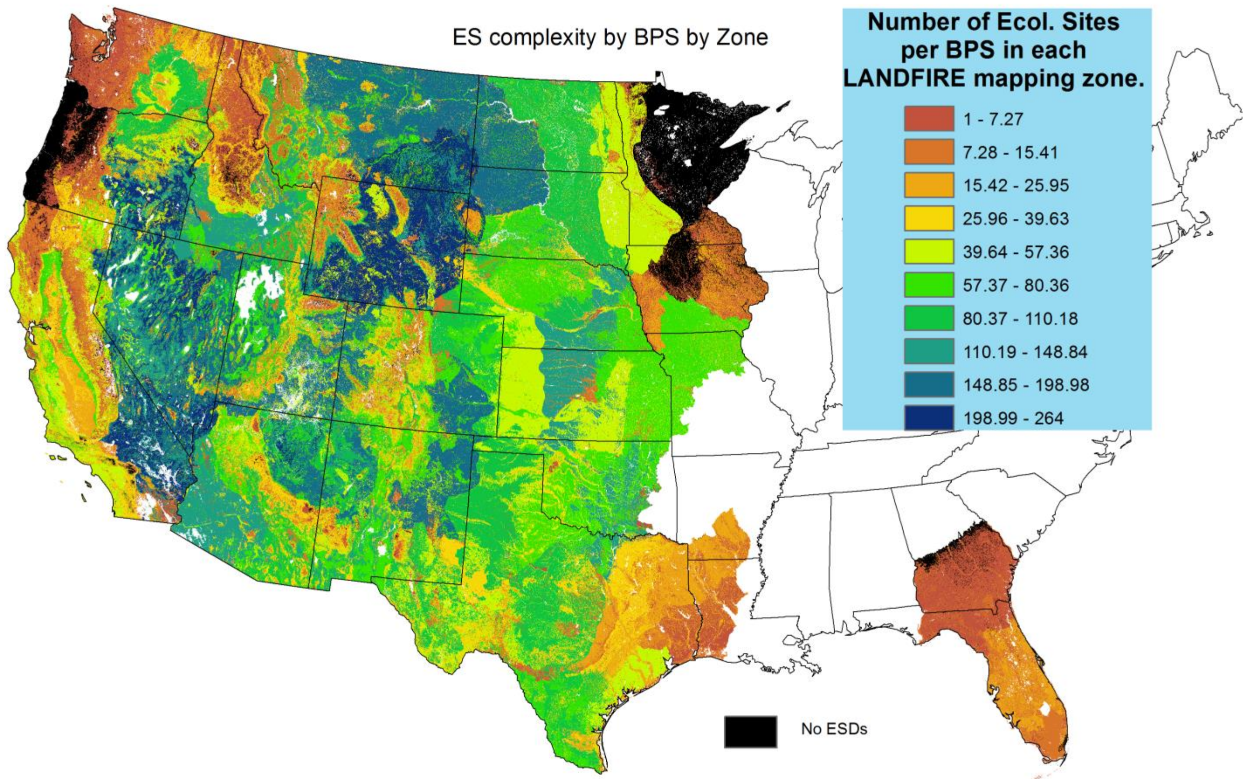


Figure 28. Number of unique ES's underlying each BPS meeting our filtering criteria.

2) For each BPS, in each mapping zone, what is the biggest ES (most coverage)? The largest ESD for each of the 891 BPSs in each Zone is reported. The remainder represents the 360 BPSs and Zones without ESDs This gets at the biggest driver across the landscape for a given BPS. Often, one or two ES's will dominate a given BPS (cover the majority of the areal extent of a given BPS). So, using this most common ES to estimate successional dynamics for a given BPS will produce the biggest "bang for the buck". A map is not produced for these data since they are too complex but for any BPS we can deliver the most dominant ES.
3) For each BPS, in each mapping zone, what proportion of each BPS has no ES? This indicates how well described each BPS is in terms ES's. Areas where a BPS has no ES underlying it can be populated using a likely candidate ES such as the most common one. This way, the spatial pattern of the BPS can be used to fill gaps in the ES database where ES's have not yet been described. The proportion of each of the 891 BPSs in each zone **without** ESD coverage range from nearly 100% (excluding those BPSs either excluded or not meeting filter criteria) to nearly 0.02%.
4) For each BPS, in each mapping zone, how many ES's does it take to cover 90% of each BPS's area? There are 42 BPSs and Zones (i.e. 28 BPSs in 12 Zones) that have ESD area coverage exceeding 90% of the BPS area in that Zone. The number of individual ESDs within these areas range from 3 to 156. This metric indicates how hard (how much it would take) to successfully simulate the dynamics of a given BPS. Areas where it takes more ES's to complete 90% of the

BPS will cost more to deal with since more ES's are required to be coded and applied across the landscape. This is reflected in Fig. 29. In this figure only those BPS's that are covered by at least 90% of ES's are shown. For example, if a BPS has 20% of its area with no ES intersecting it, it will not be shown. The estimated area of BPS's intersected by ES's where the ES's occupy at least 90% of this area, is about 56 million acres.

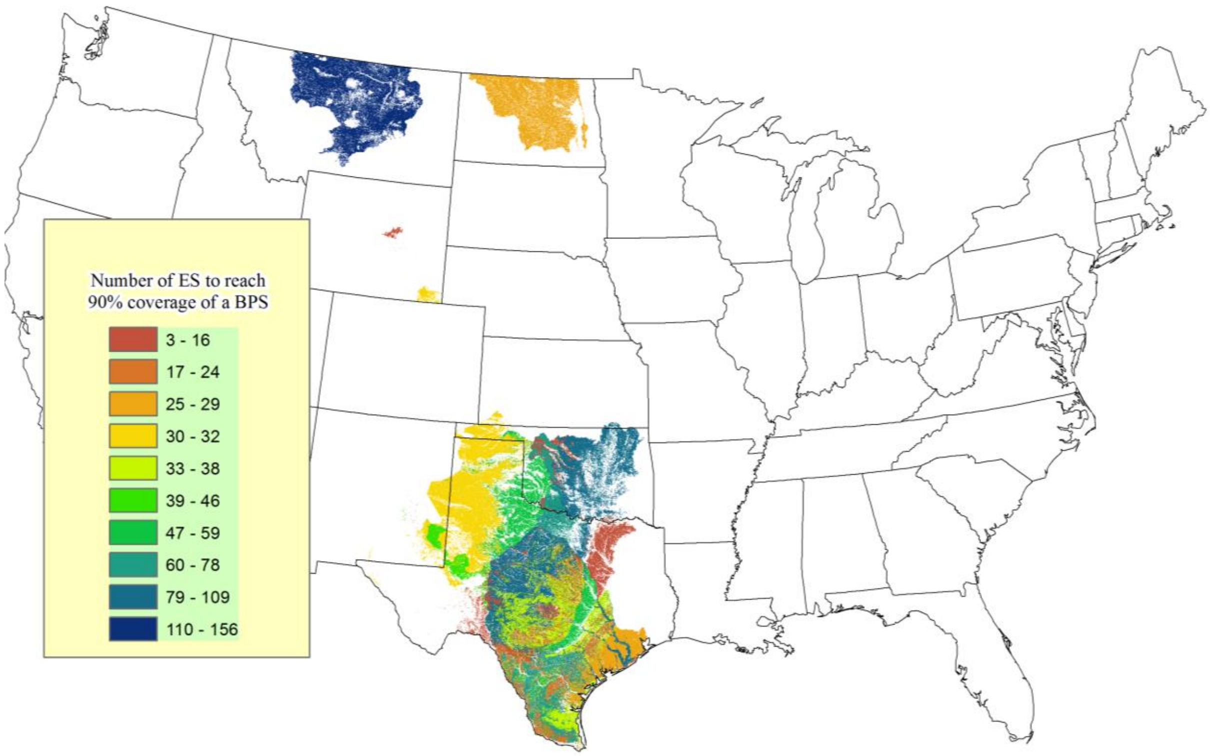


Figure 29. Number of ES's required to cover 90% of a BPS in BPS's where at least 90% is covered by ES's.

5) For each BPS, in each mapping zone, what are the top 3 (greatest areal coverage) ES's? This is contained in a database and an example of what this looks like is contained in Table 18.

In a similar manner, looking at BPS and ES combinations reveals that only a few combinations make up a large majority of the total coverage of the area investigated here. Of the total number (n=267) and area of BPSs containing ESDs (n=23,030) considered here, a little over half of this total area is represented by Ecological Site Descriptions. Beginning first with the largest BPSs containing the largest areas occupied by ESDs, the relatively quick divergence of both cumulative areas through the 8,000th ESD, indicate that there is a declining cumulative representation of ESDs, as BPS areas continue to increase at a faster rate than associated areas of ESDs (Fig. 30).

Table 18. Top 3 ES's (by areal coverage) in each BPS. This is an example, and the full database, of course, contains all the BPS's examined in this report.

BPS	**Ecological Site ID**
Great Basin Pinyon-Juniper Woodland	R038XA104AZ
	R030XC355AZ
	F030XC375AZ
Northwestern Great Plains Mixedgrass Prairie	R052XN161MT
	R052XC217MT
	R046XC508MT
Chihuahuan Mixed Salt Desert Scrub	R041XA007NM
	R041XA002NM
	R042XB011NM
Western Great Plains Sandhill Steppe	R041XB212AZ
	R041XB214AZ
	R041XB206AZ
Western Great Plains Shortgrass Prairie	R077CY037TX

As increasingly smaller BPSs and associated ESDs are added, relative ESD coverage declines less rapidly until the asymptote (after 21,000 ESDs), where about 53% of overall ESD coverage is eventually reached over all the BPSs. There are a handful of large BPSs that have a higher relative ESD representation than most others. In fact, the largest 18 BPSs, comprising 50% (2.5 million km2) of the BPS total cumulative area, are represented by nearly a little more than a third of all the ESDs (n=8842). These ESDs alone comprise 64% of the largest 18 BPS total area and 61% of the total cumulative ESD area. The remaining 50% (2.5 million km2) of BPS area consists of 249 BPSs and 14,188 ESDs, and only 41% of the total cumulative BPS area and 39% of the total cumulative ESD are.

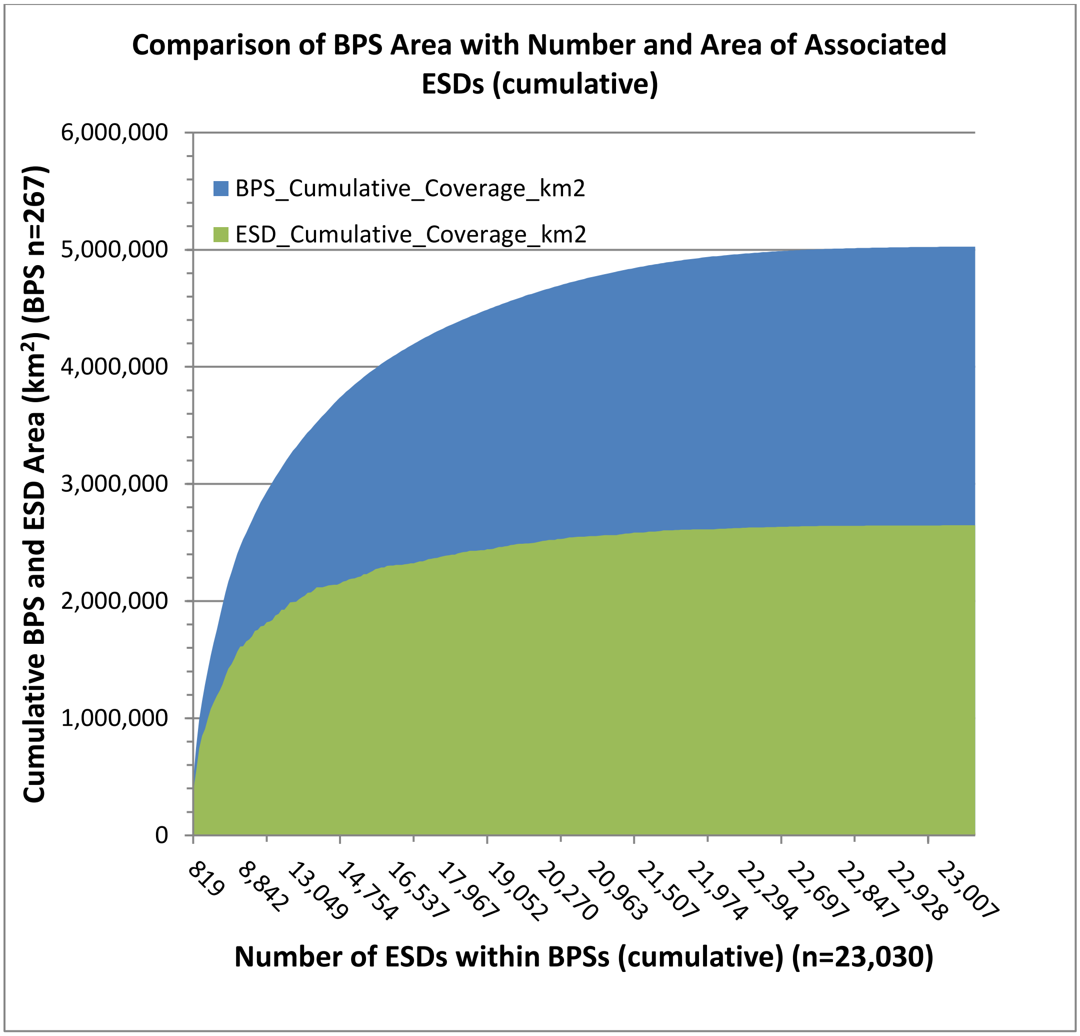


Figure 30. Cumulative area of BPS and ES's. This can be used to determine how much more cumulative area can be covered by each additional BPS and ES combination.

6) Without respect to zone, what is the biggest ESD across all BPSs?. The largest ESD in our dataset is R077CY022TX, representing a total acreage of nearly 7.3 million acres, spanning both Texas and New Mexico. This ES is shown in Fig. 31. The implications of this is that for the same amount of resources we can simulate ecological dynamics on 7.3 million acres as we can on 100 acres since the time required to code and create a vetted STSM would be the same or similar.

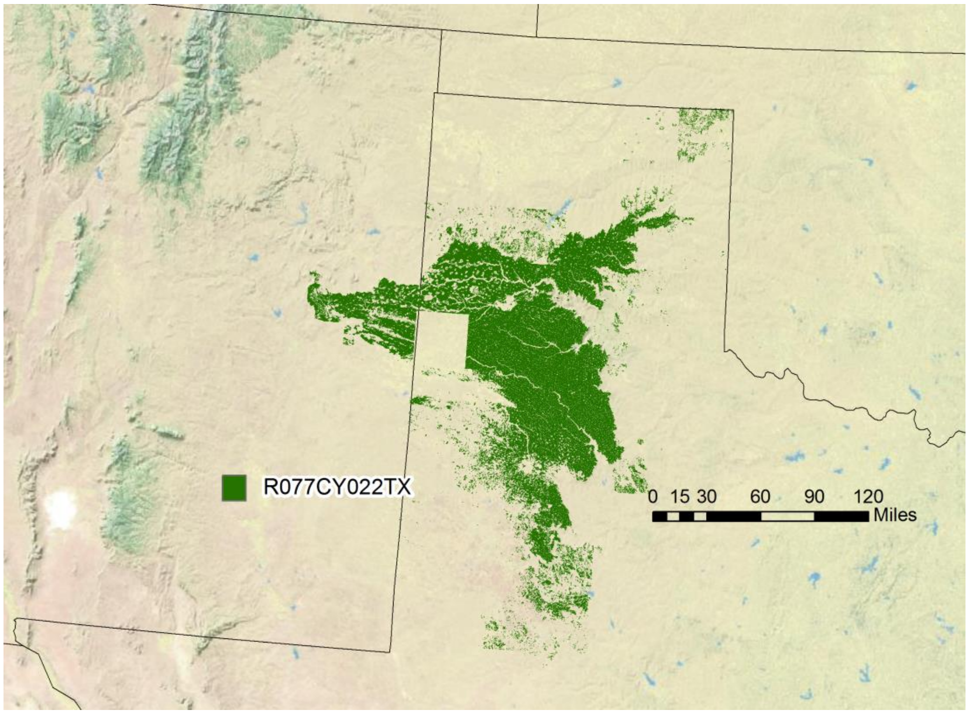


Figure 31. Extent of the largest ES in the United States. The ES is R077CY022TX and covers at least 7 million acres.

2.0.4 Implications

This assessment of the arrangement and complexity of ES's within the context of LANDFIRE's BPS provides badly needed insight to the possibility of improving ecological modeling in rangelands for the purposes of fire management. Using the analyses and underlying databases we created can assist fire managers and modelers in designing a national strategy for updating the static LANDFIRE fuel maps to be more realistic after wildfire and in areas where grazing intensity is quantified across the landscape. In addition, the modeling conducted using the prototype ES above indicates that there is significant potential for linking the RVS with ST-SIM for quantitative simulation modeling and rich characterization of fuelbed elements. The modeling process, when properly calibrated, yields realistic results and can be applied through space and time in across the range of observed growing conditions in a spatially explicit manner. As a result, we suggest that fire managers and national fire leadership should consider this type of strategy for managing any broad scale characterization of fuel models across the landscape each year. Presently, in most non-forest landscapes in the LANDFIRE fuel datasets remain static after a fire and "stuck" in an herbaceous state. This is not always a bad assumption but it is overly simplistic and can easily and quickly be fixed. Another benefit of this project is the demonstration of the use of simulation modeling with ES's as part of a national strategy for fuel treatment effectiveness, even for herbivory as a treatment option. This kind of simulation for grazing has not been applied at meaningful scales in the past or the present but the ability certainly exists presently.

Given advances in technology and the advancement of programs like the RVS and ST-SIM, large landscapes can be simulated and richly quantified in a cost effective manner. For example, it is estimated that a given ES costs between 8 and 24 hours (but can be much shorter where redundancies between ES descriptions exist) to make available in a simulation environment. As a result of this project we have demonstrated that some ES's can be used to simulate dynamics on millions of acres. So, for a minimal amount of resources the framework for national simulation of ecological dynamics and fuelbed properties can be developed. The macro-scale view of this process reveals several steps towards developing a national level simulation system for evaluating treatment effectiveness and ecological response. These are represented in 6 steps below:

1) Get all ecological sites to cover at least 90% of each BPS (separating signal form noise ecologically, thematically, and economically). From these ES's collapse to disturbance response groups such as those developed in Nevada by Dr. Tamzen Stringam. This will permit great economies of scale and should provide regionally realistic results. This makes sense in a national framework especially since if, for example, two different sites are occupied Wyoming big sagebrush, they will response reasonably somewhat similarly if other factors are equal. As a result it makes sense to collapse these state-transition models to one.
2) Code each of the unique ES's in ST-SIM and prepare workshops to add nuances to models where they might not exist in the vetted ES description.
3) Gather all data from every reasonable kind that could be used for calibration and validation. Data from remote sensing (to quantify post-fire recovery and other attributes), Long Term Ecological Research (LTER) vegetation composition, structure, and production data. Cross – walk to each ES to which they correspond.
4) Use RVS growing condition index for driving simulations. These were developed from observed precipitation and vegetation growth patterns and are spatially explicit. However, other types of climate scenarios could be used (e.g. climate change scenarios).
5) Quantify current conditions describing vegetation structure, composition, and production. A good starting point for this is the LANDFIRE Existing Vegetation Type, Height, and Cover (EVT, EVH, and EVC respectively).
6) Create regionally appropriate "what if" management questions. For example, we may wish to find treatment designs that optimize abundance of forbs and sagebrush cover in support of sage grouse conservation.

OBJECTIVE 3: Developing Understory Predictive Equations

3.0.1 Introduction

Numerous ecological studies have focused on better understanding how overstory and understory vegetation interact with one another in forested environments. It has been long understood that these interactions are both very complex and dynamic, and can have potentially profound effects on the composition, structure, and productivity of understory vegetation. Considerable silvicultural research in the past century has revealed the effects of overstory tree density upon understory vegetation production through various management interventions such as thinning, prescribed burning, and wildland fire. Enhancement of understory vegetation production has been achieved in many of these studies by strategic removal of overstory trees through these management practices.

Understanding the effects of overstory structure and density upon understory vegetation also contributes to a better understanding of understory fuel loading and carbon stocks, both of which are a function of understory production. Such information is useful for fuel modeling purposes, which forecast both fire behavior and severity, and estimate biomass accumulation. Taken together, the prediction as to how forest understory vegetation will change in response to proposed management, disturbance, and natural succession is a paramount endeavor in modeling forest change through time. One such model, developed by the USFS in the early 1980s, is the Forest Vegetation Simulator (FVS), which consists of a family of forest growth simulation models based on decades of forestry research and experience and seeks to simulate a broad range of silvicultural treatments. It addresses the effects of thinning, fire, insect and disease, and climate upon forest growth and yield, while simulating calibrated treatments and disturbances over distinct geographical regions throughout the United States.

One current and particular need in the FVS model is the estimation of understory vegetation biomass accumulation and production as a function of overstory attributes. We addressed this need by examining the relationship between overstory attributes and understory vegetation and developing predictive models to estimate vegetation height and cover, and consequently biomass accumulation. Our approach was that of a data mining study and we broadly considered many public forest datasets for suitability in our model development before selecting one national dataset with sufficiently collected overstory and understory data suitable to our task.

3.0.2 Methods

3.0.2.1 Databases

We used FIA (Forest Inventory and Analysis) data for our study since it contains a large assemblage of measured overstory and understory vegetation attributes suitable to our task of understanding how understory vegetation varies with overstory components. It also represents a long term and systematic plot framework over the entire U.S. that is measured and remeasured consistently over time. There are an estimated 125,000 permanent plots nationwide representing approximately one plot for every 6,000 acres (Woodall et al., 2010). A further advantage is that all FIA data is thoroughly checked and validated for quality and accuracy to within strict tolerances and standards, making it one of the most rigorously collected and maintained forest inventory databases in the world.

FIA data was obtained from two sources covering the western contiguous United States. First, plot data from the Pacific Northwest (PNW) FIA Region (Washington, Oregon, and California) were obtained directly through FIA as a ready-made Access database called the 2011 PNW FIADB Annual Inventory Database (available at: http://www.fs.fed.us/pnw/rma/fia-topics/inventory-data/index.php). Second, plot data from the Interior West FIA Region (IW-FIA) (Arizona, Colorado, Idaho, Montana, Utah, New Mexico, Nevada, Utah, and Wyoming) were obtained directly through their public website (available at: http://apps.fs.fed.us/fiadb-downloads/datamart.html) as CSV files. These were subsequently imported into both Microsoft Access and Excel (MS Office 2010) as tables where all later queries and attribute calculations were conducted.

3.0.2.2 Plot description

The current national standard FIA plot design consists of 4 circular subplots with 3 subplots concentrically arranged around a single center subplot at a predetermined distance and azimuth (Fig. 32). Each subplot has a 24-foot radius (approximately 1/24 acre) where trees greater than or equal to 5” DBH (diameter at breast height) are measured. Within each subplot is a nested 6.8 foot radius microplot (1/300 acre) for measurement of seedlings and saplings between 1”and 4.9” DBH. Understory vegetation is measured on each entire subplot in an ocular fashion. For very large diameter trees exceeding a predetermined diameter threshold, an optional 58.9-foot radius (1/4 acre) macroplot is also used (FIA National Core Field Guide, 2014).

3.0.2.3 Data screening

Prior to the adoption of the current national fixed-plot radius design, FIA implemented many other sample designs, including variable-radius ones that were measured on a periodic basis. We decided to use the current design for its measurement consistency and ease of scalability. The current inventory design is also annual, in that plots within a sampling panel are measured on an annual, instead of on a periodic basis, which was the case with the earlier inventory. The annual inventory design for western states was initiated on an individual state basis starting in 2000 (Woudenberg et al., 2010). The historical range for all available data used in this study is from 2000-2012, with the number of data collection years for most states varying between 9 to 13 years. The notable exception here is with the PNW data, in which only 1 year could be used due to inconsistent vegetation measurement protocols (described below).

We prioritized forest types within our FIA databases according to ones commonly found throughout the western U.S. and based our selection using LANDFIRE’s Existing Vegetation Type (EVT) taken from NatureServe's Ecological Systems classification (Comer et al., 2003). We chose EVTs with the largest extents and ones reflecting our combined knowledge of these systems. We then cross-walked them to their FIA Forest Type equivalent (Table 1) according to one developed internally between FIA and LANDFIRE. These were ultimately cross-walked to Douglas-fir, lodgepole pine, ponderosa pine, and grand fir FIA forest types, which are based on types described by the Society of American Foresters (Eyre, 1980).

We further delineated annual inventory plots comprising only one forested condition, that is, plots containing single uniform stand conditions such as tree density, forest type, and stand size class, etc. We decided this would reduce variability and minimize any edge effects that might be present with more than one forested condition on a given plot. Plots with recently cleared overstories and with complete and consistent vegetation measurements on all 4 subplots were also included. Restricting plots in these ways also facilitated the upward scaling of measured attributes for subsequent analysis. In the end, we identified a total of 6,716 plots in twelve western states for our analysis (Table 1).

3.0.2.4 Dependent/independent variables

Our goal was to determine how understory cover and height varied with overstory conditions. Thus, our independent variables for this study consisted of those attributes most relevant for describing overstory conditions as they might influence understory vegetation. These included plot-, condition-, subplot-, and tree-level measurements that FIA routinely collects at these measurement scales on each plot. Similarly, for our response variables, we sought like attributes that characterized understory vegetation abundance, which are measurements carried out at the subplot level. Data tables from both FIA databases were screened for attribute and measurement consistency, and their ecological relevance in describing both overstory and understory conditions evaluated. We identified 30 measured attributes as important independent variables (Tables 2a-b) for predicting understory vegetation growth and abundance. These included several regional variables collected within each of the two FIA regions. In addition, 18 derived variables were calculated from tree-based measured ones based both on their perceived and understood importance in characterizing overall stand structure and effects on understory vegetation levels (Tables 2a-b).

We also obtained an additional 25 variables from an FIA-developed model that calculates overstory canopy cover for FIA plots using individual plot tree information (Table 2c). FIA does not generally collect measurements of canopy cover and this is an important stand characteristic that affects understory vegetation (Toney RMRS P-56, 2008). Other associated variables that were calculated by this model from FIA tree information were also included in our analyses. In total, 73 independent variables, both measured and derived, were included in our analysis (Tables 2a-c).

For our dependent variables describing understory vegetation, we used attributes of height and percent cover by vegetation lifeform to broadly characterize measured understory conditions (Table 2d). FIA collects vegetation height and cover for 4 commonly recognized lifeforms (small (tally) trees, shrubs, forbs, and grasses). However, due to inconsistent measurement protocols of understory vegetation for most years of the PNW data (2001-2011), we could only use the last year of data (2011) that was provided, since the national measurement protocols for understory vegetation were not adopted until then. This resulted in only 362 single condition PNW plots available for analysis (Table 1). This was not the case with the IW-FIA data where all understory vegetation was either consistently measured or revised appropriately according to national protocols to allow for between-year comparisons. In the end, we determined 8 response variables representing height and percent cover for each lifeform for each dataset (Table 2d).

3.0.2.4.1 Scaling variables

1) Independent variables - Once all selected attributes were assessed for their overall suitability, we determined that the plot level was the most appropriate sampling unit by which to conduct our analyses. This meant that all variables measured at scales below this required upward scaling. These included ones that were collected at the individual tree- and subplot-levels. In many cases, scaling was achieved by simply taking the mode, average, or sum over all tree and subplot measurements within a given plot. However, there were several special cases encountered where summarizing measured attributes proved more cumbersome, such as aspect and habitat type (see Table 2a). For condition-level variables, no scaling was needed since our plots represented only single forested conditions.
2) Response variables - Understory vegetation measured in each subplot also needed to be scaled differently to the plot level. FIA collects the percent cover for each lifeform at each of 5 individual layers. The first 4 layers are separate height classes in feet (0-2, 2.1-6, 6.1-16, 16.1+) while the 5th layer represents an aerial cover estimate. In determining our estimates of average plot lifeform cover, we used the aerial cover estimate associated

with each lifeform for each subplot, which is a top-down view of the vegetation cover through all of the layers, thus representing its full cover extent. By definition, aerial cover cannot exceed the sum of all cover measured for individual height layers, but can be less. Average plot lifeform cover is then obtained by averaging the aerial percent covers for each lifeform over all subplots.

For calculation of average plot lifeform height, we adopted a simplistic approach to scale each lifeform height using a method of cover-weighted averages. This is obtained by first calculating a lifeform's relative cover for each height class layer by summing the total lifeform covers over all 4 height layers and then determining the relative proportion of cover for each individual height layer. The resulting relative cover proportions, which always sum to 1, are then multiplied by their respective height class midpoints to obtain its cover-weighted height. These weighted heights are then summed together for each lifeform and averaged over each subplot to obtain an overall plot mean. We calculated our 8 response variables in this way, consisting of plot average cover-weighted height and average percent cover for the 4 lifeforms measured (Table 2d).

3.0.2.5 Analytical Methods

We consulted with RMRS statistical staff as to the best approach to take with these data. Since we wanted a set of regression equations that predicted each response as a function of the most relevant of many predictor variables, we adopted a GLM approach using an automated variable selection procedure. Since we also identified 8 response variables for each dataset, a total of 16 individual models were developed in this way. Several steps were taken to prepare data, eliminate variables, and perform regression analyses.

3.0.2.6 Data Preparation

The understory response variables representing both percent cover and height were transformed prior to variable selection using the following approach to ensure predictions are always between 0 and 1 for the percentages and greater than 0 for the vegetation heights:

1) Observations with zero-responses are removed. The remaining responses are then transformed as follows such that the resulting range is defined on the interval $(-\infty, \infty)$:
    a. Responses on the interval $(0,1)$ are *logit*-transformed as follows:

    $$z = ln\left(\frac{y}{1-y}\right)$$

    b. Responses on the interval $(0, \infty)$ are *log*-transformed as follows:

    $$z = ln(y)$$

    where y is the original response.

2) All 2-way interactions were then created from the input data, resulting in over 10,000 potential predictors.
    a. For continuous x continuous predictors, the interactions involve the element-wise product between two data vectors.

b. For factor x continuous predictors, the interactions involve the element-wise product of each factor level and the continuous predictor.
c. For factor x factor predictors, the interactions involve the element-wise products of each factor level for both factors.

The resulting predictor set from the step above includes all main effects and second-order interactions. Not all of the predictors are candidates for variable selection due to singularities or correlation between pairs and linear combinations of predictors. The predictor set is therefore filtered as follows prior to any variable selection:

a. All columns that represent less than 20% of the responses are removed. This includes columns that involve factor levels that represent any classification containing less than 20% of the observations.
b. Columns with zero variation are removed. This includes constant covariates or interactions that involve only a single pair of interacted factor levels for the entire sample.
c. Remove one of any pair of predictors with a correlation greater than 0.8 in absolute value. The removed predictor is the one with the largest average correlation with all other predictors.
d. Remove any predictors that are linear combinations of other predictors.

3.0.2.7 Variable Selection

The first stage of variable selection involves the use of elastic net regularization to isolate a subset of potential predictors (Zou and Hastie, 2005). The best model is selected using *leave-one-out cross validation* based on a mean squared error loss function.

The second stage of variable selection involves use of a stepwise selection method based on corrected *Akaike's Information Criteria* (AICc). The first subset of predictors found by elastic net is therefore reduced to a more conservative subset in order to prevent overfitting (Venables and Ripley, 2002).

The resulting subset of predictors is then modeled on the original response scale using a Generalized Linear Model that allows for use of appropriate link functions. Responses on the interval $(0,1)$ are modeled using a logit-link while responses on the interval $(0, \infty)$ are modeled using a log-link. By using a GLM, the inverse-linked predictions are free from retransformation bias.

3.0.2.8 Prediction

1) Define $g(x)$ as the linear function derived from the selected subset of predictors. The function includes an estimated intercept, β_0, along with estimated regression coefficients that model the response on the link scale. Linear predictions on the link-scaled response are linear functions as follows:

$$g(x) = \sum_{k=0}^{K} \beta_k x_k$$

where $g(x)$ is the link corresponding to the particular response.

2) In order to predict on the response scale, inverse-link the final prediction functions as follows:

   a. For responses on the original scale of $(0,1)$, final prediction function is:

$$f(x) = \frac{\exp(g(x))}{1 + \exp(g(x))}$$

   b. For nonnegative responses on the original scale of $(0, \infty)$, the final prediction function is:

$$f(x) = \exp\left(g(x)\right)$$

All analyses were done using R version 3.1.2 (R development Core Team, 2014) including the following libraries:

a) ade4
b) BaylorEdPsych
c) Caret
d) DAAG
e) doParallel
f) ggplot2
g) glmnet
h) gtools
i) Hmisc
j) MASS
k) matrixStats

3.03 Results

All final GLM regression models contained only interaction terms while no main effects were evident in any of the models (Tables 3a-b). Final models contained as few as 4 (PNW-AvgOfWeighted Height FORB) and as many as 33 two-way interaction terms (IW-AvgOfCOVER PCT GRASS), with only a few variables not significant (P>0.1). Interactions were present between many different predictor variables, and consisted of factor-factor, factor-continuous, and continuous-continuous terms. Regression coefficients estimates for the PNW models ranged from -0.67 to 0.75, and averaged -0.016, excluding intercepts (Table 3a). For the IW models, regression coefficient estimates ranged in magnitude from -0.75 to 1.32, and averaged 0.005, also excluding intercepts (Table 3b).

Several similar interaction terms were present in models for both datasets. Elevation and site index (ELEV x SICOND) appeared in 4 of the 8 PNW models and also in 4 of the 8 IW models. Average crown ratio and total canopy cover (AvgOfCR.x.model_crcov) also appeared in 4 of the 8 models for each dataset while presence of disturbance and elevation (D_DSTRBCD1.0.x.ELEV and D_DSTRBCD2.0.x.ELEV) appeared 2 (PNW) and 3 (IW) times for each dataset. Crown class code and average slope (CCLCD_Mode.3.x.AvgOfSLOPE) appeared in 4 models for the IW and in 2 models for the PNW dataset. Forest type and average slope (FLDTYPCD.221.x.AvgOfSLOPE) and ownership and presence of disturbance (OWNCD.11.x.D_DSTRBCD1.0) both appeared in 2 models for each dataset. Remaining relatively frequent variables appearing at least 4 times within an interaction term for the IW datasets include elevation (ELEV) forest type (FLDTYPCD), physiographic class (PHYSCLCD), crown class code (CCLCD), site class code (SITECLCD), and presence of disturbance (D_DSTRBCD2) and treatment (D_TRTCD1). For the PNW models, average breast height age (AvgOfBHAGE) and forest type (FLDTYPCD) each appeared 3 times.

For the PNW data, 25 predictors out of a possible total of 66 failed to appear in any of the models as either main effects or interactions (Table 4). The remaining 41 predictors appeared at least once in a model regression term. Of these, 21 variables appeared at least 5 times and 8 variables appeared at least 10 times in a second order interaction. For the IW data, 33 predictors out of a possible total of 72 failed to appear in any of the models. The remaining 39 predictors appeared at least once in a model. Of these, 26 variables appeared at least 5 times and 16 variables appeared at least 10 times in an interaction term. Three variables appeared more than 20 times: forest type (FLDTYPCD), elevation (ELEV), and average slope (AvgOfSLOPE). Between the two datasets, 19 variables did not appear in either of them.

Overall, the PNW models performed better for each corresponding lifeform cover and height. McFadden statistics, which are goodness of fit measures similar in interpretation to R-squared, ranged from 0.22 for average weighted forb height to 0.87 for average tally tree cover (Table 3a). For the IW data, McFadden statistics ranged from 0.06 for average weighted forb height to 0.36 for average weighted shrub height (Table 3b). McFadden goodness of fit measures were higher in all corresponding models for the PNW than IW. The differences were smallest in the case of average weighted shrub height (0.37 and 0.36) but much higher in the cases of average weighted tally tree height and tally tree cover (0.84 and 0.87 vs. 0.21 and 0.30) for PNW and IW models, respectively.

In looking at predicted versus observed plots, better fits are also seen with the PNW data (Fig.'s 33 a-p). In most cases, predicted values more closely agreed with observed values for the PNW plots more so than with the IW plots, despite the narrower range of cover and heights and the much larger sample sizes of the IW data (Fig.'s 34 a-p). For percent cover models in both datasets, the most notable departures between observed and predicted were found in the smallest cover classes (<5%) where the models generally underpredicted values. For the majority of the remaining cover classes greater than about 5% cover, the models tended to overpredict values, except for tally tree cover in the PNW dataset, where predictions generally agreed with observed values. The worst fitting cover models for each dataset were average forb cover with McFadden values of 0.34 (PNW) and 0.23 for average shrub cover (IW) (Tables 3a and 3b, Fig.'s 33a, 33b, 34e, and 34f). The best fitting cover models for each dataset were both for average tally tree cover with McFadden values of 0.87 (PNW) and 0.3 (IW)(Tables 3a and 3b, Fig.'s 33g, 33h, 34g, and 34h).

The lifeform height models tended to overpredict values for height classes greater than 1 foot, but tended to underpredict vegetation heights approximating 1 foot, with the exception of tally tree heights, where predictions generally agreed with observed values. Heights less than 1 foot for all lifeforms and greater than 2 feet for forbs and grasses were rarely predicted at all, possibly due to a lack of observations in these height classes. Similarly, heights greater than 5-6 feet for shrubs and greater than 12 feet for tally trees (IW only) were also rarely predicted, also possibly due to a lack of observations. Overall, the PNW lifeform height models represented better fits to observed data than did the IW models. The worst fitting height models for each dataset were both for average weighted forb height with McFadden values of 0.22 (PNW) and 0.06 (IW) (Tables 3a and 3b, Fig.'s 33i, 33j, 34i, and 34j). The best fitting height models for each dataset were for average tally tree height with McFadden values of 0.87 (PNW) and 0.36 for average weighted shrub height (IW) (Tables 3a and 3b, Fig.'s 33o, 33p, 34m, and 34n).

3.0.4 Discussion and Future Work

Given that only interaction terms were present in all of the models without any main effects may suggest that had 3-way interactions been included, then perhaps they would have appeared in these models as well. Interactions occur when one explanatory variable influences how another explanatory variable affects the response variable. More specifically, for continuous x continuous interactions, it means that the slope of one continuous variable on the response variable changes as the values on a second continuous variable change. For factor x continuous interactions, it means that the continuous variable is only affected by the level of the factor. For a factor x factor interaction, it means the response is only affected by the condition where both factor levels exist.

All models contained numerous combinations of the above kinds of interactions between continuous and factor variables, making their interpretation both cumbersome and difficult. This is suggestive of the complexity and interaction of many attributes needed to predict understory vegetation and it is perhaps not surprising that these many variables often interact with one another and depict complex relationships. Most of the variables and especially those most frequently occurring in the models are ones that FIA readily measures or that can be easily computed from them. For forest simulation models such as FVS, which incorporates FIA data for its predictions, this could signify a first attempt to integrate FIA data to uncover these relationships in making understory vegetation cover and height predictions. The next step for successful integration of this information into FVS is to identify the best combination of predictive variables that FVS has readily available and then possibly simplify the equations presented here to accommodate the logic represented in this report.

3.0.5 Overall feasibility of simulating understory vegetation in FVS using FIA data?

One of the likely approaches for model improvement lies with stratification. The relatively poorer predictive models for the IW data could be due, in large part, to the much larger geographical area that it represents in combination with the more moisture-limited habitats.

Stratification could occur geographically based on some measure of climate regime which may not be evident within our selected attribute of habitat types. For example, the Douglas-fir type that we identified has such a broad ecological amplitude that differences in climate may not be readily discernible. To a lesser but still possibly significant degree this may be also the case with lodgepole pine, another very broadly distributed conifer.

Another acknowledged limitation in these models is the difficulty in obtaining precise height and cover data for understory vegetation. For this study, height class midpoints were used since actual heights were not collected and are not part of the current measurement protocol. Ocular estimates of vegetation cover over an entire subplot are also relatively subjective and vary from observer to observer, despite many historical efforts to correct for this. In both of these dimensions, more precise measurements would likely improve the predictive ability of these models.

There also opportunities for additional variable selection and further tweaking of the current models. For example, variable selection could include additional removal of predictors deemed of even lesser importance as a result of this analysis or be recoded into possibly more meaningful categories.

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3.0.8 Appendices

Appendix 1. A list of BPS's for which succession is either fully or partly simulated, depending on several factors, the most important of which is the presence of trees in any of the 3 or less successional stages. To learn more about any of the BPS's on the list visit http://www.landfire.gov/national_veg_models_op2.php. In this table, Limited Successional Dynamics means that succession will stop being simulated when trees enter the system, and a "Y" value indicates this condition. The attribute "Multiple Cohort Types", indicates that a BPS has more than one kind of successional trajectory depending on where the BPS is located in space. For example, central mixed grass prairie can have multiple successional trajectories depending on where the site is located as denoted by the "Y" in the "Multiple Cohort Types" column.

BpS Name	Limited Successional Dynamics[1]	Multiple Cohort Types
Apacherian-Chihuahuan Mesquite Upland Scrub	N	Y
Apacherian-Chihuahuan Semi-Desert Grassland and Steppe	N	Y
Atlantic Coastal Plain Peatland Pocosin and Canebrake	Y	N
California Central Valley and Southern Coastal Grassland	N	N
California Lower Montane Blue Oak-Foothill Pine Woodland and Savanna	Y	Y
California Maritime Chaparral	Y	N
California Mesic Chaparral	Y	N
California Mesic Serpentine Grassland	N	N
California Montane Jeffrey Pine(-Ponderosa Pine) Woodland	Y	Y
California Montane Woodland and Chaparral	Y	Y
California Northern Coastal Grassland	N	N
California Xeric Serpentine Chaparral	Y	N
Central Mixedgrass Prairie	N	Y

Central Tallgrass Prairie	N	N
Chihuahuan Creosotebush Desert Scrub	N	N
Chihuahuan Grama Grass-Creosote Steppe	N	N
Chihuahuan Gypsophilous Grassland and Steppe	N	Y
Chihuahuan Loamy Plains Desert Grassland	N	N
Chihuahuan Mixed Desert and Thorn Scrub	N	Y
Chihuahuan Mixed Desert Shrubland	N	N
Chihuahuan Mixed Salt Desert Scrub	Y	Y
Chihuahuan Sandy Plains Semi-Desert Grassland	N	Y
Chihuahuan Stabilized Coppice Dune and Sand Flat Scrub	N	Y
Chihuahuan Succulent Desert Scrub	N	N
Chihuahuan-Sonoran Desert Bottomland and Swale Grassland	N	Y
Chihuahuan-Sonoran Desert Bottomland and Swale Grassland - Alkali Sacaton	N	N
Chihuahuan-Sonoran Desert Bottomland and Swale Grassland - Tobosa Grassland	N	N
Colorado Plateau Blackbrush-Mormon-tea Shrubland	N	N
Colorado Plateau Mixed Low Sagebrush Shrubland	N	N
Colorado Plateau Pinyon-Juniper Shrubland	Y	Y
Colorado Plateau Pinyon-Juniper Woodland	Y	Y
Columbia Basin Foothill and Canyon Dry Grassland	N	Y
Columbia Basin Palouse Prairie	N	Y
Columbia Plateau Low Sagebrush Steppe	N	Y
Columbia Plateau Scabland Shrubland	N	Y
Columbia Plateau Steppe and Grassland	N	Y
Columbia Plateau Western Juniper Woodland and Savanna	Y	Y
Edwards Plateau Limestone Savanna and Woodland	Y	N
Edwards Plateau Limestone Shrubland	N	N
Florida Dry Prairie	Y	N
Florida Peninsula Inland Scrub	Y	N
Great Basin Pinyon-Juniper Woodland	Y	Y
Great Basin Semi-Desert Chaparral	N	N
Great Basin Xeric Mixed Sagebrush Shrubland	Y	Y
Great Plains Prairie Pothole	N	N
Inter-Mountain Basins Big Sagebrush Shrubland	Y	Y
Inter-Mountain Basins Big Sagebrush Shrubland - Basin Big Sagebrush	N	N
Inter-Mountain Basins Big Sagebrush Shrubland - Wyoming Big Sagebrush	N	N
Inter-Mountain Basins Big Sagebrush Steppe	N	Y
Inter-Mountain Basins Curl-leaf Mountain Mahogany Woodland and Shrubland	Y	Y
Inter-Mountain Basins Greasewood Flat	N	Y
Inter-Mountain Basins Juniper Savanna	Y	Y
Inter-Mountain Basins Mat Saltbush Shrubland	N	Y
Inter-Mountain Basins Mixed Salt Desert Scrub	N	Y
Inter-Mountain Basins Mixed Salt Desert Scrub - North	N	N
Inter-Mountain Basins Mixed Salt Desert Scrub - South	N	N
Inter-Mountain Basins Montane Sagebrush Steppe	Y	Y
Inter-Mountain Basins Montane Sagebrush Steppe - Low Sagebrush	N	N
Inter-Mountain Basins Montane Sagebrush Steppe - Mountain Big Sagebrush	Y	N
Inter-Mountain Basins Semi-Desert Grassland	N	Y
Inter-Mountain Basins Semi-Desert Shrub-Steppe	N	Y
Madrean Encinal	Y	Y
Madrean Juniper Savanna	Y	N
Madrean Oriental Chaparral	N	N
Madrean Pinyon-Juniper Woodland	Y	N
Mediterranean California Alpine Dry Tundra	N	N
Mediterranean California Mesic Serpentine Woodland and Chaparral	Y	N
Mediterranean California Subalpine Meadow	N	Y
Mogollon Chaparral	N	Y
Mojave Mid-Elevation Mixed Desert Scrub	N	N

North Pacific Alpine and Subalpine Dry Grassland	N	N
North Pacific Montane Grassland	N	N
North-Central Interior Sand and Gravel Tallgrass Prairie	Y	N
Northern and Central California Dry-Mesic Chaparral	N	N
Northern Rocky Mountain Lower Montane-Foothill-Valley Grassland	N	Y
Northern Rocky Mountain Montane-Foothill Deciduous Shrubland	Y	Y
Northern Rocky Mountain Subalpine-Upper Montane Grassland	Y	Y
Northern Tallgrass Prairie	Y	Y
Northwestern Great Plains Mixedgrass Prairie	N	Y
Northwestern Great Plains Shrubland	N	N
Rocky Mountain Alpine Fell-Field	N	N
Rocky Mountain Alpine Turf	N	N
Rocky Mountain Foothill Limber Pine-Juniper Woodland	Y	Y
Rocky Mountain Gambel Oak-Mixed Montane Shrubland	N	N
Rocky Mountain Gambel Oak-Mixed Montane Shrubland - Continuous	N	N
Rocky Mountain Gambel Oak-Mixed Montane Shrubland - Patchy	N	N
Rocky Mountain Lower Montane-Foothill Shrubland	Y	Y
Rocky Mountain Lower Montane-Foothill Shrubland - No True Mountain Mahogany	N	N
Rocky Mountain Lower Montane-Foothill Shrubland - True Mountain Mahogany	N	N
Rocky Mountain Subalpine-Montane Mesic Meadow	N	Y
Sierra Nevada Alpine Dwarf-Shrubland	N	N
Sonora-Mojave Creosotebush-White Bursage Desert Scrub	N	N
Sonora-Mojave Mixed Salt Desert Scrub	N	N
Sonora-Mojave Semi-Desert Chaparral	N	N
Sonoran Granite Outcrop Desert Scrub	Y	N
Sonoran Mid-Elevation Desert Scrub	N	Y
Sonoran Paloverde-Mixed Cacti Desert Scrub	Y	N
South Texas Lomas	N	Y
South Texas Sand Sheet Grassland	N	N
Southeastern Great Plains Tallgrass Prairie	Y	N
Southern Blackland Tallgrass Prairie	Y	N
Southern California Coastal Scrub	N	N
Southern California Dry-Mesic Chaparral	N	N
Southern Colorado Plateau Sand Shrubland	N	N
Southern Rocky Mountain Juniper Woodland and Savanna	Y	Y
Southern Rocky Mountain Montane-Subalpine Grassland	N	Y
Southern Rocky Mountain Pinyon-Juniper Woodland	Y	Y
Southern Rocky Mountain Ponderosa Pine Savanna	Y	Y
Tamaulipan Calcareous Thornscrub	N	N
Tamaulipan Clay Grassland	N	N
Tamaulipan Mixed Deciduous Thornscrub	Y	N
Tamaulipan Savanna Grassland	Y	N
Texas-Louisiana Coastal Prairie	N	Y
Texas-Louisiana Saline Coastal Prairie	N	N
West Gulf Coastal Plain Northern Calcareous Prairie	Y	N
West Gulf Coastal Plain Southern Calcareous Prairie	Y	N
Western Great Plains Depressional Wetland Systems	N	Y
Western Great Plains Depressional Wetland Systems - Playa	N	N
Western Great Plains Depressional Wetland Systems - Saline	N	N
Western Great Plains Foothill and Piedmont Grassland	N	N
Western Great Plains Mesquite Woodland and Shrubland	Y	Y
Western Great Plains Sand Prairie	N	Y
Western Great Plains Sandhill Steppe	N	Y
Western Great Plains Shortgrass Prairie	N	Y
Western Great Plains Tallgrass Prairie	Y	N
Wyoming Basins Dwarf Sagebrush Shrubland and Steppe	N	Y

1. Y is yes, and N is no.

Appendix 2. Appendices for Tables and Figures of the Overstory / understory project.

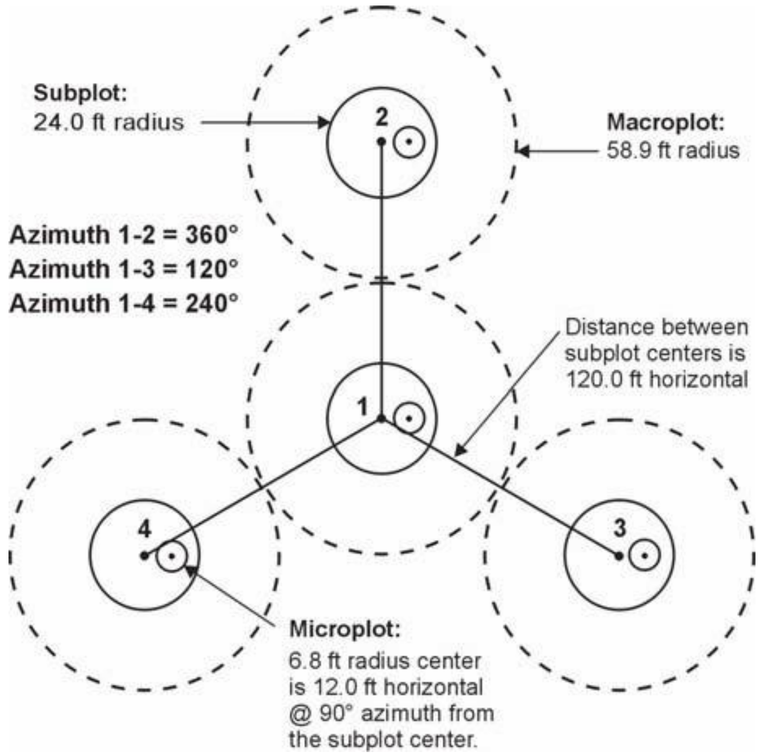

Figure 32. FIA National Annual Inventory Plot Design.

Table 1. FIA single condition plot summary for Interior West (IW) and Pacific Northwest (PNW) datasets (2011 data for PNW only).

	FIA Forest Type	Existing Vegetation Type* (EVT)	# Plots (single condition)	# Subplots (single condition)	# Plots with Live Overstory and Complete Understory Vegetation	# Plots with Complete Understory Vegetation **
Interior West (2000-2012)						
Douglas-fir	201	2045/2166/2051	2,529	10,116	2,438	2,529
ponderosa pine	221	2053/2054	2,001	8,004	1,910	2,001
grand fir	267	2047	332	1,328	327	332
lodgepole pine	281	2050	1,492	5,968	1,359	1,492
Total	-	-	6,354	25,416	6,034	**6,354**
Pacific Northwest (2011 only)						
Douglas-fir	201	2045/2166/2051	203	812	191	203
ponderosa pine	221	2053/2054	95	380	85	95
grand fir	267	2047	27	108	27	27
lodgepole pine	281	2050	37	148	35	37
Total	-	-	362	1,448	338	**362**
Combined Total						**6,716**

* EVT descriptions are as follows: 2045 - Northern Rocky Mountain Dry-Mesic Montane Mixed Conifer Forest; 2166 - Middle Rocky Mountain Montane Douglas-fir Forest and Woodland ; 2047 - Northern Rocky Mountain Mesic Montane Mixed Conifer Forest; 2051 - Southern Rocky Mountain Dry-Mesic Montane Mixed Conifer Forest and Woodland; 2050 - Rocky Mountain Lodgepole Pine Forest; 2053 - Northern Rocky Mountain Ponderosa Pine Woodland and Savanna; 2054 - Southern Rocky Mountain Ponderosa Pine Woodland (Comer et al., 2003)

** denotes all 4 subplots measured

Table 2a. Independent variables for IW and PNW datasets measured or derived from plot-, condition-, and subplot- level FIA measurements. NA denotes that no scaling to the plot level was needed and/or the actual measured values were used.

#	Variable Name	Description	Variable Type	Scaling Method
1	ELEV	Plot elevation above sea level (in feet) (NAD 83 datum).	Continuous	NA
2	TOPO_POSITION_PNW (PNW only)	Plot topographic position on landscape (9 classes).	Categorical	NA
3	SITECLCD	Site productivity class code (7 classes).	Categorical	NA
4	D_DSTRBCD1	Indicator variable for disturbance code #1 for condition, 0 indicates no disturbance observed/evident, and is populated for all forested plots. A code indicating the kind of disturbance occurring since the last measurement or within the last 5 years for new plots. The area affected by the disturbance must be at least 1 acre in size.	Categorical	NA
5	D_DSTRBCD2	Indicator variable for disturbance code #2 for condition, 0 indicates no disturbance observed/evident. A code indicating the kind of disturbance occurring since the last measurement or within the last 5 years for new plots. The area affected by the disturbance must be at least 1 acre in size.	Categorical	NA
6	FLDTYPCD	FIA field forest type code that is assigned in the field and based on the tree species or species groups forming a plurality of all live stocking (DF=201, 221=PP, 267=GF, 281=LP).	Categorical	NA
7	HT_Series	This represents the truncation of measured habitat types (series/type/phase) to the series level only. This was done to increase the number of observations per habitat type level.	Categorical	NA
8	OWNCD	Ownership code for the condition. See FIA National Core Field Gide for definitions.	Categorical	NA
9	PHYSCLCD	Physiographic class code for the condition within xeric, mesic, and hydric categories. It is a coded measure of available moisture to stands as affected by topographic landform.	Categorical	NA
10	SICOND	Site index for the condition using 50, 80 or 100 years as the base age (see SIBASE). Site index is the estimated/expected average height of dominant/codominant trees at the specified base age.	Continuous	NA
11	FLDSZCD	Field stand-size class code (codes 0-6). A coded field measure of predominant diameter class of live trees.	Categorical	NA
12	STDSZCD	Stand-size class code (4 codes). A coded classification of the predominant diameter class of live trees in the condition using an algorithm.	Categorical	NA

13	D_TRTCD1	Indicator variable for stand treatment 1 code. A code indicating the type of stand treatment that has occurred since the last measurement or within 5 years for new plots. The treatment must be >=1 acre (0 indicates no observable treatment).	Categorical	NA
14	D_TRTCD2	Indicator variable for stand treatment 2 code. A code indicating the type of stand treatment that has occurred since the last measurement or within 5 years for new plots. The treatment must be >=1 acre (0 indicates no observable treatment).	Categorical	NA
15	LIVE_CANOPY_CVR_PCT (IW only)	The percentage of live canopy cover for the condition including live tally trees, saplings, and seedlings.	Continuous	NA
16	LIVE_MISSING_CANOPY_CVR_PCT (IW only)	Live plus estimated missing canopy cover for the condition of missing live and dead tally trees, saplings and seedling due to disturbance, treatment, etc., based on observation, stand history, and historical aerial imagery. This percentage cannot exceed 100%.	Continuous	NA
17	Eastness (derived)	Subplot aspect (n=4), in degrees, that is averaged for the plot and transformed into eastness (sin[aspect]). See Zar 1999 for methods.	Continuous	Circular Average
18	Northness (derived)	Subplot aspect (n=4), in degrees, that is averaged for the plot and transformed into northness (cos[aspect]). See Zar 1999 for methods.	Continuous	Circular Average
19	Final_Mean_Aspect (derived)	Transformation of average eastness and northness components into mean aspect (in degrees). See Zar 1999 for methods.	Continuous	Circular Average
20	Coded_Aspect (derived)	Reclassification of Final_Mean Aspect into 8 groups starting with 337.5 degrees and containing 45 degree classes (e.g. 1= 337.5-22.5 degrees, 2= 22.5-67.5 degrees,….) 0= flat areas.	Categorical	NA
21	Cardinal_Direction (derived)	Recoding of Coded_Aspect into 8 cardinal directions, including flat areas.	Categorical	NA
22	AvgOfSLOPE	Mean slope for plot after averaging over each subplot (n=4) (in percent).	Continuous	Average

Table 2b. Independent variables for IW and PNW datasets measured or derived from tree and seedling-level FIA measurements. NA denotes that no scaling to the plot level was needed and/or the actual measured values were used.

#	Variable Name	Description	Variable Type	Scaling method
23	CountOfTREE	Number of sampled trees per plot greater than or equal to 1" DBH and used for calculation of tree level attributes. Only live trees are considered.	Continuous	Sum
24	SumOfTPA_UNADJ	Trees per acre unadjusted for all live trees 1" or greater DBH that are measured on microplots, subplots, and macroplots (PNW only), and summed over all trees for plot-level estimate.	Continuous	Sum

25	AvgOfDIA	Average diameter of all measured live trees greater than or equal to 1"DBH (in inches).	Continuous	Average
26	AvgOfACTUALHT	Average of actual tree height (ground to existing tip plus estimated lengths of broken tops)(in feet). Averaged for measured trees only greater than or equal to 1" DBH.	Continuous	Average
27	AvgOfBHAGE	Average of tree breast height age, in years, collected for a subset of measured live trees greater than or equal to 1" DBH for each species, diameter class, and crown class (PNW).	Continuous	Average
28	CCLCD_Mode	Mode of tree crown class for measured trees greater than or equal to 1" DBH.	Categorical	Mode
29	AvgOfCR	Average of tree compacted crown ratio, in percent, for measured live trees greater than or equal to 1" DBH.	Continuous	Average
30	SumOfBASAL_AREA	Sum of basal area per tree of measured live trees (in square feet) greater than or equal to 1"DBH.	Continuous	Sum
31	SumOfVOLCFNET	Sum of net tree cubic volume, in cubic feet, for each sample tree greater than or equal to 5" DBH, without rotten, cull or defected wood.	Continuous	Sum
32	SumOfVOLCFGRS	Sum of gross tree cubic volume, in cubic feet, for each sample tree greater than or equal to 5" DBH, with rotten, cull or defected wood.	Continuous	Sum
33	AvgOfUNCRCD (IW only)	Average of uncompacted live crown ratio, in percent. Measured for sampled live trees greater or equal to 5" DBH and determined by dividing the live crown length by the actual height. This is a measure of tree crown vigor.	Continuous	Average
34	SumOfSeedling_TPA_UNADJ	Sum of number of seedling trees per acre (unadjusted) from microplot (1/300 acre) measurements where 1 tree= 74. 965282 TPA.	Continuous	Sum
35	SumDBH_AC	Sum of live tree diameters over all subplots for measured trees greater than or equal to 1" DBH and expanded based on sample plot size (inches/acre).	Continuous	Sum
36	QMD	Quadratic mean diameter or diameter of a tree of average BA for plot, in inches, used for calculation of SDI. Only live measured trees greater than or equal to 1" DBH are considered. See Curtis and Marshall 2000.	Continuous	NA
37	BA_AC	Independently calculated basal area, in square feet, per acre of live trees greater than or equal to 1"DBH.	Continuous	NA
38	VOLCFNET_AC	Net tree cubic volume per acre, in cubic feet/acre, for each sample tree greater than or equal to 5" DBH, without rotten, cull or defected wood.	Continuous	NA
39	VOLCFGRS_AC	Gross tree cubic volume per acre, in cubic feet/acre, for each sample tree greater than or equal to 5" DBH, without rotten, cull or defected wood.	Continuous	NA

40	SDI_10	Stand Density Index (Reineke) in TPA based on a stand QMD of 10" DBH. This is a relative measure of stand density/competition and includes trees greater than or equal to 1" DBH. See Long and Shaw 2010.	Continuous	NA
41	Max_Forest_SDI	Maximum Stand Density Index, in trees per acre, based on predetermined values for each forest type and used in calculation of other SDI variables below, such as the percentage of actual SDI to maximum SDI that a plot represents of a given forest type. See Witt et al. 2012.	Categorical	NA
42	PCT_Max_Occupancy_10	Percent maximum tree occupancy based on SDI_10, (QMD=10" DBH) using actual TPA (actual plot TPA/SDI_10) and includes live trees greater than or equal to 1" DBH.	Continuous	NA
43	PCT_Max_Forest_SDI_10	Percent tree occupancy based on maximum SDI for forest type using SDI_10, (=SDI_10/Max_Forest_SDI) and includes live trees greater than or equal to 1" DBH.	Continuous	NA
44	PCT_Max_Forest_SDI	Percent tree occupancy based on maximum SDI for forest type (=actual plot TPA/Max_Forest_SDI) and includes live trees greater than or equal to 1" DBH. See Long and Shaw 2010.	Continuous	NA
45	SDI_sum	Stand Density Index (Reineke) in TPA based on the summation method for uneven aged stands and includes live trees greater than or equal to 1" DBH. See Long and Shaw 2010.	Continuous	NA
46	PCT_Max_Occupancy_sum	Percent maximum tree occupancy based on SDI_summation method (=actual plot TPA/SDI_sum) and includes live trees greater than or equal to 1" DBH.	Continuous	NA
47	PCT_Max_Forest_SDI_sum	Percent tree occupancy based on maximum SDI for forest type using summation method (=SDI_sum/Max_Forest_SDI) and includes live trees greater than or equal to 1" DBH. See Long and Shaw 2010.	Continuous	NA
48	SDI_sum_SDI_10	Ratio of the two SDIs as an index of structural diversity/even-agedness (=SDI_sum/SDI_10), and includes live trees greater than or equal to 1" DBH. Uneven-agedness increases as the ratio decreases from 1. See Long and Shaw 2010.	Continuous	NA

Table 2c. Independent variables for IW and PNW datasets derived from FIA canopy cover model (see Toney et al. 2009). NA denotes that no scaling to the plot level was needed and the actual calculated values were used.

#	Variable Name	Description	Variable Type	Scaling method
49	map_crcov_subp	Canopy cover, in percent, of live trees greater than or equal to 5" DBH. This is computed as the average of	Continuous	NA

		the 4 subplots. See Toney et al. 2009 for this and all remaining variables derived from FIA canopy cover model.		
50	map_crcov_micr	Canopy cover, in percent, of live sapling trees (1-4.9" DBH). This is computed as the average of the 4 microplots.	Continuous	NA
51	model_crcov	Estimated total canopy cover, in percent, of live trees greater than or equal to 1" DBH from subplots, and a regression estimate of the sapling component.	Continuous	NA
52	numTrees	Number of live trees on plot greater than or equal to 5" DBH and used for Stem Map calculations.	Continuous	NA
53	meanTreeHt	Mean tree height of live trees, in feet, greater than or equal to 5" DBH.	Continuous	NA
54	meanTreeHtBAW	Basal area-weighted mean tree height, in feet, of all lives trees greater than or equal to 5" DBH. Also known as Lorey's mean height which is the sum of each tree HT * BA divided by total BA.	Continuous	NA
55	meanTreeHtDom	Mean height, in feet, of canopy dominant/codominant live trees greater than or equal to 5" DBH.	Continuous	NA
56	meanTreeHtDomBAW	Basal area-weighted mean height, in feet, of canopy dominant/codominant lives trees greater than or equal to 5" DBH. Also known as Lorey's mean height which is the sum of each tree HT *BA divided by total BA.	Continuous	NA
57	predomTreeHt	Mean height, in feet, of the tallest live trees greater than or equal to 5" DBH and greater than or equal to 16 TPA (arbitrary TPA).	Continuous	NA
58	numSaplings	Number of live saplings in plot (1-4.9" DBH).	Continuous	NA
59	meanSapHt	Mean height, in feet, of live saplings (1-4.9" DBH).	Continuous	NA
60	maxSapHt	Maximum height, in feet, of live saplings (1-4.9" DBH).	Continuous	NA
61	standHt	Stand height, in feet. StandHt is based on the basal area-weighted mean height of trees with greater than or 5 " DBH and is therefore often the same value as meanTreeHtDomBAW. However, it excludes trees with intermediate or overtopped crown class codes from its calculation.	Continuous	NA
62	K_6ft	Estimate of K Ripley function at 6 feet. This is a measure of tree dispersion/clustering.	Continuous	NA
63	K_8ft	Estimate of K Ripley function at 8 feet. This is a measure of tree dispersion/clustering.	Continuous	NA
64	K_10ft	Estimate of K Ripley function at 10 feet. This is a measure of tree dispersion/clustering.	Continuous	NA
65	K_12ft	Estimate of K Ripley function at 12 feet. This is a measure of tree dispersion/clustering.	Continuous	NA

66	L_6ft	Estimate of L Ripley function at 6 feet. This is a square root transformation of K that stabilizes the variance.	Continuous	NA
67	L_8ft	Estimate of L Ripley function at 8 feet. This is a square root transformation of K that stabilizes the variance.	Continuous	NA
68	L_10ft	Estimate of L Ripley function at 10 feet. This is a square root transformation of K that stabilizes the variance.	Continuous	NA
69	L_12ft	Estimate of L Ripley function at 12 feet. This is a square root transformation of K that stabilizes the variance.	Continuous	NA
70	G_6ft (IW only)	Estimate of nearest neighbor distribution function at 6 feet. Additional measure of tree dispersion/clustering.	Continuous	NA
71	G_8ft (IW only)	Estimate of nearest neighbor distribution function at 8 feet. Additional measure of tree dispersion/clustering.	Continuous	NA
72	G_10ft (IW only)	Estimate of nearest neighbor distribution function at 10 feet. Additional measure of tree dispersion/clustering.	Continuous	NA
73	G_12ft (IW only)	Estimate of nearest neighbor distribution function at 12 feet. Additional measure of tree dispersion/clustering.	Continuous	NA

Table 2d. Dependent variables for IW and PNW datasets derived from subplot-level FIA understory vegetation measurements. See methods for description of cover-weighted height calculations.

#	Variable Name	Description	Variable Type	Scaling method
1	AvgOfCOVER_PCT_FORB	Percent cover of all forb species found on plot based on the average aerial cover layer for each subplot (n=4).	Continuous	Average
2	AvgOfWeighted_Height_FORB	Cover-weighted height of forbs, in feet, based on the cover-weighted height for each subplot and averaged for each plot.	Continuous	Average
3	AvgOfCOVER_PCT_GRASS	Percent cover of all grass species found on plot based on the average aerial cover layer for each subplot (n=4).	Continuous	Average
4	AvgOfWeighted_Height_GRASS	Cover-weighted height of grass, in feet, based on the cover-weighted height for each subplot and averaged for each plot.	Continuous	Average
5	AvgOfCOVER_PCT_SHRUB	Percent cover of all shrub species found on plot based on the average aerial cover layer for each subplot (n=4).	Continuous	Average
6	AvgOfWeighted_Height_SHRUB	Cover-weighted height of shrubs, in feet, based on the cover-weighted height for each subplot and averaged for each plot.	Continuous	Average

7	AvgOfCOVER_PCT_TALLY_TREE	Percent cover tally trees. This is based on the average aerial cover layer for each subplot (n=4). Tally trees are species on the FIA unit's list of species and include all seedling, sapling, and mature trees.	Continuous	Average
8	AvgOfWeighted_Height_TALLY_TREE	Cover-weighted height of tally trees, in feet, based on the cover-weighted height for each subplot and averaged for each plot.	Continuous	Average

Table 3a. Lifeform percent cover and height regression models for the PNW dataset.

1. AvgOfCOVER_PCT_FORB					
	Estimate	**Std. Error**	**t value**	**Pr(>|t|)**	**McFadden**
(Intercept)	-2.482812	0.312161	-7.950	0.000000	0.3383583
TOPO_POSITION_PNW.3.x. PCT_Max_Forest_SDI	0.003971	0.001642	2.420	0.016300	
TOPO_POSITION_PNW.4.x.SDI_sum_SDI_10	0.366339	0.160474	2.280	0.023300	
OWNCD.46.x.meanSapHt	0.029480	0.006805	4.330	0.000022	
FLDSZCD.3.x.AvgOfSLOPE	0.012759	0.003187	4.000	0.000083	
FLDSZCD.3.x. SumOfTPA_UNADJ	-0.000918	0.000331	-2.780	0.005900	
CCLCD_Mode.3.x.AvgOfCR	-0.026556	0.004368	-6.080	0.000000	
CCLCD_Mode.3.x.numTrees	-0.018604	0.006156	-3.020	0.002800	
CCLCD_Mode.3.x.meanTreeHtBAW	0.014817	0.001923	7.700	0.000000	
AvgOfBHAGE.x.numTrees	-0.000259	0.000059	-4.360	0.000020	
AvgOfCR.x.model_crcov	0.000591	0.000100	5.890	0.000000	
2. AvgOfCOVER_PCT_GRASS					
	Estimate	**Std. Error**	**t value**	**Pr(>|t|)**	**McFadden**
(Intercept)	-1.905614	0.213126	-8.940	0.000000	0.423791
FLDTYPCD.221.x.Northness	0.567305	0.123609	4.590	0.000007	
FLDTYPCD.221.x.AvgOfSLOPE	0.022103	0.004267	5.180	0.000000	
PHYSCLCD.22.x.meanSapHt	0.020788	0.008280	2.510	0.012750	
FLDSZCD.3.x.Final_Mean_Aspect	0.002439	0.000653	3.740	0.000240	
FLDSZCD.3.x.CountOfTREE	-0.013368	0.007708	-1.730	0.084240	
STDSZCD.1.x.ELEV	0.000152	0.000040	3.780	0.000200	
D_DSTRBCD1.0.x.ELEV	0.000057	0.000038	1.510	0.132370	
D_DSTRBCD1.0.x.AvgOfSLOPE	-0.002791	0.004098	-0.680	0.496420	
HT_Series.TSHE.x.ELEV	-0.000818	0.000603	-1.360	0.176130	
AvgOfSLOPE.x.SumOfSeedling_TPA_UNADJ	-0.000006	0.000002	-2.560	0.011270	
AvgOfCR.x. PCT_Max_Forest_SDI_sum	-0.000362	0.000100	-3.630	0.000340	
3. AvgOfCOVER_PCT_SHRUB					

	Estimate	Std. Error	t value	Pr(>|t|)	McFadden
(Intercept)	-0.162625	0.195609	-0.830	0.406590	0.369986
TOPO_POSITION_PNW.3.x.Eastness	0.752044	0.222574	3.380	0.000850	
TOPO_POSITION_PNW.4.x.FLDSZCD.3	-0.357077	0.160806	-2.220	0.027320	
SITECLCD.5.x.SumOfVOLCFNET	0.000261	0.000097	2.700	0.007500	
FLDTYPCD.221.x.AvgOfSLOPE	-0.031041	0.008650	-3.590	0.000400	
OWNCD.11.x.Final_Mean_Aspect	-0.001029	0.000739	-1.390	0.165210	
OWNCD.11.x.map_crcov_micr	0.027798	0.007454	3.730	0.000240	
PHYSCLCD.23.x.Eastness	-0.670811	0.167590	-4.000	0.000084	
FLDSZCD.3.x.Eastness	-0.628390	0.157493	-3.990	0.000088	
CCLCD_Mode.3.x.ELEV	-0.000196	0.000042	-4.690	0.000005	
CCLCD_Mode.3.x.AvgOfSLOPE	0.008895	0.002880	3.090	0.002250	
HT_Series.PSME.x.Final_Mean_Aspect	0.002236	0.000663	3.370	0.000880	
HT_Series.TSHE.x.ELEV	0.000247	0.000066	3.720	0.000250	
Northness.x.Eastness	-0.656620	0.199719	-3.290	0.001160	
Final_Mean_Aspect.x.numTrees	-0.000094	0.000021	-4.410	0.000016	
FLDTYPCD.221.x.Northness	-0.413349	0.240675	-1.720	0.087200	
4. AvgOfCOVER_PCT_TALLY_TREE					
	Estimate	**Std. Error**	**t value**	**Pr(>|t|)**	**McFadden**
(Intercept)	-1.269514	0.186980	-6.790	0.000000	0.871671
TOPO_POSITION_PNW.3.x.Eastness	-0.162813	0.097617	-1.670	0.096710	
TOPO_POSITION_PNW.3.x. PCT_Max_Forest_SDI	0.002358	0.000688	3.430	0.000730	
FLDTYPCD.201.x.D_DSTRBCD1.0	0.236362	0.080437	2.940	0.003640	
FLDTYPCD.201.x.SumOfSeedling_TPA_UNADJ	-0.000072	0.000042	-1.730	0.084810	
FLDTYPCD.221.x.Northness	-0.190764	0.090911	-2.100	0.036970	
FLDTYPCD.221.x.PCT_Max_Forest_SDI	-0.003066	0.000639	-4.800	0.000003	
OWNCD.11.x.D_DSTRBCD1.0	0.206735	0.075093	2.750	0.006380	
OWNCD.11.x.Northness	0.271680	0.064892	4.190	0.000040	
OWNCD.46.x.SumOfBASAL_AREA	0.006385	0.002469	2.590	0.010340	
PHYSCLCD.22.x.FLDSZCD.3	-0.448338	0.122292	-3.670	0.000310	
PHYSCLCD.22.x.Northness	-0.238361	0.076181	-3.130	0.001980	
PHYSCLCD.22.x.meanTreeHtDom	0.004205	0.001356	3.100	0.002170	
FLDSZCD.3.x.D_TRTCD1.0	0.198433	0.078398	2.530	0.012040	
STDSZCD.1.x.SumDBH_AC	0.000243	0.000046	5.310	0.000000	
STDSZCD.1.x.map_crcov_micr	-0.026354	0.005228	-5.040	0.000001	
CCLCD_Mode.3.x.SICOND	0.006546	0.000983	6.660	0.000000	
CCLCD_Mode.3.x.AvgOfBHAGE	-0.004338	0.000865	-5.010	0.000001	
D_DSTRBCD1.0.x.map_crcov_micr	0.013219	0.003751	3.520	0.000510	
D_DSTRBCD1.1.x.Eastness	0.159655	0.089134	1.790	0.074580	
D_TRTCD1.0.x.meanTreeHtBAW	0.004443	0.000808	5.500	0.000000	

D_TRTCD2.0.x.AvgOfCR	-0.019293	0.002523	-7.650	0.000000	
HT_Series.TSHE.x.PCT_Max_Occupancy_10	-0.000662	0.000299	-2.210	0.028130	
ELEV.x.SICOND	-0.000002	0.000000	-7.670	0.000000	
AvgOfBHAGE.x.PCT_max_occupancy_sum	0.000018	0.000003	5.640	0.000000	
AvgOfCR.x.model_crcov	0.000604	0.000049	12.370	0.000000	
SumOfSeedling_TPA_UNADJ.x. PCT_Max_Occupancy_10	0.000000	0.000000	6.190	0.000000	
5. AvgOfWeighted_Height_FORB					
	Estimate	**Std. Error**	**t value**	**Pr(>|t|)**	**McFadden**
(Intercept)	0.260448	0.041107	6.340	0.000000	0.220794
CCLCD_Mode.3.x.ELEV	-0.000051	0.000010	-4.990	0.000001	
CCLCD_Mode.3.x.AvgOfSLOPE	0.002653	0.000755	3.510	0.000530	
Northness.x.meanSapHt	0.004807	0.001523	3.160	0.001790	
AvgOfBHAGE.x.PCT_max_occupancy_sum	-0.000005	0.000002	-2.590	0.010160	
6. AvgOfWeighted_Height_GRASS					
	Estimate	**Std. Error**	**t value**	**Pr(>|t|)**	**McFadden**
(Intercept)	0.529383	0.125941	4.200	0.000038	0.306790
FLDTYPCD.201.x.OWNCD.11	-0.185625	0.050125	-3.700	0.000270	
PHYSCLCD.22.x.FLDSZCD.3	0.104208	0.045384	2.300	0.022580	
FLDSZCD.3.x.CountOfTREE	-0.001967	0.001406	-1.400	0.163370	
D_DSTRBCD1.0.x.numTrees	-0.003508	0.001419	-2.470	0.014180	
D_DSTRBCD1.1.x.SumOfSeedling_TPA_UNADJ	-0.000044	0.000029	-1.520	0.129200	
D_TRTCD2.0.x.SDI_sum_SDI_10	-0.586040	0.108236	-5.410	0.000000	
HT_Series.TSHE.x.Eastness	-0.261758	0.074397	-3.520	0.000520	
ELEV.x.SICOND	0.000000	0.000000	3.140	0.001910	
AvgOfSLOPE.x.map_crcov_micr	-0.000114	0.000044	-2.590	0.010160	
7. AvgOfWeighted_Height_SHRUB					
	Estimate	**Std. Error**	**t value**	**Pr(>|t|)**	**McFadden**
(Intercept)	1.332181	0.130893	10.180	0.000000	0.371444
OWNCD.46.x.SumOfBASAL_AREA	0.004875	0.001786	2.730	0.006820	
PHYSCLCD.22.x.meanTreeHtDom	-0.002463	0.001139	-2.160	0.031570	
STDSZCD.1.x.meanSapHt	0.007381	0.002887	2.560	0.011170	
D_DSTRBCD1.0.x.ELEV	-0.000046	0.000023	-1.990	0.047660	
ELEV.x.SICOND	-0.000001	0.000000	-3.600	0.000380	
AvgOfSLOPE.x.AvgOfCR	0.000060	0.000027	2.220	0.027570	
AvgOfBHAGE.x. PCT_max_occupancy_sum	-0.000015	0.000005	-3.250	0.001310	
AvgOfCR.x.model_crcov	0.000086	0.000033	2.600	0.009970	
8. AvgOfWeighted_Height_TALLY_TREE					

	Estimate	Std. Error	t value	Pr(>|t|)	McFadden
(Intercept)	2.315896	0.052042	44.500	0.000000	0.837120
TOPO_POSITION_PNW.4.x.Eastness	0.045413	0.016673	2.720	0.006950	
TOPO_POSITION_PNW.4.x. SumOfSeedling_TPA_UNADJ	0.000057	0.000015	3.860	0.000150	
TOPO_POSITION_PNW.4.x. PCT_Max_Occupancy_10	-0.000277	0.000068	-4.040	0.000072	
FLDTYPCD.201.x.OWNCD.11	-0.119216	0.023546	-5.060	0.000001	
FLDTYPCD.201.x.AvgOfBHAGE	0.000938	0.000214	4.380	0.000018	
FLDTYPCD.221.x.PCT_Max_Forest_SDI	0.000410	0.000165	2.490	0.013600	
OWNCD.11.x.D_DSTRBCD1.0	0.128379	0.023595	5.440	0.000000	
PHYSCLCD.22.x.Eastness	-0.056944	0.019235	-2.960	0.003400	
STDSZCD.1.x.D_DSTRBCD2.0	0.056320	0.029411	1.910	0.056750	
STDSZCD.1.x.ELEV	0.000052	0.000009	5.580	0.000000	
STDSZCD.1.x.map_crcov_micr	-0.004611	0.000819	-5.630	0.000000	
STDSZCD.1.x.K_10ft	-0.000093	0.000030	-3.080	0.002330	
CCLCD_Mode.3.x.L_6ft	0.004611	0.002313	1.990	0.047410	
D_DSTRBCD1.1.x.Eastness	0.072954	0.023622	3.090	0.002260	
D_DSTRBCD1.1.x.Final_Mean_Aspect	0.000451	0.000108	4.180	0.000042	
D_TRTCD2.0.x.SICOND	0.002455	0.000342	7.190	0.000000	
D_TRTCD2.0.x.AvgOfCR	-0.007327	0.000624	-11.750	0.000000	
HT_Series.PSME.x. Final_Mean_Aspect	0.000269	0.000070	3.850	0.000150	
ELEV.x.SICOND	-0.000001	0.000000	-6.930	0.000000	
ELEV.x.AvgOfBHAGE	0.000000	0.000000	-3.250	0.001320	
ELEV.x.SumOfBASAL_AREA	0.000000	0.000000	-2.500	0.013000	
ELEV.x.numTrees	0.000001	0.000000	3.940	0.000110	
Final_Mean_Aspect.x. SumOfSeedling_TPA_UNADJ	0.000000	0.000000	-5.140	0.000001	
AvgOfSLOPE.x.SumOfSeedling_TPA_UNADJ	-0.000001	0.000000	-2.350	0.019840	
AvgOfCR.x.model_crcov	0.000106	0.000010	10.290	0.000000	
SumOfSeedling_TPA_UNADJ.x. PCT_Max_Occupancy_10	0.000000	0.000000	-0.810	0.417370	
meanSapHt.x.K_6ft	0.000010	0.000004	2.690	0.007570	

Table 3b. Lifeform percent cover and height regression models for the IW dataset.

1. AvgOfCOVER_PCT_FORB					
	Estimate	**Std. Error**	**t value**	**Pr(>|t|)**	**McFadden**
(Intercept)	-2.806272	0.107374	-26.140	0.000000	0.260302
SITECLCD.6.x.FLDTYPCD.201	0.243717	0.064514	3.780	0.000160	
FLDTYPCD.221.x.SDI_10	-0.003038	0.000488	-6.220	0.000000	
FLDTYPCD.281.x.QMD	0.045004	0.006360	7.080	0.000000	
PHYSCLCD.12.x.LIVE_MISSING_CANOPY_CV R_PCT	-0.003012	0.001065	-2.830	0.004700	

STDSZCD.1.x.D_DSTRBCD1.0	-0.151030	0.039402	-3.830	0.000130	
CCLCD_Mode.3.x.AvgOfBHAGE	-0.001323	0.000569	-2.320	0.020180	
D_TRTCD1.0.x.ELEV	-0.000083	0.000016	-5.190	0.000000	
D_TRTCD1.0.x.meanTreeHt	0.010150	0.001335	7.600	0.000000	
HT_Series.ABLA.x.Northness	-0.282385	0.052702	-5.360	0.000000	
HT_Series.ABLA.x.QMD	0.007295	0.005335	1.370	0.171530	
HT_Series.PSME.x.LIVE_CANOPY_CVR_PCT	-0.008571	0.001135	-7.550	0.000000	
ELEV.x.SICOND	0.000003	0.000000	10.310	0.000000	
ELEV.x.AvgOfDIA	-0.000009	0.000001	-6.550	0.000000	
ELEV.x.numTrees	-0.000001	0.000000	-4.300	0.000018	
AvgOfSLOPE.x.PCT_Max_Occupancy_sum	0.000007	0.000004	2.010	0.044680	
AvgOfBHAGE.x.PCT_Max_Occupancy_sum	-0.000009	0.000002	-4.040	0.000054	
AvgOfCR.x.meanTreeHt	0.000121	0.000025	4.730	0.000002	
LIVE_MISSING_CANOPY_CVR_PCT.x.QMD	0.000534	0.000086	6.200	0.000000	
FLDTYPCD.201.x.K_6ft	0.000203	0.000070	2.910	0.003610	
2. AvgOfCOVER_PCT_GRASS					
	Estimate	**Std. Error**	**t value**	**Pr(>|t|)**	**McFadden**
(Intercept)	-1.730989	0.235913	-7.340	0.000000	0.283702
SITECLCD.5.x.CCLCD_Mode.3	0.148879	0.064274	2.320	0.020590	
SITECLCD.6.x.PHYSCLCD.22	0.196526	0.050159	3.920	0.000091	
SITECLCD.6.x.HT_Series.PSME	-0.473010	0.072880	-6.490	0.000000	
SITECLCD.6.x.AvgOfSLOPE	0.009825	0.002034	4.830	0.000001	
SITECLCD.6.x.meanSapHt	0.010554	0.003089	3.420	0.000640	
SITECLCD.6.x.K_12ft	0.000122	0.000031	3.940	0.000084	
FLDTYPCD.201.x.OWNCD.11	0.247481	0.067054	3.690	0.000230	
FLDTYPCD.201.x.HT_Series.PSME	0.300343	0.074341	4.040	0.000054	
FLDTYPCD.221.x.Final_Mean_Aspect	0.000921	0.000241	3.810	0.000140	
OWNCD.11.x.AvgOfCR	-0.006049	0.000835	-7.240	0.000000	
PHYSCLCD.22.x.meanSapHt	-0.008486	0.003430	-2.470	0.013400	
STDSZCD.1.x.AvgOfSLOPE	0.005333	0.001472	3.620	0.000300	
CCLCD_Mode.3.x.SICOND	-0.008824	0.001478	-5.970	0.000000	
CCLCD_Mode.3.x.L_6ft	0.024527	0.004515	5.430	0.000000	
D_DSTRBCD2.0.x.ELEV	-0.000131	0.000028	-4.640	0.000004	
D_DSTRBCD2.0.x.SDI_sum_SDI_10	1.321798	0.267301	4.940	0.000001	
D_TRTCD1.0.x.SDI_sum_SDI_10	0.544962	0.162923	3.340	0.000830	
D_TRTCD1.0.x.meanTreeHt	-0.006178	0.002928	-2.110	0.034950	
HT_Series.PSME.x.LIVE_CANOPY_CVR_PCT	0.003756	0.001465	2.560	0.010360	
ELEV.x.SICOND	0.000001	0.000000	2.980	0.002860	
ELEV.x.AvgOfSLOPE	-0.000004	0.000000	-10.520	0.000000	
ELEV.x.AvgOfBHAGE	0.000000	0.000000	-1.900	0.057270	

ELEV.x.LIVE_MISSING_CANOPY_CVR_PCT	0.000002	0.000001	3.290	0.001020	
ELEV.x.numTrees	-0.000002	0.000000	-5.570	0.000000	
ELEV.x.meanTreeHt	0.000001	0.000001	1.790	0.072940	
Final_Mean_Aspect.x.AvgOfBHAGE	-0.000003	0.000005	-0.640	0.521050	
Final_Mean_Aspect.x.SDI_sum_SDI_10	-0.000097	0.000436	-0.220	0.824610	
AvgOfSLOPE.x.K_6ft	-0.000011	0.000002	-4.450	0.000009	
AvgOfCR.x.LIVE_MISSING_CANOPY_CVR_PCT	0.000185	0.000039	4.740	0.000002	
AvgOfCR.x.model_crcov	-0.000250	0.000038	-6.520	0.000000	
LIVE_MISSING_CANOPY_CVR_PCT.x.QMD	0.000364	0.000159	2.290	0.021890	
LIVE_MISSING_CANOPY_CVR_PCT.x.SDI_sum_SDI_10	-0.027691	0.003863	-7.170	0.000000	
SumOfSeedling_TPA_UNADJ.x.QMD	-0.000008	0.000002	-3.760	0.000180	
3. AvgOfCOVER_PCT_SHRUB					
	Estimate	**Std. Error**	**t value**	**Pr(>|t|)**	**McFadden**
(Intercept)	-2.522430	0.102240	-24.670	0.000000	0.231536
SITECLCD.6.x.STDSZCD.1	-0.234879	0.050737	-4.630	0.000004	
SITECLCD.6.x.meanSapHt	0.008305	0.002445	3.400	0.000690	
FLDTYPCD.221.x.Final_Mean_Aspect	-0.001580	0.000487	-3.240	0.001200	
FLDTYPCD.221.x.AvgOfSLOPE	0.004755	0.002607	1.820	0.068260	
FLDTYPCD.221.x.SDI_10	-0.001642	0.000574	-2.860	0.004240	
FLDTYPCD.281.x.AvgOfSLOPE	0.008784	0.001304	6.730	0.000000	
PHYSCLCD.22.x.Eastness	0.226877	0.046324	4.900	0.000001	
PHYSCLCD.22.x.Final_Mean_Aspect	0.001471	0.000296	4.960	0.000001	
PHYSCLCD.22.x.AvgOfSLOPE	-0.005190	0.001428	-3.630	0.000280	
PHYSCLCD.23.x.PCT_Max_Occupancy_sum	0.000752	0.000161	4.660	0.000003	
FLDSZCD.2.x.Final_Mean_Aspect	0.001387	0.000278	4.980	0.000001	
FLDSZCD.3.x.Final_Mean_Aspect	0.001442	0.000257	5.600	0.000000	
D_DSTRBCD1.0.x.AvgOfSLOPE	0.007914	0.001491	5.310	0.000000	
D_DSTRBCD1.1.x.LIVE_MISSING_CANOPY_CVR_PCT	0.005216	0.001186	4.400	0.000011	
D_TRTCD1.0.x.AvgOfDIA	-0.046599	0.009523	-4.890	0.000001	
D_TRTCD1.0.x.meanTreeHt	0.014988	0.001745	8.590	0.000000	
HT_Series.ABLA.x.QMD	0.019695	0.005444	3.620	0.000300	
ELEV.x.SICOND	-0.000002	0.000000	-7.750	0.000000	
ELEV.x.numTrees	0.000001	0.000000	3.410	0.000650	
SICOND.x.AvgOfCR	0.000288	0.000021	13.490	0.000000	
Final_Mean_Aspect.x.AvgOfBHAGE	-0.000011	0.000002	-4.520	0.000006	
AvgOfSLOPE.x.numSaplings	-0.000821	0.000147	-5.590	0.000000	
QMD.x.numTrees	-0.000690	0.000246	-2.800	0.005110	
D_DSTRBCD1.0.x.meanSapHt	-0.007794	0.002421	-3.220	0.001290	
CCLCD_Mode.3.x.AvgOfSLOPE	0.002412	0.001267	1.900	0.057040	

FLDTYPCD.281.x.SumOfSeedling_TPA_UNADJ	0.000032	0.000012	2.610	0.009190	
4. AvgOfCOVER_PCT_TALLY_TREE					
	Estimate	**Std. Error**	**t value**	**Pr(>|t|)**	**McFadden**
(Intercept)	-1.894894	0.187041	-10.130	0.000000	0.295935
SITECLCD.6.x.OWNCD.11	-0.157688	0.041769	-3.780	0.000160	
SITECLCD.6.x.numSaplings	0.016788	0.003275	5.130	0.000000	
FLDTYPCD.201.x.Final_Mean_Aspect	-0.000873	0.000154	-5.680	0.000000	
FLDTYPCD.221.x.Final_Mean_Aspect	-0.000774	0.000211	-3.670	0.000250	
OWNCD.11.x.HT_Series.PSME	-0.226301	0.048706	-4.650	0.000003	
OWNCD.11.x.Final_Mean_Aspect	0.000658	0.000156	4.230	0.000024	
PHYSCLCD.23.x.PCT_Max_Occupancy_sum	0.000514	0.000110	4.660	0.000003	
FLDSZCD.3.x.numTrees	-0.004822	0.000974	-4.950	0.000001	
CCLCD_Mode.3.x.AvgOfSLOPE	0.002882	0.001002	2.880	0.004050	
CCLCD_Mode.3.x.PCT_Max_Occupancy_sum	0.000338	0.000122	2.770	0.005690	
CCLCD_Mode.3.x.SDI_sum_SDI_10	-0.185535	0.083917	-2.210	0.027100	
D_DSTRBCD2.0.x.ELEV	0.000081	0.000020	4.140	0.000035	
D_DSTRBCD2.0.x.SDI_sum_SDI_10	-0.755521	0.192329	-3.930	0.000087	
D_TRTCD1.0.x.meanTreeHt	0.004189	0.001209	3.470	0.000530	
HT_Series.ABLA.x.Final_Mean_Aspect	-0.000573	0.000189	-3.030	0.002460	
ELEV.x.AvgOfDIA	-0.000013	0.000002	-6.270	0.000000	
AvgOfSLOPE.x.SumOfSeedling_TPA_UNADJ	0.000000	0.000000	-1.700	0.088850	
AvgOfCR.x.model_crcov	0.000260	0.000021	12.570	0.000000	
LIVE_MISSING_CANOPY_CVR_PCT.x.QMD	-0.000140	0.000162	-0.870	0.386590	
LIVE_MISSING_CANOPY_CVR_PCT.x.SDI_sum_SDI_10	0.014564	0.001649	8.830	0.000000	
SumOfSeedling_TPA_UNADJ.x.QMD	0.000010	0.000002	6.380	0.000000	
5. AvgOfWeighted_Height_FORB					
	Estimate	**Std. Error**	**t value**	**Pr(>|t|)**	**McFadden**
(Intercept)	0.299116	0.028473	10.510	0.000000	0.060985
FLDTYPCD.221.x.SumOfTPA_UNADJ	-0.000113	0.000030	-3.740	0.000190	
PHYSCLCD.22.x.D_DSTRBCD1.0	0.037594	0.012201	3.080	0.002080	
CCLCD_Mode.3.x.AvgOfUNCRCD	-0.000976	0.000244	-3.990	0.000066	
ELEV.x.numTrees	0.000000	0.000000	-7.450	0.000000	
SICOND.x.AvgOfCR	0.000037	0.000007	5.590	0.000000	
AvgOfBHAGE.x.AvgOfUNCRCD	-0.000012	0.000002	-5.120	0.000000	
FLDSZCD.3.x.AvgOfSLOPE	0.000854	0.000273	3.120	0.001790	
6. AvgOfWeighted_Height_GRASS					
	Estimate	**Std. Error**	**t value**	**Pr(>|t|)**	**McFadden**
(Intercept)	0.291850	0.030657	9.520	0.000000	0.076675

SITECLCD.5.x.Northness	0.051439	0.025078	2.050	0.040320	
SITECLCD.6.x.OWNCD.11	0.067661	0.016111	4.200	0.000027	
SITECLCD.6.x.Northness	0.043720	0.020267	2.160	0.031050	
FLDTYPCD.201.x.D_DSTRBCD1.0	0.053829	0.015789	3.410	0.000660	
FLDTYPCD.221.x.SumOfTPA_UNADJ	-0.000184	0.000048	-3.870	0.000110	
FLDTYPCD.221.x.SDI_10	0.000819	0.000120	6.810	0.000000	
OWNCD.11.x.FLDSZCD.3	-0.069608	0.018109	-3.840	0.000120	
OWNCD.11.x.Northness	-0.052928	0.020041	-2.640	0.008300	
OWNCD.11.x.numSaplings	-0.006622	0.001969	-3.360	0.000780	
OWNCD.46.x.Northness	-0.065813	0.023964	-2.750	0.006050	
PHYSCLCD.12.x.LIVE_MISSING_CANOPY_CVR_PCT	-0.000820	0.000301	-2.730	0.006420	
PHYSCLCD.22.x.meanSapHt	-0.002702	0.000885	-3.050	0.002270	
PHYSCLCD.23.x.PCT_Max_Occupancy_sum	-0.000194	0.000070	-2.790	0.005270	
FLDSZCD.3.x.ELEV	0.000015	0.000003	5.590	0.000000	
CCLCD_Mode.3.x.SICOND	0.001620	0.000478	3.390	0.000700	
CCLCD_Mode.3.x.AvgOfUNCRCD	-0.001305	0.000330	-3.950	0.000079	
HT_Series.PSME.x.PCT_Max_Occupancy_sum	0.000191	0.000048	4.010	0.000062	
ELEV.x.meanTreeHt	0.000000	0.000000	-3.370	0.000770	
AvgOfSLOPE.x.AvgOfBHAGE	-0.000010	0.000003	-3.400	0.000670	
LIVE_MISSING_CANOPY_CVR_PCT.x.QMD	0.000072	0.000035	2.060	0.039120	
QMD.x.numTrees	-0.000415	0.000061	-6.810	0.000000	
7. AvgOfWeighted_Height_SHRUB					
	Estimate	**Std. Error**	**t value**	**Pr(>|t|)**	**McFadden**
(Intercept)	0.345172	0.133522	2.590	0.009770	0.359741
SITECLCD.6.x.OWNCD.11	-0.127970	0.022737	-5.630	0.000000	
FLDTYPCD.201.x.ELEV	0.000018	0.000003	5.350	0.000000	
FLDTYPCD.221.x.Eastness	0.086497	0.025494	3.390	0.000700	
FLDTYPCD.221.x.AvgOfSLOPE	0.001071	0.000814	1.320	0.188370	
FLDTYPCD.221.x.SDI_10	-0.000618	0.000175	-3.530	0.000420	
OWNCD.11.x.D_DSTRBCD1.0	0.092983	0.021077	4.410	0.000011	
FLDSZCD.3.x.CCLCD_Mode.3	0.199488	0.027309	7.300	0.000000	
FLDSZCD.3.x.numTrees	-0.003581	0.000850	-4.210	0.000026	
CCLCD_Mode.3.x.AvgOfSLOPE	0.002762	0.000777	3.550	0.000390	
CCLCD_Mode.3.x.AvgOfUNCRCD	-0.003601	0.000590	-6.110	0.000000	
D_DSTRBCD1.0.x.AvgOfSLOPE	0.003031	0.000779	3.890	0.000100	
D_DSTRBCD1.1.x.LIVE_MISSING_CANOPY_CVR_PCT	0.001934	0.000613	3.150	0.001630	
D_DSTRBCD2.0.x.AvgOfUNCRCD	0.004189	0.000931	4.500	0.000007	
D_DSTRBCD2.0.x.SDI_sum_SDI_10	-0.239258	0.114288	-2.090	0.036380	
D_TRTCD1.0.x.SICOND	0.009479	0.000706	13.440	0.000000	

D_TRTCD1.0.x.SDI_sum_SDI_10	-0.507280	0.059549	-8.520	0.000000	
D_TRTCD2.0.x.SDI_sum_SDI_10	0.708510	0.172864	4.100	0.000042	
ELEV.x.SICOND	-0.000001	0.000000	-12.270	0.000000	
AvgOfBHAGE.x.LIVE_MISSING_CANOPY_CVR_PCT	-0.000023	0.000006	-4.060	0.000050	
AvgOfBHAGE.x.AvgOfUNCRCD	-0.000023	0.000005	-4.560	0.000005	
AvgOfCR.x.model_crcov	0.000043	0.000012	3.580	0.000340	
AvgOfCR.x.meanTreeHt	0.000074	0.000011	6.650	0.000000	
8. AvgOfWeighted_Height_TALLY_TREE					
	Estimate	**Std. Error**	**t value**	**Pr(>|t|)**	**McFadden**
(Intercept)	2.096104	0.052165	40.180	0.000000	0.209798
SITECLCD.6.x.OWNCD.11	-0.044226	0.015888	-2.780	0.005400	
SITECLCD.6.x.meanSapHt	0.003303	0.000744	4.440	0.000009	
FLDTYPCD.201.x.Final_Mean_Aspect	-0.000250	0.000058	-4.280	0.000019	
FLDTYPCD.221.x.Final_Mean_Aspect	-0.000368	0.000089	-4.140	0.000035	
FLDTYPCD.221.x.K_12ft	-0.000051	0.000021	-2.440	0.014880	
OWNCD.11.x.D_DSTRBCD1.0	0.040032	0.012718	3.150	0.001660	
PHYSCLCD.22.x.meanSapHt	0.002121	0.000596	3.560	0.000380	
CCLCD_Mode.3.x.AvgOfSLOPE	0.001625	0.000314	5.170	0.000000	
D_DSTRBCD2.0.x.ELEV	0.000021	0.000004	4.710	0.000003	
D_DSTRBCD2.0.x.SDI_sum_SDI_10	-0.239021	0.053304	-4.480	0.000008	
D_TRTCD1.0.x.SICOND	0.001814	0.000401	4.530	0.000006	
ELEV.x.AvgOfDIA	-0.000004	0.000000	-11.740	0.000000	
Final_Mean_Aspect.x.L_6ft	0.000019	0.000007	2.630	0.008660	
AvgOfSLOPE.x.SumOfSeedling_TPA_UNADJ	-0.000001	0.000000	-8.580	0.000000	
AvgOfSLOPE.x.K_6ft	-0.000003	0.000001	-3.210	0.001350	
AvgOfCR.x.model_crcov	0.000060	0.000008	7.200	0.000000	
AvgOfCR.x.G_12ft	0.000409	0.000441	0.930	0.353780	
QMD.x.numTrees	0.000355	0.000043	8.200	0.000000	

Table 4. Frequency of occurrence of individual predictors within 2-way interactions for both PNW and IW regression models. NA refers to regionally-specific variables that were not measured. In the case of the nearest neighbor functions (G), these were not calculated for the PNW dataset.

#	Variable	PNW	IW
1	ELEV	15	22
2	TOPO_POSITION_PNW (PNW only)	9	NA
3	SITECLCD	1	17
4	D_DSTRBCD1	12	10

5	D_DSTRBCD2	1	8
6	FLDTYPCD	12	25
7	HT_Series	6	10
8	OWNCD	10	14
9	PHYSCLCD	8	13
10	SICOND	6	10
11	FLDSZCD	10	8
12	STDSZCD	8	3
13	D_TRTCD1	2	10
14	D_TRTCD2	4	1
15	LIVE_CANOPY_CVR_PCT_(IW only)	NA	2
16	LIVE_MISSING_CANOPY_CVR_PCT_(IW_only)	NA	13
17	Eastness (derived)	10	2
18	Northness (derived)	7	5
19	Final_Mean_Aspect (derived)	7	15
20	Coded_Aspect (derived)	0	0
21	Cardinal_Direction (derived)	0	0
22	AvgOfSLOPE	10	21
23	CountOfTREE	2	0
24	SumOfTPA_UNADJ	1	2
25	AvgOfDIA	0	4
26	AvgOfACTUALHT	0	0
27	AvgOfBHAGE	7	9
28	CCLCD_Mode	10	15
29	AvgOfCR	9	11
30	SumOfBASAL_AREA	3	0
31	SumOfVOLCFNET	1	0
32	SumOfVOLCFGRS	0	0
33	AvgOfUNCRCD (IW only)	NA	6
34	SumOfSeedling_TPA_UNADJ	8	5
35	SumDBH_AC	1	0
36	QMD	0	12
37	BA_AC	0	0
38	VOLCFNET_AC	0	0
39	VOLCFGRS_AC	0	0
40	SDI_10	0	4
41	Max_Forest_SDI	0	0
42	PCT_Max_Occupancy_10	4	0
43	PCT_Max_Forest_SDI_10	0	0
44	PCT_Max_Forest_SDI	4	0

45	SDI_sum	0	0
46	PCT_Max_Occupancy_sum	3	7
47	PCT_Max_Forest_SDI_sum	1	0
48	SDI_sum_SDI_10	2	11
49	map_crcov_subp	0	0
50	map_crcov_micr	5	0
51	model_crcov	4	4
52	numTrees	5	9
53	meanTreeHt	0	8
54	meanTreeHtBAW	2	0
55	meanTreeHtDom	2	0
56	meanTreeHtDomBAW	0	0
57	predomTreeHt	0	0
58	numSaplings	0	3
59	meanSapHt	5	7
60	maxSapHt	0	0
61	standHt	0	0
62	K_6ft	1	3
63	K_8ft	0	0
64	K_10ft	1	0
65	K_12ft	0	2
66	L_6ft	1	2
67	L_8ft	0	0
68	L_10ft	0	0
69	L_12ft	0	0
70	G_6ft	NA	0
71	G_8ft	NA	0
72	G_10ft	NA	0
73	G_12ft	NA	1

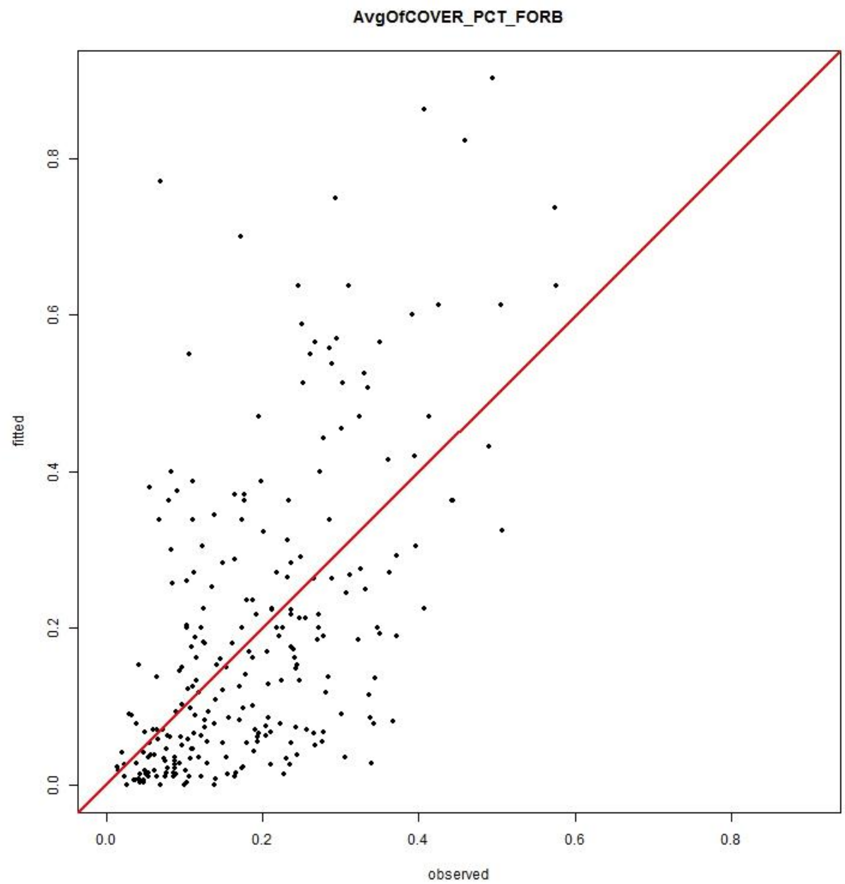

Figure 33 a. Plot of predicted versus observed values for mean percent forb cover for the PNW dataset. The one to one line is represented in red. Both axes are retransformed to their original units (i.e. percent cover) and expressed as a proportion.

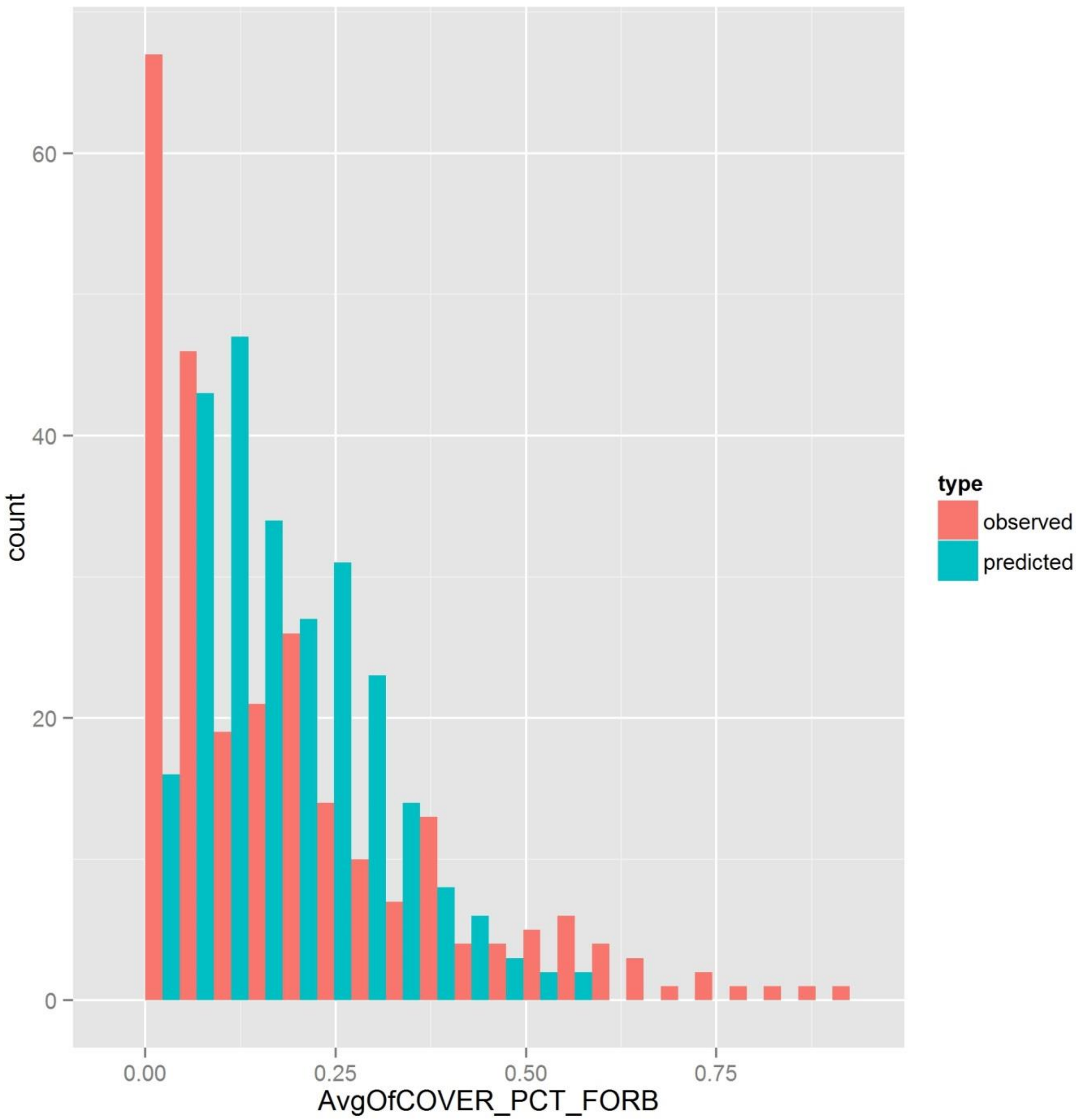

Figure 33b. Predicted versus observed bar graphs for mean percent forb cover for the PNW dataset. The classes represent the range of the data divided by 20 and count values along the y-axis represent the number of observations (plots). The x-axis is retransformed to its original units (i.e. percent cover) and expressed as a proportion.

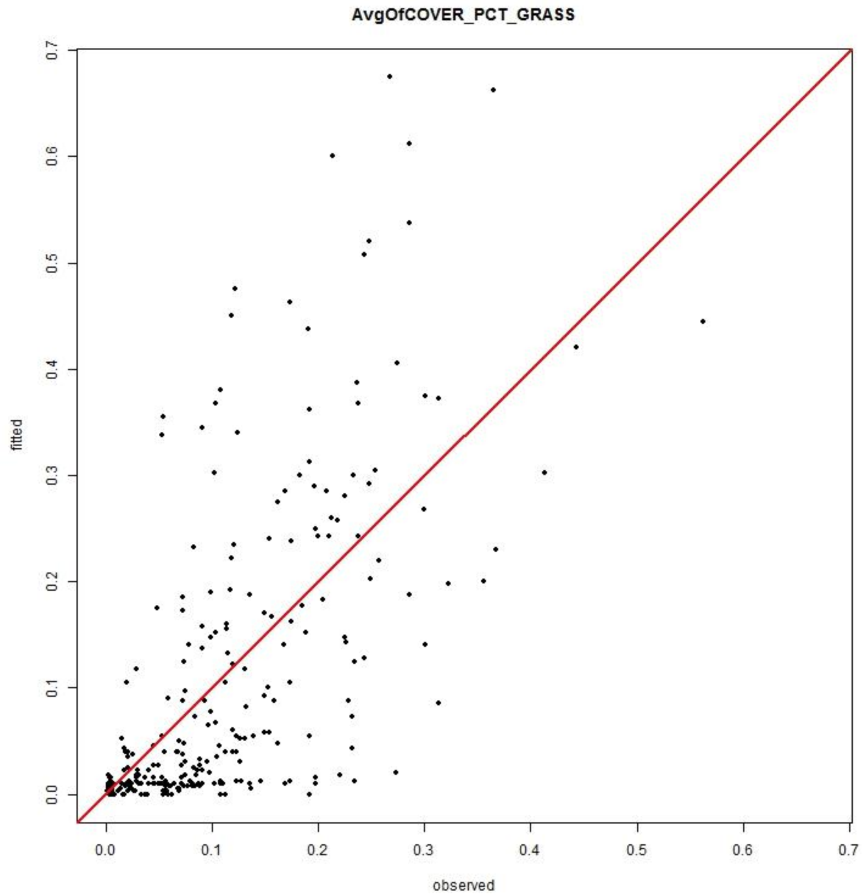

Figure 33c. Plot of predicted versus observed values for mean percent grass cover for the PNW dataset. The one to one line is represented in red. Both axes are retransformed to their original units (i.e. percent cover) and expressed as a proportion.

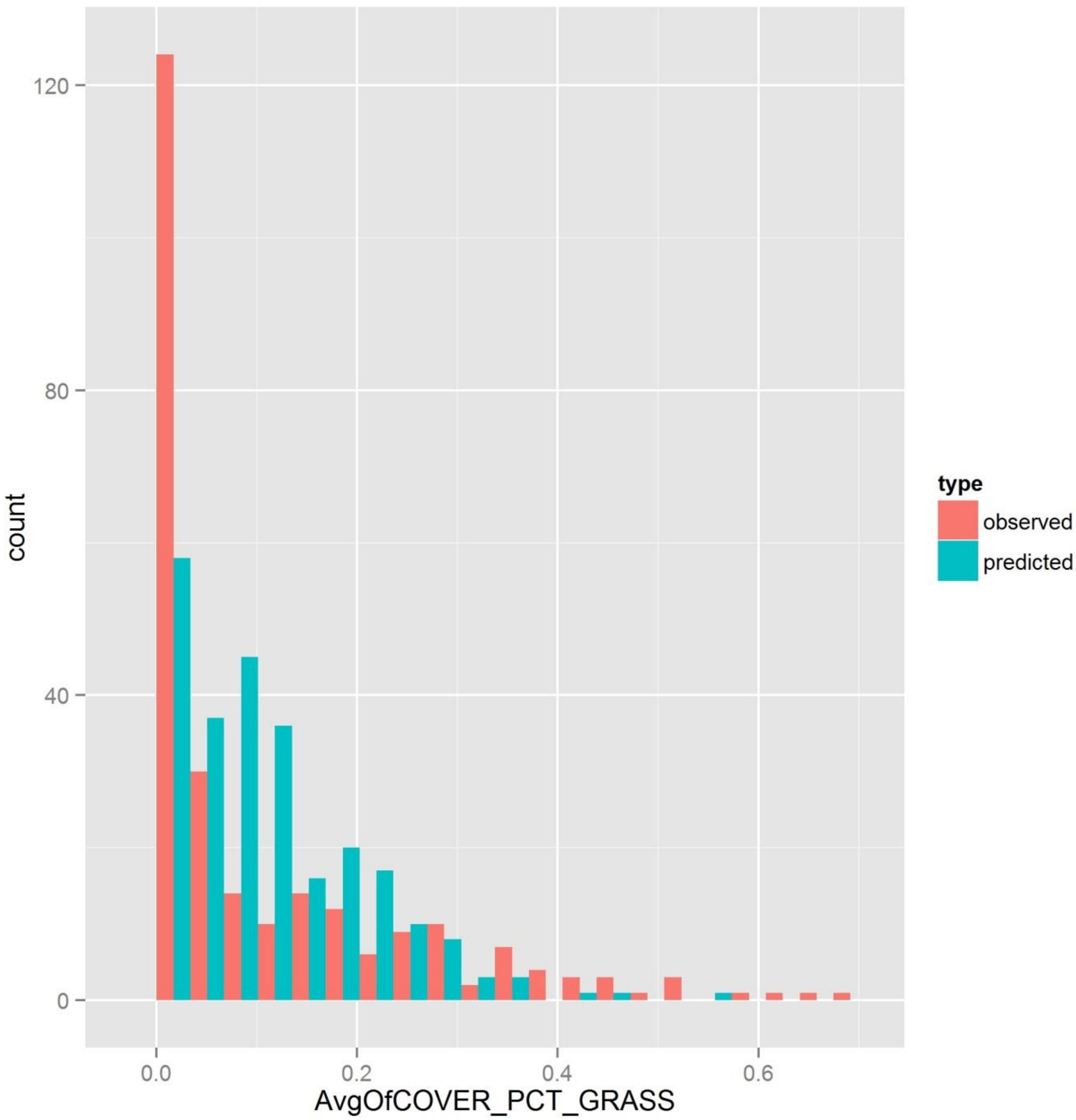

Figure 33d. Predicted versus observed bar graphs for mean percent grass cover for the PNW dataset. The classes represent the range of the data divided by 20 and count values along the y-axis represent the number of observations (plots). The x-axis is retransformed to its original units (i.e. percent cover) and expressed as a proportion.

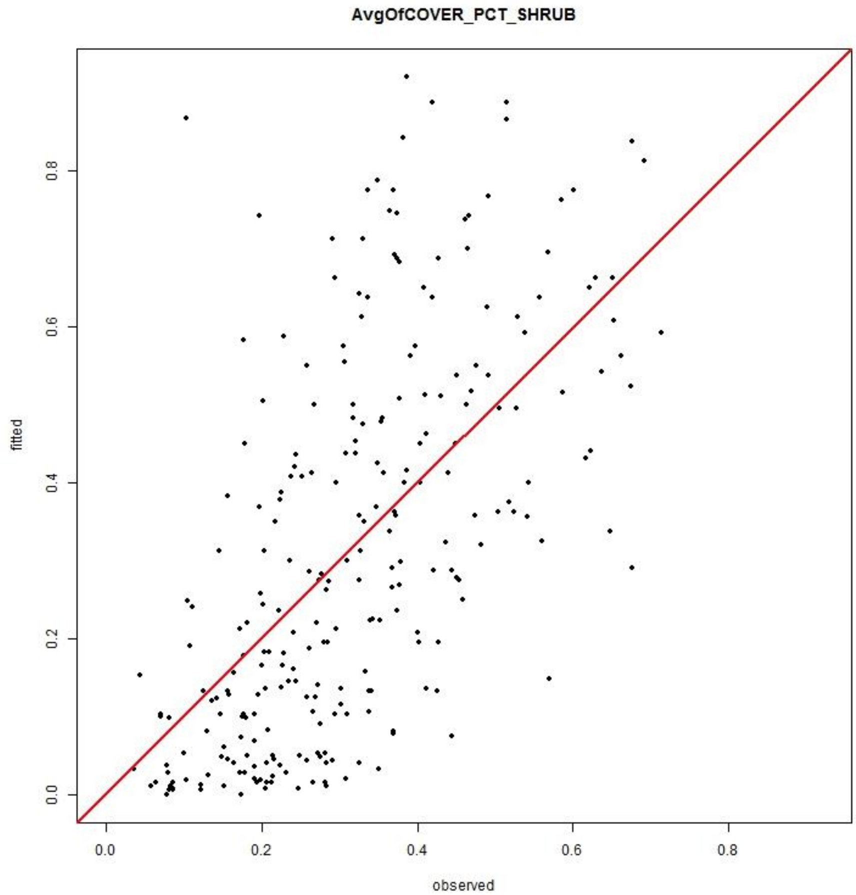

Figure 33e. Plot of predicted versus observed values for mean percent shrub cover for the PNW dataset. The one to one line is represented in red. Both axes are retransformed to their original units (i.e. percent cover) and expressed as a proportion.

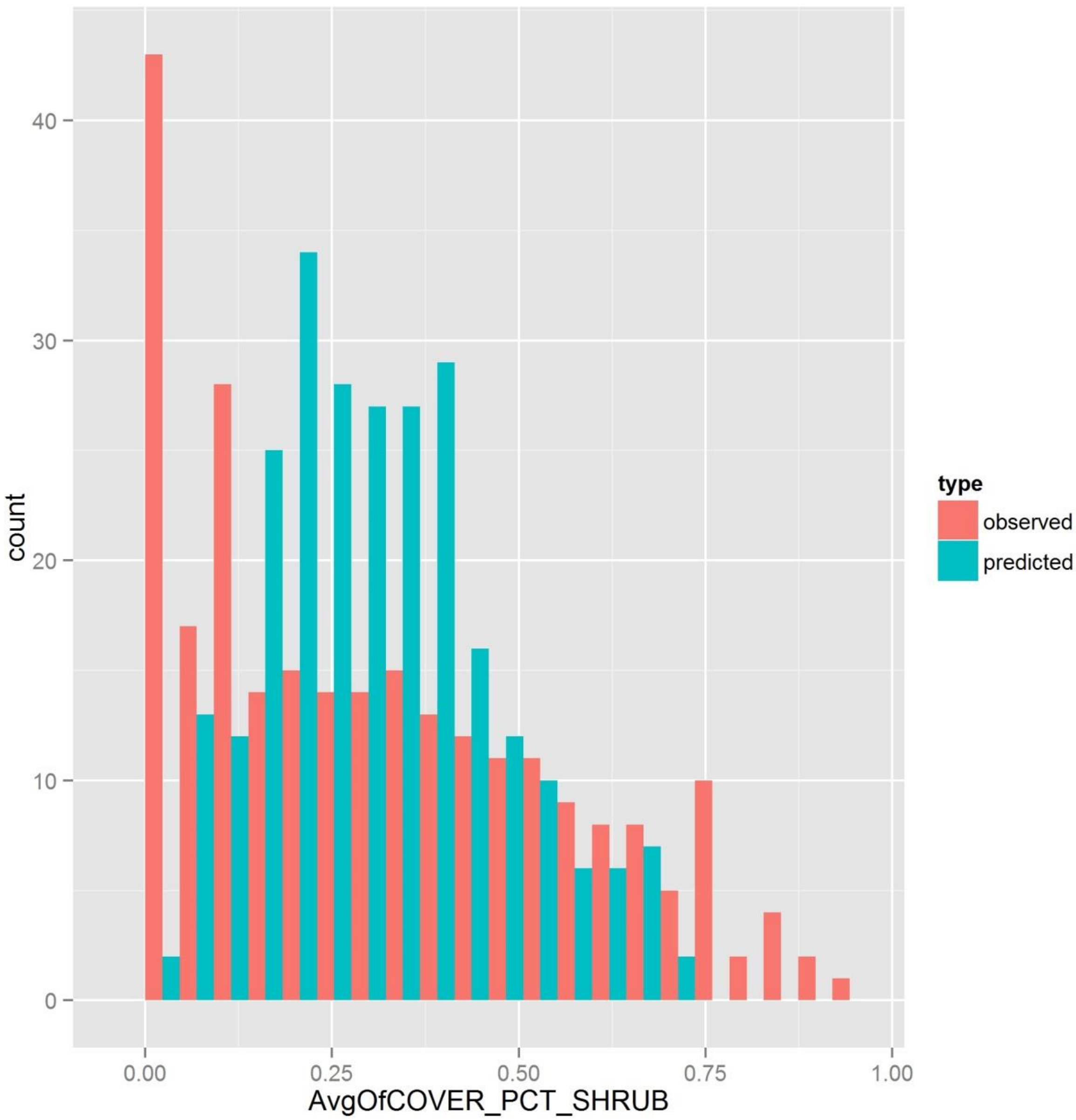

Figure 33f. Predicted versus observed bar graphs for mean percent shrub cover for the PNW dataset. The classes represent the range of the data divided by 20 and count values along the y-axis represent the number of observations (plots). The x-axis is retransformed to its original units (i.e. percent cover) and expressed as a proportion.

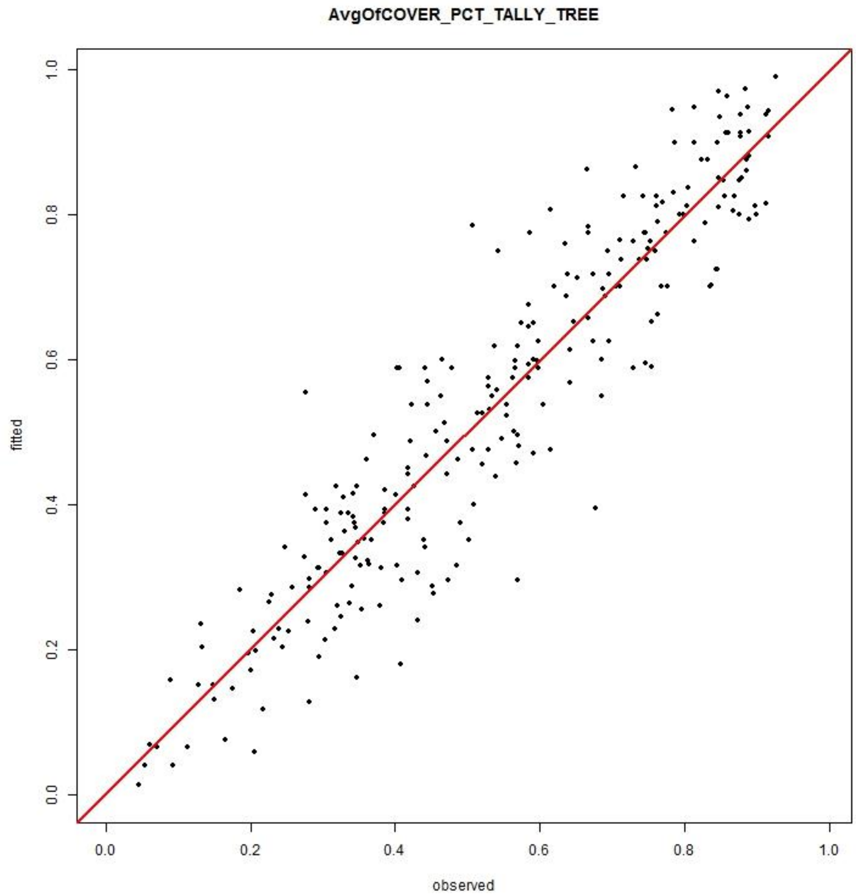

Figure 33g. Plot of predicted versus observed values for mean percent tally tree cover for the PNW dataset. The one to one line is represented in red. Both axes are retransformed to their original units (i.e. percent cover) and expressed as a proportion.

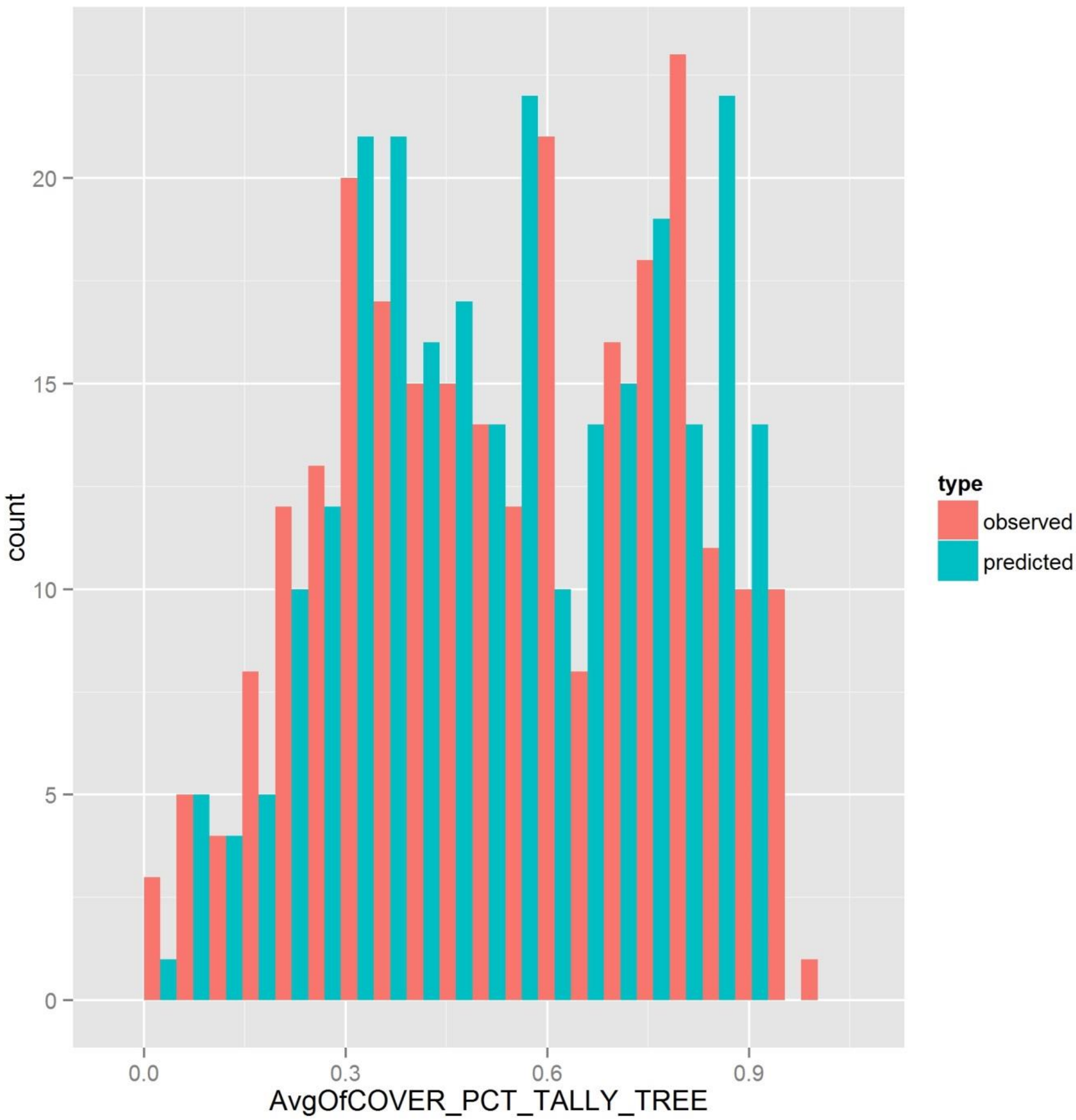

Figure 33h. Predicted versus observed bar graphs for mean percent tally tree cover for the PNW dataset. The classes represent the range of the data divided by 20 and count values along the y-axis represent the number of observations (plots). The x-axis is retransformed to its original units (i.e. percent cover) and expressed as a proportion.

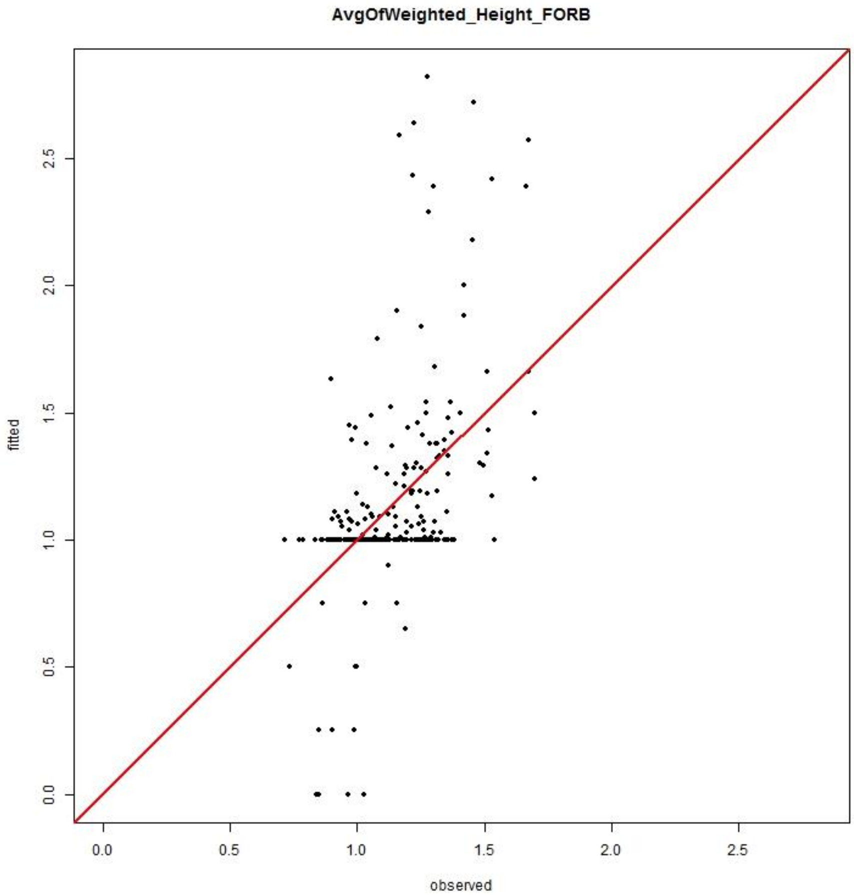

Figure 33i. Plot of predicted versus observed values for mean forb height for the PNW dataset. The one to one line is represented in red. Both axes are retransformed to their original units and expressed in feet.

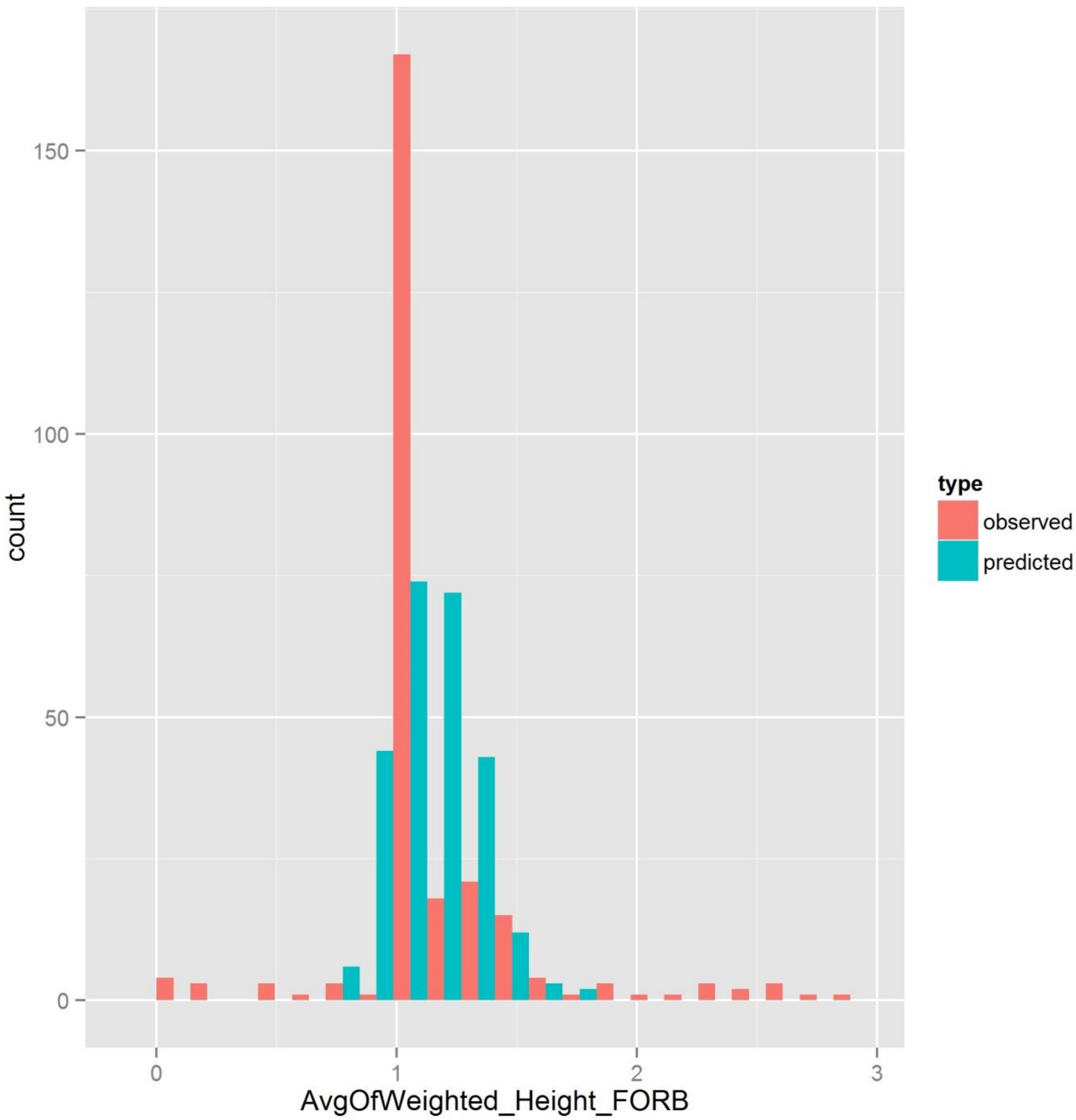

Figure 33j. Predicted versus observed bar graphs for mean forb height for the PNW dataset. The classes represent the range of the data divided by 20 and count values along the y-axis represent the number of observations (plots). The x-axis is retransformed to its original units and expressed in feet.

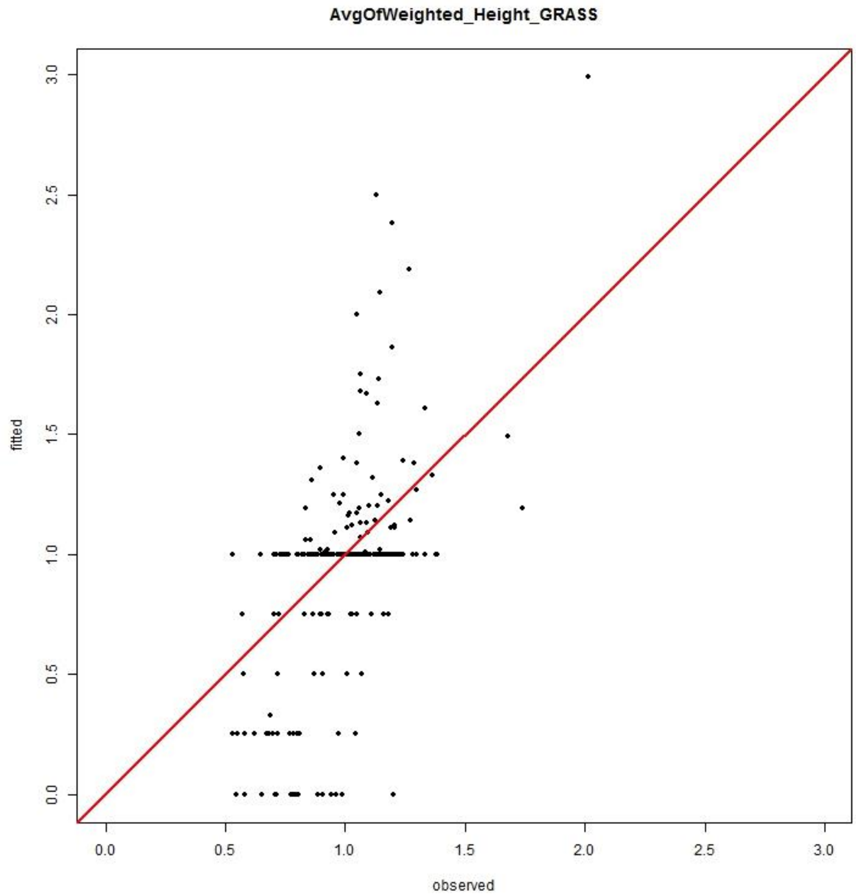

Figure 33k. Plot of predicted versus observed values for mean grass height for the PNW dataset. The one to one line is represented in red. Both axes are retransformed to their original units and expressed in feet.

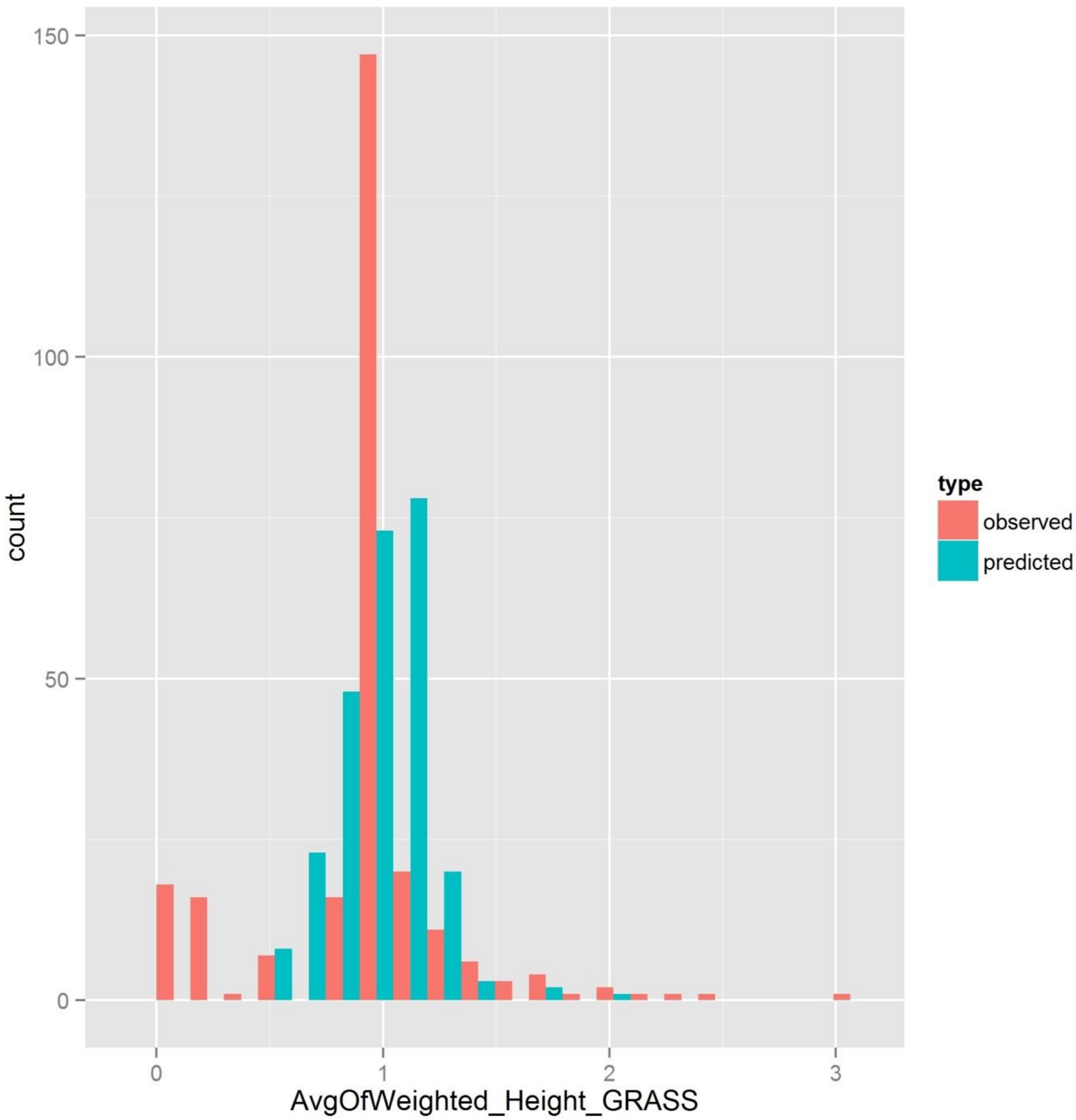

Figure 33l. Predicted versus observed bar graphs for mean grass height for the PNW dataset. The classes represent the range of the data divided by 20 and count values along the y-axis represent the number of observations (plots). The x-axis is retransformed to its original units and expressed in feet.

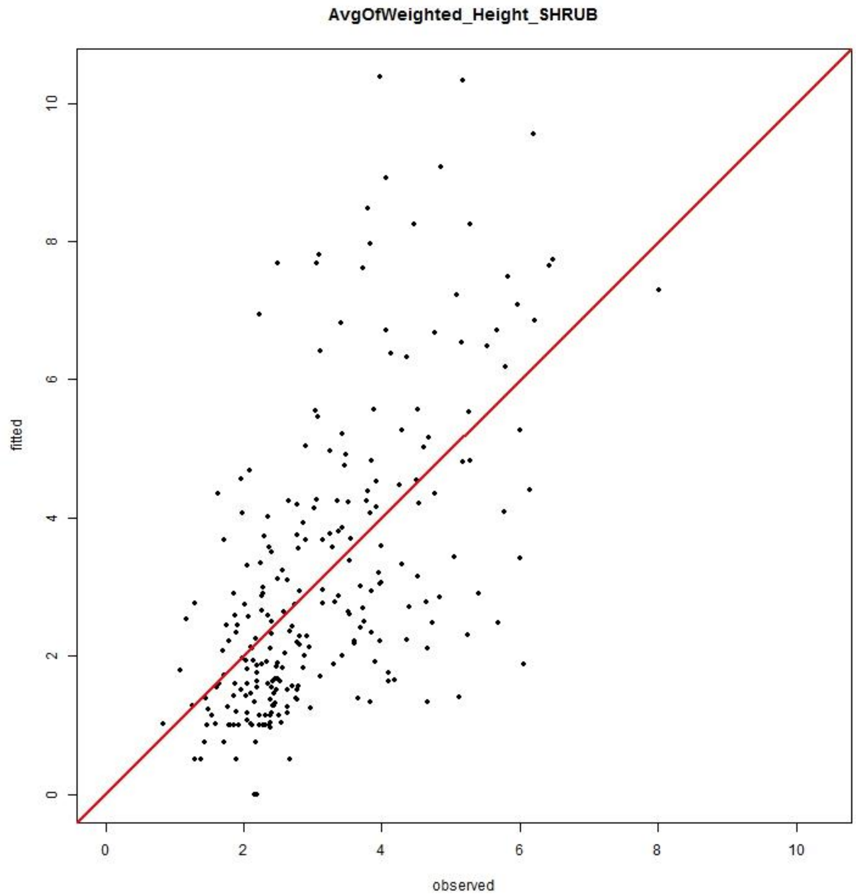

Figure 33m. Plot of predicted versus observed values for mean shrub height for the PNW dataset. The one to one line is represented in red. Both axes are retransformed to their original units and expressed in feet.

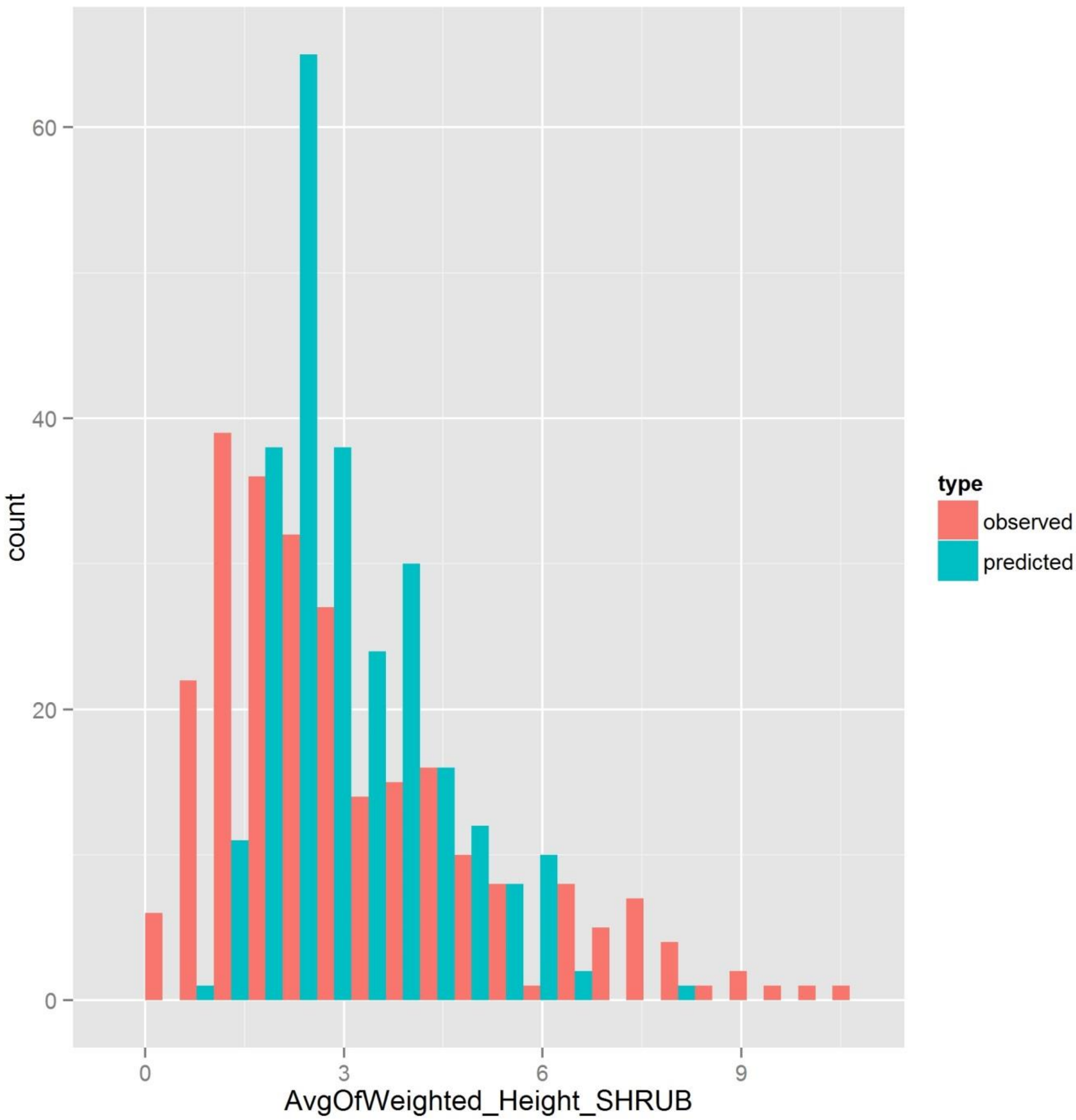

Figure 33n. Predicted versus observed bar graphs for mean shrub height for the PNW dataset. The classes represent the range of the data divided by 20 and count values along the y-axis represent the number of observations (plots). The x-axis is retransformed to its original units and expressed in feet.

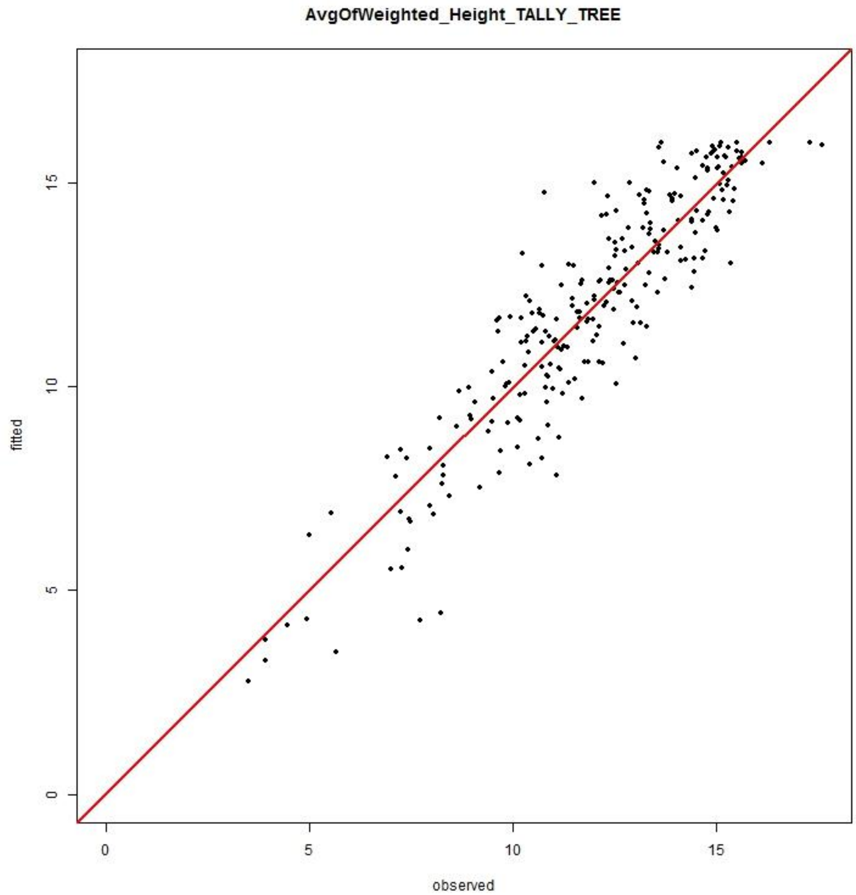

Figure 33o. Plot of predicted versus observed values for mean tally tree height for the PNW dataset. The one to one line is represented in red. Both axes are retransformed to their original units and expressed in feet.

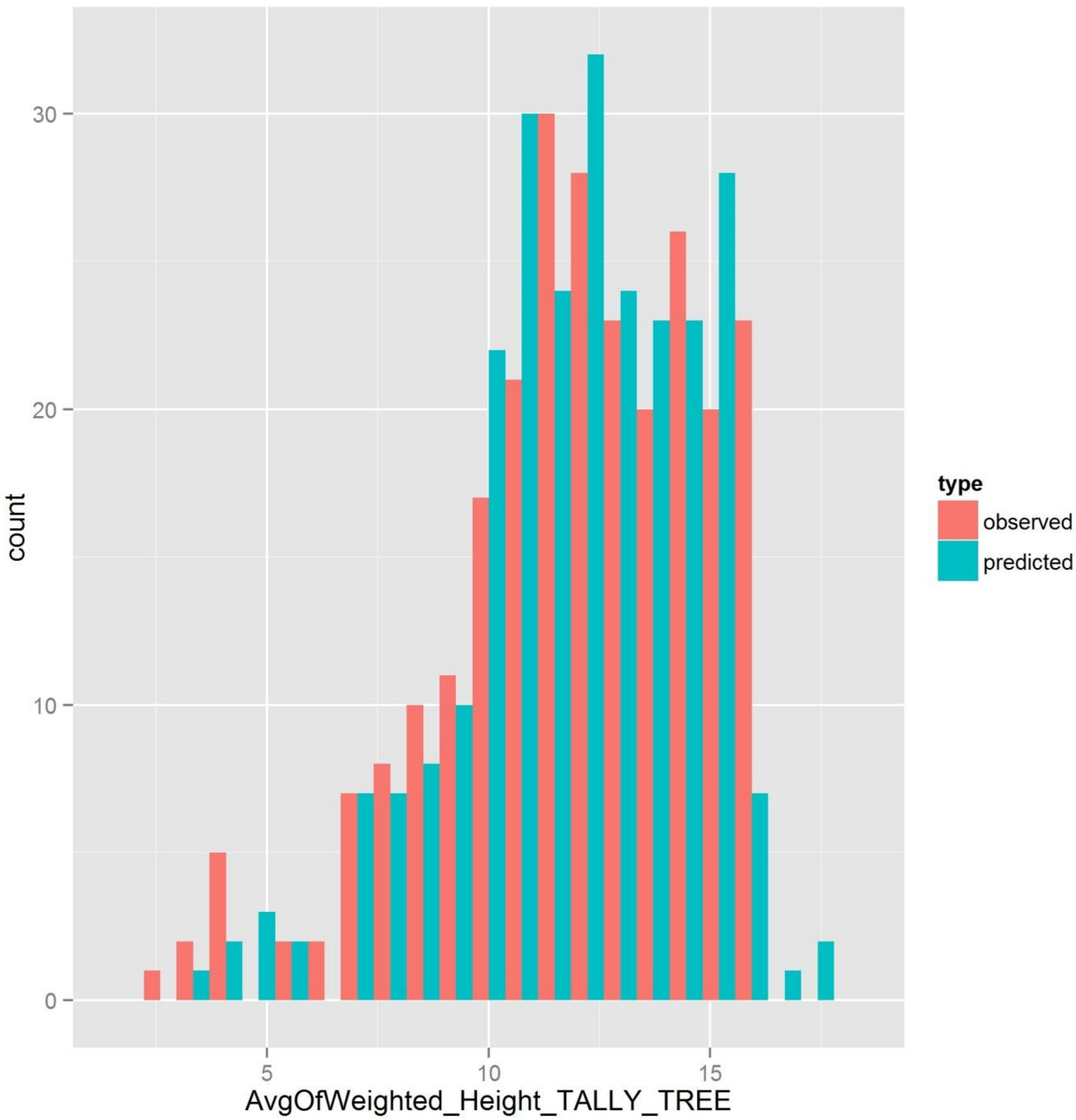

Figure 33p. Predicted versus observed bar graphs for mean tally tree height for the PNW dataset. The classes represent the range of the data divided by 20 and count values along the y-axis represent the number of observations (plots). The x-axis is retransformed to its original units and expressed in feet.

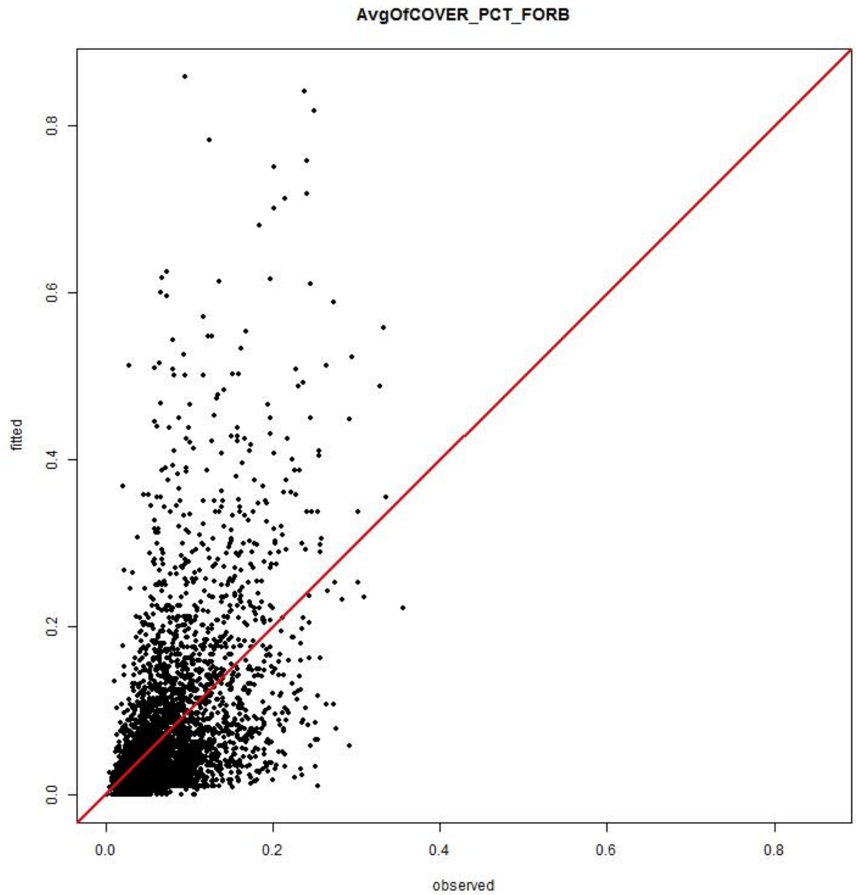

Figure 34a. Plot of predicted versus observed values for mean percent forb cover for the IW dataset. The one to one line is represented in red. Both axes are retransformed to their original units (i.e. percent cover) and expressed as a proportion.

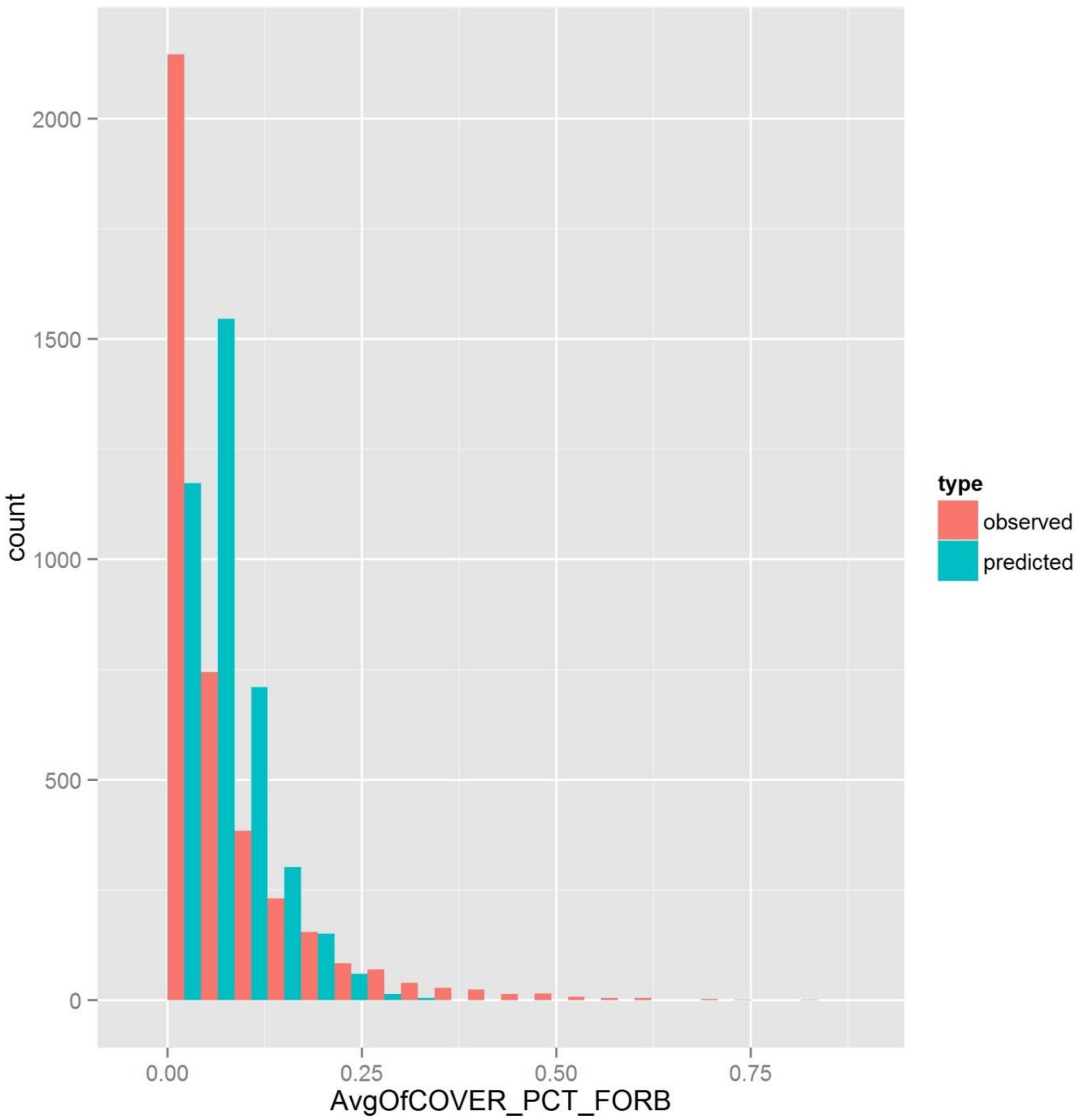

Figure 34b. Predicted versus observed bar graphs for mean percent forb cover for the IW dataset. The classes represent the range of the data divided by 20 and count values along the y-axis represent the number of observations (plots). The x-axis is retransformed to its original units (i.e. percent cover) and expressed as a proportion.

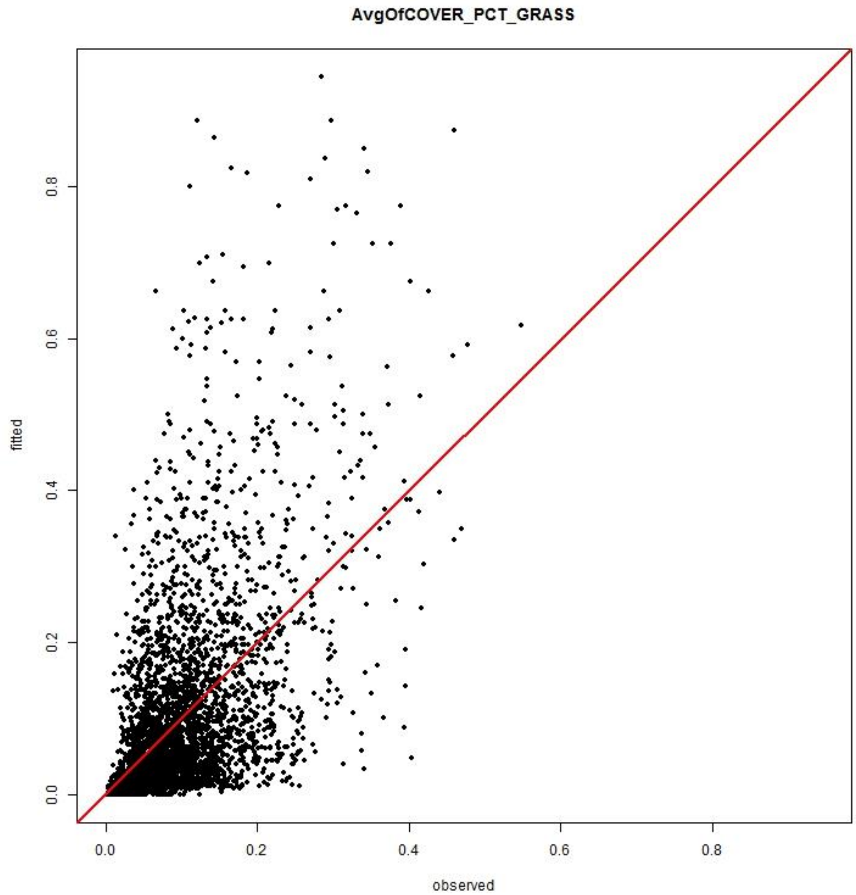

Figure 34c. Plot of predicted versus observed values for mean percent grass cover for the IW dataset. The one to one line is represented in red. Both axes are retransformed to their original units (i.e. percent cover) and expressed as a proportion.

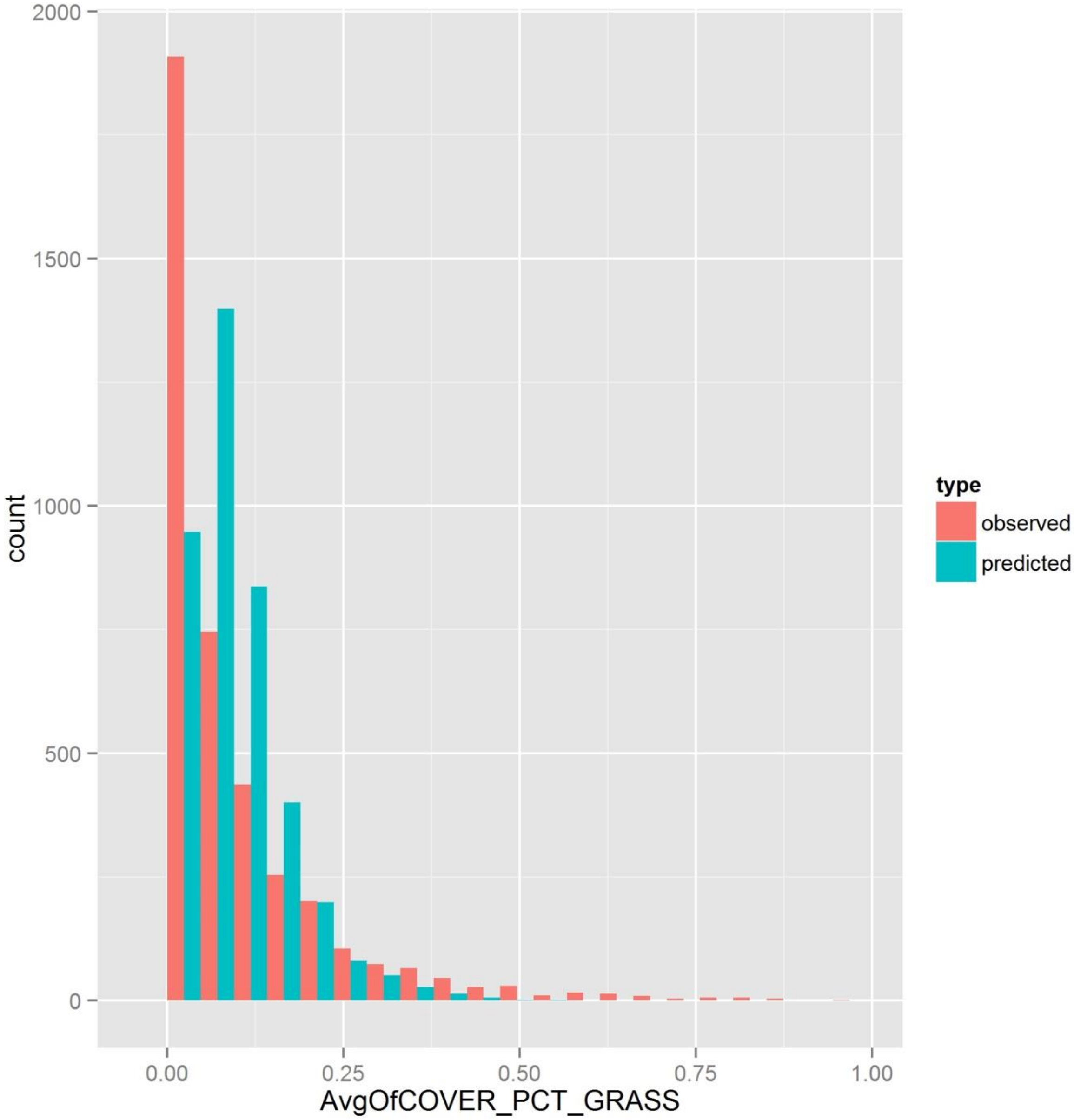

Figure 34d. Predicted versus observed bar graphs for mean percent grass cover for the IW dataset. The classes represent the range of the data divided by 20 and count values along the y-axis represent the number of observations (plots). The x-axis is retransformed to its original units (i.e. percent cover) and expressed as a proportion.

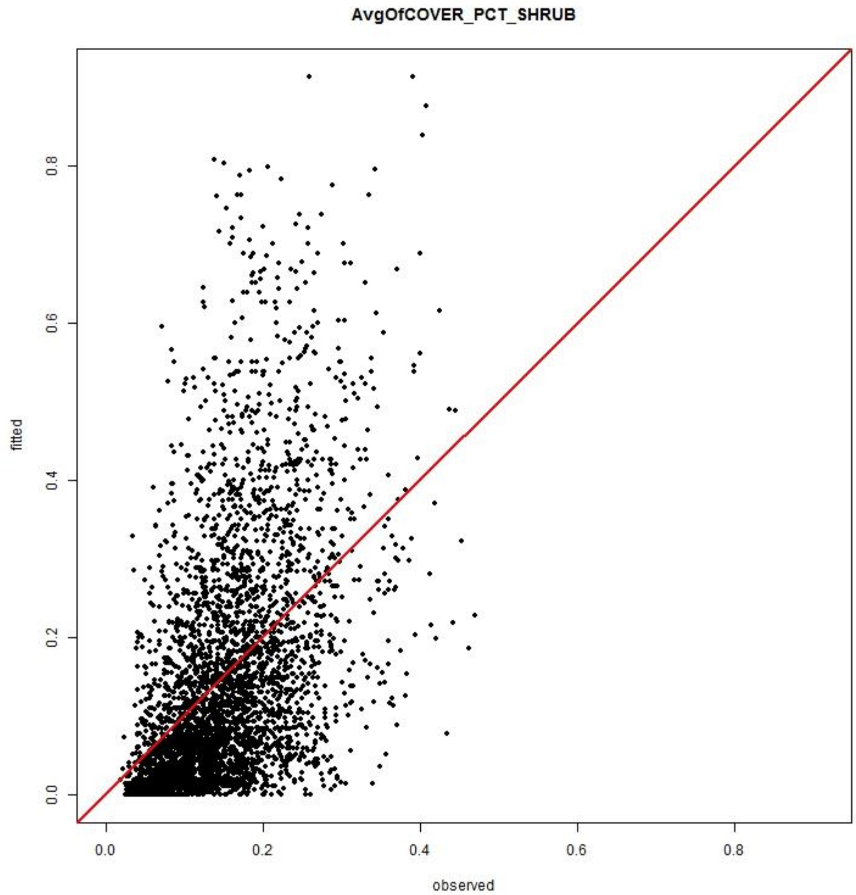

Figure 34e. Plot of predicted versus observed values for mean percent shrub cover for the IW dataset. The one to one line is represented in red. Both axes are retransformed to their original units (i.e. percent cover) and expressed as a proportion.

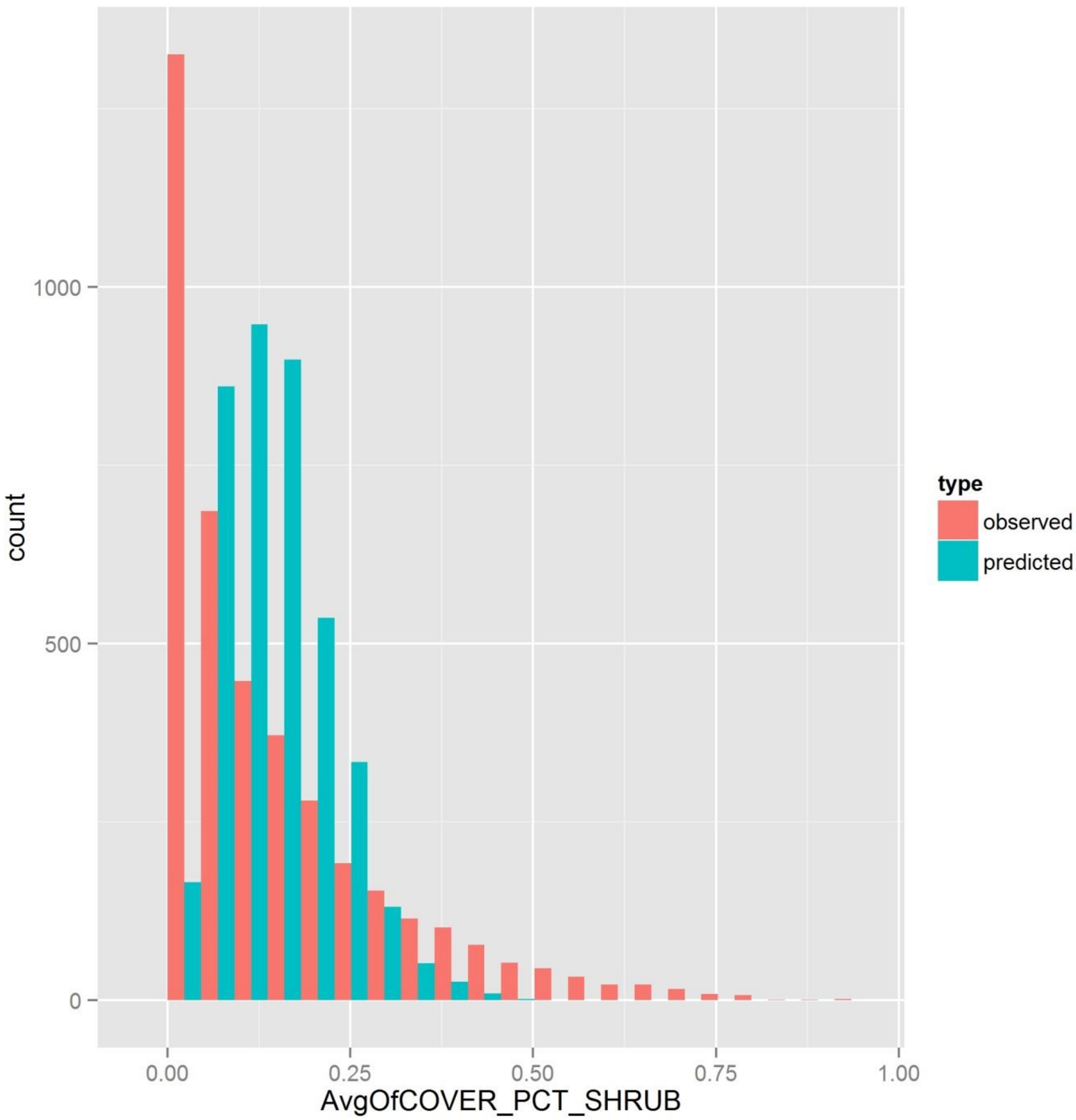

Figure 34f. Predicted versus observed bar graphs for mean percent shrub cover for the IW dataset. The classes represent the range of the data divided by 20 and count values along the y-axis represent the number of observations (plots). The x-axis is retransformed to its original units (i.e. percent cover) and expressed as a proportion.

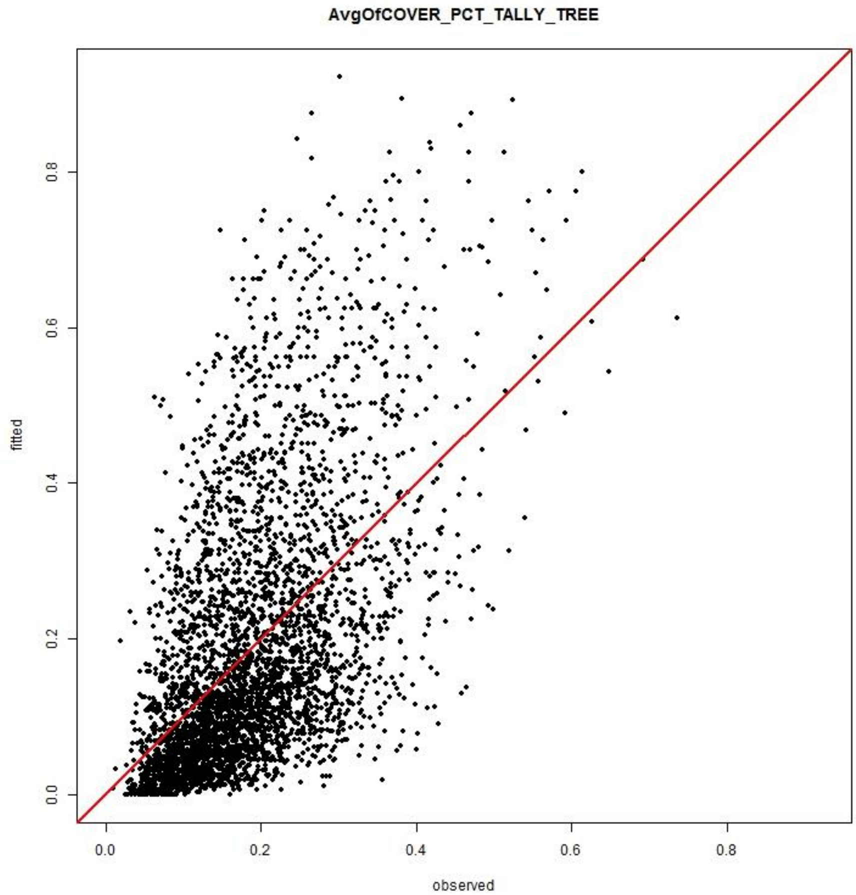

Figure 34g. Plot of predicted versus observed values for mean percent tally tree cover for the IW dataset. The one to one line is represented in red. Both axes are retransformed to their original units (i.e. percent cover) and expressed as a proportion.

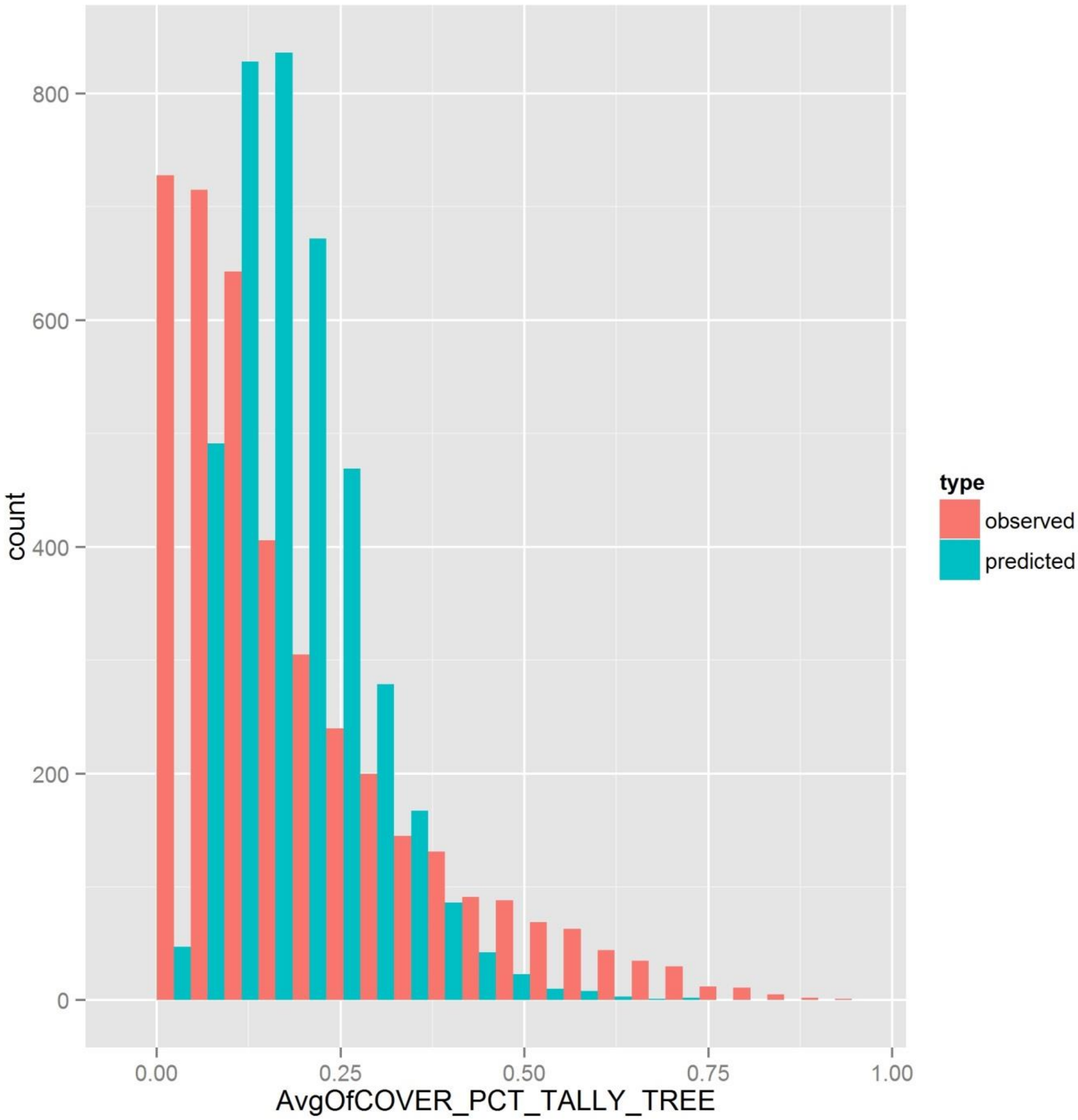

Figure 34h. Predicted versus observed bar graphs for mean percent tally tree cover for the IW dataset. The classes represent the range of the data divided by 20 and count values along the y-axis represent the number of observations (plots). The x-axis is retransformed to its original units (i.e. percent cover) and expressed as a proportion.

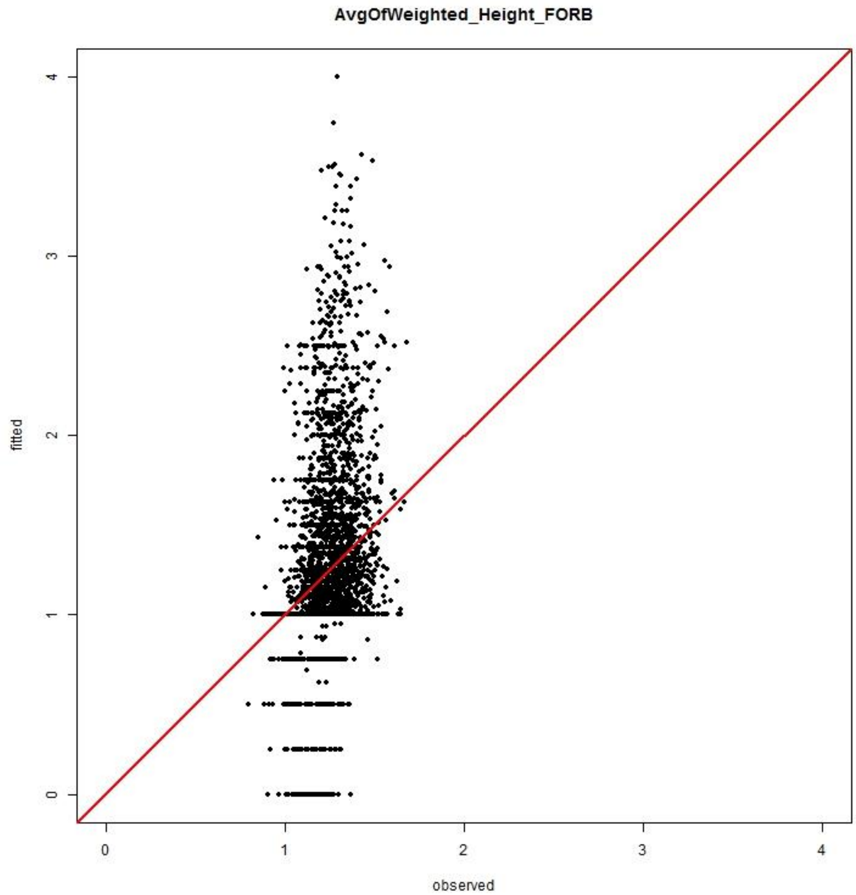

Figure 34i. Plot of predicted versus observed values for mean height forb cover for the IW dataset. The one to one line is represented in red. Both axes are retransformed to their original units and expressed in feet.

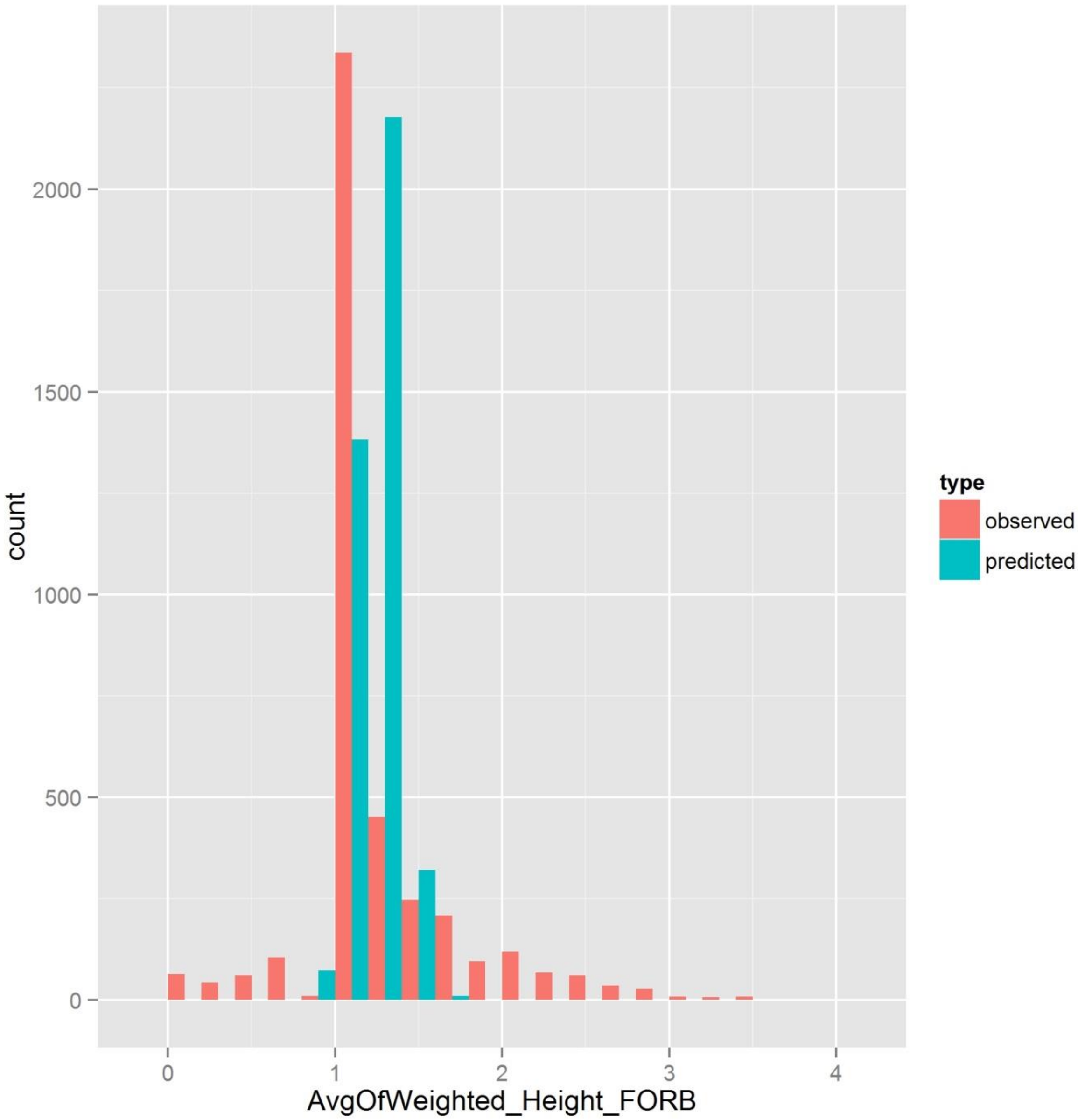

Figure 34j. Predicted versus observed bar graphs for mean forb height for the IW dataset. The classes represent the range of the data divided by 20 and count values along the y-axis represent the number of observations (plots). The x-axis is retransformed to its original units and expressed in feet.

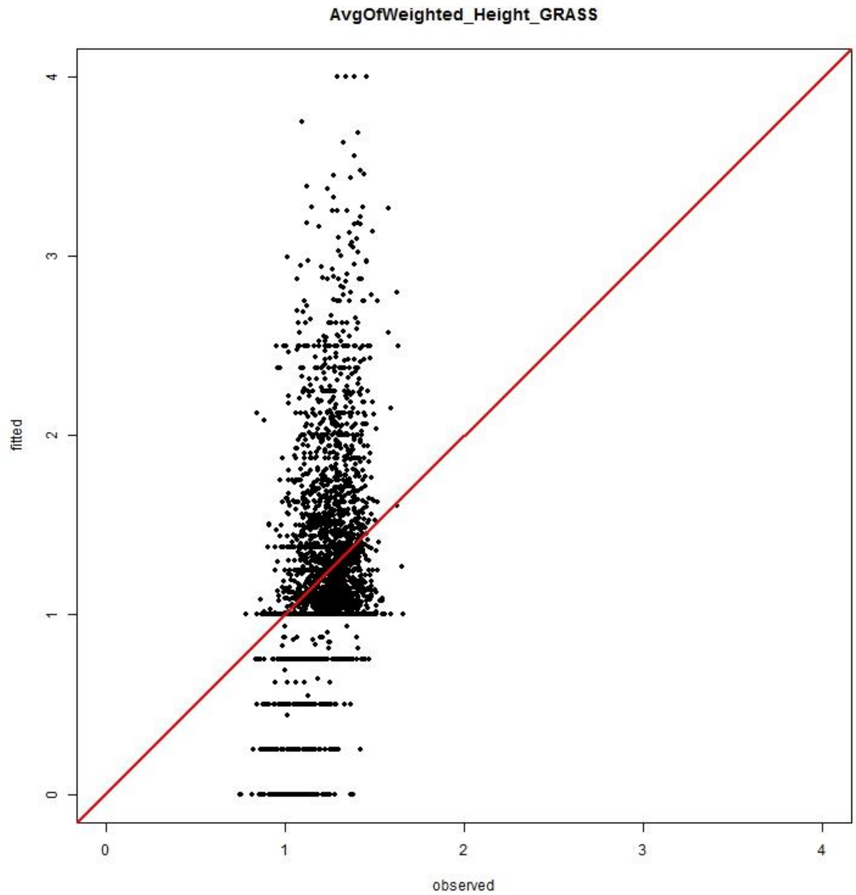

Figure 34k. Plot of predicted versus observed values for mean grass height for the IW dataset. The one to one line is represented in red. Both axes are retransformed to their original units and expressed in feet.

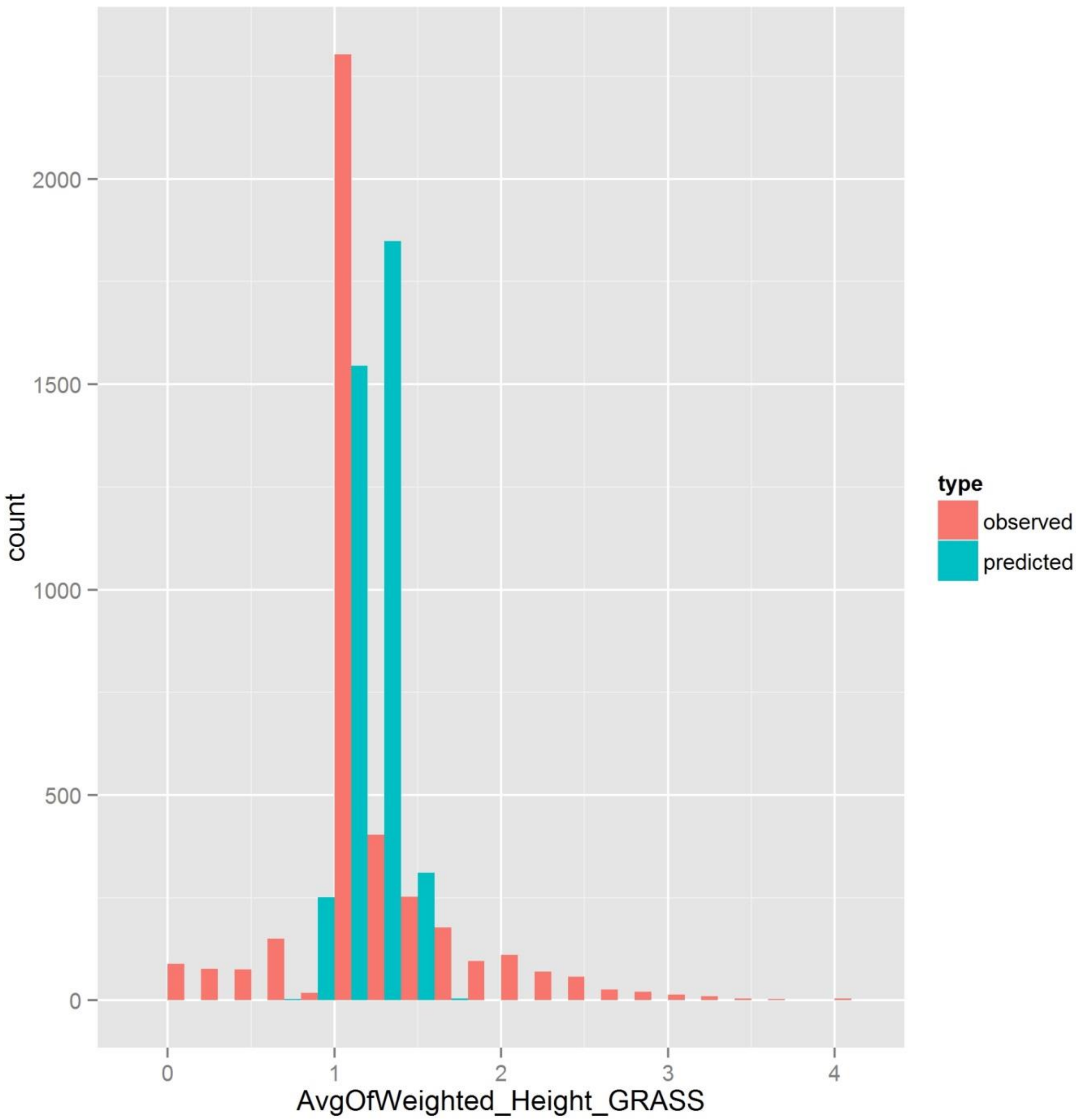

Figure 34l. Predicted versus observed bar graphs for mean grass height for the IW dataset. The classes represent the range of the data divided by 20 and count values along the y-axis represent the number of observations (plots). The x-axis is retransformed to its original units and expressed in feet.

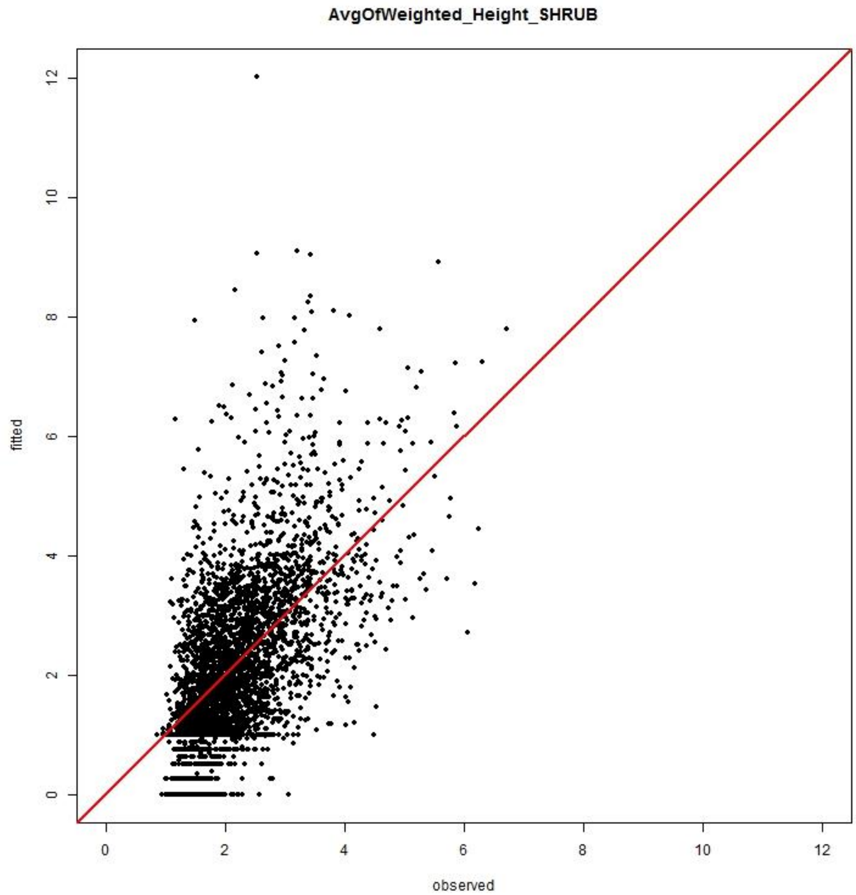

Figure 34m. Plot of predicted versus observed values for mean shrub height for the IW dataset. The one to one line is represented in red. Both axes are retransformed to their original units and expressed in feet.

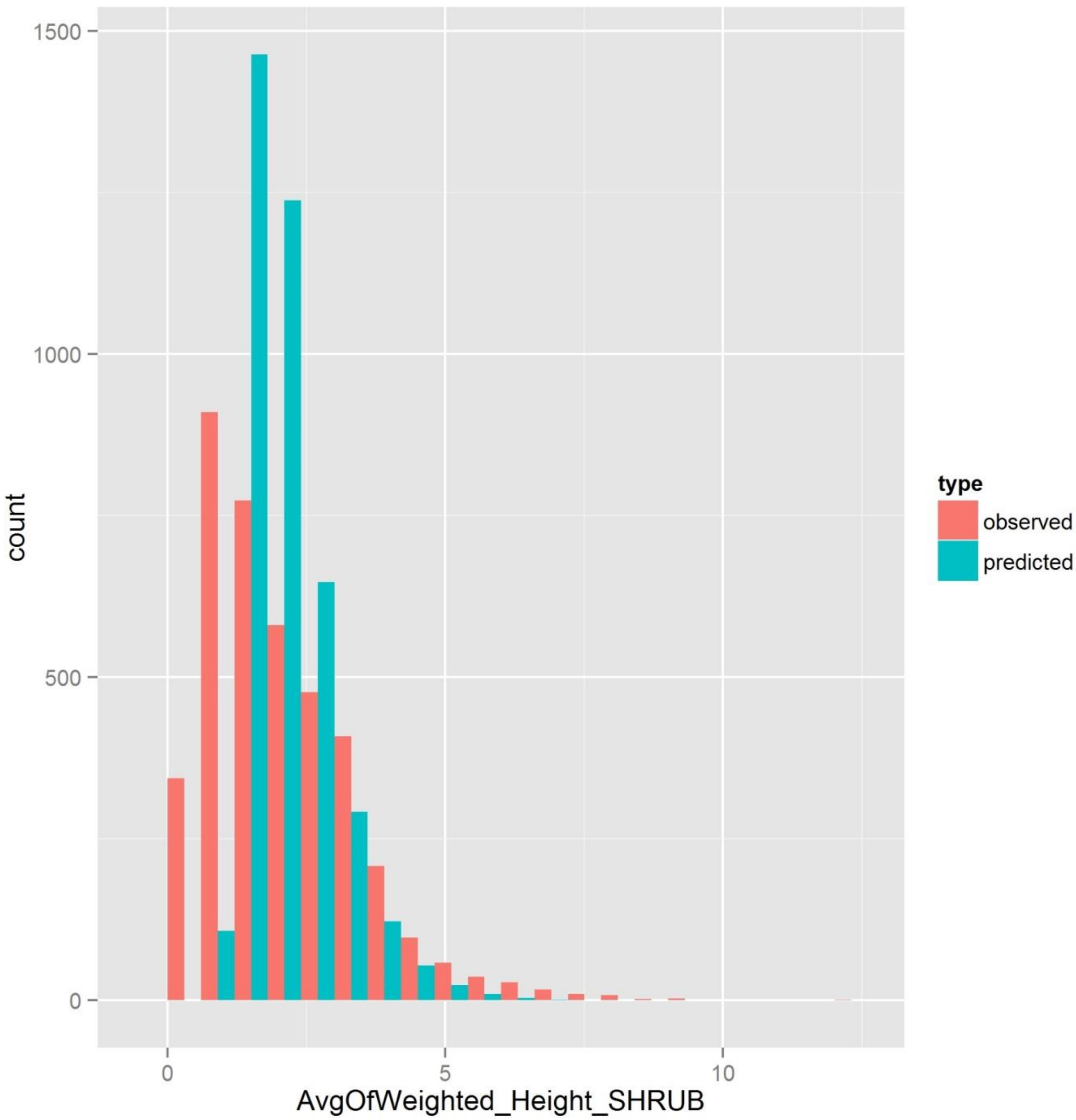

Figure 34n. Predicted versus observed bar graphs for mean shrub height for the IW dataset. The classes represent the range of the data divided by 20 and count values along the y-axis represent the number of observations (plots). The x-axis is retransformed to its original units and expressed in feet.

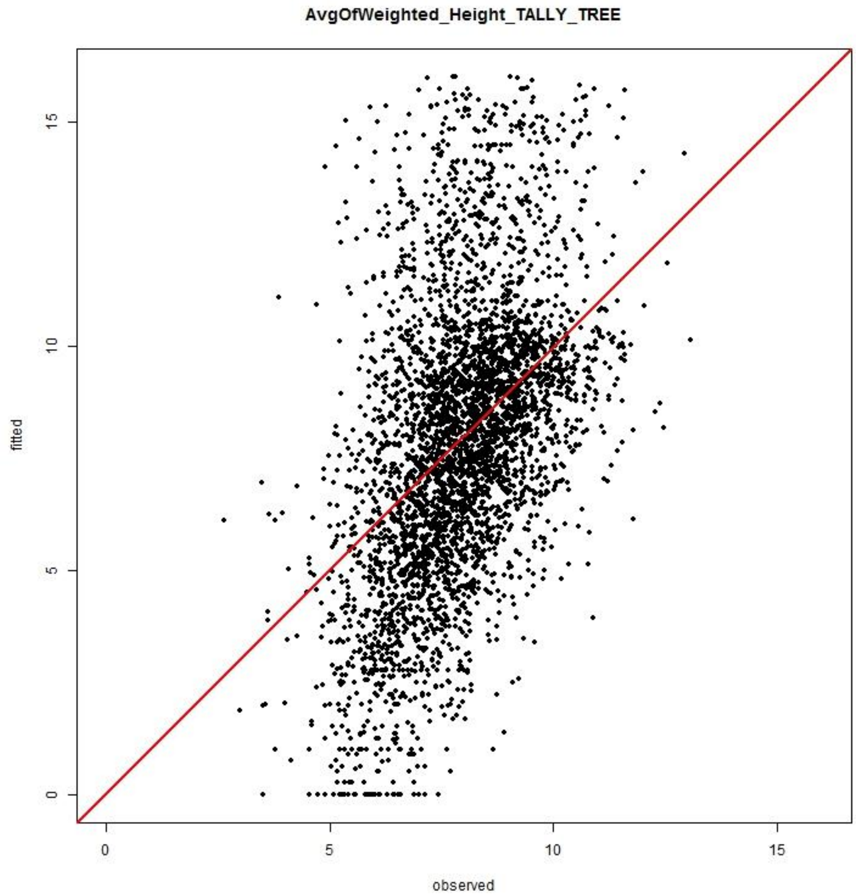

Figure 34o. Plot of predicted versus observed values for mean tally tree height for the IW dataset. The one to one line is represented in red. Both axes are retransformed to their original units and expressed in feet.

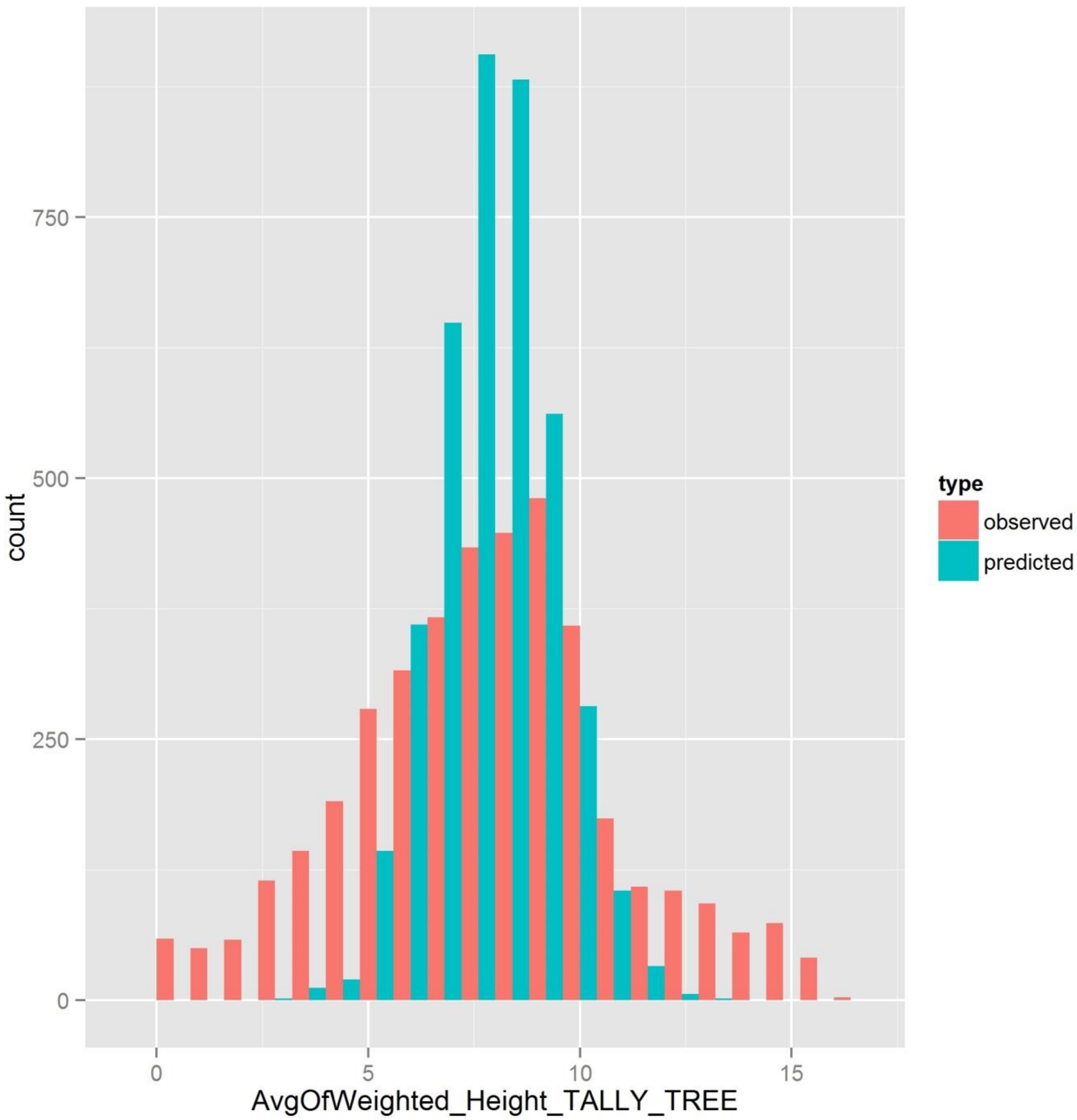

Figure 34p. Predicted versus observed bar graphs for mean tally tree height for the IW dataset. The classes represent the range of the data divided by 20 and count values along the y-axis represent the number of observations (plots). The x-axis is retransformed to its original units and expressed in feet.