Southeast Oregon NN Vegetation Composition Map Accuracy Report – 2016 Imagery Year

Emilie Henderson

Institute for Natural Resources,

Oregon State University

August 22, 2018 – Updated September 5, 2019

Table of Contents

Introduction

This report contains information detailing the model used to build the imputed vegetation map for southeastern Oregon. It contains only information that can be calculated from species x cover vegetation survey plot data records. All attributes distributed with the raster data layer have been assessed for accuracy here. The best citation for this map is:

Henderson, E. B., Bell, D. M., and Gregory, M. J.. 2019. Vegetation mapping to support greater sage-grouse habitat monitoring and management: multi- or univariate approach? Ecosphere 10(8):e02838. 10.1002/ecs2.2838

See the Package Contents section below for instructions about how to get started with this map.

Package Contents

Selected individual map indicators can be viewed and downloaded via a web map from https://tools.oregonexplorer.info/OE_HtmlViewer/index.html?viewer=sagegrouse.

The full version of this map containing all mapped variables and supplemental information can be downloaded from: https://oe.oregonexplorer.info/externalcontent/sagecon/datafordownload/SoutheastOregon_Vegetation_2016.zip.

The full version contains two subfolders: one named “Documentation”, and another labeled “GIS Data”. The Documentation subfolder contains a copy of this document, as well as a supplemental excel file describing accuracy for one categorical variable with too many categories to display within this word document (referenced below in the text). The “GIS Data” subfolder contains a geodatabase which houses four tables, and three raster data layers. The tables hold vegetation descriptor attributes that can be joined to the “nn1_VegComp” raster layer for display on the field named ‘Value_’. To join the attributes to the raster in ArcMap, add both the nn1_VegComp raster and the attribute table of interest, right click on the raster, and select Join from the menu.

The table named ‘All’ contains all variables that are described in this document, while the other tables contain subsets of these variables. They are included for ease of display, as most users will find the ‘All’ table unwieldy. The supplemental grids ‘nn1_dist’, and ‘nn1_edst’ are different indicators of map confidence, and are described fully under the Methods/Map assessment/ Supplemental data layers’ section.

To support the ecostate map variables, the package also includes a pdf document explaining the purpose and rule set used to derive the ecostate map variables based on a threat-based model of rangeland ecosystem function.

Additional Notes

In the discussion section, we address the implications of some of the accuracy assessments for different data uses. For further discussion on the use of this type of vegetation map for different applications, please see the publication listed above (Henderson 2019).

Methods

This report references the Southeast Oregon modeling region, indicated in blue in Panel a (Figure 1). Panels b, c, and d show hexagons used for multi-scaled accuracy assessments. Hexagon sizes are 16,000 ha for the Hex1 scale (39,540 ac), 64,000 ha for the Hex2 scale (158,150 ac), and 256,000 ha (632,590 ac) in size for the Hex3 scale.

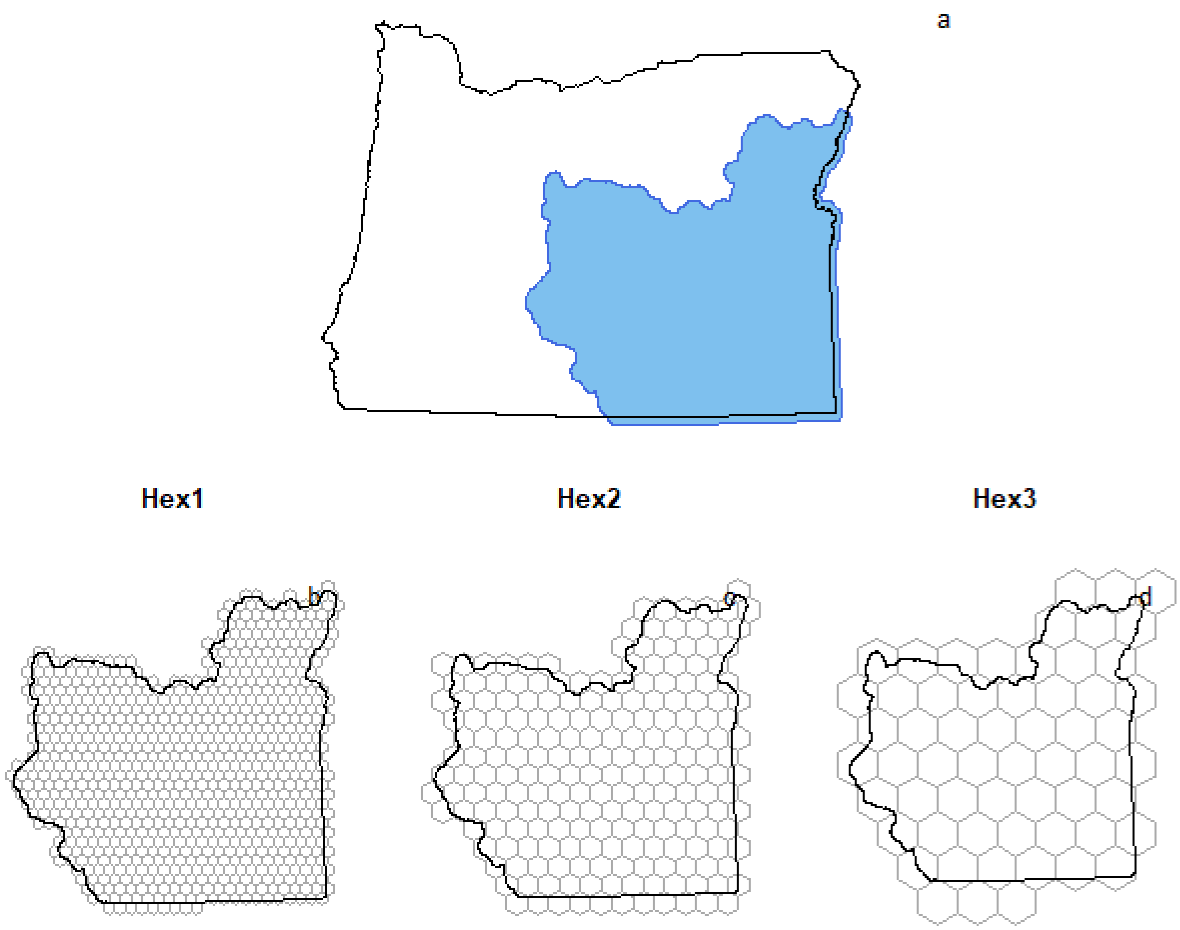


Figure 1: Southeast Oregon model region and hexagons used for accuracy assessment. Note that the plot data sample is uneven.

Data

Plot

We used 3,366 vegetation plots data from 7 data sources (Table 1), which contained species-cover information. Most plots were surveyed between 2011 and 2017, but a few were drawn from earlier dates. These older vegetation survey plots were added to represent portions of the landscape with trees (e.g., northwestern corner of the study area), because the more recent plots under-represent this portion of the landscape.

Table 1: Vegetation survey plot data used for input plot data sample, by data source, and survey year.

	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	Total
BLM - Assessment, Inventory and Monitoring (AIM)	0	0	0	0	0	0	0	0	0	0	0	1	0	0	3	550	604	1158
BLM - Rangeland Monitoring	0	0	9	0	0	0	0	0	0	0	0	226	0	0	0	0	0	235
BLM_LMF	0	0	0	0	0	0	0	0	0	0	85	336	0	280	260	0	0	961
Institute for Natural Resources	0	0	0	0	0	128	86	45	60	27	27	30	251	0	0	0	0	654
Landfire Plot Reference Database	33	38	90	9	0	0	0	0	0	0	0	0	0	0	0	0	0	170
Malheur Wetland Vegetation Survey	0	0	0	0	0	0	0	0	0	0	0	21	20	0	75	0	0	116
USFS - Ecoplots	0	2	17	32	21	0	0	0	0	0	0	0	0	0	0	0	0	72
Total	33	40	116	41	21	128	86	45	60	27	112	614	271	280	338	550	604	3366

Spatial

Raster explanatory variables included variables representing topography (extracted from national elevation dataset, Gesch et al. 2002), climate (derivatives of PRISM climate 30 year normal, Daly et al. 2008), soil (principal components analysis (PCA) summaries of POLARIS soil properties, Ramcharan et al. 2018)), and remote sensing imagery information. Remote sensing information was extracted from a LANDSAT mosaic showing 2012 conditions, and also PCA summaries of image texture metrics (Nielsen and Noone 2014) extracted from 2016 airphotos taken for the national airphoto inventory program. Variables selected for modeling vegetation described by this map are described in detail in Appendix 1a.

Imputation model

Background on imputation

The model used to create the map is a member of a family of methods called imputation. Imputation refers to a procedure using observations that have a full suite of variables to inform predictions of missing values for observations that contain only some of the variables (Eskelson et al. 2009). It is a particularly useful technique for mapping multiple, co-varying response variables (Henderson et al. 2014), and is often used in to inform landscape management questions that require multivariate information (Ohmann et al. 2011). In our application, vegetation plot locations contain contain a full suite of information on vegetation, and also a full suite of information from raster data describing the environment, such as topography and remote sensing. The unsampled locations (pixels) across our raster data only contain environmental information. The imputation model applies the measured vegetation information in the plot locations to all pixels in the maps based on the universally available environmental information.

The root of the imputation procedure uses a distance metric that illustrates environmental similarity (not geographic proximity) to identify one or more plot observations that are close matches to the conditions in the target pixel. In our application, we simply choose the closest match. All values from the chosen plot are mapped to the predicted pixel via the plot identifier. This approach has the advantage of maintaining the covariance structure of the vegetation information embodied in the original input data, rendering our maps appropriate for more flexible summary variable configurations. Map attributes that are derived from multiple plot variables (e.g., proportion of all grasses that are non-native) can be calculated and displayed in the map without creating a new model.

There are many variants of imputation that have been used in mapping forest inventory information (e.g., kNN: Tomppo and Katila 1991, MSN: Moeur and Stage 1995, GNN: Ohmann and Gregory 2002, and RFNN: Crookston and Finley 2008). We rely on the RFNN procedure here, which uses information from internal random forest models to calculate the neighbor-distance metric used to identify plots for new predictions.

Imputation modeling has a shorter history as a tool for mapping the arid portion of the landscape, but see Creutzburg, Henderson, and Conklin (2015) for an example of its use.

Y variables to structure the imputation model

The *yaImpute* imputation algorithm in R (Crookston and Finley 2008), builds one random forest model for each response variable. We calculated three categorical response variables for this purpose, one categorization based on species composition, one based on the relative abundance (cover) of life forms within the vegetation (e.g., trees, shrubs, grasses, and forbs and herbs), and one based on a suite of variables designed to indicate landscape condition (See Appendix 1b. Variables with a prefix of "Ind" were used to build the third classified y-variable). We generated the categories based on a hierarchical clustering algorithm and Ward's linkage method. We used our judgement to cut the hierarchical cluster object, aiming each time to obtain 30 or fewer categories to illustrate the range of variability in the data. Categorizations with fewer than 30 variables were used when the classification contained more than two categories whose size was prohibitively small (< 5).

Our final modeling y-variables included 29 species composition categories, and 30 structural categories, 31 indicator categories, and a binary variable describing *Juniperus occidentalis* presence and absence.

Explanatory variable selection

We selected explanatory variables using a conditional variable importance measurement with the cforest algorithm (Strobl et al. 2008). The variable importance metrics associated with this random forest variant provide more robust estimates of variable importance when explanatory variables are strongly correlated (Strobl et al. 2007). Variable selection is conducted in a stepwise reverse selection fashion, starting with a full list of variables, eliminating variables (or variable-groups) until none are left. At each step, the reduced model's accuracy is assessed via AUC of a probability prediction (average multi-class AUCs calculated for yvariables with more than one category). Variable importances are calculated with the R function '`varImpAUC`' for the binary y-variable, and '`varImp`' for multi-category y-variables. When the stepwise selection has been completed, the final variable list is selected as the shortest list that still attains at least 95% of the best possible model accuracy, in comparison with the minimum remaining variables.

Due to the large initial list of possible explanatory variables (91), we reduced our variables through a three-phase process. First, we extracted the primary information from the largest groups of variables (soil, and airphoto) into axes of variation with principal components analysis. This reduced the lists from 60 soil variables and 98 airphoto variables to 18 soil summaries and 37 airphoto texture summaries. Second, we selected the best variables within each category (i.e., soil, climate, topography, etc.). Finally, we selected the full explanatory variable list from within the lists developed during the second phase. The third phase of variable selection proceeded with smaller steps (eliminating 5% of variables at a step) and also more inclusive standards for retaining variables (final model selected retains the model with an accuracy of 98% of the maximum, in comparison with the minimum).

Our final variable list (45 variables) to use for imputation included all variables selected for the species-group, and the structure group models. These variables are listed and described in Appendix 1a.

Model assessment

Variable importance

We show the relative importance of each variable for predicting each categorical y-variable (species composition, and structure groups), extracting two variable importance measures, the GINI index (indicates each variable's contribution to reducing the class impurity in the model prediction), and the mean decrease accuracy measure, (the reduction in model accuracy for the y-variable that results from randomly permuting the values in each explanatory variable, one at a time). We report both metrics because they are complementary in their information content.

Accuracy for response variables

We assess the model's capacity to predict several variables of three different types. For nearly all of the statistics that report, larger values (approaching one) indicate stronger model performance. The Kolmogorof-smirnof (KS) test is the one exception to this rule, where smaller values (approaching zero) indicate stronger model performance.

For species-cover model predictions, we assess the model's capacity to predict range on a binary transformation of species cover using the kappa statistic (Cohen 1960, all results shown in Appendix 2, select species shown in Results section).

For continuous variables describing community-level cover summaries (e.g., shrub cover, tree cover, % cover of exotic annual grasses), we report a regression-based analysis of model accuracy (Riemann et al. 2010). This approach relies on three statistics that report on a regression model of observed and predicted values. The Systematic Agreement Coefficient (AC_sys) indicates how well the regression line matches a 1:1 line. Values less than 1 indicate that the regression line diverges from a 1:1 line, either with respect to slope or position. This metric is tuned to highlight bias in the model prediction. The Unsystematic Agreement Coefficient (AC_uns) indicates the degree of scatter around that regression line, or model precision. AC_uns values less than 1 indicate more scatter around the regression line, and a poorer model fit. The overall Agreement Coefficient (AC) merges information from both AC_sys and AC_uns to give an indication of overall model performance in terms of both precision and bias (again, values approaching 1 for this statistic indicate strong performance, while those that are zero, or even negative indicate poor performance). We illustrate these statistics graphically, using scatterplots for four sample variables at four spatial scales of summary (Plot, Hex1, Hex2, and Hex3, see Figure 1 for scale illustration). We also report these statistics at all spatial scales for species abundance predictions for forty four individual species in Appendix 3, and thirty seven continuous vegetation summary variables in Appendix 4.

We report more detailed results on four sample variables, showing scatterplots and regression lines associated with the statistics discussed above. For these sample variables we also report empirical cumulative distribution functions (ecdf), and Kolmogorov-smirnoff (KS) statistics. The ecdf graphics indicate how well the model prediction's statistical distribution matched that for relationship with the distribution of observed values (Lopes, Reid, and Hobbes 2007), and the KS statistics measure how close the observed and predicted ecdf lines are to one another. When the observed, and predicted ecdf curves are very similar, it indicates a strong model, and the KS statistic will be correspondingly small.

For those four sample variables, we also illustrate the spatial distribution of different map errors by summarizing plot-level observations and predictions (average) over the assessment hexagons. Differences between hexagon level averages of observations and predictions are shown graphically.

For multi-cateogry variables, we report overall and class-level statistics (kappa and % accuracy). We also provide error matrices to allow map users to evaluate each categorical variable's fitness to provide information to their current project when a particular category is of primary importance.

Vegetation summary variables that are included with the distributed maps are described in Appendix 1b and 1c.

Mapping

The final imputation model was used to generate a prediction of the nearest neighbor plot for all pixels in the area of interest. This raw grid was converted to an integer, and areas that were outside of the scope of our model were masked using three ancillary data sources. Developed areas, cultivated crops, and water were masked from information in the National Land Cover Datasest (NLCD, Homer et al. 2015). Forested areas were masked from information in the USGS Gap Analysis Program's landcover layer (GAP, Gap Analysis Program 2011). A supplemental local mask was also developed from airphoto interpreted points to supplement NLCD's information cultivated crops and water, as well as estimate and barren lands with no vegetation. This local map was build using a random forest (classification mode) model. These three data sources were combined in to a mask that is applied to the distributed grid.

Attributes describing vegetation are contained in three tables in the file geodatabase. They may be joined to the final raster grid using the 'Value_' field, and displayed in a GIS.

Map assessment

Map Review

In the drafting process, we assessed the map's congruence with local expert knowledge through a series of online meetings. Over the course of these meetings, some fixable problems such as errors in summarizing plot data, and missing but needed explanatory data layers were corrected. Other problems identified during the expert review process, which includes problems that were unfixable at this time. These are documented within the results and discussion section. Some of the currently-unfixable problems may be resolved in future drafts with additional plot data, and others may require a stronger suite of imagery variables to improve.

Supplemental data layers

As well as providing a raster data layer containing vegetation attributes, we provide two additional layers that depict two other aspects of map quality: nearest neighbor distances and euclidean environmental distances (named “nn1_dst”“, and”nn1_edst"" respectively in the geodatabase).

The nearest neighbor distance map indicates the distance between each pixel, and the plot imputed to that pixel within the space defined by the imputation model. In some imputation variants, this distance is analogous to environmental distance, but in random forest nearest neighbor imputation, it is not. The random forest nearest neighbor-based distance metric calculates imputation distances based on how plots are sorted by the classification trees that comprise the two random forest models. The space defined by this distance metric is nonlinear, and also non-euclidean, but it can be interpreted as an index of model certainty. When imputation distances are shorter, the imputation model has a clearer choice of the best plot match. Longer imputation distances indicate less certainty about the optimal plot choice. Short imputation distances often arise in areas of the landscape that are less well-sampled because it is more likely that only one plot is a reasonable choice. In portions of the landscape that are well-described by the plot data sample, imputation distances are often longer because the identity of the best possible plot is less clear when there are many good choices. Confoundingly, in portions of the landscape that are poorly-described by the plot data, it is also possible to have long imputation distances when the model is choosing from several equally poor plot choices.

Because the imputation distance metric is sometimes uninformative about how closely a given plot is matched to each pixel, we also provide a euclidean distance map that shows the euclidean distance between each pixel’s native values in the explanatory variables, and the explanatory data values associated with the plot imputed to that pixel. This environmental distance map helps illustrate areas in the map that are less well-described by the plot data sample. To calculate our environmental distance metric, we normalized all explanatory variables to range from zero to one. In future drafts, we are considering weighting the normalization to reflect variable importance, but as this has not yet been tested we have mapped values from the former calculation for this project.

Results

Variable importance

For the structure-group y-variable, climate, soil and imagery variables were selected. Three climate variables (growing season temperature, average annual temperature and the seasonal continuity of precipitation) were the strongest variables for predicting the structure-groups. Landsat imagery variables were important, and airphoto and soil summaries were also included (Figure 2a).

For the species-group y-variable, elevation was the most important predictor variable. Summer temperatures were also important (growing season temperatures, and august maximum temp). Elevation was also an important predictor of the species-groups. Landsat and soil variables were somewhat important, and one airphoto variable was included in the random forest model for this y-variable (Figure 2b). The most important variables for the indicator-group y-variable included imagery (naip), elevation, landsat, and climate (summer temperature) (Figure 2c). The binary juniper variable relied on topography and climate more strongly than did the other variables, as well as imagery (Figure 2d).

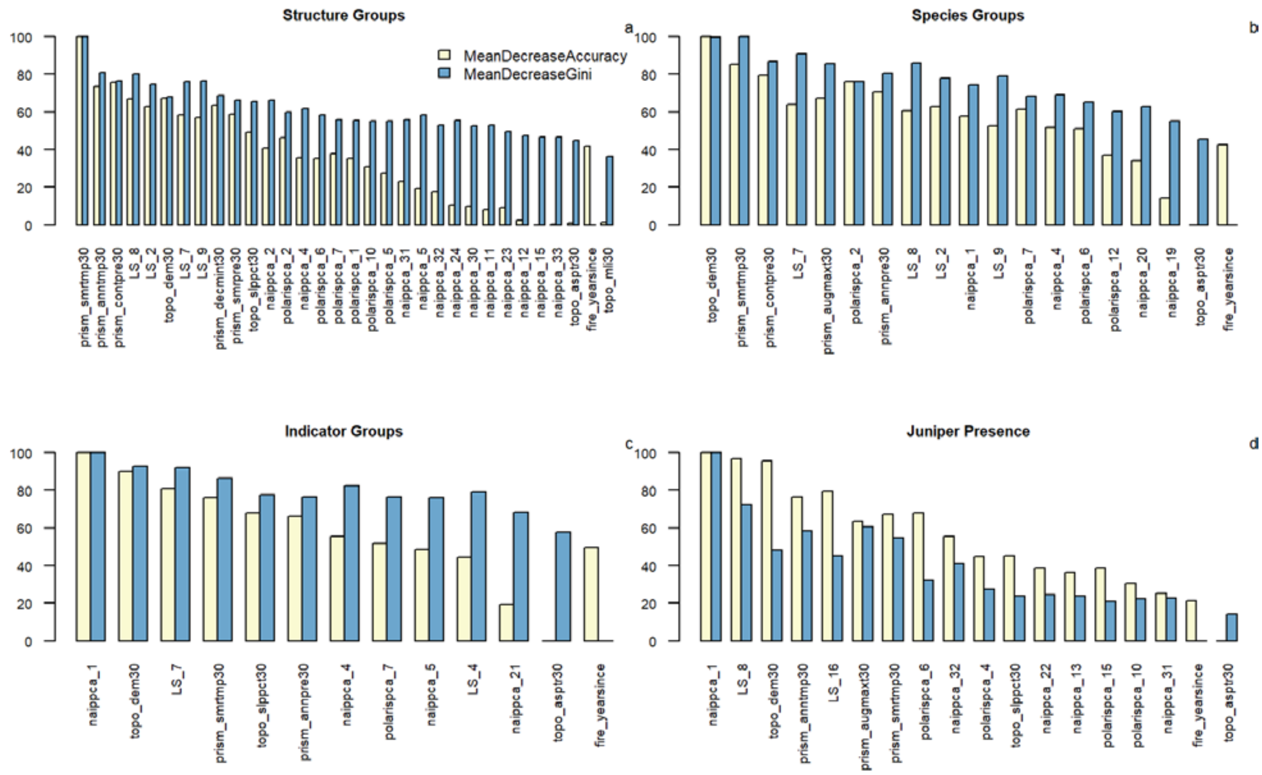


Figure 2: Variable importance metrics for each y-variable. The order of variables corresponds to the combined ranking of both metrics.

Species range

At the plot scale, 44% of range predictions for the common species shown in Table 2 had kappa statistics of greater than 0.4. This generally improved at the broader scales of summary, with 100, 100 and 98% of these species surpassing this threshold at the Hex1, Hex2 and Hex3 scales, respectively. Species range accuracy was most often at its' peak at the Hex3 scale.

Additional details on the accuracy of model predictions for all 112 species present in more than 5% of the input plot data for this model are shown in Appendix 2 and 3 (range and cover respectively).

Table 2: Kappa Statistics for all species that are present in more than 10% of the input plot data. Kappa values of 0.4, a cutoff that suggests that species range predictions are accurate enough to provide useful information. Standard error of the kappa statistic is shown in parentheses.

	Scientific.Name	Count	Plot	Hex1	Hex2	Hex3
ACMI2	*Achillea millefolium*	571	0.49 *(0.02)*	0.69 *(0.04)*	0.69 *(0.07)*	0.54 *(0.24)*
ACHY	*Achnatherum hymenoides*	395	0.31 *(0.02)*	0.50 *(0.05)*	0.58 *(0.07)*	0.93 *(0.07)*
ACTH7	*Achnatherum thurberianum*	1260	0.35 *(0.02)*	0.54 *(0.07)*	0.69 *(0.11)*	0.48 *(0.31)*
AGCR	*Agropyron cristatum*	436	0.54 *(0.02)*	0.67 *(0.04)*	0.64 *(0.07)*	0.72 *(0.13)*
ALAC4	*Allium acuminatum*	467	0.45 *(0.02)*	0.62 *(0.04)*	0.63 *(0.07)*	0.64 *(0.15)*
ANDI2	*Antennaria dimorpha*	478	0.34 *(0.02)*	0.50 *(0.05)*	0.52 *(0.08)*	0.62 *(0.17)*
ARAR8	*Artemisia arbuscula*	884	0.59 *(0.02)*	0.80 *(0.03)*	0.66 *(0.07)*	0.76 *(0.13)*
ARTRT	*Artemisia tridentata ssp. tridentata*	900	0.38 *(0.02)*	0.56 *(0.05)*	0.72 *(0.07)*	0.81 *(0.13)*
ARTRV	*Artemisia tridentata ssp. vaseyana*	366	0.61 *(0.02)*	0.75 *(0.04)*	0.75 *(0.06)*	0.70 *(0.14)*
ARTRW8	*Artemisia tridentata ssp. wyomingensis*	1730	0.48 *(0.02)*	0.56 *(0.08)*	0.64 *(0.13)*	0.85 *(0.15)*
ASFI	*Astragalus filipes*	357	0.24 *(0.02)*	0.46 *(0.05)*	0.55 *(0.07)*	0.76 *(0.13)*
ASPU9	*Astragalus purshii*	511	0.22 *(0.02)*	0.52 *(0.05)*	0.44 *(0.08)*	0.55 *(0.18)*
BRTE	*Bromus tectorum*	2523	0.50 *(0.02)*	0.66 *(0.14)*	0.58 *(0.19)*	1.00 *(0.00)*
CETE5	*Ceratocephala testiculata*	471	0.31 *(0.02)*	0.56 *(0.05)*	0.65 *(0.06)*	0.78 *(0.10)*
CHVI8	*Chrysothamnus viscidiflorus*	1558	0.40 *(0.02)*	0.62 *(0.07)*	0.70 *(0.11)*	1.00 *(0.00)*
COPA3	*Collinsia parviflora*	852	0.34 *(0.02)*	0.52 *(0.05)*	0.56 *(0.09)*	0.69 *(0.17)*
CRAC2	*Crepis acuminata*	1205	0.31 *(0.02)*	0.66 *(0.05)*	0.61 *(0.10)*	0.73 *(0.18)*
CROC	*Crepis occidentalis*	459	0.31 *(0.02)*	0.52 *(0.05)*	0.51 *(0.08)*	0.85 *(0.10)*
DEPI	*Descurainia pinnata*	414	0.34 *(0.02)*	0.49 *(0.05)*	0.58 *(0.07)*	0.76 *(0.13)*
DRVE2	*Draba verna*	382	0.42 *(0.02)*	0.47 *(0.05)*	0.55 *(0.07)*	0.76 *(0.11)*
ELEL5	*Elymus elymoides*	2339	0.37 *(0.02)*	0.70 *(0.10)*	0.48 *(0.18)*	0.00 *(0.00)*
ERNA10	*Ericameria nauseosa*	1072	0.35 *(0.02)*	0.52 *(0.06)*	0.51 *(0.11)*	0.65 *(0.23)*
ERLI	*Erigeron linearis*	413	0.32 *(0.02)*	0.53 *(0.05)*	0.62 *(0.07)*	0.83 *(0.10)*
EROV	*Eriogonum ovalifolium*	393	0.33 *(0.02)*	0.47 *(0.05)*	0.56 *(0.07)*	0.59 *(0.15)*
FEID	*Festuca idahoensis*	1188	0.54 *(0.02)*	0.68 *(0.04)*	0.58 *(0.10)*	0.66 *(0.32)*
GRSP	*Grayia spinosa*	489	0.53 *(0.02)*	0.68 *(0.04)*	0.84 *(0.05)*	0.81 *(0.09)*
JUOC	*Juniperus occidentalis*	700	0.82 *(0.01)*	0.87 *(0.03)*	0.85 *(0.05)*	0.92 *(0.08)*
KOMA	*Koeleria macrantha*	428	0.52 *(0.02)*	0.66 *(0.04)*	0.68 *(0.06)*	0.80 *(0.11)*
LEPE2	*Lepidium perfoliatum*	508	0.34 *(0.02)*	0.55 *(0.05)*	0.70 *(0.06)*	1.00 *(0.00)*
LECI4	*Leymus cinereus*	546	0.26 *(0.02)*	0.48 *(0.05)*	0.67 *(0.07)*	0.64 *(0.15)*
LIPU11	*Linanthus pungens*	396	0.31 *(0.02)*	0.53 *(0.05)*	0.59 *(0.07)*	0.75 *(0.12)*
LUCA	*Lupinus caudatus*	346	0.38 *(0.03)*	0.56 *(0.05)*	0.68 *(0.06)*	0.67 *(0.14)*
MIGR	*Microsteris gracilis*	676	0.31 *(0.02)*	0.45 *(0.05)*	0.59 *(0.08)*	0.69 *(0.17)*
NOTR2	*Nothocalais troximoides*	446	0.44 *(0.02)*	0.63 *(0.04)*	0.53 *(0.07)*	0.54 *(0.15)*
PHHO	*Phlox hoodii*	609	0.35 *(0.02)*	0.58 *(0.05)*	0.59 *(0.08)*	0.73 *(0.15)*
PHLO2	*Phlox longifolia*	983	0.42 *(0.02)*	0.61 *(0.04)*	0.55 *(0.08)*	0.83 *(0.12)*
POBU	*Poa bulbosa*	354	0.47 *(0.03)*	0.69 *(0.04)*	0.62 *(0.07)*	0.46 *(0.14)*
POSE	*Poa secunda*	2749	0.60 *(0.02)*	0.57 *(0.12)*	0.65 *(0.16)*	1.00 *(0.00)*
PSSP6	*Pseudoroegneria spicata*	1952	0.53 *(0.01)*	0.65 *(0.06)*	0.79 *(0.12)*	1.00 *(0.00)*
PUTR2	*Purshia tridentata*	460	0.48 *(0.02)*	0.69 *(0.04)*	0.64 *(0.07)*	0.58 *(0.15)*
SIAL2	*Sisymbrium altissimum*	474	0.35 *(0.02)*	0.53 *(0.05)*	0.65 *(0.07)*	0.72 *(0.13)*
TACA8	*Taeniatherum caput-medusae*	364	0.44 *(0.02)*	0.79 *(0.04)*	0.72 *(0.06)*	0.64 *(0.11)*
TRDU	*Tragopogon dubius*	454	0.27 *(0.02)*	0.59 *(0.04)*	0.51 *(0.08)*	0.69 *(0.16)*

Continuous variables

We report in detail for three continuous variables here: Juniper, *Artemisia tridentata*, *Artemisia arbuscula* and Invasive Annual Grass. For assessments of all continuous, summarized variables available in the map, see Appendix 3.

Juniper

The variable showing the percent cover of Juniper performed well overall. At the plot scale, the model prediction was farly unbiased, although not very precise (AC_sys = 0.99, AC_uns = 0.02, Figure 3a). At broader scales of summary, the model's precision improved dramatically, although a small bias became more apparent at broader scales (AC_uns = 0.73, 0.87, 0.94, and AC_sys = 0.98, 0.97, 0.95 for Hex1, Hex2, and Hex3 scales respectively, Figure 3b, c and d).

The model prediction effectively reproduced the distribution of values in the observations for AllJuniper at the plot scale (Figure 4a). At the broader spatial scales, the small bias noted above was apparent in an under-representation of some of the lower values in themodel prediction (Figure 4b,c and d). This was reflected by the KS statistic at those scales (KS = 0.55, 0.08, and 0.11 for the Hex1, Hex2, and Hex3 scales respectively).

The spatial patterns of prediction errors appear well-dispersed throughout the sampled portion of the modeling region on visual inspection (Figure 5c, f and i). The slight biases discussed above are apparent in the predominance of the blue hexagons (most visible in panels f and I of Figure 5).

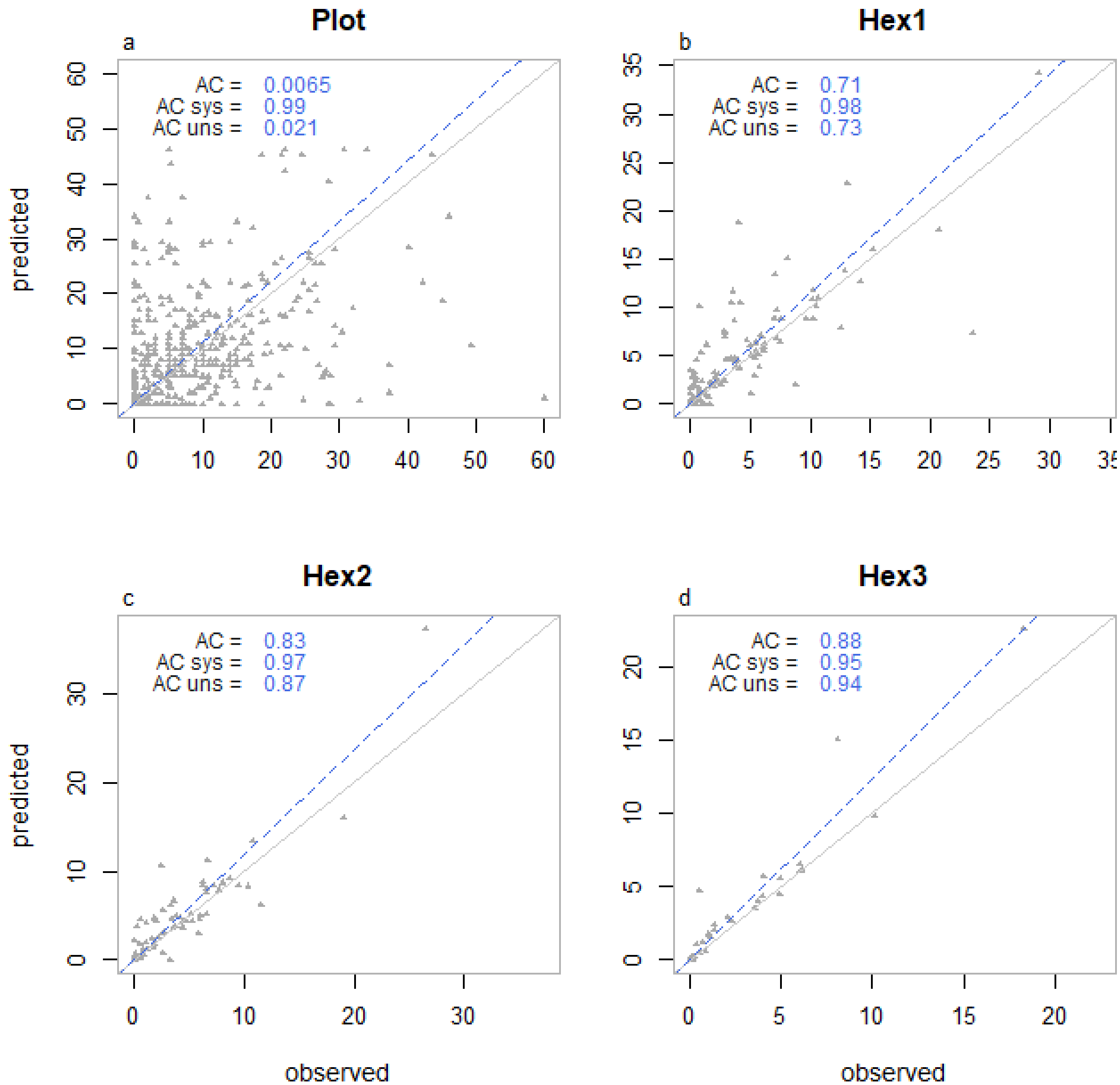


Figure 3: GMFR-based accuracy statistics for AllJuniper variable, at Plot, Hex 1, Hex 2, and Hex 3 scales of summary (Panels a,b,c and d respectively). AC_sys = 'Systematic Agreement Coefficient', and indicates how well the regression line matches a 1:1 line. AC_uns = 'Unsystematic Agreement Coefficient' indicates scatter around the regression line. AC = 'Agreement Coefficient', integrates the two components of accuracy and indictes overall fit. All three statistics indicate good fit as they approach 1.

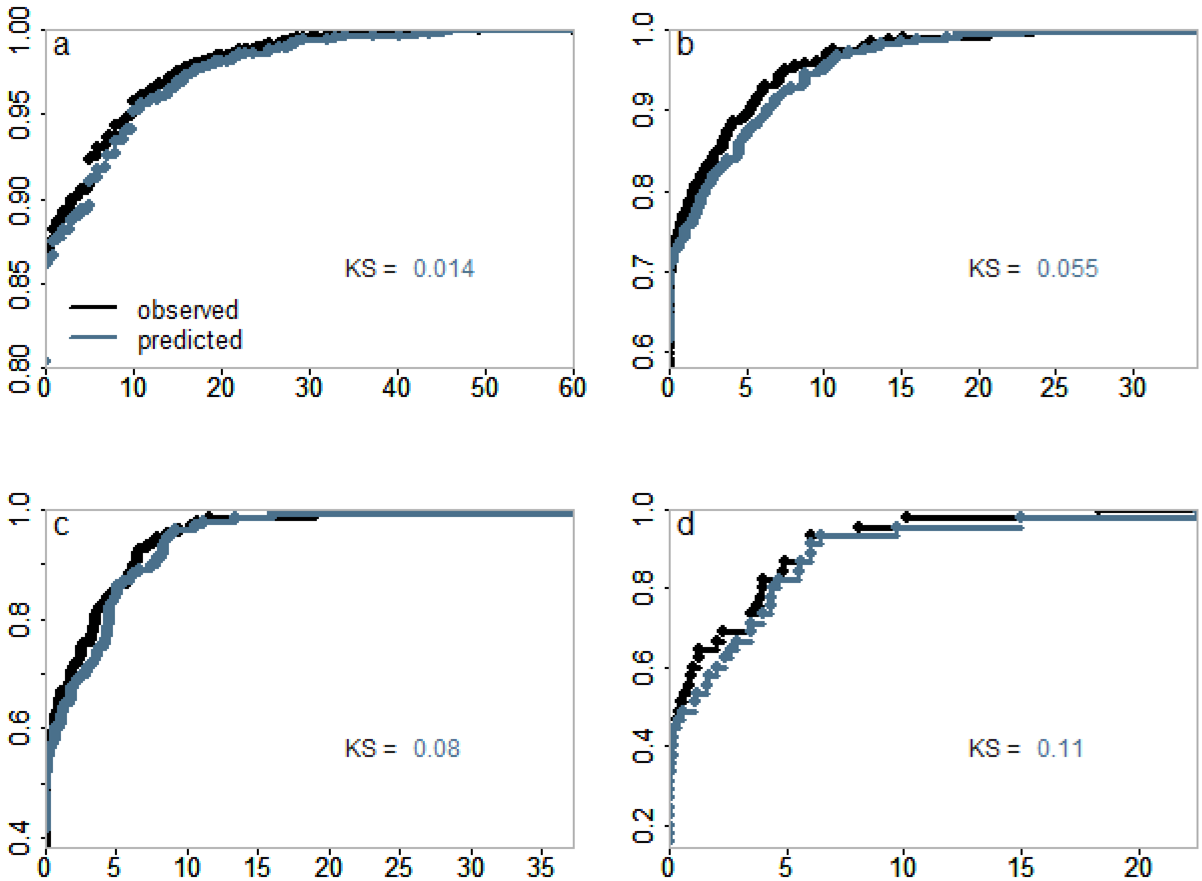


Figure 4: Distributional accuracy for AllJuniper variable, at Plot, Hex 1, Hex 2, and Hex 3 scales of summary (Panels a,b,c and d respectively). When the two lines are closely matched, the statistical distribution of values contained in the observations and predictions are similar.

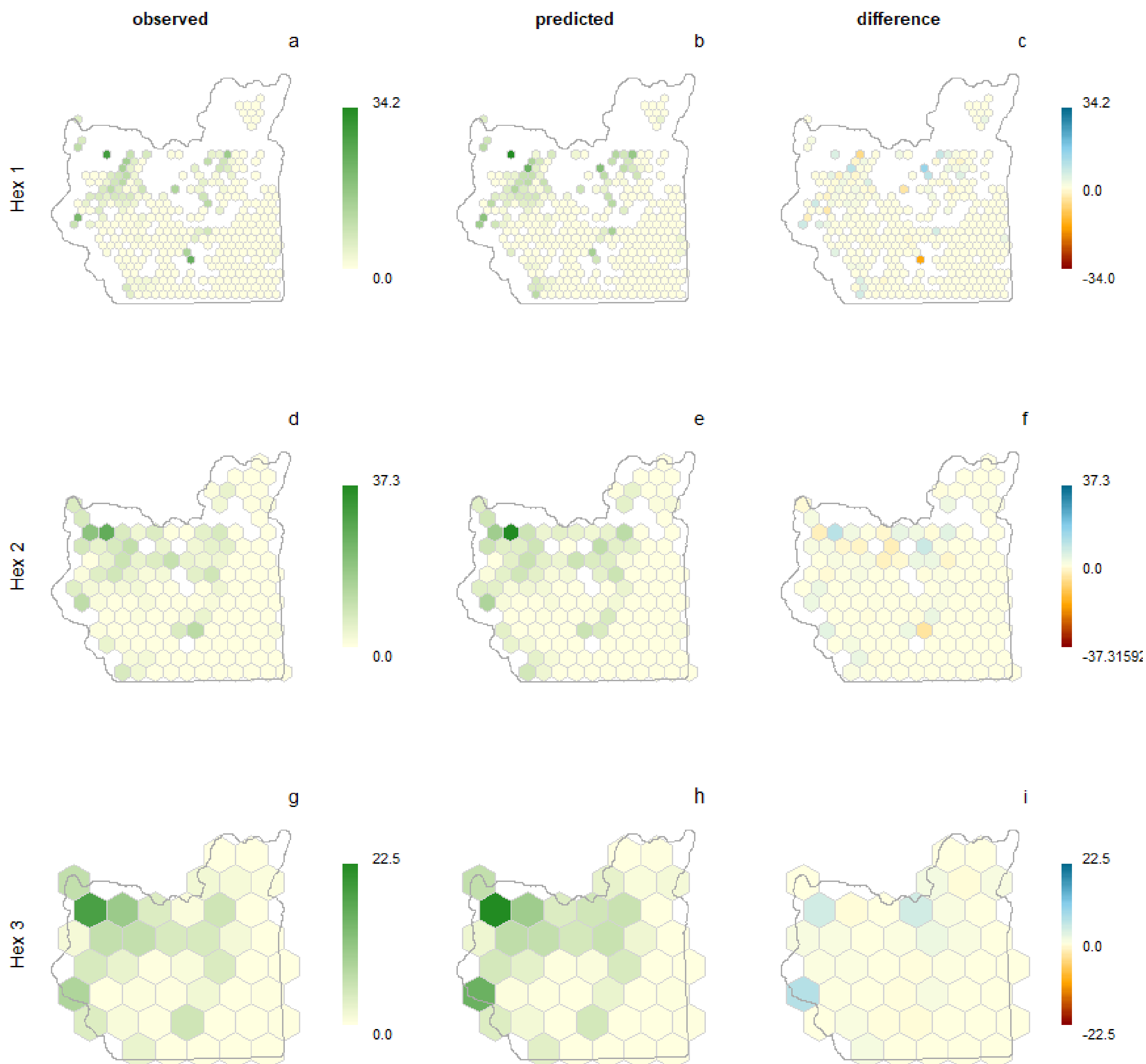


Figure 5: Average values of the AllJuniper variable from measured plots within hexagons (panels a,d and g for Hex1, Hex2 and Hex3 scales respectively), average values from modeled predictions of the AllJuniper at those plots (panels b,e and h), and the difference between those averages (panels c,f and j). In the third column, blue hexagons indicate areas where the model is over-predicting cover values, and orange hexagons show areas where the model is under-predicting cover.

Artemisia tridentata

The variable showing the percent cover of *Artemisia tridentata* performed well overall. At the plot scale, the model prediction was unbiased, although not very precise (AC_sys = 1, AC_uns = -0.13, Figure 6a). At broader scales of summary, the model's precision improved, and remained unbiased (AC_sys = 1, 0.99, 0.99, and AC_uns = 0.7, 0.71, 0.87 for Hex1, Hex2, and Hex3 scales respectively, Figure 6b, c and d).

The model prediction reproduced the distribution of values in the observations for SageTridentata quite consistently across all spatial scales (Figure 7).

The spatial patterns of prediction errors appear well-dispersed throughout the sampled portion of the modeling region on visual inspection (8c, f and i).

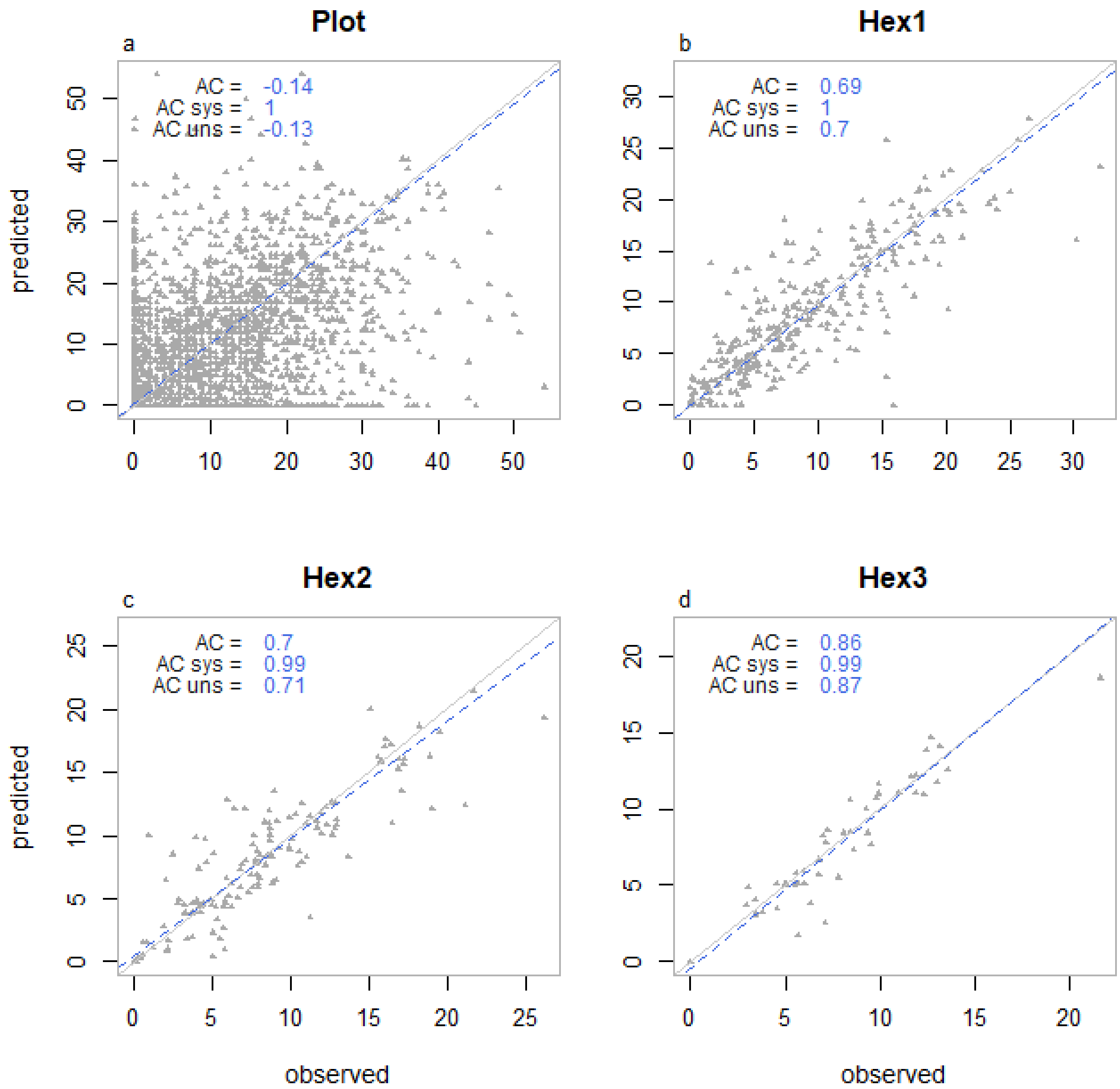


Figure 6: GMFR-based accuracy statistics for SageTridentata variable, at Plot, Hex 1, Hex 2, and Hex 3 scales of summary (Panels a,b,c and d respectively). AC_sys = 'Systematic Agreement Coefficient', and indicates how well the regression line matches a 1:1 line. AC_uns = 'Unsystematic Agreement Coefficient' indicates scatter around the regression line. AC = 'Agreement Coefficient', integrates the two components of accuracy and indictes overall fit. All three statistics indicate good fit as they approach 1.

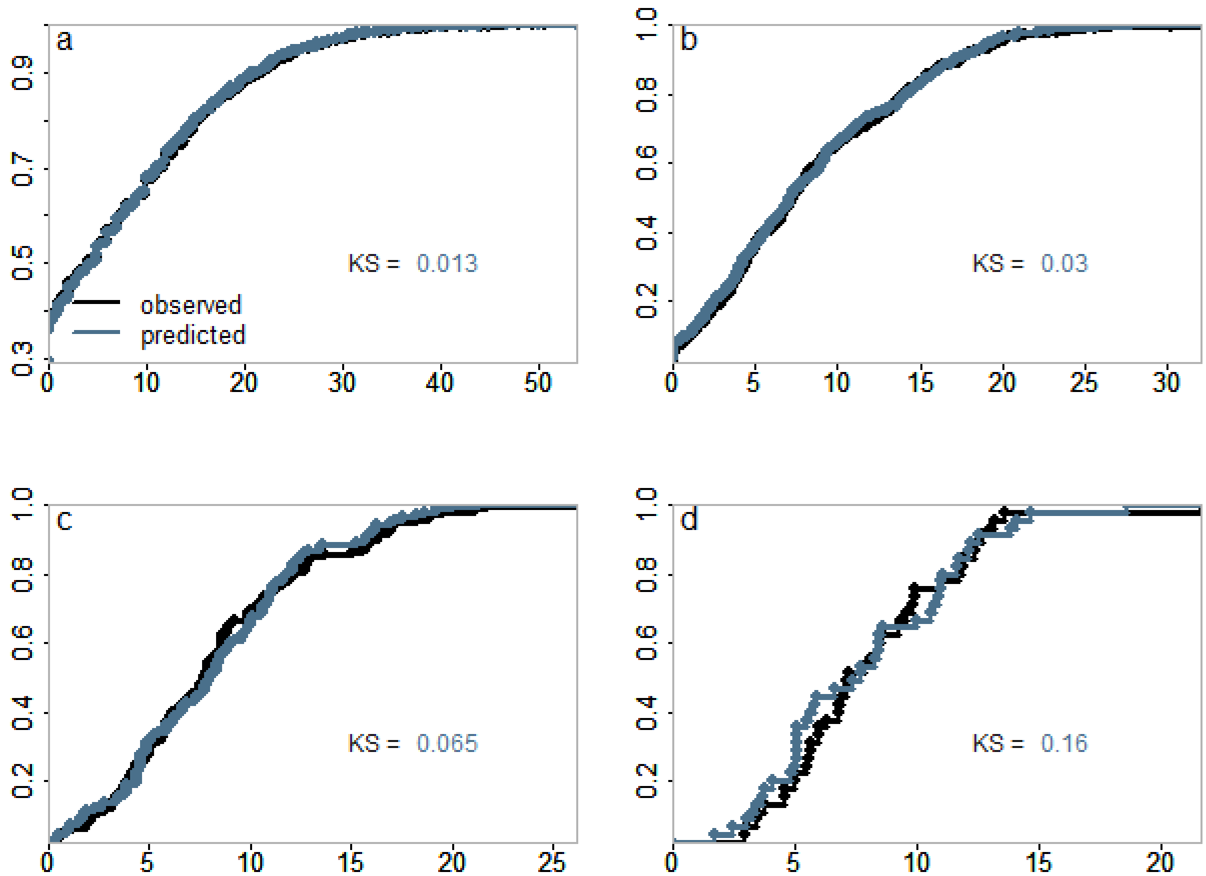


Figure 7: Distributional accuracy for SageTridentata variable, at Plot, Hex 1, Hex 2, and Hex 3 scales of summary (Panels a,b,c and d respectively). When the two lines are closely matched, the statistical distribution of values contained in the observations and predictions are similar.

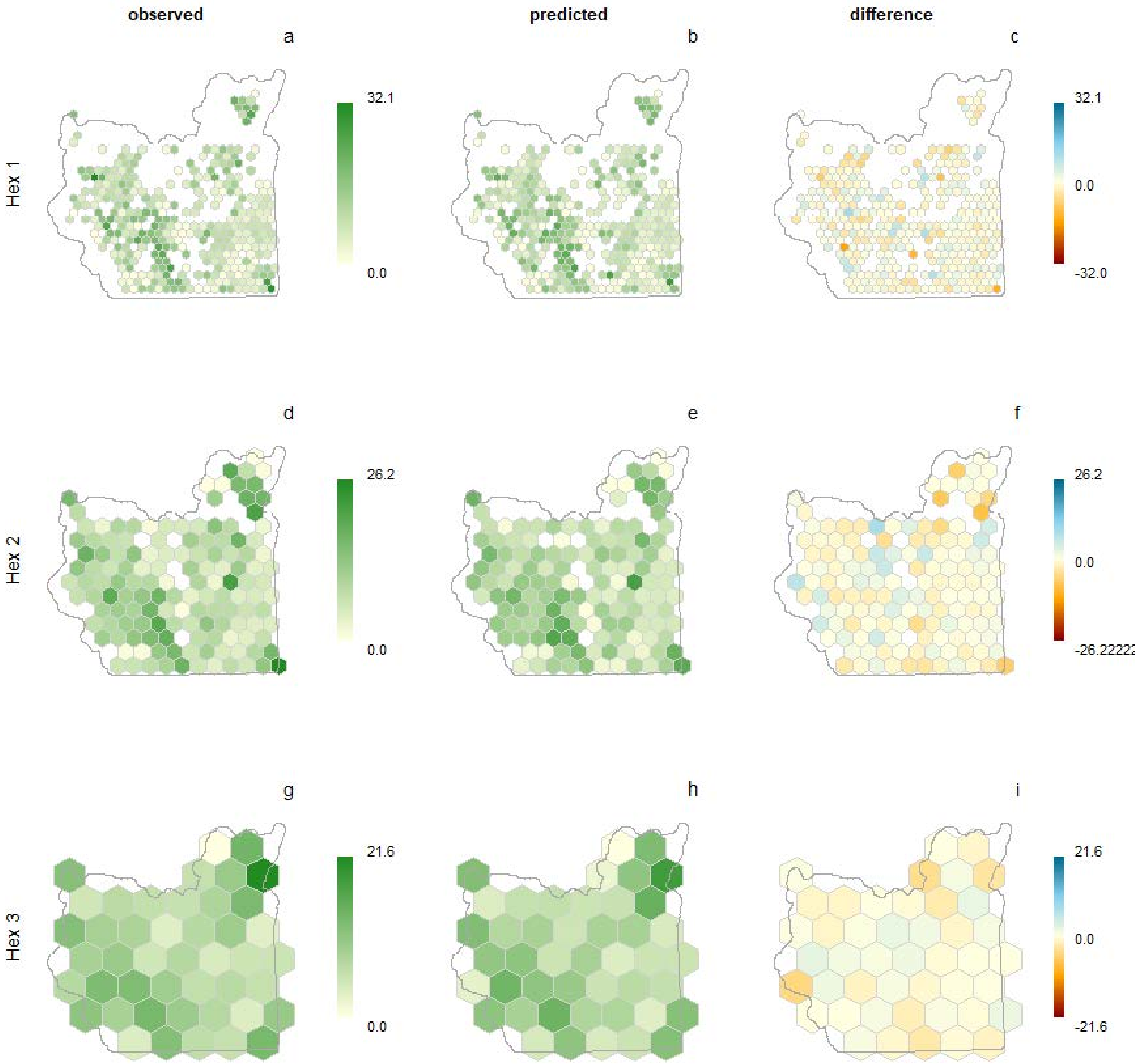


Figure 8: Average values of the SageTridentata variable from measured plots within hexagons (panels a,d and g for Hex1, Hex2 and Hex3 scales respectively), average values from modeled predictions of the SageTridentata at those plots (panels b,e and h), and the difference between those averages (panels c,f and j). In the third column, blue hexagons indicate areas where the model is over-predicting cover values, and orange hexagons show areas where the model is under-predicting cover.

Artemisia arbuscula

The variable showing the percent cover of *Artemisia arbuscula* (ARAR8) performed well overall. At the plot scale, the model prediction was unbiased, although not very precise (AC_sys = 1, AC_uns = -0.02, Figure 9a). At broader scales of summary, the model's precision improved, and remained unbiased (AC_sys = 0.99, 1, 1, and AC_uns = 0.76, 0.8, 0.92 for Hex1, Hex2, and Hex3 scales respectively, Figure 9b, c and d).

The model prediction reproduced the distribution of values in the observations for ARAR8 quite consistently across all spatial scales (Figure 10).

The spatial patterns of prediction errors appear well-dispersed throughout the sampled portion of the modeling region on visual inspection (11c, f and i).

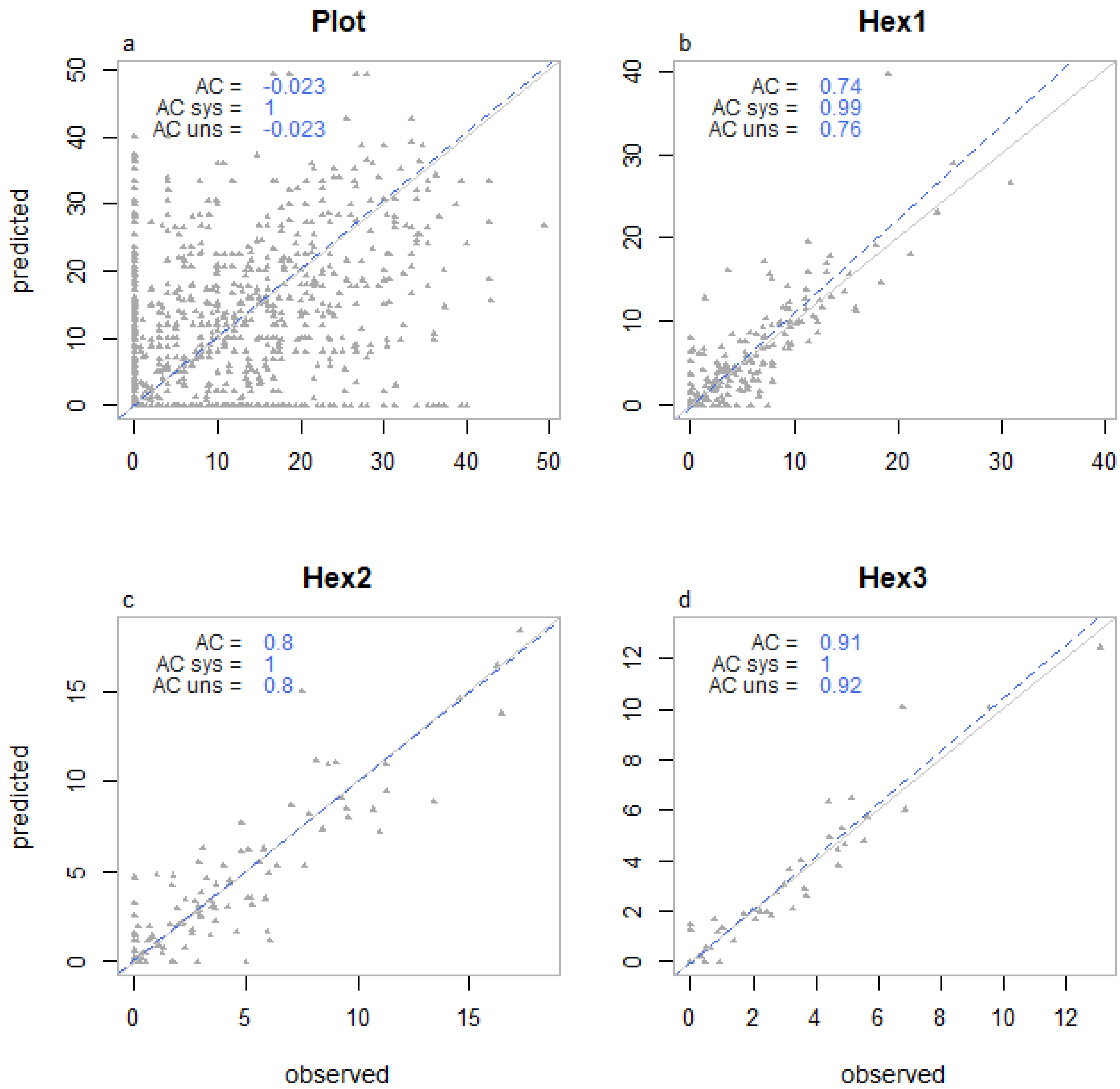


Figure 9: GMFR-based accuracy statistics for ARAR8 variable, at Plot, Hex 1, Hex 2, and Hex 3 scales of summary (Panels a,b,c and d respectively). AC_sys = 'Systematic Agreement Coefficient', and indicates how well the regression line matches a 1:1 line. AC_uns = 'Unsystematic Agreement Coefficient' indicates scatter around the regression line. AC = 'Agreement Coefficient', integrates the two components of accuracy and indictes overall fit. All three statistics indicate good fit as they approach 1.

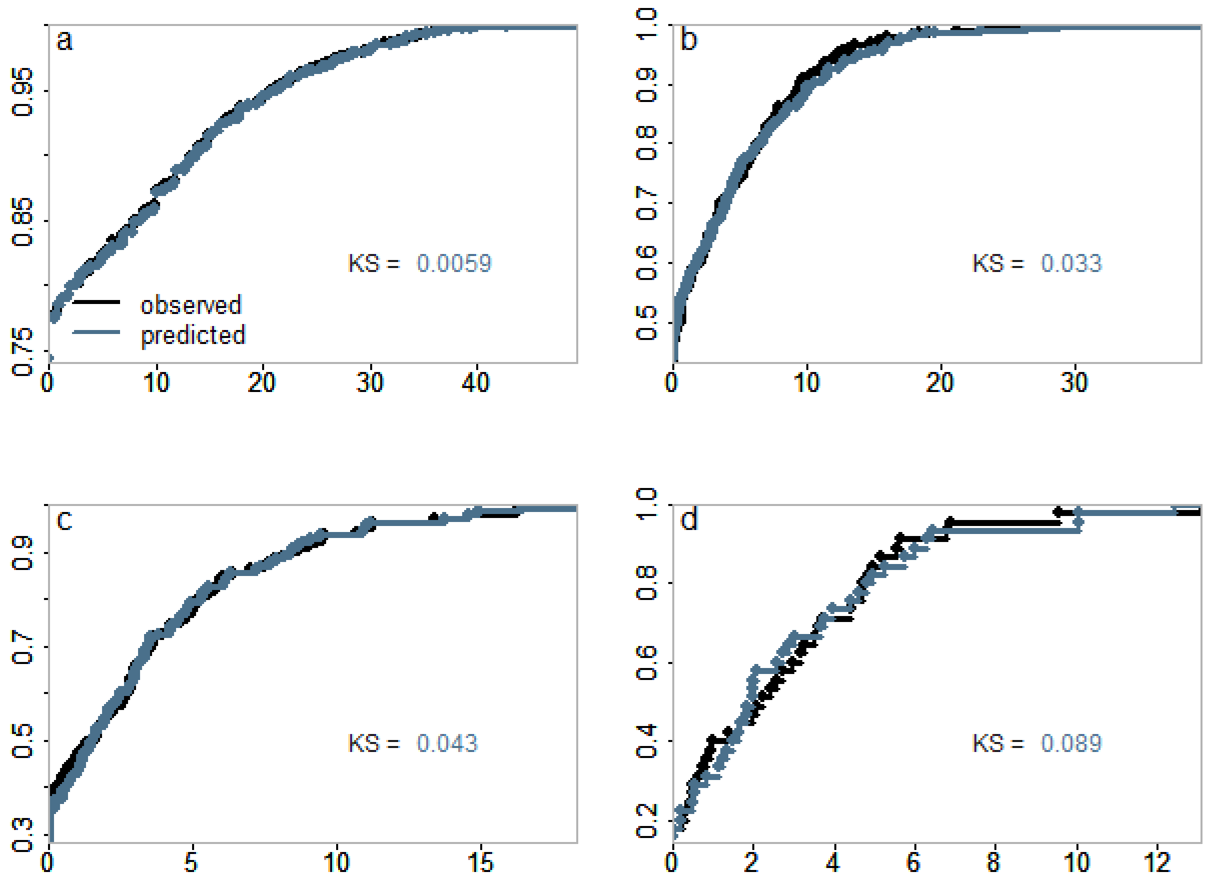


Figure 10: Distributional accuracy for the ARAR8 variable, at Plot, Hex 1, Hex 2, and Hex 3 scales of summary (Panels a,b,c and d respectively). When the two lines are closely matched, the statistical distribution of values contained in the observations and predictions are similar.

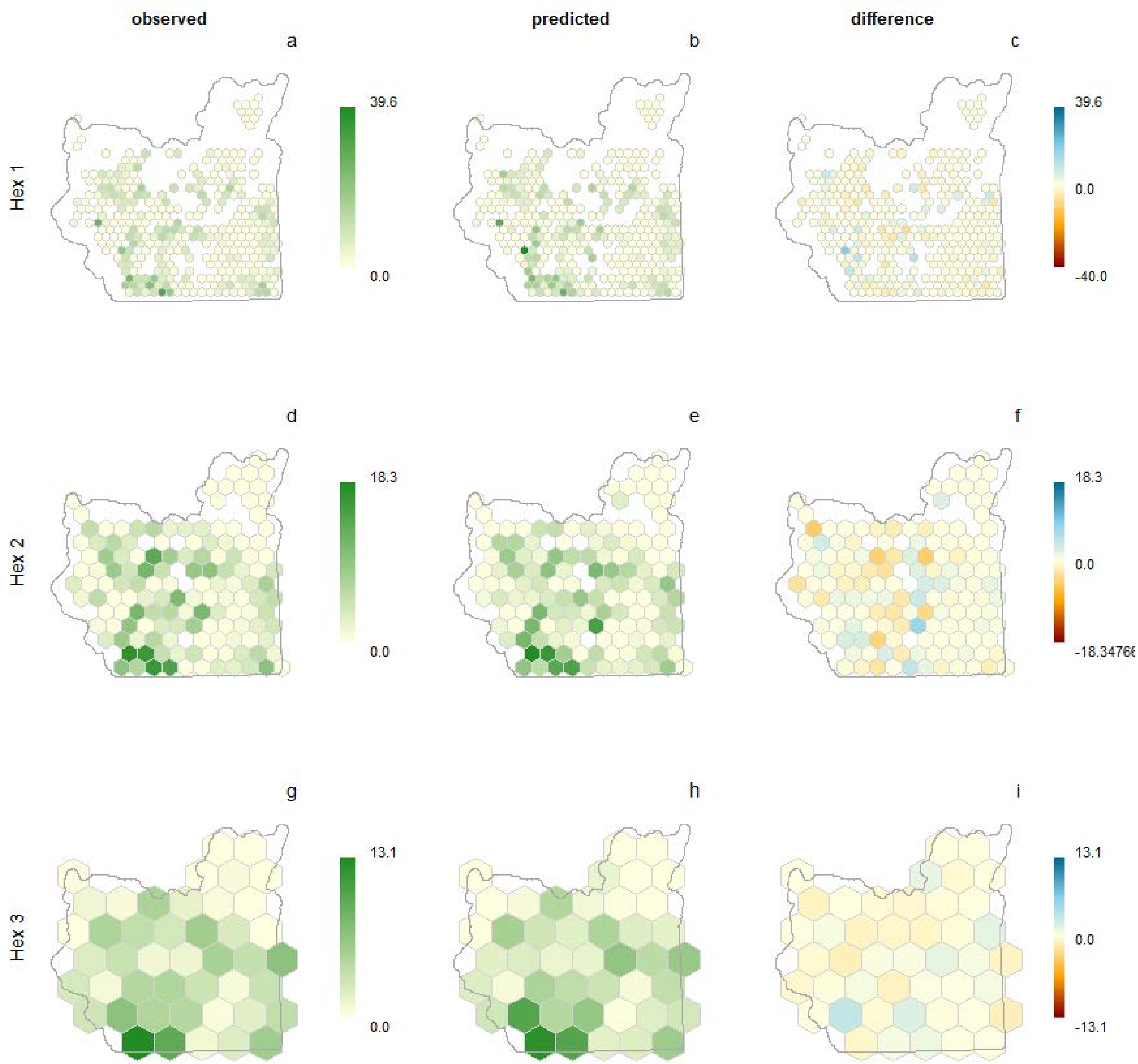


Figure 11: Average values of the ARAR8 variable from measured plots within hexagons (panels a,d and g for Hex1, Hex2 and Hex3 scales respectively), average values from modeled predictions of the ARAR8 at those plots (panels b,e and h), and the difference between those averages (panels c,f and j). In the third column, blue hexagons indicate areas where the model is over-predicting cover values, and orange hexagons show areas where the model is under-predicting cover.

Invasive Annual Grass

The variable showing the percent cover of Invasive Annual Grass performed well overall. At the plot scale, the model prediction was unbiased, although not very precise (AC_sys = 0.99, AC_uns = -0.09, Figure 12a). At broader scales of summary, the model's precision improved, and remained unbiased (AC_sys = 1, 0.99, 0.99, and AC_uns = 0.68, 0.87, 0.97 for Hex1, Hex2, and Hex3 scales respectively, Figure 12b, c and d).

The model prediction reproduced the distribution of values in the observations for InvasiveAnnualGrass quite consistently across all spatial scales (Figure 13).

The spatial patterns of prediction errors appear well-dispersed throughout the sampled portion of the modeling region on visual inspection (14c, f and i).

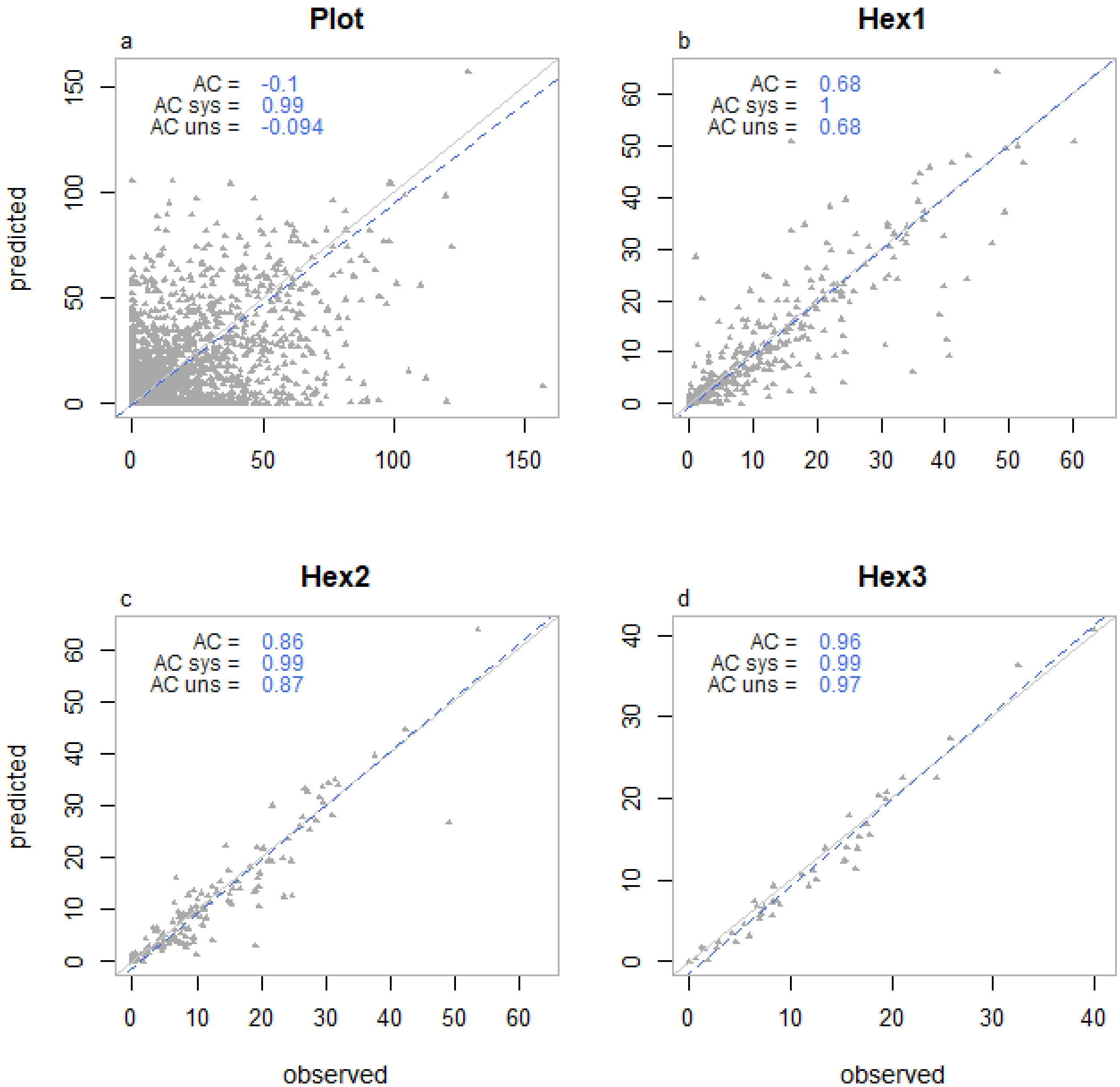


Figure 12: GMFR-based accuracy statistics for InvasiveAnnualGrass variable, at Plot, Hex 1, Hex 2, and Hex 3 scales of summary (Panels a,b,c and d respectively). AC_sys = 'Systematic Agreement Coefficient', and indicates how well the regression line matches a 1:1 line. AC_uns = 'Unsystematic Agreement Coefficient' indicates scatter around the regression line. AC = 'Agreement Coefficient', integrates the two components of accuracy and indictes overall fit. All three statistics indicate good fit as they approach 1.

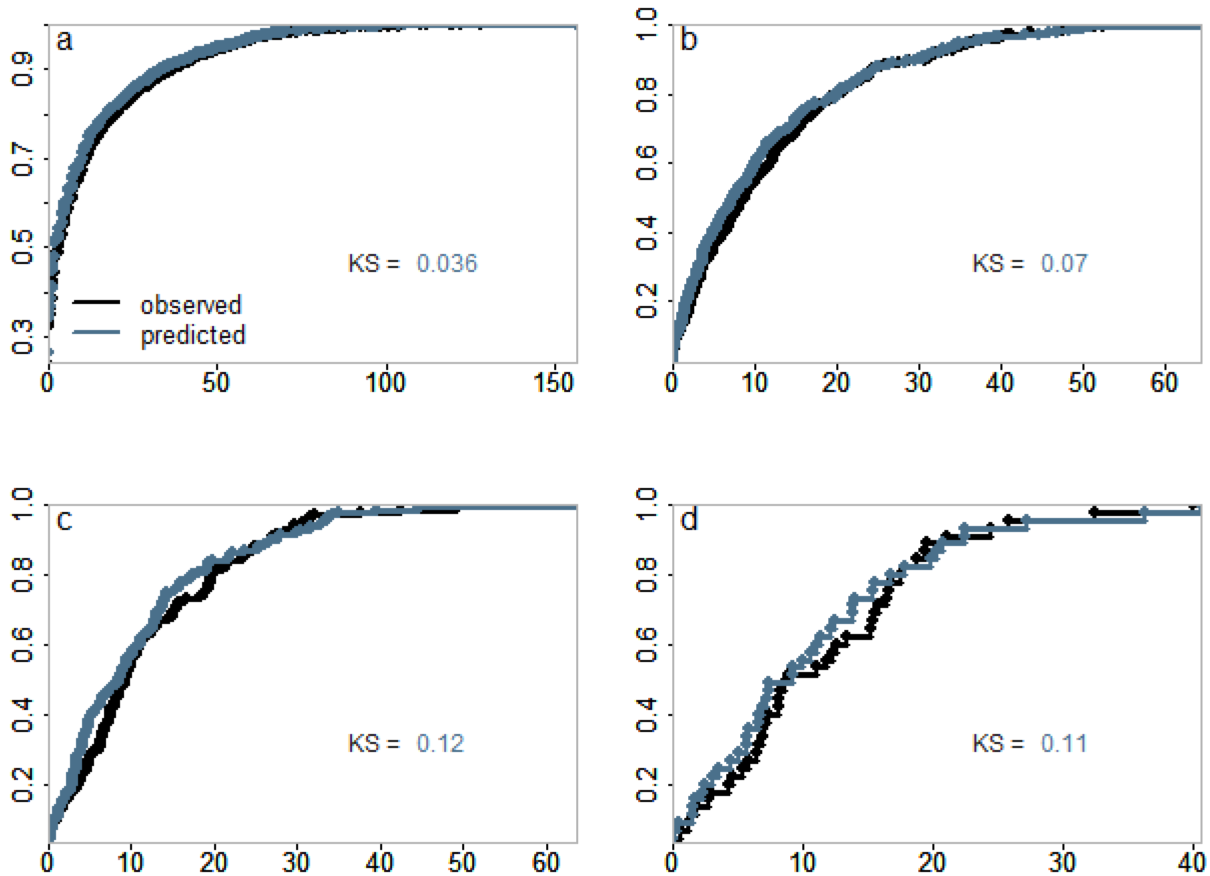


Figure 13: Distributional accuracy for InvasiveAnnualGrass variable, at Plot, Hex 1, Hex 2, and Hex 3 scales of summary (Panels a,b,c and d respectively). When the two lines are closely matched, the statistical distribution of values contained in the observations and predictions are similar.

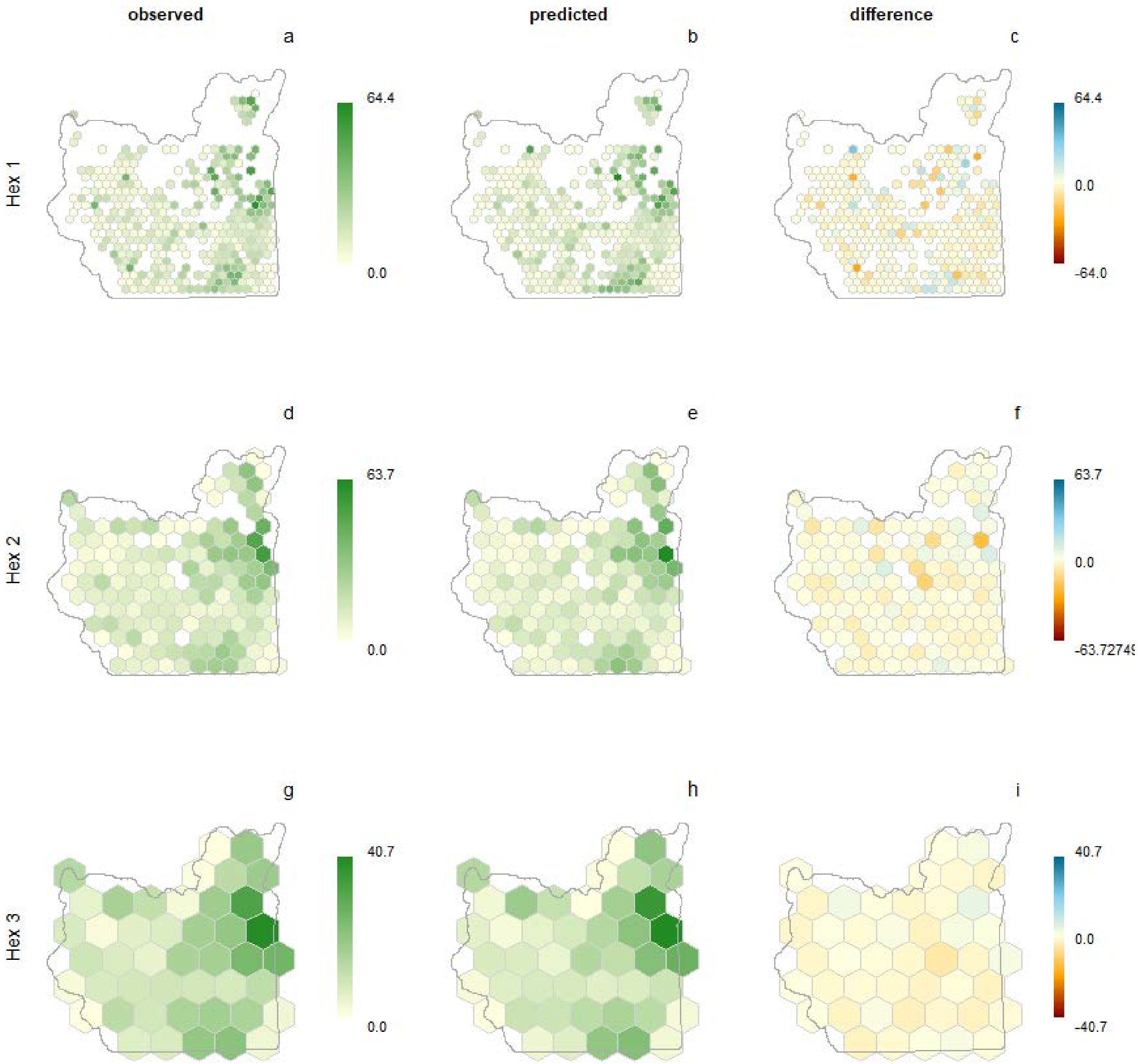


Figure 14: Average values of the InvasiveAnnualGrass variable from measured plots within hexagons (panels a,d and g for Hex1, Hex2 and Hex3 scales respectively), average values from modeled predictions of the InvasiveAnnualGrass at those plots (panels b,e and h), and the difference between those averages (panels c,f and j). In the third column, blue hexagons indicate areas where the model is over-predicting cover values, and orange hexagons show areas where the model is under-predicting cover.

Categorical variables

Sagebrush Class

Overall, the model was marginal at identifying the most common species in its predictions (Overall Kappa: 0.335). The accuracy for any individual species was frequently low, but category 1 performed well. Class-level statistics ranged from 0.263 to 0.579. Although the overall Kappa statistic was fairly low, we note that most of the confusion is constrained to adjacent classes (see Table 3). For example, the class showing 5.01 to 15% sagebrush cover is primarily confused with the second and fourth classes (0.01 to 5, and 15.01 to 25%) , and only sometimes confused with the first and fifth (0%, and > 25%). The first and fifth classes are only very rarely confused.

Table 3: Error matrix for Sagebrush_Class.

	0	0.01 to 5	5.01 to 15	15.01 to 25	> 25	Row_Accuracy	*Kappa*	*ASE*
0	301	109	41	15	7	*63.6%*	0.579	0.020
0.01 to 5	102	325	192	57	19	*46.8%*	0.314	0.019
5.01 to 15	55	223	577	218	70	*50.5%*	0.276	0.017
15.01 to 25	8	51	212	291	137	*41.6%*	0.263	0.020
> 25	4	15	71	118	148	*41.6%*	0.328	0.025
Column_Accuracy	*64.0%*	*45.0%*	*52.8%*	*41.6%*	*38.8%*	*48.8%*	0.335	0.011

Ecological State

Ecological State: Detailed

Ecological state describes rangeland vegetation condition and major threats present based on a threat-based model (Johnson et al 2019). Ecological state was assigned based on understory condition (combination of perennial grass, invasive annual grass, and undesirable annual forbs), cover of sagebrush, and relative cover of juniper (representing juniper site dominance).

Overall, the model was marginal at identifying the most likely Ecological State, as described by a cover categorization and a grade based on understory condition (Overall Kappa: 0.395). The accuracy for any individual category was often low, but a few categories performed well. Class-level statistics ranged from -0.003 to 0.601. When generealized to the Ecological State Summary variable, accuracy is improved (reported below).

Error matrix and class-level kappa statistics are available in:
`ErrorMatrix_Ecological_State_Detail.xlsx’

Table 4: Class-level kappa statistics for Ecological_State_Detail. Overall Kappa Statistic: 0.395, ase =0.01.

	Kappa	ASE
A : Good Condition Sagebrush	0.481	0.016
A-C : Potentially Poor Condition Sagebrush	0.163	0.029
B : Good Condition Grassland	0.387	0.018
B-D : Potentially Poor Condition Grassland	0.196	0.028
C1 : Poor Condition Sagebrush	0.320	0.031
C2 : Early Juniper Encroachment with Good Condition	0.502	0.027
C3 : Mid Juniper Encroachment with Good Condition	0.387	0.042
D1 : Poor Condition Grassland	0.346	0.029
D2 : Early Juniper Encroachment with Poor Condition	-0.003	0.001
D3 : Mid Juniper Encroachment with Poor Condition	-0.001	0.000
D4 : Late Juniper Encroachment	0.322	0.087
N/A	0.601	0.033
Overall	0.395	0.010

Ecological State: Juniper Phase

Overall, the model was acceptable at identifying the cover component of Ecological State (Overall Kappa: 0.504). The accuracy for any individual category was often low, but a few categories performed well. Class-level statistics ranged from 0.322 to 0.601.

Table 5: Error matrix for JuniperPhase.

	Grassland	Juniper_I	Juniper_II	Juniper_III	NA	Sage	Row_Accuracy	*Kappa*	*ASE*
Grassland	889	20	3	0	40	337	*69.0%*	0.485	0.015
Juniper_I	34	160	44	5	5	34	*56.7%*	0.515	0.027
Juniper_II	3	60	46	9	4	8	*35.4%*	0.373	0.041
Juniper_III	0	9	7	8	1	1	*30.8%*	0.322	0.087
NA	39	8	1	1	102	14	*61.8%*	0.601	0.033
Sage	346	36	2	0	12	1078	*73.1%*	0.523	0.015
Column_Accuracy	*67.8%*	*54.6%*	*44.7%*	*34.8%*	*62.2%*	*73.2%*	*67.8%*	0.504	0.012

Ecological State: Summary

Overall, the model was acceptable at predicting the summary version of Ecological State (Overall Kappa: 0.469). The accuracy for any individual category was often low, but a few categories performed well. Class-level statistics ranged from 0.258 to 0.719.

Table 6: Class-level kappa statistics for Ecological_State_Summary. Overall Kappa Statistic: 0.469, ase =0.011.

	A : Good Condition Sagebrush	B : Good Condition Grassland	C : Juniper Encroachment	C : Poor Condition Sagebrush	D : Juniper Encroachment with Poor Condition	D : Poor Condition Grassland	N/A	Row_Accuracy	*Kappa*	*ASE*
A : Good Condition Sagebrush	691	188	35	97	2	48	3	*64.9%*	0.481	0.016
B : Good Condition Grassland	180	447	18	44	1	120	24	*53.6%*	0.387	0.018
C : Juniper Encroachment	40	32	294	1	24	3	9	*73.0%*	0.719	0.019
C : Poor Condition Sagebrush	108	40	1	182	0	70	9	*44.4%*	0.376	0.024
D : Juniper Encroachment with Poor Condition	2	0	20	0	10	2	1	*28.6%*	0.258	0.068
D : Poor Condition Grassland	51	91	2	62	2	231	16	*50.8%*	0.410	0.022
N/A	3	29	9	11	1	10	102	*61.8%*	0.601	0.033
Column_Accuracy	*64.3%*	*54.1%*	*77.6%*	*45.8%*	*25.0%*	*47.7%*	*62.2%*	*58.1%*	0.469	0.011

Expert map reviews

Expert reviews of this map suggest some remaining issues beyond the fine-scale noise that is attributable to our statistical technique.

The first involves the mapping of western juniper. Although our model assessments indicate that this was a particularly robust variable, it is also a variable of critical concern in the area, and hence we attach greater importance to its' accuracy. While our map is fairly good at indicating the abundance of juniper, especially at broader spatial scales, we sometimes fail to adequately represent the range of juniper in this part of the state. For example, each expert reviewer confirmed that there is currently no juniper growing in the trout creek mountains, near the southeast corner of the map. However, our map places some small patches of juniper, mostly on hillslopes, and near streams. Reviewers suggested that these areas were more likely other trees, such as aspen (streamsides), and mountain mahogany (hilltops) in the area. It is possible that extra plot data describing these types of areas in the trout creek range could improve the model's performance in this respect. Given the need to understand the process of juniper expansion in the sage-steppe, improving this aspect of map performance may be worthwhile. In other portions of the landscape (especially along the margins of areas with heavier juniper cover in the northwest quadrant of the map), there are extensive areas mapped as showing a 'trace' of juniper, when investigation of airphotos indicates that juniper is absent. It is possible that these areas may contain very small numbers of very young junipers currently. It is also possible that the model maps this category with poor precision since juniper at such a low coverage level will not strongly affect the landsat spectral reflectance, or image texture remotely sensed imagery resources that we are using. This issue is compounded in the northwestern corner of the map due to a dearth of recent plot data describing the juniper woodlands. Additions of more plots arrayed to describe the full plant compositional gradient from sage-steppe to juniper woodlands would likely improve model performance in this area.

Three of our expert reviewers noted that low sagebrush cover in the Beatys PAC area seemed a bit high. Some of this impression may stem from viewing a single-variable illustration of low sagebrush. It often mixes with other species, and is not the dominant sagebrush species in the area of concern. However, there is a zone within the PAC, within Hart Mountain Wildlife Refuge, where plot data are very sparse. The question of whether low sagebrush cover is mapping appropriately in the area could be better addressed were there additional plots in the area. Older vegetation survey plots from the area may contain useful information, so long as they fall outside of areas affected by recent fires.

The third area of concern that was highlighted in the map review process is the performance of the variable describing deep-rooted perennial grasses, near in the northeastern corner of the map within the Baker Priority Area for Conservation. This variable showed considerably higher values in this area than in others, and as such was chosen for a focused review. The targeted review in the Baker area revealed that this variable was not performing well in concert with the two summaries of introduced species, invasive annual grasses, and undesirable annual forbs, especially around the area of the 2012 Sardine fire. An additional summary variable tallying the cover of noxious weeds listed by counties was added to the map to assist in evaluating the model's performance with respect to fire's effects on species invasions.

Further exploration of the relationship between our mapped variables and known recent fire data (from Monitoring Trends in Burn Severity) indicated that while some variables appeared to reflect recent fire history in a model with only imagery (shrub species abundances), other fire-related vegetation changes did not. This is unsurprising as the transition from native grasslands to non-native grasslandsis unlikely to show up in either landsat spectral reflectance, or in airphoto-based texture summaries. Because fire-related transitions from native-dominated to invasive-dominated communities are of particular interest in the area, we concluded that adding a fire history variable to the model was merited. We considered using fire intensity from the Monitoring Trends in Burn Severitiy data, but due to the mapping artifacts from the failure of the landsat 7 sensor in 2012, we concluded that this variable was not of adequate quality for use in modeling, and selected simply years since fire for our fire history response variable. During this same review session, we also observed that known vegetation transitions from north to south sloping aspects were not illustrated in the model. Because of this, we chose to reintroduce the raster variable describing aspect in to our final model. These variable re-introductions had very small effects on the resultant maps (most of the problems documented here remain in the final map), and almost no effects on model accuracy statistics.

Discussion

Overall map assessment

For most of the southwest Oregon modeling region, this map contains information that is accurate enough to inform management planning processes that encompass larger areas. For some variables, it may be useful at finer scales as well, but only with appropriate caution. The multi-scale accuracy assessments shown in the figures, tables, and appendices support these recommendations. For uses that require precise information at fine spatial scales, field visits or other local data sources are highly recommended for all variables. This map is best-suited for providing a broader-context background in which to frame information at finer spatial scales.

Despite the issues discussed above under ‘expert review’, most of the review sessions confirm the findings from the formal accuracy assessments. Despite the fine-scale noise, the map is robust enough to provide broad overviews of vegetation patterns across the landscape for a variety of summary variables. Although many single-species predictions variables are problematic, most of the summarized variables that aggregate the cover of many species contain meaningful information.

A particular strength of this map is that it generally provides unbiased estimates of continuous variables, something that is not always well-addressed in other rangeland map products (e.g., see Figure 5 in Jones et al. (2018), and Figure 5 in Homer et al. (2012). Observed-predicted regression line slope departs notably from 1:1).

Scale and accuracy

For both binary (species presence-absence) and continuous variables, we have assessed model accuracy at multiple scales. For continuous variables, model precision improves with summaries over larger areas. For species presence-absence, model predictions are strongest at intermediate scales. The latter pattern often emerges from a failure to predict species absences (low specificity) at broad scales of summary. In other words, infrequent plot-level false positive predictions yield errors over the largest hexagons used for summary.

We do not assess model accuracy at broader spatial scales for multi-category response variables. This is not because the assessment is not useful, but rather because we still lack an appropriate tool for multi-scale accuracy assessment of multi-category variables. Research into appropriate methods to do so is a priority for future work.

Monitoring context: change detection

This map is the fourth in a series of similar maps for the area. The first was completed in 2010 (imagery date 2006) for the Integrated Landscape Assessment Project. The second was completed in 2011 (2011 imagery), in support of the Climate-Management-Habitat, USGS-funded project. The second map was updated shortly thereafter (2013, imagery date 2011, with 2013 imagery in areas burned in 2012) in support of greater sage-grouse management planning. While there is a need for illustrating change across the landscape, we caution users against using this suite of maps specifically for change detection because none of them were created to support that application. Real landscape changes are confounded among these maps with an array of technical differences. Data availability in terms of both plot and raster data have improved since the first version. In the most recent draft, significant improvements to both imagery data (especially handling of NAIP NTMs), and soil data have yielded marked improvements to map quality. In addition, we have made improvements to our modeling process in terms of y-variable configurations, and also the explanatory variable selection process. Taken together these changes are a net positive for each map as accuracy improves, but they also confound the process of change detection. It is possible to build a framework for change detection and monitoring with imputation mapping (see Ohmann et al. 2012; Kennedy et al. 2018 for examples in forests), but this requires a platform for maximizing methodological consistency between the maps that are to be compared.

Acknowledgements

This work was supported by a cooperative Agreement with the Bureau of Land Management: "BLM OR/WA CESU Sage Grouse Habitat Monitoring and Assessment" (#L16AC00091).

We very much appreciate the time donated by our expert map reviewers: Jaqueline Cupples and Angela Sitz (US Fish and Wildlife Service), John Owens (US Bureau of Land Management), and Lee Foster (Oregon Department of Fish and Wildlife). This map was greatly improved from its earliest drafts because of the feedback that they provided.

This document was modified from a series of reports that serve as supporting information for analogous vegetation maps in Arizona and New Mexico (INR Existing Vegetation, or INREV project). It has been modified to apply to this particular mapping project specifically.

The text of this document was also improved significantly with feedback from Megan Creutzberg.

References

Cohen, J. 1960. A Coefficient of Agreement for Nominal Scales" Educational and Psychological Measurement.

Creutzburg, MK, EB Henderson, and DR Conklin. 2015. Climate Change and Land Management Impact Rangeland Condition and Sage-Grouse Habitat in Southeastern Oregon. AIMS Environmental Science 2: 203–36. https://doi.org/http://dx.doi.org/10.3934/environsci.2015.2.203.

Crookston, NL., and AO Finley. 2008. yaImpute: An R Package for kNN Imputation. Journal of Statistical Software 23.

Daly, C, M Halbleib, JI Smith, WP Gibson, MK Doggett, GH Taylor, J Curtis, and PP Pasteris. 2008. Physiographically Sensitive Mapping of Climatological Temperature and Precipitation Across the Conterminous United States. International Journal of Climatology 28: 2031–64.

Eskelson, BN, IH Temesgen, V Lemay, TM Barrett, NL Crookston, and AT Hudak. 2009. The Roles of Nearest Neighbor Methods in Imputing Missing Data in Forest Inventory and Monitoring Databases. Scandinavian Journal of Forest Research 24: 235–46. https://doi.org/10.1080/02827580902870490.

Gap Analysis Program, US Geological Survey. 2011. National Land Cover, Version 2.

Gesch, D, M Oimoen, S Greenlee, C Nelson, M Steuk, and T Tyler. 2002. The National Elevation Dataset. Photogrammetric Engineering and Remote Sensing 68.

Henderson, EB, DM Bell, and MJ Gregory. 2019. Vegetation Mapping to Support Greater Sage-Grouse Habitat Monitoring and Management: Multi-or Univariate Approach? Ecosphere 10 (8): e02838.

Henderson, EB, JL. Ohmann, MJ Gregory, HM Roberts, and H Zald. 2014. Species Distribution Modelling for Plant Communities: Stacked Single Species or Multivariate Modelling Approaches? Applied Vegetation Science 17: 516–27.

Homer, CG, CL Aldridge, DK Meyer, and SJ Schell. 2012. Multi-scale remote sensing sagebrush characterization with regression trees over Wyoming, USA: laying a foundation for monitoring. International Journal of Applied Earth Observation and Geoinformation 14(1): 233-244.

Homer, C, J Dewitz, L Yang, S Jin, P Danielson, G Xian, J Coulston, N Herold, J Wickham, and K Megown. 2015. Completion of the 2011 National Land Cover Database for the Conterminous United States–Representing a Decade of Land Cover Change Information. Photogrammetric Engineering & Remote Sensing 81 (5): 345–54.

Jones, MO, BW Allred, DE Naugle, JD Maestas, P Donnelly, LJ Metz, J Karl, R Smith, B Bestelmeyer, C Boyd, JD and Kerby, 2018. Innovation in rangeland monitoring: annual, 30 m, plant functional type percent cover maps for US rangelands, 1984–2017. Ecosphere, 9(9), p.e02430.

Johnson, D, M Cahill, C Boyd, V Schroeder, L Foster, A Sitz, J Kerby, T Svejcar, and J Cupples. 2019. Threat-Based Land Management in the Northern Great Basin: A Manager's Guide. PNW 722, https://catalog.extension.oregonstate.edu/pnw722. Corvallis, OR: Oregon State University Extension Service.

Kennedy, RE, J Ohmann, M Gregory, H Roberts, Z Yang, DM Bell, V Kane, MJ Hughes, WB Cohen, S Powell, N Neeti, T Larrue, S Hooper, J Kane, DL Miller, J Perkins, J Braaten and Rupert Seidl, 2018. "An Empirical, Integrated Forest Biomass Monitoring System." Environmental Research Letters 13 (2): 025004.

Lopes, R, I Reid, and P Hobbes. 2007. "The Two-Dimensional Kolmogorov–Smirnov Test Xi International Workshop on Advanced Computing and Analysis Techniques in Physics Research, Amsterdam." Published by Proceedings of Science.

Moeur, M, and AR Stage. 1995. "Most Similar Neighbor: An Improved Sampling Inference Procedure for Natural Resource Planning." Forest Science 41: 337–59.

Nielsen, EM, and MD Noone. 2014. "Tree Cover Mapping for Assessing Greater Sage-Grouse Habitat in Eastern Oregon." PhD thesis, Portland, OR: Report. Portland State University.

Ohmann, JL, and MJ Gregory. 2002. "Predictive Mapping of Forest Composition and Structure with Direct Gradient Analysis and Nearest- Neighbor Imputation in Coastal Oregon, U.S.A." Canadian Journal of Forest Research 32 (April): 725–41. https://doi.org/10.1139/x02-011.

Ohmann, JL, MJ Gregory, EB Henderson, and HM Roberts. 2011. “Mapping Gradients of Community Composition with Nearest-Neighbour Imputation: Extending Plot Data for Landscape Analysis.” Journal of Vegetation Science 22: 660–76. https://doi.org/10.1111/j.1654-1103.2010.01244.x.

Ohmann, JL, MJ Gregory, HM Roberts, WB Cohen, RE Kennedy, and Z Yang. 2012. “Mapping Change of Older Forest with Nearest-Neighbor Imputation and Landsat Time-Series.” Forest Ecology and Management 272: 13–25.

Ramcharan, A, T Hengl, T Nauman, C Brungard, S Waltman, S Wills, and J Thompson. 2018. “Soil Property and Class Maps of the Conterminous United States at 100-Meter Spatial Resolution.” Soil Science Society of America Journal.

Riemann, R., BT Wilson, A Lister, and S Parks. 2010. “An Effective Assessment Protocol for Continuous Geospatial Datasets of Forest Characteristics Using USFS Forest Inventory and Analysis (FIA) Data.” Remote Sensing of Environment 114: 2337–52.

Strobl, C, A-L Boulesteix, T Kneib, T Augustin, and A Zeileis. 2008. “Conditional Variable Importance for Random Forests.” BMC Bioinformatics 9: 1–11. https://doi.org/10.1186/1471-2105-9-307.

Strobl, C, A-L Boulesteix, A Zeileis, and T Hothorn. 2007. “Bias in Random Forest Variable Importance Measures: Illustrations, Sources and a Solution.” BMC Bioinformatics 8: 25.

Tomppo, E, and M Katila. 1991. “Satellite Image-Based National Forest Inventory of Finland for Publication in the Igarss’91 Digest.” In, 3:1141–4. https://doi.org/10.1109/igarss.1991.579272.

Appendices

Appendix 1a: Variables selected for final model

Variable Name	Description
LS_2	NDFI - Normalized Difference Forestness Index
LS_4	NDGR – Normalized Difference between red and green bands
LS_7	NDSWI – Normalized Difference Shortwave Index
LS_8	NDVI Normalized Difference Vegetation Index
LS_9	Landsat OLI band 2
LS_16	Tasseled cap greenness
naippca_1	Principal component axis from NAIP NTMs - 1
naippca_2	Principal component axis from NAIP NTMs - 2
naippca_4	Principal component axis from NAIP NTMs - 4
naippca_5	Principal component axis from NAIP NTMs - 5
naippca_11	Principal component axis from NAIP NTMs - 11
naippca_12	Principal component axis from NAIP NTMs - 12
naippca_13	Principal component axis from NAIP NTMs - 13
naippca_15	Principal component axis from NAIP NTMs - 15
naippca_19	Principal component axis from NAIP NTMs - 19
naippca_20	Principal component axis from NAIP NTMs - 20
naippca_21	Principal component axis from NAIP NTMs - 21
naippca_22	Principal component axis from NAIP NTMs - 22
naippca_23	Principal component axis from NAIP NTMs - 23
naippca_24	Principal component axis from NAIP NTMs - 24
naippca_30	Principal component axis from NAIP NTMs - 30
naippca_31	Principal component axis from NAIP NTMs - 31
naippca_32	Principal component axis from NAIP NTMs - 32
naippca_33	Principal component axis from NAIP NTMs - 33
polarispca_1	Principal component axis from POLARIS soil data layers - 1
polarispca_2	Principal component axis from POLARIS soil data layers - 2
polarispca_4	Principal component axis from POLARIS soil data layers - 4
polarispca_5	Principal component axis from POLARIS soil data layers - 5
polarispca_6	Principal component axis from POLARIS soil data layers - 6
polarispca_7	Principal component axis from POLARIS soil data layers - 7
polarispca_10	Principal component axis from POLARIS soil data layers - 10
polarispca_12	Principal component axis from POLARIS soil data layers - 12
polarispca_15	Principal component axis from POLARIS soil data layers - 15
prism_annpre30	Average Annual Precipitation
prism_anntmp30	Average Annual Temperature
prism_augmaxt30	August Maximum Temperature
prism_contpre30	Continuity of Precipitation
prism_decmint30	December Minimum Temperature
prism_smrpre30	Growing Season Precipitation (JJA)
prism_smrtmp30	Growing Season Temperature(JJA)
topo_asptr30	Aspect
topo_dem30	Elevation
topo_mli30	McComb's Landform Index
topo_slppct30	Percent slope
fire_yearsince	Years since most recent fire, according to Monitoring Trends in Burn Severity raster data.

Appendix 1b: Vegetation summary response variable definitions

List of summarized variables and descriptions.

Variable.Name	Description
TotalTree	Total cover of all tree species
TotalShrub	Total cover of all shrub species
TotalGrass	Total cover of all grass species
TotalForb	Total cover of all forb and herb species
BareGround	Estimated bare ground from line-intercept data. When line-intercept is unavailable, estimated by subtracting total cover from 100. **
TotalCov	Total cover of all plants
SageGrousePreferredForbs_High*	Total cover of perennial forbs with high value as GSG food.
SageGrousePreferredForbs_All*	Total cover of perennial forbs with any value as GSG food.
AllSage*	Total cover of all Artemisia species.
SageClass	Categorical variable relating to AllSage: 0%, trace - 5%, 5-15%,15-25%, and >25%
AllJuniper*	Total cover of all members of the genus *Juniperus*
SageTridentata*	Total cover of all subspecies of *Artemisia tridentata*
SageShallowSoil*	Total cover of *Artemisia* species that indicate shallow soils
EarlySeralShrub*	Total cover of early seral shrub species
DeepRootPerennialGrass*	Total cover of perennial grass species with very deep roots (high potential for restoration).
SandbergBluegrass*	Total cover of all *Poa secunda* and subspecies
SeededGrass*	Total cover of grass species that are commonly seeded into pastures.
InvasiveAnnualGrass*	Total cover of invasive annual grass species
UndesirableAnnualForbs*	Total of all forbs labeled ‘undesirable’ as indicating degraded conditions.
EcologicalStateSummary	Vegetation condition as described in the Oregon threat-based model framework, summarized to 6 main classes.
EcologicalStateDetail	Vegetation condition as described in the Oregon threat-based model framework, including 11 classes.
NoxiousWeeds*	Total cover of all “A-level” noxious weeds listed for relevant counties.
JuniperPhase	Classified variable describing dominant lifeform category, including sagebrush-domintaed, grass-dominated, and levels of juniper site dominance.
PerennialGrass*	Total cover of all perennial grasses

** Species lists for these variables can be found in Appendix C.*
*** Please note that this variable estimates the area not covered by live foliage, which is not necessarily the same thing as bare mineral soil. Locations with high values for “BareGround” could be somewhat protected from erosion by leaf litter.*

Appendix 1c: Species lists for select summary response variables

Genus and species for data entries tallied for each summary variable. In some cases, field data were identified as subspecies or varieties. For both data summaries and analysis, we tallied subspecies and varieties with their parent taxa, with few relevant exceptions (e.g., *Artemisia tridentata* subspecies). Where genera are listed alone, this indicates that there were observations where identifications were only available to the genus level.

SageGrousePreferredForbs_High

Agoseris aurantiaca
Agoseris glauca
Agoseris grandiflora
Agoseris heterophylla
Aliciella leptomeria
Arenaria aculeata
Arenaria capillaris
Arenaria congesta
Arenaria
Arenaria kingii
Astragalus atratus
Astragalus conjunctus
Astragalus collinus
Astragalus curvicarpus
Astragalus filipes
Astragalus lentiginosus
Astragalus malacus
Astragalus obscurus
Astragalus purshii
Astragalus sclerocarpus
Astragalus
Claytonia perfoliata
Collomia grandiflora
Collomia linearis
Crepis acuminata
Crepis atribarba
Crepis intermedia
Crepis modocensis
Crepis occidentalis
Erodium cicutarium
Eriastrum sparsiflorum
Eriastrum wilcoxii
Geum triflorum
Gilia brecciarum
Gilia inconspicua
Gilia sinuata
Holosteum umbellatum
Hydrophyllum capitatum
Lathyrus lanszwertii
Lathyrus rigidus
Lactuca serriola
Leptosiphon liniflorus
Lewisia rediviva
Leptosiphon septentrionalis
Lithophragma glabrum
Lithophragma parviflorum
Linanthus pungens
Lithophragma tenellum
Mentzelia albicaulis
Mentzelia dispersa
Mentzelia veatchiana
Mimulus cusickii
Microsteris gracilis
Microseris laciniata
Mimulus nanus
Microseris nutans
Montia linearis
Navarretia breweri
Navarretia capillaris
Navarretia divaricata
Nemophila pedunculata
Nothocalais troximoides
Phlox austromontana
Phacelia heterophylla
Phlox hoodii
Phacelia humilis
Phacelia linearis
Phlox longifolia
Phlox
Plectritis macrocera
Potentilla arguta
Potentilla glandulosa
Polemonium micranthum
Silene douglasii
Silene menziesii
Sidalcea oregana
Silene scaposa
Sphaeralcea munroana
Stellaria nitens
Trifolium arvense
Tragopogon dubius
Trifolium macrocephalum
Trifolium oliganthum
Trifolium repens
Vicia americana
Viola beckwithii
Viola nuttallii
Viola praemorsa
Viola purpurea
Viola trinervata

SageGrousePreferredForbs_All

Abronia mellifera
Achillea millefolium
Acroptilon repens
Agoseris aurantiaca
Agoseris glauca
Agoseris grandiflora
Agoseris heterophylla
Agastache urticifolia
Allium acuminatum
Alyssum alyssoides
Alyssum desertorum
Delphinium andersonii
Delphinium bicolor
Delphinium distichum
Delphinium glareosum
Descurainia incana
Delphinium nuttallianum
Delphinium nuttallii
Descurainia pinnata
Descurainia sophia
Dodecatheon pulchellum
Draba verna
Lomatium tracyi
Lomatium triternatum
Lomatium vaginatum
Machaeranthera canescens
Madia citriodora
Madia exigua
Madia glomerata
Madia gracilis
Madia sativa
Mentzelia albicaulis
Mentzelia dispersa

Allium douglasii
Allium fibrillum
Allium lemmonii
Aliciella leptomeria
Allium nevadense
Allium parvum
Allium tolmiei
Amsinckia lycopsoides
Amsinckia menziesii
Amsinckia tessellata
Antennaria corymbosa
Antennaria dimorpha
Antennaria geyeri
Antennaria luzuloides
Antennaria microphylla
Antennaria rosea
Antennaria stenophylla
Antennaria umbrinella
Arenaria aculeata
Arenaria capillaris
Arabis cobrensis
Arenaria congesta
Arabis drummondii
Arenaria
Arabis hirsuta
Arabis holboellii
Arenaria kingii
Arnica rydbergii
Arnica sororia
Astragalus atratus
Astragalus conjunctus
Astragalus collinus
Astragalus curvicarpus
Asclepias fascicularis
Astragalus filipes
Astragalus lentiginosus
Astragalus malacus
Astragalus obscurus
Astragalus purshii
Astragalus sclerocarpus
Astragalus
Balsamorhiza hookeri
Balsamorhiza incana
Balsamorhiza sagittata
Balsamorhiza serrata
Balsamorhiza sericea
Blepharipappus scaber
Castilleja angustifolia
Castilleja linariifolia
Calochortus
Calochortus macrocarpus
Castilleja miniata
Castilleja pilosa
Castilleja
Camissonia tanacetifolia
Ceratocephala testiculata
Epilobium brachycarpum
Epilobium ciliatum
Epilobium glaberrimum
Epilobium minutum
Erigeron aphanactis
Eriogonum baileyi
Erigeron bloomeri
Ericameria bloomeri
Eriogonum caespitosum
Erigeron chrysopsidis
Erodium cicutarium
Eriogonum compositum
Erigeron corymbosus
Erigeron divergens
Eriogonum douglasii
Erigeron filifolius
Erigeron foliosus
Eriogonum heracleoides
Eriophyllum lanatum
Erigeron linearis
Eriogonum microthecum
Ericameria nauseosa
Eriogonum niveum
Eriogonum ovalifolium
Erigeron poliospermus
Erigeron pumilus
Erigeron simplex
Eriastrum sparsiflorum
Eriogonum sphaerocephalum
Eriogonum strictum
Eriogonum thymoides
Eriogonum umbellatum
Eriogonum vimineum
Eriastrum wilcoxii
Fritillaria pudica
Galium ambiguum
Galium aparine
Gayophytum diffusum
Galium glabrescens
Galium parisiense
Gayophytum racemosum
Gayophytum ramosissimum
Galium tricornutum
Geum triflorum
Gilia brecciarum
Gilia inconspicua
Gilia sinuata
Gutierrezia sarothrae
Hackelia cusickii
Hieracium cynoglossoides
Hieracium longiberbe
Hieracium scouleri
Holosteum umbellatum
Hydrophyllum capitatum
Idahoa scapigera
Iva axillaris
Mertensia longiflora
Mertensia oblongifolia
Mentzelia veatchiana
Mimulus cusickii
Microsteris gracilis
Microseris laciniata
Mimulus nanus
Microseris nutans
Montia linearis
Myosotis discolor
Navarretia breweri
Navarretia capillaris
Navarretia divaricata
Nemophila pedunculata
Nothocalais troximoides
Orobanche corymbosa
Orthocarpus tenuifolius
Packera cana
Perideridia bolanderi
Penstemon cusickii
Penstemon deustus
Penstemon gairdneri
Penstemon humilis
Penstemon laetus
Perideridia oregana
Penstemon seorsus
Phlox austromontana
Phoenicaulis cheiranthoides
Phacelia heterophylla
Phlox hoodii
Phacelia humilis
Phacelia linearis
Phlox longifolia
Phlox
Plectritis macrocera
Plagiobothrys tenellus
Potentilla arguta
Polygonum douglasii
Potentilla glandulosa
Polemonium micranthum
Polygonum parryi
Polygonum polygaloides
Polygonum ramosissimum
Ranunculus glaberrimus
Salvia aethiopis
Salvia dorrii
Salsola kali
Salsola tragus
Scutellaria angustifolia
Scutellaria antirrhinoides
Scutellaria nana
Senecio crassulus
Senecio integerrimus
Senecio vulgaris
Sisymbrium altissimum
Silene douglasii

Chenopodium leptophyllum
Cirsium canovirens
Cirsium undulatum
Cirsium vulgare
Clarkia gracilis
Claytonia perfoliata
Cordylanthus capitatus
Collinsia grandiflora
Collomia grandiflora
Collomia linearis
Collinsia parviflora
Cordylanthus ramosus
Crepis acuminata
Cryptantha affinis
Cryptantha ambigua
Crepis atribarba
Cryptantha circumscissa
Cryptantha flaccida
Cryptantha gracilis
Crepis intermedia
Cryptantha intermedia
Cryptantha interrupta
Crepis modocensis
Crepis occidentalis
Cryptantha torreyana
Cryptantha watsonii
Layia glandulosa
Lathyrus lanszwertii
Lagophylla ramosissima
Lathyrus rigidus
Lactuca serriola
Leptosiphon liniflorus
Leucocrinum montanum
Lepidium oblongum
Lepidium perfoliatum
Lewisia rediviva
Leptosiphon septentrionalis
Lithophragma glabrum
Lithophragma parviflorum
Linanthus pungens
Lithospermum ruderale
Lithophragma tenellum
Lomatium canbyi
Lomatium cous
Lomatium dissectum
Lomatium donnellii
Lomatium grayi
Lomatium macrocarpum
Lomatium
Lomatium nevadense
Lomatium nudicaule
Lomatium packardiae
Silene menziesii
Sidalcea oregana
Silene scaposa
Sphaeralcea munroana
Stenotus acaulis
Stellaria nitens
Tetradymia canescens
Tetradymia glabrata
Tetradymia spinosa
Trifolium arvense
Tragopogon dubius
Trifolium macrocephalum
Trifolium oliganthum
Trifolium repens
Verbascum thapsus
Vicia americana
Viola beckwithii
Viola nuttallii
Viola praemorsa
Viola purpurea
Viola trinervata
Wyethia mollis
Zigadenus
Zigadenus paniculatus
Zigadenus venenosus

AllJuniper

Juniperus communis
Juniperus horizontalis
Juniperus occidentalis
Juniperus osteosperma
Juniperus scopulorum

SageTridentata

Artemisia tridentata
Artemisia tridentata ssp. spiciformis
Artemisia tridentata ssp. tridentata
Artemisia tridentata ssp. vaseyana
Artemisia tridentata ssp. wyomingensis

SageShallowSoil

Artemisia arbuscula
Artemisia rigida
Artemisia nova

EarlySeralShrub

Chrysothamnus
Chrysothamnus viscidiflorus
Ericameria
Ericameria nauseosa
Gutierrezia sarothrae

DeepRootPerennialGrass

Achnatherum hymenoides
Achnatherum lemmonii
Achnatherum nelsonii
Achnatherum occidentale
Achnatherum speciosum
Achnatherum thurberianum
Achnatherum webberi
Danthonia californica
Deschampsia cespitosa
Elymus elymoides
Elymus glaucus
Elymus lanceolatus
Elymus trachycaulus
Festuca idahoensis
Hesperostipa comata
Koeleria
Koeleria macrantha
Leymus cinereus
Leymus triticoides
Poa cusickii
Pseudoroegneria spicata
Sporobolus cryptandrus

SandbergBluegrass

Poa secunda

SeededGrass

Agropyron cristatum
Agropyron desertorum
Agropyron
Thinopyrum intermedium

InvasiveAnnualGrass

Aegilops cylindrica
Bromus tectorum
Poa bulbosa
Taeniatherum caput-medusae
Ventenata dubia
Ventenata

UndesirableAnnualForbs

Alyssum alyssoides
Alyssum desertorum
Alyssum
Amsinckia lycopsoides
Amsinckia menziesii
Amsinckia
Amsinckia tessellata
Centaurea cyanus
Centaurea diffusa
Centaurea solstitialis
Chorispora tenella
Descurainia sophia
Erodium botrys
Erodium cicutarium
Erodium
Lactuca serriola
Salsola kali
Salsola
Salsola tragus
Sisymbrium altissimum
Sisymbrium loeselii
Sisymbrium officinale
Sisymbrium
Tragopogon
Tragopogon dubius
Tragopogon miscellus
Tragopogon porrifolius
Tragopogon pratensis

NoxiousWeeds

Acroptilon repens
Aegilops cylindrica
Alhagi maurorum
Berteroa incana
Brachypodium sylvaticum
Carduus nutans
Carduus
Centaurea calcitrapa
Centaurea diffusa
Centaurea macrocephala
Centaurea solstitialis
Chondrilla juncea
Crupina vulgaris
Cynoglossum officinale
Cytisus scoparius
Daucus carota
Euphorbia esula
Hieracium aurantiacum
Linaria dalmatica
Linaria vulgaris
Ludwigia palustris
Onopordum acanthium
Polygonum cuspidatum
Potentilla recta
Salvia aethiopis
Senecio jacobaea
Silybum marianum
Solanum rostratum
Taeniatherum caput-medusae
Ventenata dubia
Xanthium spinosum

AllSage

Artemisia absinthium
Artemisia annua
Artemisia arbuscula
Artemisia arctica
Artemisia campestris
Artemisia cana
Artemisia douglasiana
Artemisia dracunculus
Artemisia frigida
Artemisia furcata
Artemisia longifolia
Artemisia ludoviciana
Artemisia michauxiana
Artemisia nova
Artemisia rigida
Artemisia scopulorum
Artemisia
Artemisia tilesii
Artemisia tridentata
Artemisia tripartita
Artemisia tridentata ssp. spiciformis
Artemisia tridentata ssp. tridentata
Artemisia tridentata ssp. vaseyana
Artemisia tridentata ssp. wyomingensis
Artemisia vulgaris
Artemisia papposa
Artemisia abrotanum

PerennialGrass

Carex praegracilis
Carex nebrascensis
Carex occidentalis
Carex pachystachya
Juncus acuminatus
Juncus alpinoarticulatus

Carex pellita
Elymus lanceolatus
Carex ovalis
Juncus arcticus
Melinis repens
Carex scirpoidea
Juncus
Poa douglasii
Spartina patens
Achnatherum hendersonii
Achnatherum
Achnatherum hymenoides
Achnatherum lemmonii
Achnatherum lettermanii
Achnatherum nelsonii
Achnatherum occidentale
Achnatherum richardsonii
Achnatherum speciosum
Achnatherum thurberianum
Achnatherum webberi
Agrostis capillaris
Agropyron cristatum
Agropyron desertorum
Agrostis exarata
Agrostis gigantea
Agrostis hallii
Agrostis humilis
Agrostis idahoensis
Agrostis mertensii
Agrostis oregonensis
Agrostis pallens
Agropyron
Agrostis
Agrostis scabra
Agrostis stolonifera
Agrostis variabilis
Alopecurus aequalis
Alopecurus magellanicus
Alopecurus
Alopecurus pratensis
Ammophila arenaria
Anthoxanthum odoratum
Arrhenatherum elatius
Aristida purpurea
Bouteloua gracilis
Bouteloua hirsuta
Bouteloua
Bromus carinatus
Bromus ciliatus
Bromus erectus
Bromus inermis
Bromus laevipes
Bromus marginatus
Bromus orcuttianus
Bromus pacificus
Bromus polyanthus
Carex parryana
Carex paysonis
Carex pelocarpa
Carex petasata
Carex phaeocephala
Carex physocarpioides
Carex platylepis
Carex podocarpa
Carex proposita
Carex praeceptorium
Carex praticola
Carex preslii
Calamagrostis purpurascens
Carex pyrenaica
Carex raynoldsii
Carex retrorsa
Carex
Carex rossii
Carex rostrata
Calamagrostis rubescens
Carex rupestris
Carex saxatilis
Carex sartwellii
Carex saximontana
Carex scopulorum
Carex senta
Carex sheldonii
Carex simulata
Carex spectabilis
Calamagrostis stricta
Carex stipata
Carex straminiformis
Carex subfusca
Carex subnigricans
Carex tahoensis
Carex tumulicola
Calamagrostis tweedyi
Carex unilateralis
Carex utriculata
Carex vallicola
Carex vesicaria
Carex viridula
Carex vulpinoidea
Cinna latifolia
Cinna
Cynosurus cristatus
Danthonia californica
Dactylis
Dactylis glomerata
Danthonia intermedia
Danthonia
Danthonia parryi
Danthonia spicata
Danthonia unispicata
Deschampsia cespitosa
Deschampsia elongata
Juncus articulatus
Juncus arcticus ssp. littoralis
Juncus brachyphyllus
Juncus castaneus
Juncus compressus
Juncus confusus
Juncus drummondii
Juncus dudleyi
Juncus effusus
Juncus ensifolius
Juncus falcatus
Juncus filiformis
Juncus hallii
Juncus howellii
Juncus lesueurii
Juncus longistylis
Juncus mertensianus
Juncus
Juncus nevadensis
Juncus nodosus
Juncus occidentalis
Juncus orthophyllus
Juncus oxymeris
Juncus parryi
Juncus patens
Juncus regelii
Juncus tenuis
Juncus tracyi
Koeleria
Koeleria macrantha
Kobresia myosuroides
Kobresia simpliciuscula
Leymus cinereus
Leymus innovatus
Leucopoa kingii
Leymus mollis
Leymus salinus
Leymus triticoides
Leucopoa
Leymus
Schedonorus arundinaceus
Lolium
Lolium perenne
Schedonorus pratensis
Luzula arcuata
Luzula comosa
Luzula divaricata
Luzula glabrata
Phleum alpinum
Phalaris aquatica
Phalaris arundinacea
Phragmites australis
Phleum
Phleum pratense
Piptatherum exiguum
Piptatheropsis micrantha

Bromus porteri
Bromus sitchensis
Bromus suksdorfii
Brachypodium sylvaticum
Bromus vulgaris
Carex abrupta
Carex albonigra
Carex amplifolia
Carex angustata
Carex aperta
Carex aquatilis
Catabrosa aquatica
Carex arcta
Carex atherodes
Carex athrostachya
Carex atrosquama
Carex aurea
Carex backii
Carex bebbii
Carex bolanderi
Carex brevior
Carex breweri
Carex brunnescens
Carex brainerdii
Carex brevicaulis
Carex buxbaumii
Carex canescens
Carex capillaris
Carex capitata
Calamagrostis canadensis
Carex californica
Carex concinna
Carex concinnoides
Carex comosa
Carex crawei
Carex crawfordii
Carex cusickii
Carex deweyana
Carex diandra
Carex disperma
Carex douglasii
Carex duriuscula
Carex eburnea
Carex echinata
Carex elynoides
Carex exsiccata
Carex filifolia
Carex flava
Carex siccata
Carex fracta
Carex garberi
Carex geyeri
Carex gynocrates
Carex halliana
Carex haydeniana
Carex hendersonii

Deschampsia
Dichanthelium acuminatum
Dichanthelium oligosanthes
Distichlis spicata
Distichlis
Luzula multiflora
Luzula parviflora
Luzula piperi
Luzula spicata
Luzula
Melica aristata
Melica bulbosa
Melica californica
Melica fugax
Melica geyeri
Melica harfordii
Melica
Melica smithii
Melica spectabilis
Melica subulata
Muhlenbergia andina
Muhlenbergia asperifolia
Muhlenbergia cuspidata
Muhlenbergia glomerata
Muhlenbergia
Muhlenbergia mexicana
Muhlenbergia racemosa
Muhlenbergia richardsonis
Nassella lepida
Nassella viridula
Oryzopsis asperifolia
Oryzopsis
Pascopyrum smithii
Dulichium arundinaceum
Eleocharis acicularis
Elymus alaskanus
Eleocharis bella
Eleocharis bolanderi
Elymus caninus
Elymus canadensis
Eleocharis elliptica
Elymus elymoides
Eleocharis
Elymus glaucus
Elymus hirsutus
Elyhordeum macounii
Elymus multisetus
Eleocharis palustris
Eleocharis quinqueflora
Elymus repens
Eleocharis rostellata
Elymus scribneri
Elymus trachycaulus
Elymus
Equisetum hyemale
Equisetum telmateia

Pleuropogon refractus
Poa
Poa abbreviata
Poa alpina
Poa arctica
Poa arnowiae
Poa arida
Poa bulbosa
Poa compressa
Poa curtifolia
Poa cusickii
Poa fendleriana
Poa glauca
Poa leibergii
Poa leptocoma
Poa lettermanii
Poa macrantha
Poa marcida
Poa nemoralis
Poa nervosa
Poa palustris
Poa pratensis
Poa pringlei
Poa reflexa
Poa secunda
Poa stenantha
Poa suksdorfii
Poa trivialis
Poa unilateralis
Poa wheeleri
Pseudelymus saxicola
Pseudoroegneria spicata
Puccinellia
Puccinellia lemmonii
Schoenoplectus acutus
Schoenoplectus americanus
Scirpus congdonii
Scirpus cyperinus
Schoenoplectus
Scirpus
Bolboschoenus maritimus
Scirpus microcarpus
Scirpus nevadensis
Scirpus pallidus
Schizachne purpurascens
Schoenoplectus subterminalis
Schoenoplectus tabernaemontani
Sporobolus airoides
Sporobolus compositus
Sporobolus cryptandrus
Spartina gracilis
Sporobolus
Thinopyrum intermedium
Thinopyrum ponticum
Torreyochloa pallida
Trisetum canescens

Carex heteroneura
Carex hoodii
Carex hystericina
Carex illota
Carex interior
Carex inops
Carex jonesii
Calamagrostis koelerioides
Carex lachenalii
Carex lasiocarpa
Carex laeviculmis
Calamagrostis
Carex leptalea
Carex leptopoda
Carex lenticularis
Carex leporinella
Carex livida
Carex limosa
Carex luzulina
Carex lyngbyei
Carex macrochaeta
Carex magellanica
Carex mertensii
Carex microptera
Calamagrostis montanensis
Carex multicaulis
Carex multicostata
Carex nardina
Carex neurophora
Carex nigricans
Carex norvegica
Carex nova
Calamagrostis nutkaensis
Carex nudata
Carex obnupta
Carex obtusata
Eriophorum angustifolium
Eriophorum chamissonis
Eriophorum gracile
Eriophorum
Eragrostis pectinacea
Eriophorum viridicarinatum
Festuca brachyphylla
Festuca californica
Festuca campestris
Festuca hallii
Festuca idahoensis
Festuca occidentalis
Festuca ovina
Festuca rubra
Festuca saximontana
Festuca
Festuca subulata
Festuca subuliflora
Festuca brevipila
Festuca viridula
Festuca viviparoidea
Glyceria borealis
Glyceria grandis
Glyceria occidentalis
Glyceria striata
Glyceria
Hesperostipa comata
Avenula hookeri
Hierochloe
Hierochloe hirta
Hierochloe occidentalis
Hordeum brachyantherum
Hordeum jubatum
Holcus lanatus
Holcus
Isoetes bolanderi
Trisetum
Triglochin palustris
Trisetum spicatum
Trisetum wolfii
Unknown perennial graminoid
Vahlodea atropurpurea
Ventenata dubia
Bromus diandrus
Carex integra
Carex muricata
Calamagrostis sesquiflora
Distichlis stricta
Festuca altaica
Hierochloe odorata
Juncus saximontanus
Luzula campestris
Luzula wahlenbergii
Alopecurus geniculatus
Elymus macrourus
Triglochin maritima
Poaceae family
Puccinellia nuttalliana
Carex sychnocephala
Cyperaceaea family
Achnatherum nevadense
Elymus ciliaris
Elymus wawawaiensis
Schizachyrium scoparium
Carex whitneyi
Leersia monandra
Nasella pulchra
Phalaris
Eragrostis spectabilis
Schoenoplectus pungens
Psathyrostachys juncea

Appendix 2: Species range accuracy

Accuracy for the prediction of the range of all species that appear in > 5% of the observations. Numbers reported at the Plot, Hex1, Hex2, and Hex3 levels are kappa statistics (standard error of kappa in parentheses). Kappa statistics approaching 1 indicate excellent agreement between observations and predictions, while kappa statistics nearing zero indicate.model predictions that are little better than random.

	Scientific.Name	Count	Plot	Hex1	Hex2	Hex3
ACMI2	*Achillea millefolium*	571	0.49 *(0.02)*	0.69 *(0.04)*	0.69 *(0.07)*	0.54 *(0.24)*
ACHY	*Achnatherum hymenoides*	395	0.31 *(0.02)*	0.50 *(0.05)*	0.58 *(0.07)*	0.93 *(0.07)*
ACTH7	*Achnatherum thurberianum*	1260	0.35 *(0.02)*	0.54 *(0.07)*	0.69 *(0.11)*	0.48 *(0.31)*
AGGL	*Agoseris glauca*	181	0.29 *(0.03)*	0.57 *(0.05)*	0.55 *(0.07)*	0.52 *(0.13)*
AGCR	*Agropyron cristatum*	436	0.54 *(0.02)*	0.67 *(0.04)*	0.64 *(0.07)*	0.72 *(0.13)*
ALAC4	*Allium acuminatum*	467	0.45 *(0.02)*	0.62 *(0.04)*	0.63 *(0.07)*	0.64 *(0.15)*
ALDE	*Alyssum desertorum*	259	0.27 *(0.03)*	0.51 *(0.05)*	0.57 *(0.07)*	0.66 *(0.13)*
AMME	*Amsinckia menziesii*	261	0.45 *(0.03)*	0.68 *(0.05)*	0.60 *(0.07)*	0.59 *(0.12)*
ANDI2	*Antennaria dimorpha*	478	0.34 *(0.02)*	0.50 *(0.05)*	0.52 *(0.08)*	0.62 *(0.17)*
ARHO2	*Arabis holboellii*	227	0.25 *(0.03)*	0.56 *(0.05)*	0.66 *(0.07)*	0.63 *(0.13)*
ARAR8	*Artemisia arbuscula*	884	0.59 *(0.02)*	0.80 *(0.03)*	0.66 *(0.07)*	0.76 *(0.13)*
ARTRT	*Artemisia tridentata ssp. tridentata*	900	0.38 *(0.02)*	0.56 *(0.05)*	0.72 *(0.07)*	0.81 *(0.13)*
ARTRV	*Artemisia tridentata ssp. vaseyana*	366	0.61 *(0.02)*	0.75 *(0.04)*	0.75 *(0.06)*	0.70 *(0.14)*
ARTRW8	*Artemisia tridentata ssp. wyomingensis*	1730	0.48 *(0.02)*	0.56 *(0.08)*	0.64 *(0.13)*	0.85 *(0.15)*
ASCU4	*Astragalus curvicarpus*	188	0.28 *(0.03)*	0.50 *(0.05)*	0.64 *(0.07)*	0.71 *(0.11)*
ASFI	*Astragalus filipes*	357	0.24 *(0.02)*	0.46 *(0.05)*	0.55 *(0.07)*	0.76 *(0.13)*
ASLE8	*Astragalus lentiginosus*	228	0.23 *(0.03)*	0.54 *(0.05)*	0.55 *(0.07)*	0.57 *(0.13)*
ASPU9	*Astragalus purshii*	511	0.22 *(0.02)*	0.52 *(0.05)*	0.44 *(0.08)*	0.55 *(0.18)*
ATCO	*Atriplex confertifolia*	228	0.55 *(0.03)*	0.70 *(0.05)*	0.84 *(0.05)*	0.78 *(0.09)*
BAHO	*Balsamorhiza hookeri*	301	0.31 *(0.03)*	0.71 *(0.04)*	0.69 *(0.06)*	0.72 *(0.10)*
BASA3	*Balsamorhiza sagittata*	307	0.32 *(0.03)*	0.60 *(0.05)*	0.62 *(0.07)*	0.74 *(0.12)*
BLSC	*Blepharipappus scaber*	332	0.42 *(0.03)*	0.53 *(0.05)*	0.55 *(0.07)*	0.59 *(0.14)*
BRHO2	*Bromus hordeaceus*	287	0.50 *(0.03)*	0.73 *(0.05)*	0.63 *(0.07)*	0.56 *(0.12)*
BRTE	*Bromus tectorum*	2523	0.50 *(0.02)*	0.66 *(0.14)*	0.58 *(0.19)*	1.00 *(0.00)*
CAMA5	*Calochortus macrocarpus*	281	0.38 *(0.03)*	0.51 *(0.05)*	0.46 *(0.08)*	0.77 *(0.11)*
CAAN7	*Castilleja angustifolia*	273	0.35 *(0.03)*	0.57 *(0.05)*	0.62 *(0.07)*	0.75 *(0.11)*
CETE5	*Ceratocephala testiculata*	471	0.31 *(0.02)*	0.56 *(0.05)*	0.65 *(0.06)*	0.78 *(0.10)*
CHDO	*Chaenactis douglasii*	233	0.21 *(0.03)*	0.54 *(0.05)*	0.61 *(0.07)*	0.85 *(0.08)*
CHVI8	*Chrysothamnus viscidiflorus*	1558	0.40 *(0.02)*	0.62 *(0.07)*	0.70 *(0.11)*	1.00 *(0.00)*
COPA3	*Collinsia parviflora*	852	0.34 *(0.02)*	0.52 *(0.05)*	0.56 *(0.09)*	0.69 *(0.17)*
COGR4	*Collomia grandiflora*	271	0.51 *(0.03)*	0.64 *(0.05)*	0.68 *(0.06)*	0.75 *(0.11)*
CRAC2	*Crepis acuminata*	1205	0.31 *(0.02)*	0.66 *(0.05)*	0.61 *(0.10)*	0.73 *(0.18)*
CRAT	*Crepis atribarba*	240	0.26 *(0.03)*	0.63 *(0.05)*	0.67 *(0.06)*	0.73 *(0.10)*
CROC	*Crepis occidentalis*	459	0.31 *(0.02)*	0.52 *(0.05)*	0.51 *(0.08)*	0.85 *(0.10)*
DEIN5	*Descurainia incana*	246	0.30 *(0.03)*	0.62 *(0.05)*	0.66 *(0.06)*	0.63 *(0.12)*
DEPI	*Descurainia pinnata*	414	0.34 *(0.02)*	0.49 *(0.05)*	0.58 *(0.07)*	0.76 *(0.13)*
DESO2	*Descurainia sophia*	197	0.29 *(0.03)*	0.61 *(0.05)*	0.61 *(0.07)*	0.61 *(0.12)*
DRVE2	*Draba verna*	382	0.42 *(0.02)*	0.47 *(0.05)*	0.55 *(0.07)*	0.76 *(0.11)*
ELEL5	*Elymus elymoides*	2339	0.37 *(0.02)*	0.70 *(0.10)*	0.48 *(0.18)*	0.00 *(0.00)*
EPBR3	*Epilobium brachycarpum*	330	0.27 *(0.03)*	0.42 *(0.05)*	0.49 *(0.07)*	0.58 *(0.13)*
EPMI	*Epilobium minutum*	326	0.46 *(0.03)*	0.64 *(0.05)*	0.60 *(0.07)*	0.54 *(0.12)*
ERNA10	*Ericameria nauseosa*	1072	0.35 *(0.02)*	0.52 *(0.06)*	0.51 *(0.11)*	0.65 *(0.23)*
ERTE18	*Ericameria teretifolia*	181	0.23 *(0.03)*	0.67 *(0.04)*	0.71 *(0.06)*	0.81 *(0.09)*
ERBL	*Erigeron bloomeri*	179	0.28 *(0.03)*	0.49 *(0.05)*	0.60 *(0.07)*	0.81 *(0.09)*
ERCH4	*Erigeron chrysopsidis*	216	0.32 *(0.03)*	0.61 *(0.05)*	0.71 *(0.06)*	0.73 *(0.10)*

ERLI	*Erigeron linearis*	413	0.32 *(0.02)*	0.53 *(0.05)*	0.62 *(0.07)*	0.83 *(0.10)*
ERPU2	*Erigeron pumilus*	192	0.35 *(0.03)*	0.52 *(0.06)*	0.56 *(0.08)*	0.44 *(0.14)*
ERCA8	*Eriogonum caespitosum*	179	0.28 *(0.03)*	0.71 *(0.04)*	0.66 *(0.07)*	0.96 *(0.04)*
EROV	*Eriogonum ovalifolium*	393	0.33 *(0.02)*	0.47 *(0.05)*	0.56 *(0.07)*	0.59 *(0.15)*
ERSP7	*Eriogonum sphaerocephalum*	177	0.22 *(0.03)*	0.56 *(0.05)*	0.63 *(0.06)*	0.85 *(0.08)*
ERST4	*Eriogonum strictum*	186	0.21 *(0.03)*	0.53 *(0.06)*	0.55 *(0.07)*	0.72 *(0.10)*
ERUM	*Eriogonum umbellatum*	178	0.34 *(0.04)*	0.58 *(0.05)*	0.63 *(0.07)*	0.72 *(0.10)*
FEID	*Festuca idahoensis*	1188	0.54 *(0.02)*	0.68 *(0.04)*	0.58 *(0.10)*	0.66 *(0.32)*
GRSP	*Grayia spinosa*	489	0.53 *(0.02)*	0.68 *(0.04)*	0.84 *(0.05)*	0.81 *(0.09)*
GUSA2	*Gutierrezia sarothrae*	185	0.33 *(0.03)*	0.56 *(0.05)*	0.59 *(0.07)*	0.56 *(0.12)*
HECO26	*Hesperostipa comata*	223	0.29 *(0.03)*	0.56 *(0.05)*	0.61 *(0.07)*	0.73 *(0.11)*
HOUM	*Holosteum umbellatum*	278	0.45 *(0.03)*	0.56 *(0.05)*	0.58 *(0.07)*	0.63 *(0.12)*
JUOC	*Juniperus occidentalis*	700	0.82 *(0.01)*	0.87 *(0.03)*	0.85 *(0.05)*	0.92 *(0.08)*
KOMA	*Koeleria macrantha*	428	0.52 *(0.02)*	0.66 *(0.04)*	0.68 *(0.06)*	0.80 *(0.11)*
LASE	*Lactuca serriola*	306	0.31 *(0.03)*	0.68 *(0.04)*	0.51 *(0.07)*	0.54 *(0.15)*
LEPE2	*Lepidium perfoliatum*	508	0.34 *(0.02)*	0.55 *(0.05)*	0.70 *(0.06)*	1.00 *(0.00)*
LERE7	*Lewisia rediviva*	185	0.37 *(0.03)*	0.41 *(0.06)*	0.53 *(0.07)*	0.85 *(0.08)*
LECI4	*Leymus cinereus*	546	0.26 *(0.02)*	0.48 *(0.05)*	0.67 *(0.07)*	0.64 *(0.15)*
LIPU11	*Linanthus pungens*	396	0.31 *(0.02)*	0.53 *(0.05)*	0.59 *(0.07)*	0.75 *(0.12)*
LIRU4	*Lithospermum ruderale*	172	0.31 *(0.03)*	0.57 *(0.05)*	0.61 *(0.07)*	0.69 *(0.13)*
LOMA3	*Lomatium macrocarpum*	326	0.34 *(0.03)*	0.56 *(0.05)*	0.51 *(0.07)*	0.59 *(0.13)*
LOTR2	*Lomatium triternatum*	334	0.41 *(0.03)*	0.62 *(0.05)*	0.58 *(0.07)*	0.86 *(0.09)*
LUAR3	*Lupinus argenteus*	222	0.32 *(0.03)*	0.56 *(0.05)*	0.62 *(0.07)*	0.68 *(0.12)*
LUCA	*Lupinus caudatus*	346	0.38 *(0.03)*	0.56 *(0.05)*	0.68 *(0.06)*	0.67 *(0.14)*
MACA2	*Machaeranthera canescens*	178	0.24 *(0.03)*	0.49 *(0.05)*	0.62 *(0.07)*	0.69 *(0.11)*
MIGR	*Microsteris gracilis*	676	0.31 *(0.02)*	0.45 *(0.05)*	0.59 *(0.08)*	0.69 *(0.17)*
NOTR2	*Nothocalais troximoides*	446	0.44 *(0.02)*	0.63 *(0.04)*	0.53 *(0.07)*	0.54 *(0.15)*
PHLI	*Phacelia linearis*	266	0.34 *(0.03)*	0.49 *(0.05)*	0.55 *(0.07)*	0.72 *(0.13)*
PHHO	*Phlox hoodii*	609	0.35 *(0.02)*	0.58 *(0.05)*	0.59 *(0.08)*	0.73 *(0.15)*
PHLO2	*Phlox longifolia*	983	0.42 *(0.02)*	0.61 *(0.04)*	0.55 *(0.08)*	0.83 *(0.12)*
PHCH	*Phoenicaulis cheiranthoides*	254	0.26 *(0.03)*	0.49 *(0.05)*	0.50 *(0.07)*	0.79 *(0.10)*
POBU	*Poa bulbosa*	354	0.47 *(0.03)*	0.69 *(0.04)*	0.62 *(0.07)*	0.46 *(0.14)*
POCU3	*Poa cusickii*	305	0.38 *(0.03)*	0.68 *(0.05)*	0.55 *(0.07)*	0.62 *(0.12)*
POSE	*Poa secunda*	2749	0.60 *(0.02)*	0.57 *(0.12)*	0.65 *(0.16)*	1.00 *(0.00)*
PSSP6	*Pseudoroegneria spicata*	1952	0.53 *(0.01)*	0.65 *(0.06)*	0.79 *(0.12)*	1.00 *(0.00)*
PUTR2	*Purshia tridentata*	460	0.48 *(0.02)*	0.69 *(0.04)*	0.64 *(0.07)*	0.58 *(0.15)*
ROWO	*Rosa woodsii*	179	0.31 *(0.03)*	0.64 *(0.06)*	0.70 *(0.07)*	0.73 *(0.10)*
SAVE4	*Sarcobatus vermiculatus*	189	0.53 *(0.03)*	0.70 *(0.05)*	0.89 *(0.04)*	0.87 *(0.07)*
SEIN2	*Senecio integerrimus*	235	0.35 *(0.03)*	0.66 *(0.05)*	0.55 *(0.07)*	0.76 *(0.11)*
SIAL2	*Sisymbrium altissimum*	474	0.35 *(0.02)*	0.53 *(0.05)*	0.65 *(0.07)*	0.72 *(0.13)*
SYOR2	*Symphoricarpos oreophilus*	169	0.51 *(0.03)*	0.73 *(0.05)*	0.61 *(0.07)*	0.77 *(0.09)*
TACA8	*Taeniatherum caput-medusae*	364	0.44 *(0.02)*	0.79 *(0.04)*	0.72 *(0.06)*	0.64 *(0.11)*
TECA2	*Tetradymia canescens*	297	0.25 *(0.03)*	0.53 *(0.05)*	0.56 *(0.07)*	0.67 *(0.14)*
TEGL	*Tetradymia glabrata*	285	0.25 *(0.03)*	0.67 *(0.04)*	0.65 *(0.06)*	0.70 *(0.11)*
TRDU	*Tragopogon dubius*	454	0.27 *(0.02)*	0.59 *(0.04)*	0.51 *(0.08)*	0.69 *(0.16)*
TRMA3	*Trifolium macrocephalum*	246	0.40 *(0.03)*	0.69 *(0.04)*	0.62 *(0.07)*	0.90 *(0.07)*
VUOC	*Vulpia octoflora*	184	0.34 *(0.03)*	0.71 *(0.05)*	0.73 *(0.07)*	0.60 *(0.12)*
ZIPA2	*Zigadenus paniculatus*	180	0.22 *(0.03)*	0.58 *(0.05)*	0.57 *(0.07)*	0.67 *(0.11)*

Appendix 3: Species cover accuracy

Accuracy statistics for species cover predictions (only those that appear in more than 5% of all observations). Species codes correspond to scientific names shown in Appendix 2. For each of four spatial scales (individual plot and hex 1-3 scales, increasing in size as shown in Figure 1), each mapped variable includes three accuracy statistics: overall accuracy (AC, left), evaluation of bias (AC_sys, middle), and evaluation of precision (AC_unsys, right), representing different components of accuracy as described in the Model assessment section. Values close to 1 indicate very high accuracy, values that are close to zero or negative indicate very low accuracy. See Figures 3, 6, 9 and 12 for examples showing scatterplots of observed vs predicted values and associated AC, AC_sys and AC_unsys values at each of the four spatial scales.

	Plot			***Hex1***			***Hex2***			***Hex3***		
	AC	AC_sys	AC_uns	AC	AC_sys	AC_uns	AC	AC_sys	AC_uns	AC	AC_sys	AC_uns
ACHY	-1.40	1.00	-1.40	0.59	1.00	0.59	-1.35	0.80	-1.15	0.70	0.96	0.75
ACMI2	-1.66	0.97	-1.63	0.23	0.99	0.24	0.49	0.69	0.80	0.79	0.99	0.80
ACTH7	-1.83	1.00	-1.83	0.19	0.97	0.22	0.39	0.99	0.40	0.69	1.00	0.70
AGCR	-0.60	1.00	-0.60	0.73	0.99	0.73	0.58	1.00	0.58	0.85	1.00	0.86
AGGL	-29.50	0.99	-29.49	0.46	0.98	0.48	0.59	0.98	0.61	0.41	0.98	0.43
ALAC4	-13.01	1.00	-13.01	-1.06	0.99	-1.04	-2.69	0.97	-2.65	0.80	1.00	0.80
ALDE	-2.48	0.99	-2.46	0.18	0.97	0.21	0.57	0.86	0.71	0.70	0.92	0.78
AMME	-8.19	0.99	-8.19	0.14	0.97	0.17	0.44	1.00	0.44	0.85	0.99	0.87
ANDI2	-17.93	0.55	-17.49	-4.17	1.00	-4.17	-1.95	0.84	-1.79	0.30	0.99	0.30
ARAR8	-0.02	1.00	-0.02	0.74	0.99	0.76	0.80	1.00	0.80	0.91	1.00	0.92
ARHO2	-124.56	0.93	-124.49	-10.32	-1.40	-7.92	-1.84	1.00	-1.83	0.91	1.00	0.91
ARTRT	-1.51	1.00	-1.51	0.13	0.99	0.15	0.49	0.99	0.50	0.72	1.00	0.73
ARTRV	-0.86	1.00	-0.86	0.57	0.99	0.58	0.65	1.00	0.65	0.80	1.00	0.80
ARTRW8	-0.22	1.00	-0.21	0.64	1.00	0.64	0.73	1.00	0.73	0.85	1.00	0.85
ASCU4	-19.04	-0.20	-17.84	0.10	1.00	0.10	-0.21	0.75	0.04	0.09	0.84	0.25
ASFI	-56.57	0.34	-55.90	-9.72	0.96	-9.68	-2.27	0.91	-2.18	0.85	0.99	0.86
ASLE8	-29.42	-0.53	-27.89	-5.44	-1.02	-3.42	-0.66	0.59	-0.25	0.32	0.95	0.37
ASPU9	-25.04	0.98	-25.02	-0.18	0.91	-0.09	0.34	0.98	0.36	0.46	0.94	0.52
ATCO	-0.17	0.98	-0.15	0.64	0.99	0.64	0.84	1.00	0.85	0.88	1.00	0.89
BAHO	-6.93	0.72	-6.65	-0.83	1.00	-0.83	-0.07	0.99	-0.06	0.21	0.93	0.29
BASA3	-4.64	0.99	-4.63	0.52	1.00	0.52	0.88	1.00	0.88	0.41	0.97	0.44
BLSC	-18.07	0.68	-17.75	-5.51	0.55	-5.07	-2.63	-0.08	-1.55	0.03	0.91	0.12
BRHO2	-4.41	1.00	-4.40	-0.25	0.97	-0.21	-0.07	1.00	-0.07	0.84	0.99	0.85
BRTE	-0.12	0.99	-0.12	0.64	0.99	0.65	0.85	0.99	0.87	0.96	0.99	0.97
CAAN7	-88.42	-5.19	-82.24	-1.36	0.90	-1.27	-0.54	0.27	0.20	-0.31	0.25	0.44
CAMA5	-106.14	-0.76	-104.38	-2.97	0.84	-2.81	-9.63	1.00	-9.63	0.32	0.94	0.38
CETE5	-2.41	1.00	-2.40	0.60	1.00	0.61	0.68	0.97	0.71	0.84	0.94	0.90
CHDO	-8.38	0.01	-7.39	0.20	0.99	0.21	0.19	0.98	0.21	-0.72	0.68	-0.40
CHVI8	-2.93	0.98	-2.91	0.36	0.96	0.40	0.38	0.95	0.43	0.51	0.90	0.61
COGR4	-5.36	0.89	-5.26	-0.77	0.84	-0.61	0.76	0.94	0.82	0.86	0.96	0.90
COPA3	-2.16	1.00	-2.15	-0.11	0.93	-0.04	0.32	0.99	0.32	0.60	0.99	0.61
CRAC2	-1.26	1.00	-1.26	-0.38	0.92	-0.30	0.32	0.97	0.35	0.55	0.95	0.60
CRAT	-4.92	0.88	-4.79	-0.81	0.57	-0.38	0.27	0.94	0.33	-1.28	0.34	-0.62
CROC	-5.73	0.93	-5.67	-1.12	0.85	-0.97	-1.59	0.98	-1.57	0.26	0.99	0.27
DEIN5	-48.89	-2.49	-45.40	-4.52	0.86	-4.38	-0.60	0.52	-0.12	-1.65	0.25	-0.90
DEPI	-4.90	0.87	-4.77	-0.41	0.83	-0.25	-0.37	0.67	-0.04	0.69	0.92	0.76
DESO2	-8.56	1.00	-8.56	0.33	0.99	0.34	-4.22	-0.79	-2.44	0.85	0.99	0.86
DRVE2	-3.98	0.99	-3.97	0.22	0.99	0.23	0.49	0.94	0.55	0.80	0.97	0.82
ELEL5	-1.39	0.98	-1.37	0.39	0.98	0.41	0.46	0.96	0.50	0.58	0.96	0.63
EPBR3	-13.46	0.07	-12.53	-4.01	0.13	-3.14	-1.65	-0.27	-0.38	-0.12	0.64	0.23
EPMI	-3.72	0.87	-3.59	-1.89	0.51	-1.40	-6.84	-3.23	-2.62	0.66	0.99	0.66

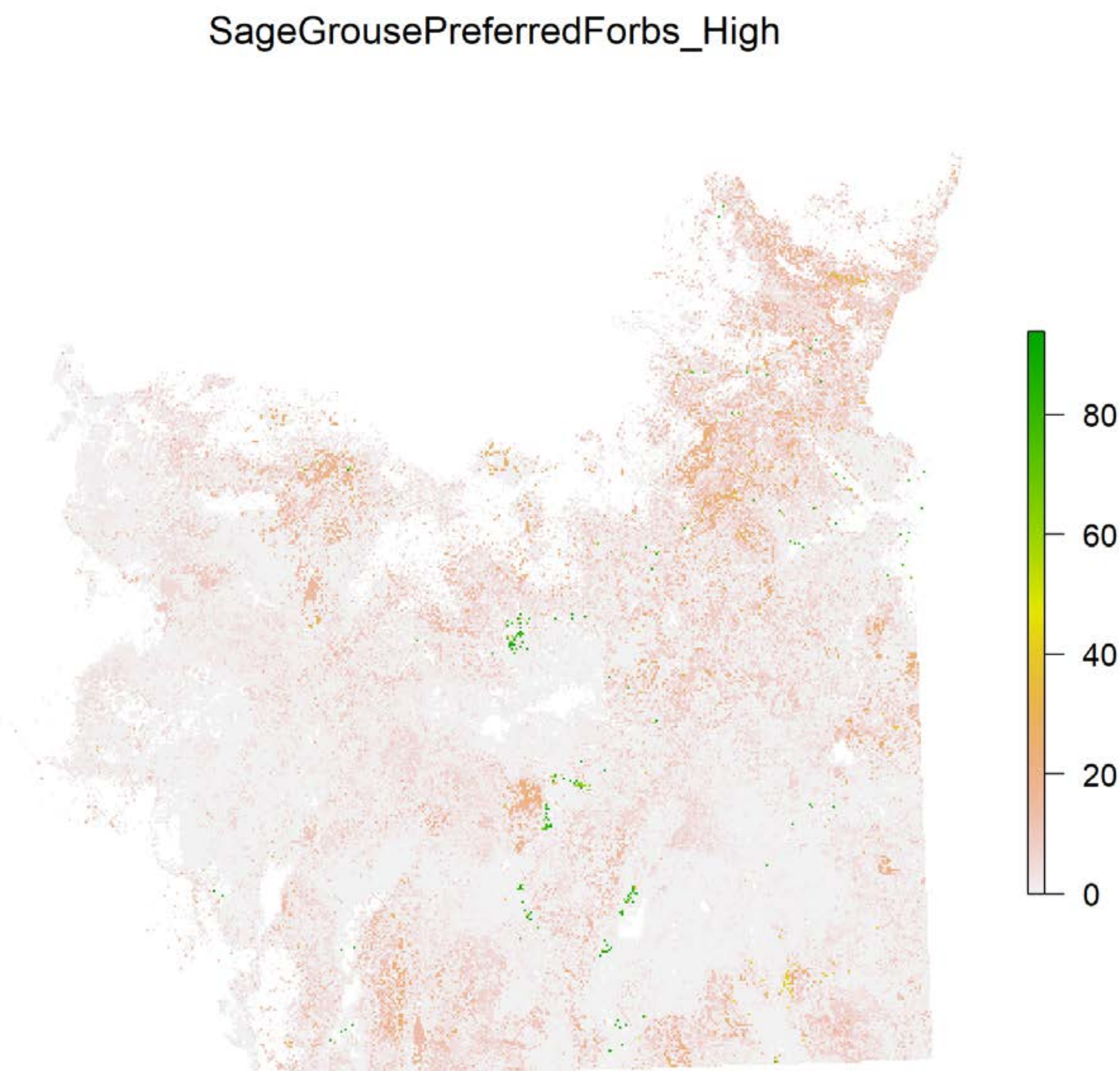
ERBL	-8.59	0.83	-8.43	-0.35	0.97	-0.33	0.01	0.76	0.25	0.50	0.93	0.57
ERCA8	-95.47	0.76	-95.23	-0.76	0.99	-0.75	0.03	0.82	0.22	0.22	0.88	0.34
ERCH4	-4.86	-1.90	-1.96	-1.12	0.49	-0.61	-1.04	0.11	-0.15	0.31	0.76	0.55
ERLI	-29.00	0.23	-28.22	-2.61	0.63	-2.24	-0.67	0.76	-0.42	0.40	0.96	0.44
ERNA10	-2.35	0.98	-2.33	0.11	0.98	0.13	0.42	1.00	0.42	0.00	0.99	0.01
EROV	-21.51	0.49	-21.00	-2.80	0.95	-2.74	-1.47	0.99	-1.46	-1.12	0.96	-1.08
ERPU2	-27.96	0.98	-27.94	-0.42	0.35	0.24	-1.16	1.00	-1.16	0.31	0.93	0.38
ERSP7	-21.16	0.99	-21.16	-0.74	0.98	-0.73	-1.48	0.89	-1.38	0.57	0.97	0.60
ERST4	-59.80	-0.34	-58.45	-1.96	0.79	-1.75	-1.83	0.58	-1.41	0.15	0.83	0.32
ERTE18	-3.52	0.93	-3.45	-0.80	0.97	-0.77	0.36	0.99	0.37	0.38	0.97	0.41
ERUM	-8.38	0.87	-8.25	0.07	0.79	0.28	-0.08	0.69	0.24	-0.43	-0.33	0.90
FEID	-0.89	0.99	-0.88	0.46	0.98	0.48	0.62	0.96	0.65	0.40	0.99	0.41
GRSP	-2.11	0.99	-2.11	0.60	1.00	0.61	-0.31	0.53	0.16	0.93	1.00	0.94
GUSA2	-1.41	0.98	-1.39	0.83	0.95	0.88	0.80	0.92	0.88	0.74	0.97	0.76
HECO26	-34.87	0.60	-34.47	-0.39	1.00	-0.38	-10.54	0.73	-10.28	0.26	0.75	0.52
HOUM	-1.99	0.92	-1.91	0.56	0.99	0.56	0.86	0.99	0.87	0.94	1.00	0.94
JUOC	0.01	0.99	0.02	0.71	0.98	0.74	0.83	0.97	0.87	0.88	0.95	0.94
KOMA	-60.80	1.00	-60.80	-0.23	0.99	-0.22	-1.31	0.82	-1.13	-0.59	0.58	-0.17
LASE	0.53	0.98	0.55	0.90	0.91	0.99	0.90	0.91	0.99	0.91	0.94	0.97
LECI4	-4.18	0.99	-4.17	-1.06	0.95	-1.01	0.67	1.00	0.68	0.37	1.00	0.37
LEPE2	-9.51	0.63	-9.14	-1.53	0.94	-1.47	0.28	0.90	0.38	0.77	0.86	0.91
LERE7	-101.78	0.43	-101.22	-2.48	0.07	-1.55	0.22	0.92	0.31	-0.42	0.72	-0.14
LIPU11	-3.06	1.00	-3.06	0.33	0.99	0.34	0.66	0.99	0.67	0.58	0.99	0.60
LIRU4	-30.30	0.93	-30.23	0.03	0.92	0.11	-0.37	1.00	-0.37	0.42	1.00	0.42
LOMA3	-18.72	0.94	-18.66	-1.36	0.93	-1.29	-0.56	1.00	-0.56	0.65	1.00	0.66
LOTR2	-28.58	-0.51	-27.07	-0.50	0.80	-0.29	0.26	0.76	0.50	0.80	0.88	0.92
LUAR3	-6.51	1.00	-6.51	-0.58	0.99	-0.57	-0.31	0.92	-0.22	0.58	1.00	0.59
LUCA	-9.03	1.00	-9.03	0.17	1.00	0.17	0.29	0.95	0.34	-0.21	1.00	-0.21
MACA2	-16.08	0.80	-15.88	-10.64	0.84	-10.48	-3.73	0.98	-3.71	-7.37	0.07	-6.44
MIGR	-2.88	0.98	-2.86	-0.63	0.87	-0.50	0.45	0.94	0.50	0.80	0.97	0.84
NOTR2	-6.58	0.96	-6.54	0.36	1.00	0.36	0.78	1.00	0.78	0.86	1.00	0.86
PHCH	-14.06	0.67	-13.73	-0.95	0.43	-0.38	-0.27	0.84	-0.11	0.36	0.98	0.38
PHHO	-4.55	0.96	-4.52	0.08	0.99	0.09	0.59	0.98	0.62	0.27	0.95	0.32
PHLI	-86.82	-3.60	-82.22	-12.45	0.18	-11.63	0.12	0.89	0.23	0.01	0.86	0.15
PHLO2	-2.45	0.98	-2.43	-1.41	0.87	-1.28	0.07	0.97	0.10	0.60	0.99	0.61
POBU	-2.67	1.00	-2.67	0.33	0.95	0.38	0.88	1.00	0.88	0.93	1.00	0.93
POCU3	-4.82	0.81	-4.64	0.10	0.99	0.11	-1.62	0.43	-1.05	-0.03	0.94	0.02
POSE	-0.32	1.00	-0.32	0.59	1.00	0.60	0.74	1.00	0.74	0.85	1.00	0.86
PSSP6	-0.67	1.00	-0.67	0.43	1.00	0.43	0.64	1.00	0.64	0.79	1.00	0.80
PUTR2	-1.07	0.97	-1.04	0.58	0.99	0.59	0.30	0.99	0.31	0.89	1.00	0.89
ROWO	-322.24	1.00	-322.24	0.22	1.00	0.22	-25.48	0.37	-24.85	-12.40	-6.42	-4.98
SAVE4	-0.46	1.00	-0.46	0.49	1.00	0.50	0.76	1.00	0.76	0.83	0.99	0.84
SEIN2	-14.88	0.33	-14.21	0.78	0.95	0.83	-1.78	0.54	-1.32	-1.04	0.53	-0.57
SIAL2	-3.36	0.99	-3.35	-0.47	0.90	-0.37	0.45	0.97	0.47	0.75	0.95	0.80
SYOR2	-2.19	0.97	-2.16	0.77	0.85	0.92	0.48	0.89	0.60	-0.07	0.98	-0.04
TACA8	-1.73	0.90	-1.64	0.26	1.00	0.26	0.15	0.99	0.16	0.90	1.00	0.90
TECA2	-2.99	0.99	-2.98	-0.36	0.95	-0.31	0.40	0.88	0.52	-0.04	0.97	-0.01
TEGL	-5.65	1.00	-5.65	-0.05	0.97	-0.02	-0.03	0.96	0.01	-0.43	0.92	-0.35
TRDU	-51.22	0.97	-51.18	-26.12	-7.47	-17.65	-2.53	0.58	-2.12	-0.42	0.97	-0.39
TRMA3	-12.33	0.89	-12.23	-0.66	0.95	-0.61	-0.80	1.00	-0.80	-0.47	0.47	0.06
VUOC	-3.79	0.94	-3.73	-0.14	0.50	0.35	-0.54	0.95	-0.49	-0.04	0.56	0.40
ZIPA2	-142.43	-2.28	-139.14	-1.83	0.91	-1.74	-1.89	0.95	-1.84	0.23	0.75	0.48

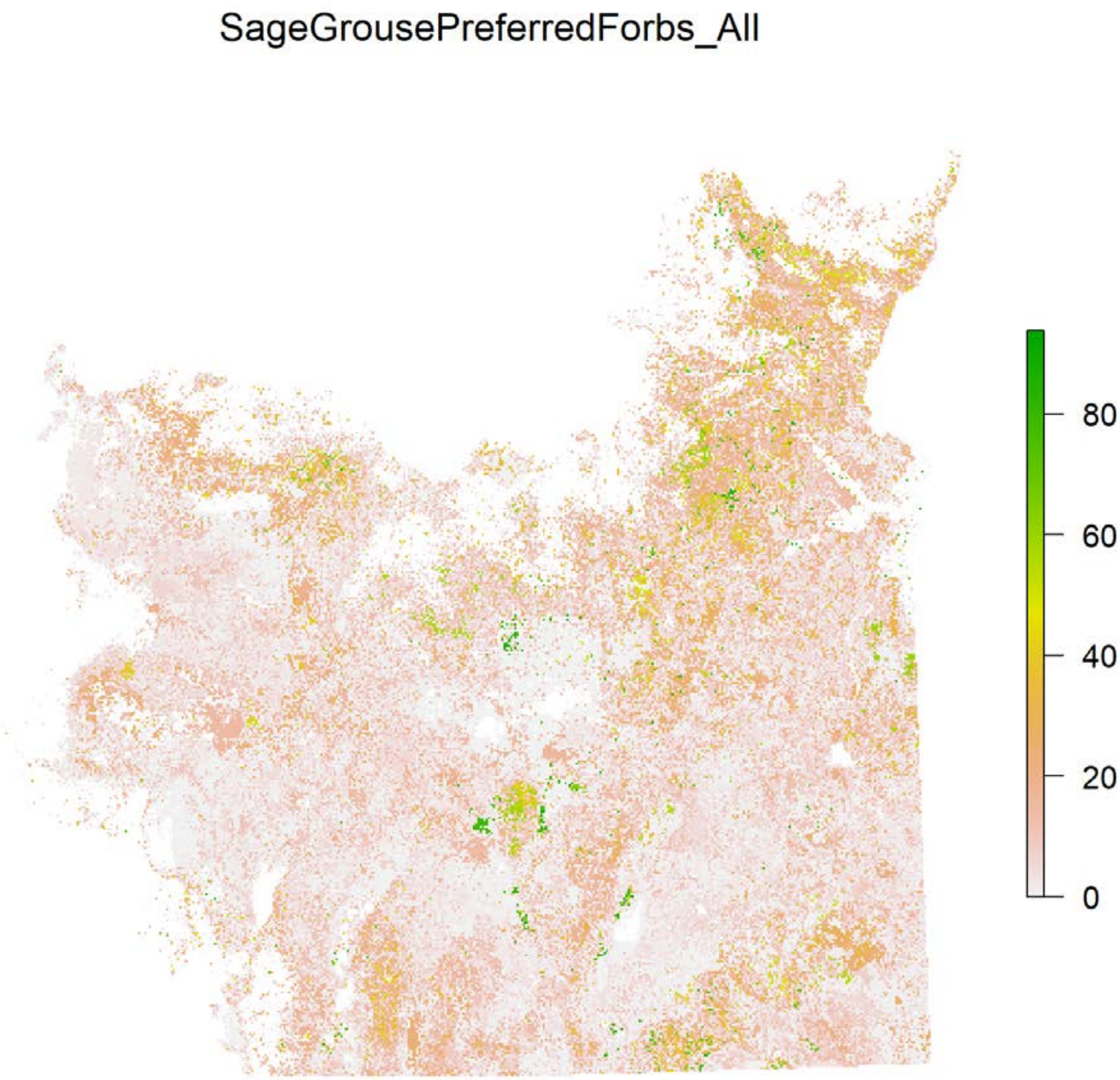
Appendix 4: Accuracy statistics for all continuous, summarized variables

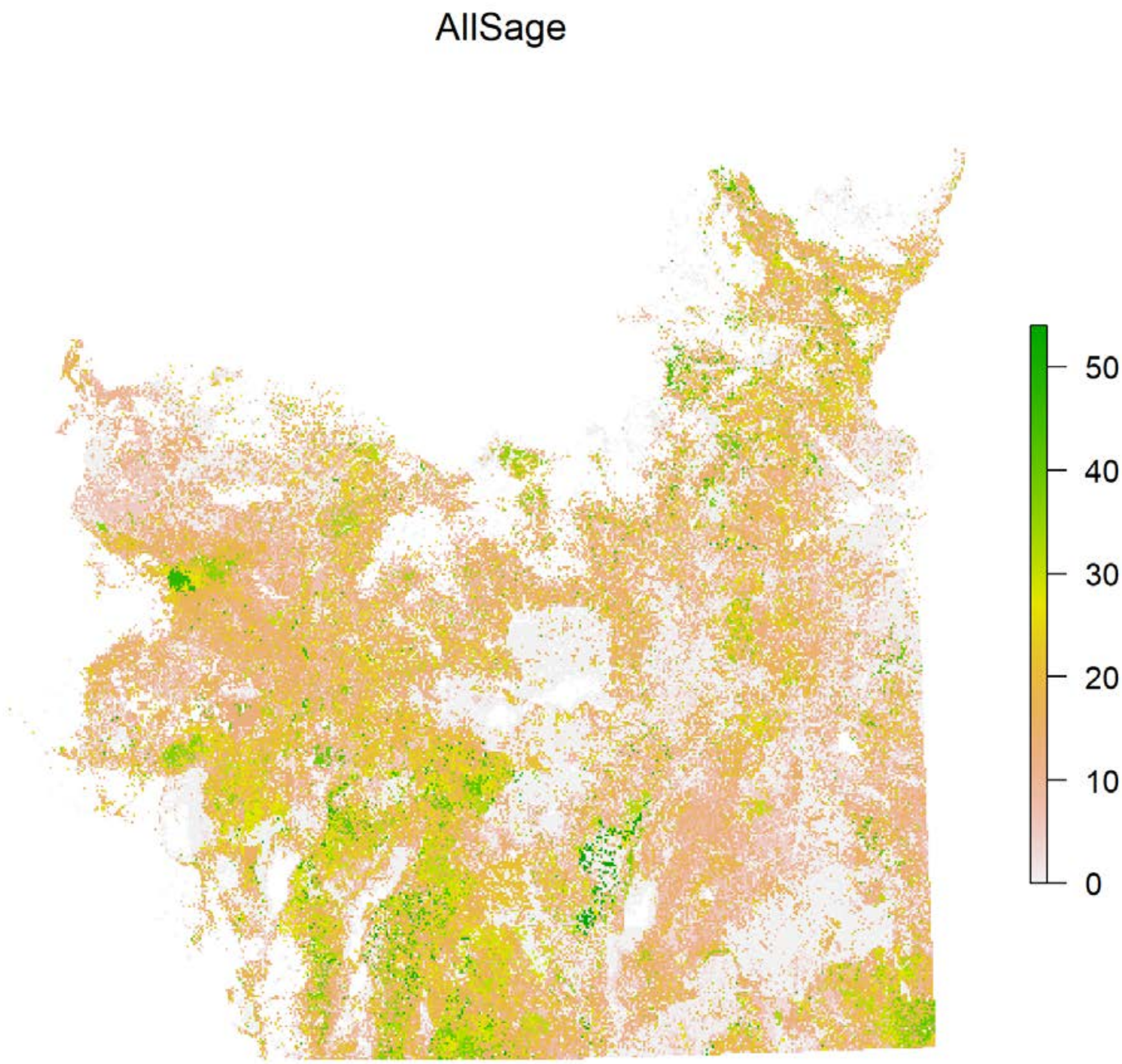
Accuracy statistics for continuous, summarized variables provided in the map. For each of four spatial scales (individual plot and hex 1-3 scales, increasing in size as shown in Figure 1), each mapped variable includes three accuracy statistics: overall accuracy (AC, left), evaluation of bias (AC_sys, middle), and evaluation of precision (AC_unsys, right), representing different components of accuracy as described in the Model assessment section. Values close to 1 indicate very high accuracy, values that are close to zero or negative indicate very low accuracy. See Figures 3, 6, 9 and 12 for examples showing scatterplots of observed vs predicted values and associated AC, AC_sys and AC_unsys values at each of the four spatial scales. See Appendix 1c for species lists included in each summarized variable.

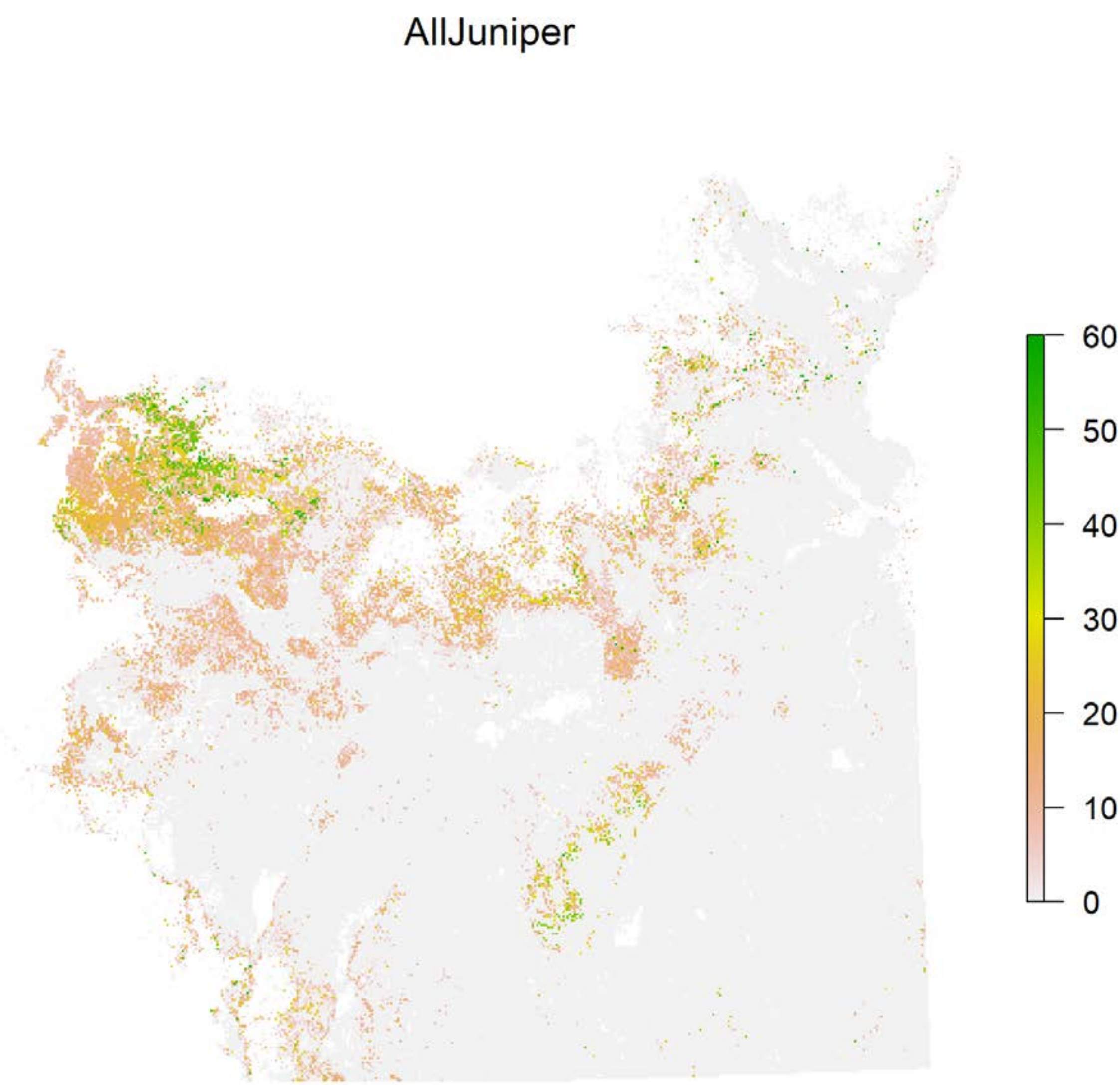
	Plot			***Hex1***			***Hex2***			***Hex3***		
	AC	AC_sys	AC_uns	AC	AC_sys	AC_uns	AC	AC_sys	AC_uns	AC	AC_sys	AC_uns
SageTridentata	-0.14	1.00	-0.13	0.69	1.00	0.70	0.70	0.99	0.71	0.86	0.99	0.87
SageShallowSoil	-0.03	1.00	-0.03	0.72	0.99	0.73	0.78	1.00	0.78	0.92	1.00	0.93
EarlySeralShrub	-1.57	0.99	-1.56	0.48	0.99	0.49	0.73	0.99	0.75	0.89	0.98	0.91
InvasiveAnnualGrass	-0.10	0.99	-0.09	0.68	1.00	0.68	0.86	0.99	0.87	0.96	0.99	0.97
DeepRootPerennialGrass	-0.55	1.00	-0.55	0.60	0.99	0.60	0.59	0.98	0.61	0.50	1.00	0.50
SeededGrass	-0.82	1.00	-0.82	0.73	0.99	0.73	0.57	1.00	0.57	0.82	1.00	0.83
SandbergBluegrass	-0.32	1.00	-0.32	0.59	1.00	0.60	0.74	1.00	0.74	0.85	1.00	0.86
AllJuniper	0.01	0.99	0.02	0.71	0.98	0.73	0.83	0.97	0.87	0.88	0.95	0.94
UndesirableAnnualForbs	-0.59	0.99	-0.58	0.17	0.95	0.22	0.41	0.99	0.41	0.80	0.96	0.84
AllSage	0.01	1.00	0.01	0.78	1.00	0.78	0.82	1.00	0.82	0.91	0.99	0.91
SageGrousePreferredForbs_High	-0.10	1.00	-0.10	0.33	0.98	0.36	0.58	1.00	0.58	0.81	0.99	0.81
SageGrousePreferredForbs_All	-0.83	1.00	-0.83	0.29	0.99	0.30	0.52	0.99	0.53	0.74	0.99	0.75
PerennialGrass	-0.12	1.00	-0.12	0.65	1.00	0.65	0.66	0.99	0.66	0.78	0.99	0.79
NoxiousWeeds	-1.74	0.92	-1.66	0.27	1.00	0.27	0.18	0.99	0.20	0.86	1.00	0.86
Conifer	0.05	0.99	0.06	0.76	0.99	0.77	0.84	0.98	0.87	0.88	0.91	0.96

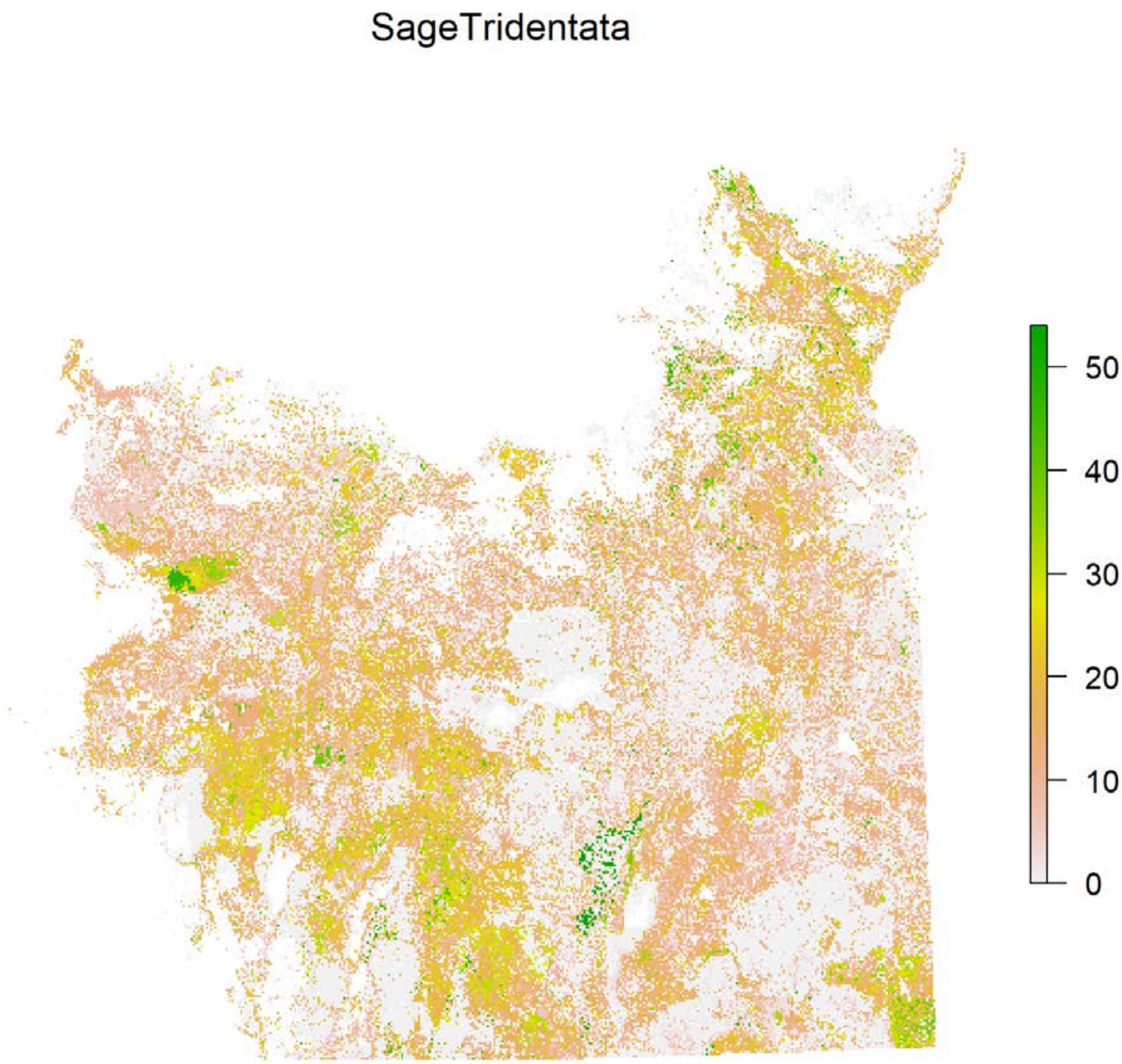
Appendix 5a: Map illustrations for variables.

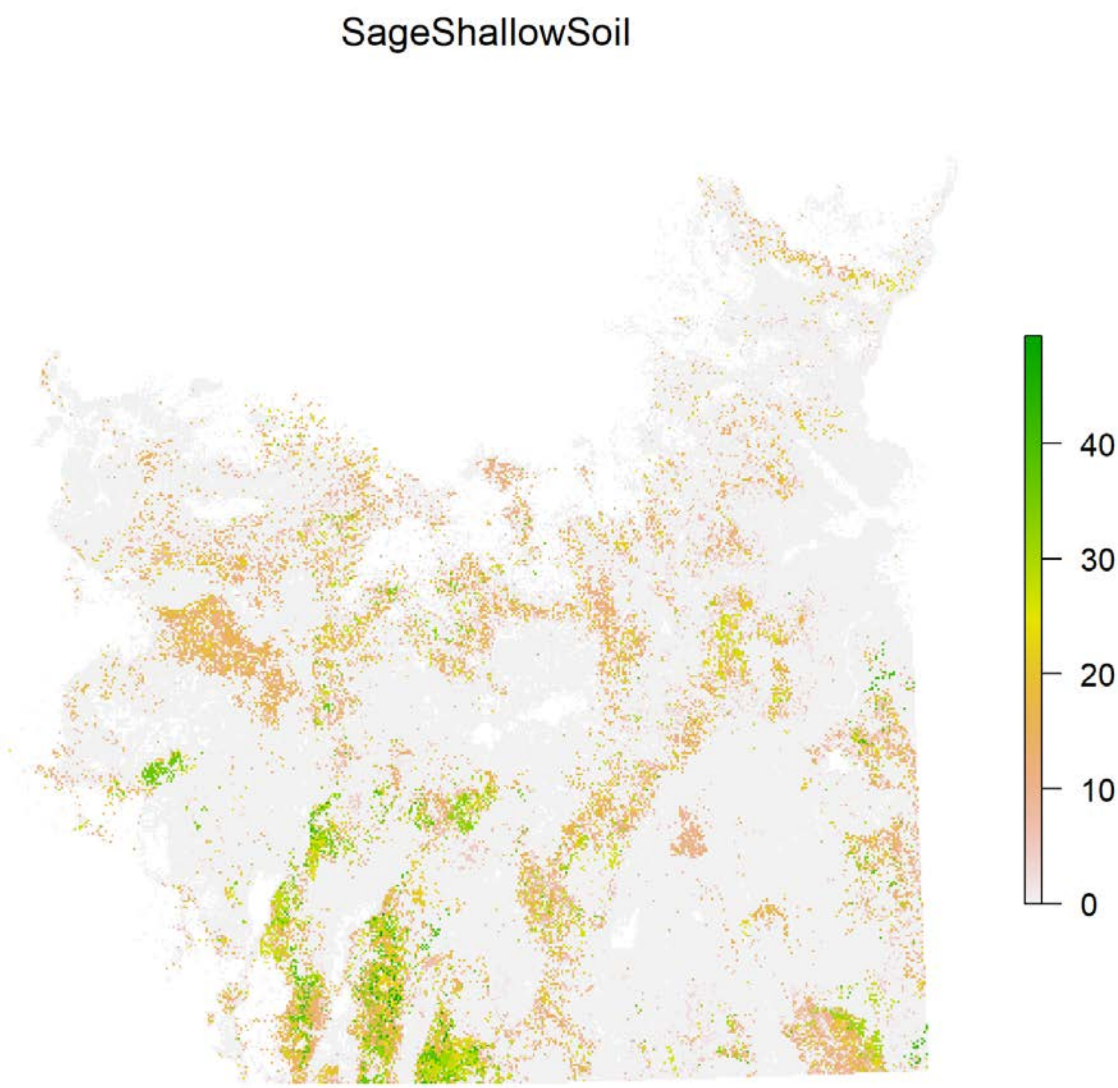



SageGrousePreferredForbs_All
80
60
40
20
0

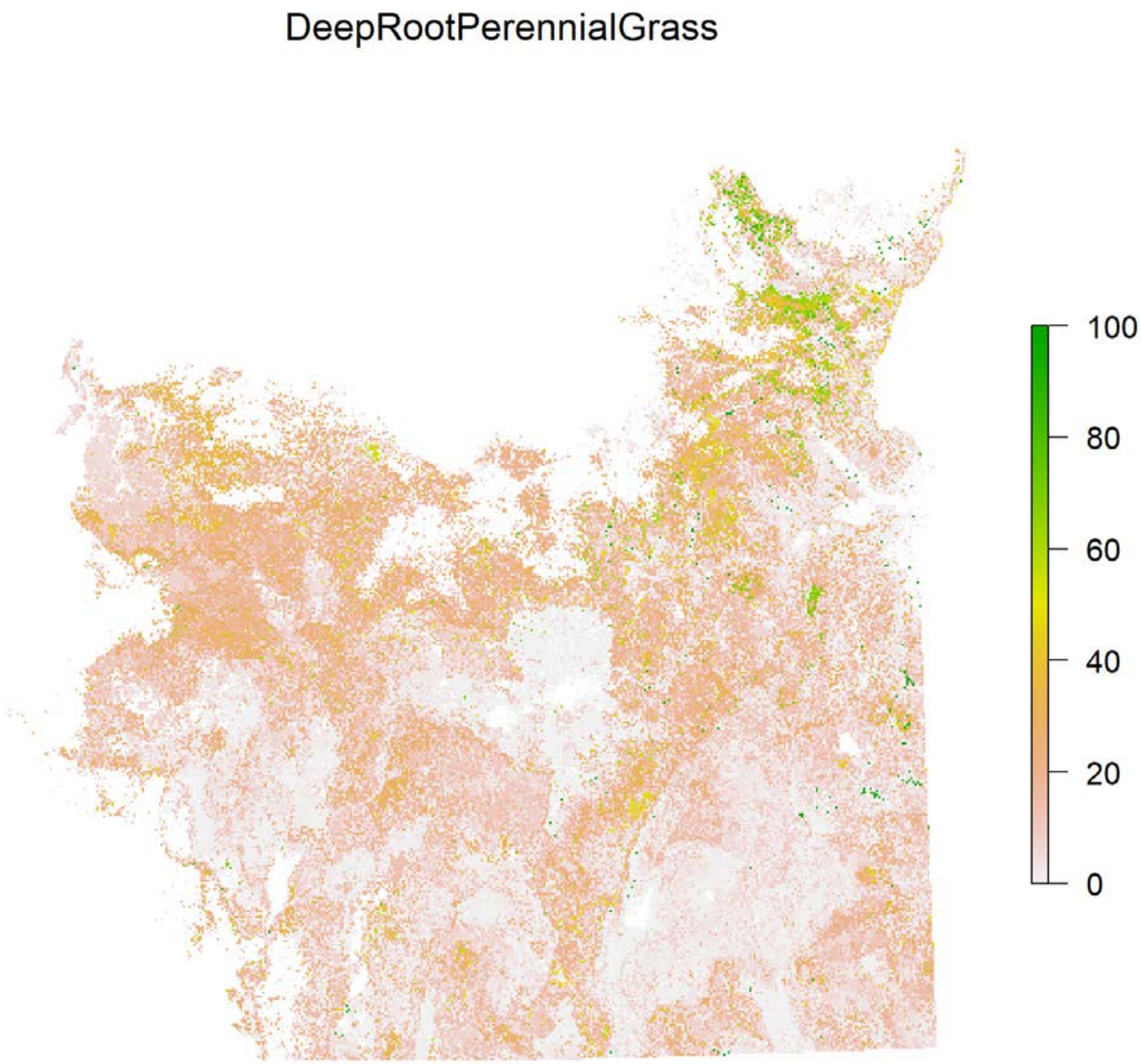

AllSage
50
40
30
20
10
0

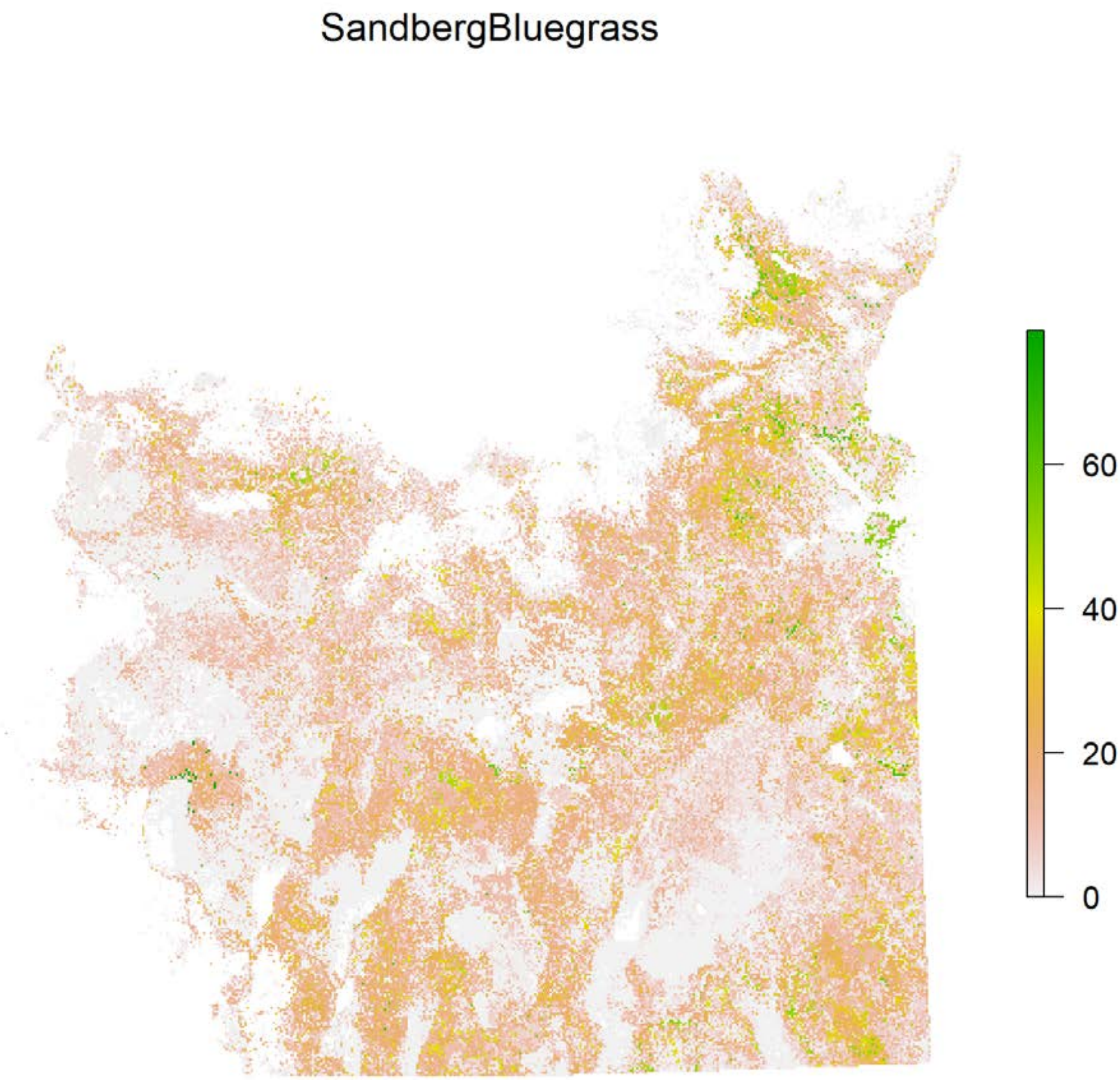

AllJuniper
60
50
40
30
20
10
0

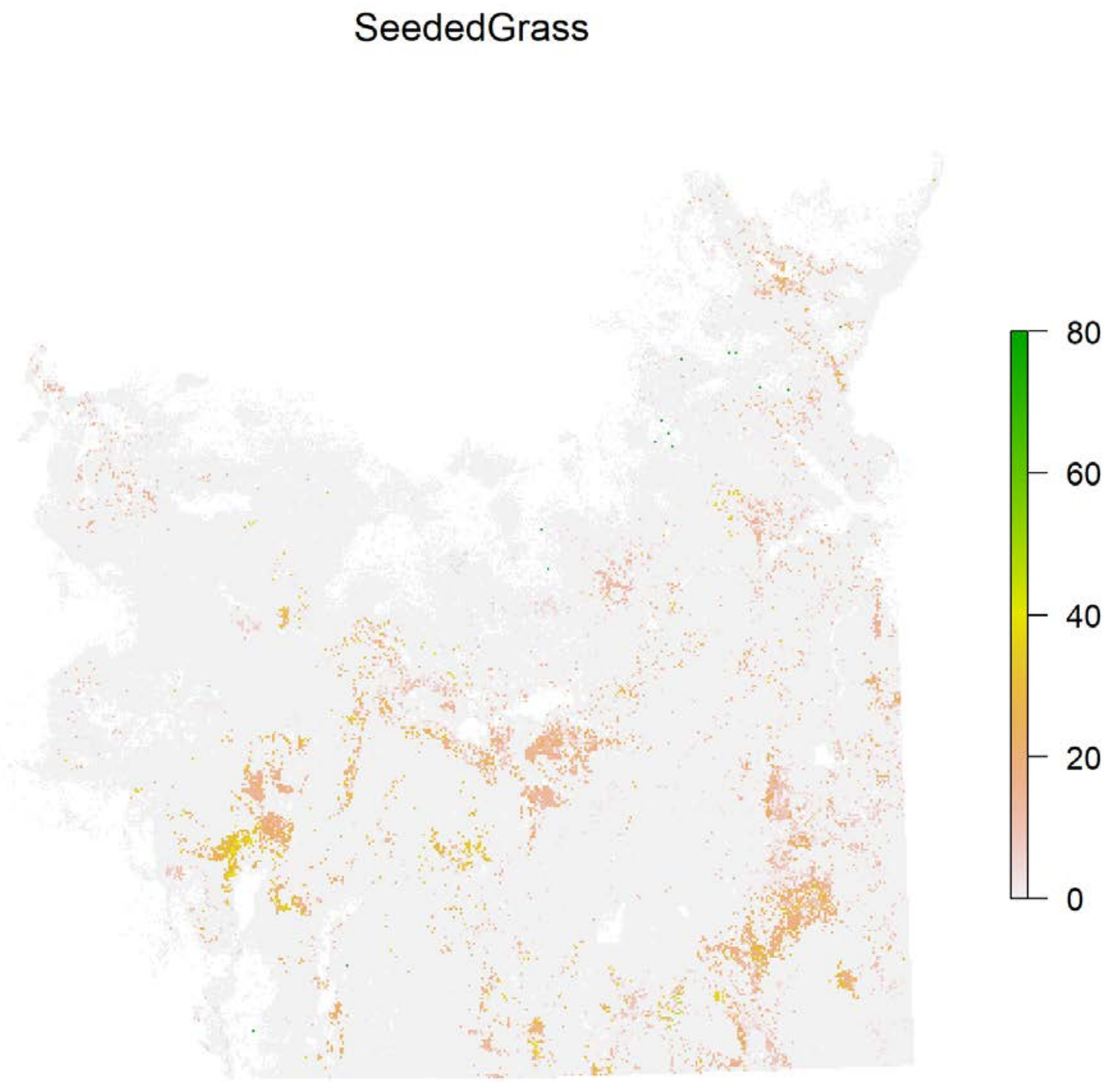

SageTridentata
50
40
30
20
10
0

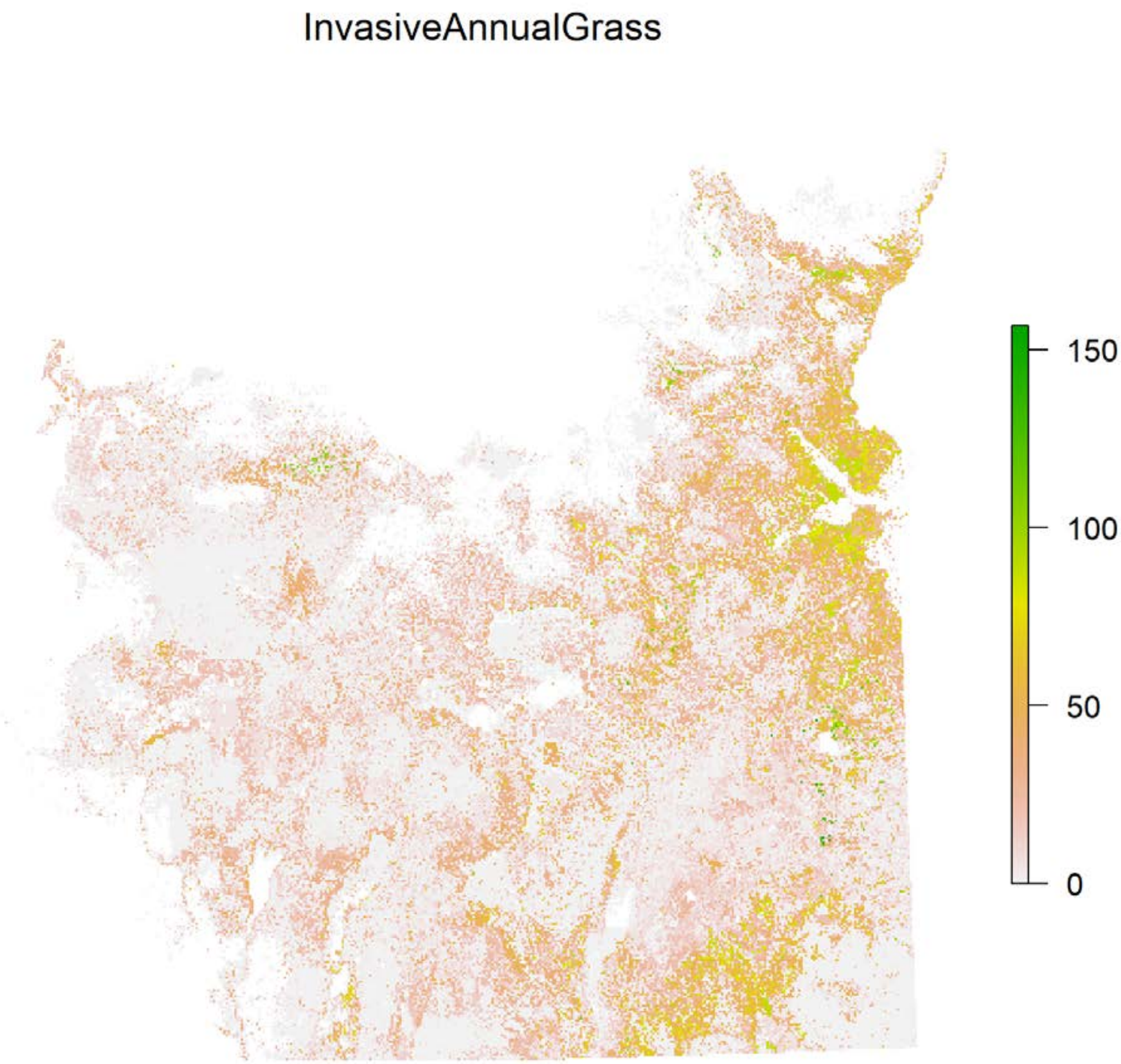

SageShallowSoil
40
30
20
10
0

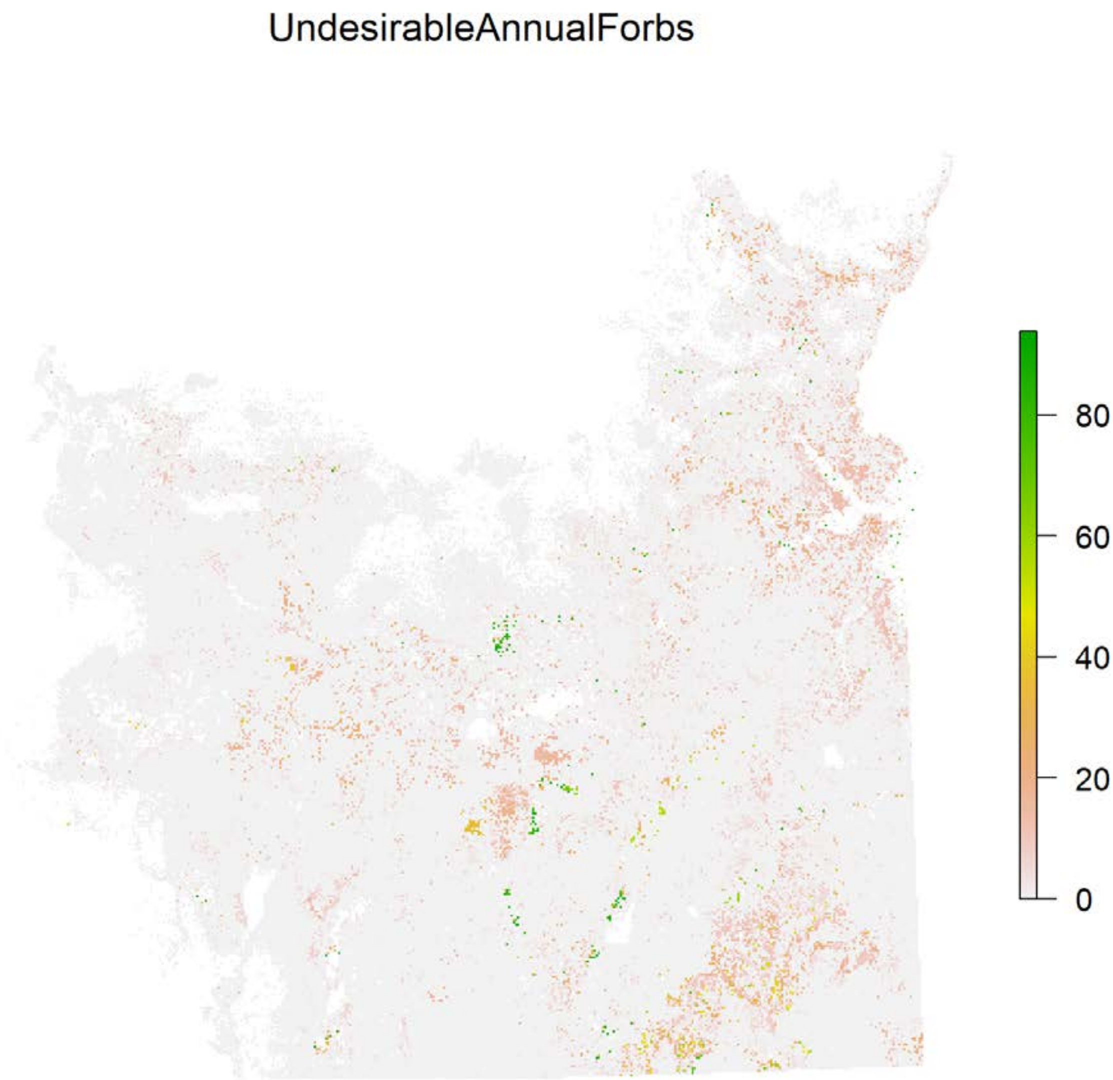
EarlySeralShrub

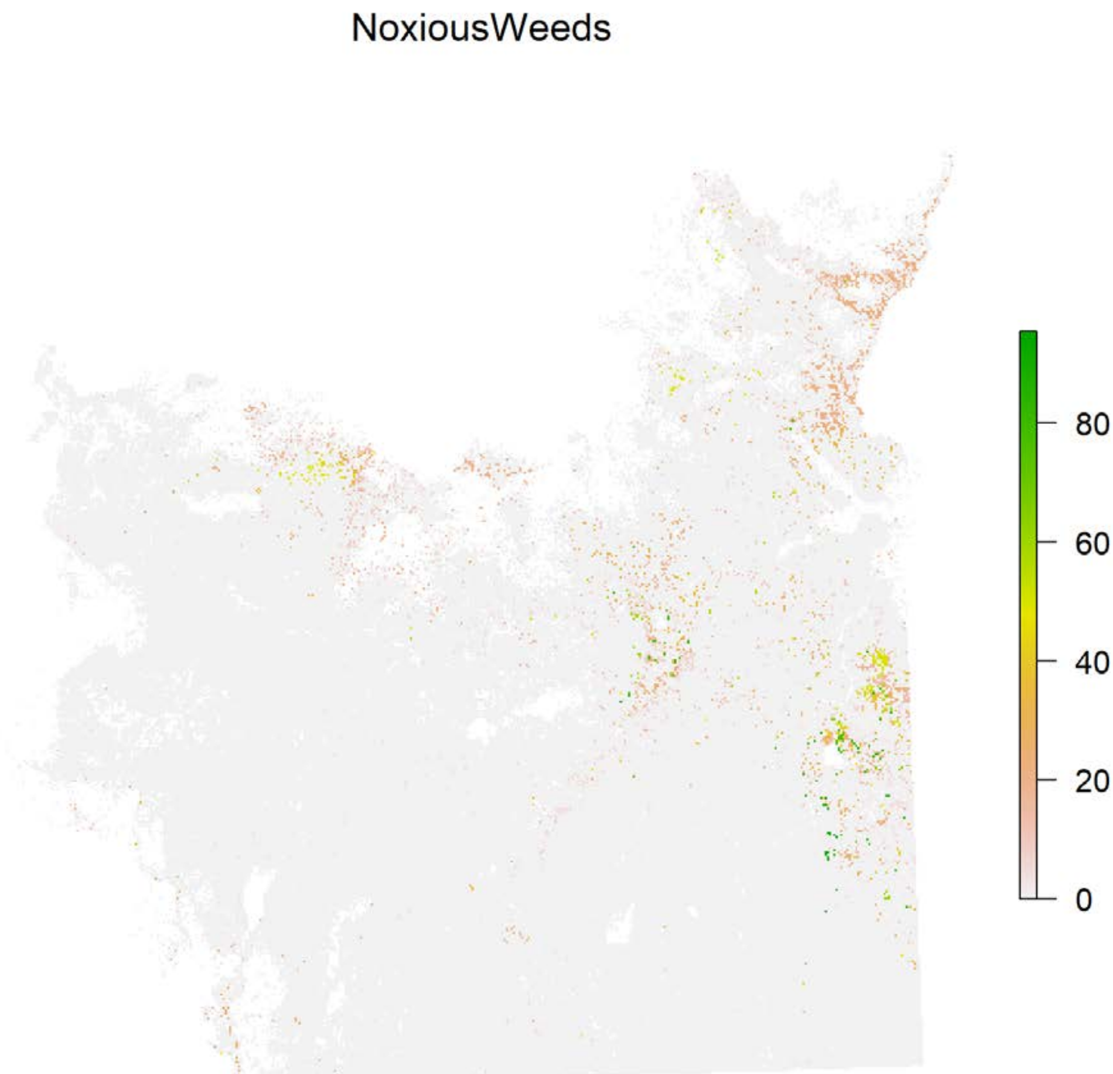

DeepRootPerennialGrass
100
80
60
40
20
0

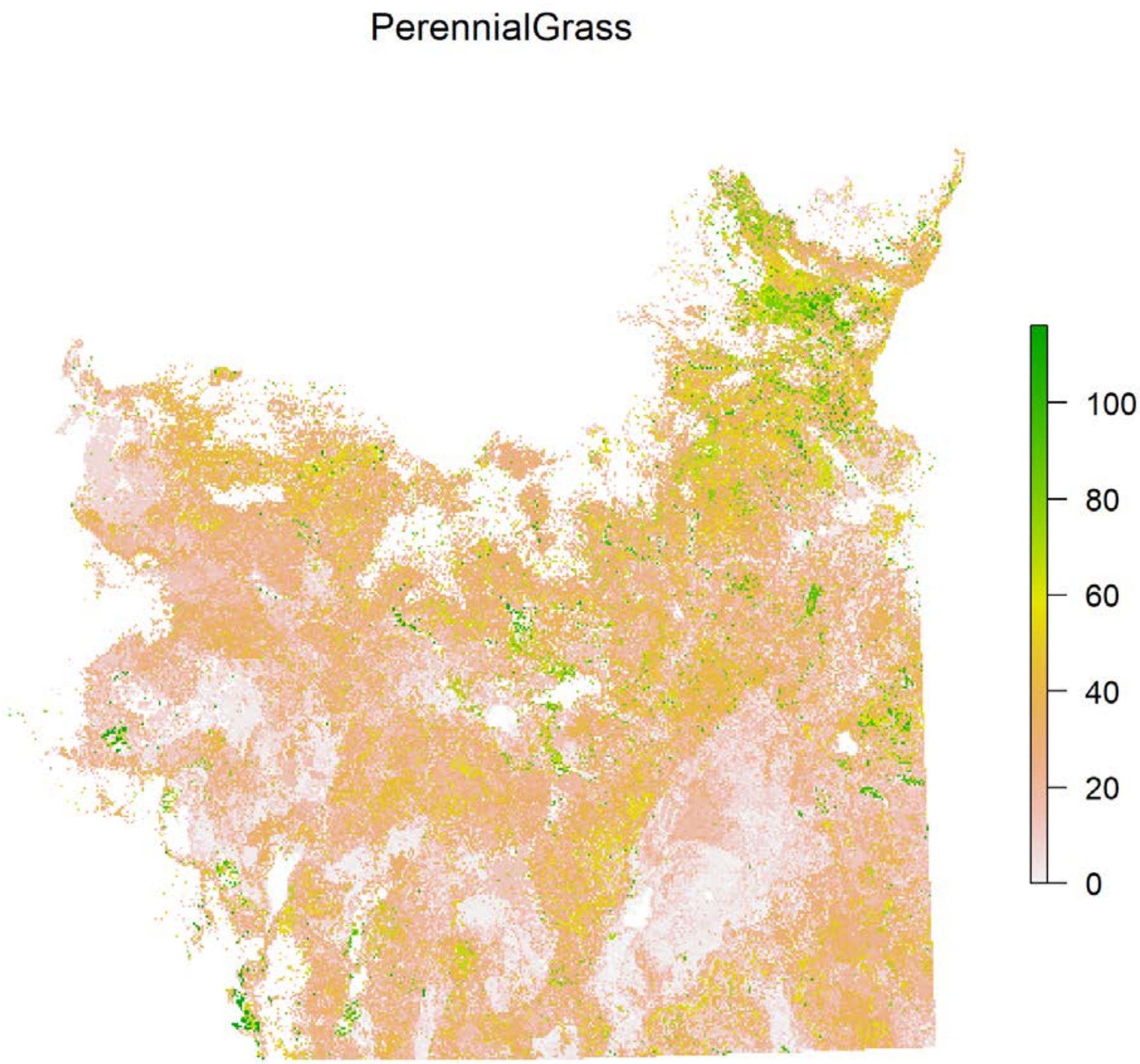

SandbergBluegrass
60
40
20
0


SeededGrass
80
60
40
20
0


InvasiveAnnualGrass
150
100
50
0


UndesirableAnnualForbs
80
60
40
20
0


NoxiousWeeds
80
60
40
20
0


PerennialGrass
100
80
60
40
20
0

Conifer