A Map of Annual Grasses in the Owyhee Uplands, Spring 2006, Derived from Multitemporal Landsat 5 TM Imagery

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SUMMARY

Annual grasses are mapped throughout the Owyhee Uplands region plus a 25 km buffer zone with an index corresponding to percent ground cover. The map illustrates relative geospatial patterns of cover by exotic annual grasses in the region for Spring, 2006. The Annual Grass Index map was developed with data from 412 field plots, Landsat 5 and MODIS satellite sensors, and climatological data from the PRISM Group using censored regression. Accuracy analyses provided variable results, and suggest a Root Mean Square Error in the range of 10 – 16 % ground cover with 75 % of plots within estimated within 14 % of measured values and a Pearson correlation (R) between 0.28 and 0.55. The results show that southern and eastern portions of the Owyhee Uplands have generally low levels of cover though invasion fronts appear to be encroaching from the Snake River Plains and the Lahontan Trough. The northwestern portion is well invaded and has two centers of heavy colonization. Overall, much of the invasion is by *Bromus tectorum* (cheatgrass), though substantial portions of the northwestern Owyhee Uplands are thickly invaded by *Taeniatherum caput-medusae* (medusahead). Another exotic annual, *Bromus arvensis* (field brome) was found frequently along roads in the lightly invaded southern portion of the Owyhee, an area that experienced substantial wildfire activity over the summer of 2006. Statistical models suggest that minimum temperatures may limit the distribution of the annual grasses (probably *B. tectorum* in particular). A temperature limitation may have important implications for the spread of this grass considering changing climates both in recent history and possibly in the future.

INTRODUCTION

The extreme threat posed by invasive annual grasses to the ecology and enonomy of the intermountain west is widely acknowledged and discussed (West 1999; Young 2006; Wisdom et al 2005; Peterson 2006). Methods for mapping these exotic grasses have recently been worked out with reasonable success (Bradley and Mustard 2005, Peterson 2003, 2005, 2006). Mapping these grasses within the Owyhee Uplands presents some relatively unique opportunities.

Vegetation in the intermountain west has strong altitudinal patterns. The Owyhee Uplands (Figure 1) are unique in that the region is a relatively flat, are geologically dominated by basalt, are at intermediate elevation, and yet have great variation in annual grass densities. The Great Basin to the south (primarily Nevada) contains hundreds of mountain ranges with steep altitudinal gradients and highly variable geology. To the north-east (primarily Idaho) lies the relatively low-altitude Snake River Plains with a high degree of land alteration for agriculture. To the northwest (primarily Oregon) the landscape has more topographic and altitudinal variation than much of the Owyhee Uplands.

The uniformity of geology and altitude compared to surrounding landscapes presents an unusual opportunity for vegetation mapping in the intermountain west – a chance to examine vegetation patterns and their underlying environmental gradients somewhat independent of geology and altitude. Simultaneous with the opportunity to work on this project, the PRISM Climate Group at Oregon State University released new high resolution datasets relating to precipitation and temperature patterns. Although the resolution of the new data is relatively coarse resolution compared to the Landsat imagery used in this project, it is a great improvement over previous data and the resolution is acceptable for regional and sub-regional vegetation modeling. One of the intriguing outcomes of this project is the separation of minimum temperature from elevation and the suggestion of minimum-temperature as a limiting factor for the spread of the dominant invasive annual grass in the Owyhee, *Bromus tectorum* (cheatgrass).

METHODS

Overview

Many invasive annual grasses have emerge early and have a short lifespan (phenology), greening-up ahead of most native perennials and senescing earlier in the season than most perennials (Figure 2). Satellite sensor data (imagery) can detect chlorophyll concentration over the landscape (Jensen 1996). Locations with abundant annual grasses should show a marked drop in chlorophyll when annual grasses senesce. Thus, the change in chlorophyll concentrations as measured by satellite sensors can be correlated with the actual ground cover of annual grasses at training sites, used to create predictive models of annual grass cover, and then those models may be applied geographically to produce maps of annual grass cover.

The methods used here are very similar to those used to model and map *Bromus tectorum* previously (Peterson 2003, 2005, 2006). Training data were collected from the field. Satellite sensor data were obtained for appropriate times during the annual grass growing season and senescence season. Statistical models based on censored-regression (Tobin 1958; Austin et al. 2000; Peterson 2005) were tested and mapped through geographic mapping algorithms for visual evaluation. Additional ground data were obtained for post-modeling map validation. During data processing and analysis, all raster data mosaics and reprojections to match the Landsat data set (below) were calculated in ENVI 4.3 (ITT Industries Inc. 2006) with nearest neighbor resampling. All statistical analyses were performed with the R statistical package version 2.4.0 (R Development Core Team 2006).

Field Data

We used a 0.1 ha circular plot (17.8 m radius) for vegetation sampling. Geographic position of plot center was usually measured with a Leica GS20 GPS receiver using WAAS correction and post-processed differential correction using data from regional public ground stations (estimated Root-Mean-Square-Error, RMSE, typically under 3 meters). A few were measured with back-up recreational-grade 12 channel GPS receivers with RMSE < 15 meters (Garmin GPS12 or Garmin eTrex Legend). Within the sampling plot, we used ocular estimation of percent cover for each species of annual grass. For analysis, cover of all annual grass species was summed (native and exotic). Additional data were also collected including slope, aspect, cover of vascular plant species visible at the time of the plot, and cover of biological soil crusts. Most data were entered directly into a Geographic Information Systems (GIS) point coverage with ArcPad 6 (ESRI 1995-2005) in order to eliminate transcription error. However, some plot data were recorded on paper for later computer entry. Plot areas were located selectively in order to incorporate a broad variety of landscape forms and vegetation types into the training dataset. Plot locations were found by driving roads throughout the project area and selecting for uniformity of vegetation over an area approximately 1 ha or larger. For efficiency, most plots were located within 0.5 km of drivable roads though efforts were made to place plots at least 100 m from roads to reduce the influence of roads on satellite data for plots. Details on sampling methods are available in Peterson (2003). All data were collected during spring and summer of

2006 by the author with assistance from Natural Heritage personnel and one 2-person field crew under the author's supervision.

Satellite Data

Satellite sensor data (imagery) for this project needed to provide measures of chlorophyll during the growing and the senescence periods for annual grasses. This limits sensor data to narrow time periods which are vulnerable to cloud cover, which obscures the landscape. The senescence period is particularly narrow as the sensor data must be collected when annual grasses have mostly senesced, yet perennial vegetation and most forbs remain photosynthetically active. The target date for growing season in the Owyhee was early May, though for a small portion on the western edge late April imagery was used due to clouds covering the early May imagery. The target date for senescence was late June. The Landsat 7 ETM+ satellite sensor originally used by Peterson (2003, 2005), developed a problem with its scan-line-corrector on 31 May 2003 (USGS 2006). While data from this satellite are still useful for many projects, substantial gaps exist near the edges of the scenes. These gaps can be filled with data from alternate scenes, but for a project where phenology is critical, use of gap-filled scenes may be problematic. No replacement for Landsat 7 will be launched in the near future. However, a predecessor, the Landsat 5 TM sensor, has remained operational and continues to yield similar spectral and spatial resolution. This sensor was successfully used for annual grass mapping previously (Peterson 2006), so it was used for the Owyhee project. All Landsat data were purchased from the U.S.G.S. EROS data center in UTM zone 11 projection, WGS 1984 datum, with terrain-level georectification, and a spatial resolution of 28.5 meters. The entire Landsat 5 TM data set of 16 scenes is summarized in Table 1.

Many areas of the Landsat data remained obscured by clouds (referred to hereafter as 'cloud gaps'). Peterson (2006) found that MODIS satellite sensor data can be used in place of Landsat TM data to 'fill-in' cloud gaps. Although the spatial resolution of MODIS data is poor relative to Landsat (250 m to 1 km resolution depending on the spectral band of interest), data are collected daily and multiple-day data composites are available that greatly reduce the problem of gaps caused by cloud cover. For this project, 16-day composite data that included vegetation indices (MOD13Q1 version 004 product; NASA 2005b) for dates that closely matched the corresponding Landsat data sets (periods of 23 April - 8 May 2006 and 10 - 25 June 2004) were downloaded from the Earth Observing System Data Gateway (NASA 2005a).

Three measures of greenness were derived from the Landsat data and tested to determine the optimal measure for annual grass mapping. The Normalized Difference Vegetation Index (NDVI; Jensen 1996) was used as in previous mapping projects (Peterson 2003, 2005, 2006). The NDVI was used both for each imagery set independently and as a simple difference ($\Delta NDVI = NDVI_{early} - NDVI_{late}$). The Soil Adjusted Vegetation Index (SAVI; Huete 1988) and its simple difference ($\Delta SAVI$) were tested in an attempt to improve sensitivity to sparsely vegetated areas (using $L = 1.0$). The Enhanced Vegetation Index (EVI; T.B.R.S. 2003) and its simple difference (ΔEVI) were tested for the same reason. Tasseled Cap transformations (Jensen 1996) were also explored, but abandoned due to slightly less statistical value than NDVI and due to the lack of an analog available for MODIS data.

Accessory Landscape Data

Statistical modeling of vegetation features from satellite imagery is generally enhanced by the use of accessory data that relate to climate and land features. Data gathered and tested for use in models included elevation-derived landforms, precipitation patterns, and temperature patterns. These are described below.

Elevation and derived land forms. A digital elevation model (DEM) covering the entire extent of all Landsat data scenes with 1 arc-second resolution (ca. 30 m) was extracted from the National Elevation Dataset (U.S.G.S. 2005a) then reprojected and resampled to match the Landsat data. In addition to altitude, slope, aspect, heat index, exposure, and aridity indices were calculated from elevation data as per Peterson (2006) with the exception that exposure was calculated with 1, 3, 5, 7, and 9 pixel neighborhoods.

Climate. Climate patterns such as precipitation and temperature correspond strongly to altitude within the intermountain west, however, the relative flatness of the Owhyee Uplands provides an opportunity to examine climatic patterns in the absence of great altitudinal trends.

Precipitation patterns were examined in three fashions: average annual precipitation, current year total precipitation, and average seasonal timing of precipitation (Figure 4). All climate data were obtained from the PRISM Group (2006). For average annual precipitation, the PRISM model derived from climate station data from 1971 – 2000 was used and altered only to align the projection and resolution of the geographic data with the Landsat data. For the current year total, the monthly total estimates provided by PRISM for the months running October, 2005, through April, 2006, were summed. For average seasonal timing, monthly estimates from the 1971 – 2000 data sets were used to calculate the average monthly precipitation from January through April, then for July through October, finally the normalized difference was calculated to provide a contrast in cool-season versus warm-season moisture: (C-W)/(C+W) where C is the cool season precipitation and W is the warm season precipitation.

Temperature was examined in three fashions: average minimum temperature, average maximum temperature, and average temperature fluctuation (Figure 5). Average minimum and maximum temperatures are provided directly from PRISM and are averages of daily minimum temperatures throughout the year. The average temperature fluctuation was calculated by simple subtracting the minimum from the maximum.

As it became clear that the average minimum temperature was a strong predictor of annual grass cover, a further refinement of the data became necessary. The low resolution of the PRISM data resulted in a strong blocking pattern in the resultant maps. Since temperature varies with altitude, the digital elevation model was used to estimate local variation in minimum annual temperature. This was tried in two ways as explained in the text box, below.

One additional climate variable was examined: annual average of daily dew-point temperatures (Figure 5). This variable is related to humidity and thus could provide a measure of moisture separate from precipitation totals (colder dew-points equate to less moisture in the air). The data were used as the mean average of annual data provided by PRISM for the years 2000 – 2005.

Statistical Analysis and Map Creation

Statistical analysis followed the methods previously developed by Peterson (2003, 2005, 2006) utilizing censored regression in a form sometimes called Tobit Regression (Tobin 1958; Austin et al. 2000). Regression was performed with plot measurements of annual grass cover as the response variable and various satellite and other landscape data for the plot sites as predictor variables. Annual grass cover may increase over certain landscape and satellite data values, but no mater how inappropriate a site may be for the grasses, the cover cannot continue below zero. Censored regression accounts for the response data being limited to positive values.

Resolution Enhancement of Temperature Data:

First, a regression of raw PRISM data for average minimum temperature (clipped roughly to the Owyhee region) was calculated with respect to the elevation model utilized by PRISM. This provided the average rate of change per meter of elevation (-0.003156 degrees C). To obtain the local deviance, the rate was then applied to each pixel by multiplying it by the difference in elevation between a bicubicly subsampled version of the PRISM elevation model and the higher resolution elevation model used in the remainder of this project. Then the local deviance was subtracted from a bicubicly subsampled PRISM data value for that location.

The second method tried to account for geographic variation in the rate of change. The method was similar to the first except that rather than using a single rate derived by regression, local rates were determined by using topographic slope calculations of the subsampled temperature map and the subsampled PRISM elevation model, determining their ratio, and obtaining the sign (positive or negative) from a topographic aspect calculation. Although this method would seem more appropriate in theory than the former, local variation in temperature in areas with little topographic variation resulted in very high rates of change which, when applied to minor topographic variations visible only in the higher resolution elevation model, resulted in wild fluctuations in estimated local temperature. Although infrequent, these anomalies rendered odd locations of extreme false-positives for annual grass estimations and was decided to be inappropriate. It may be possible to remove

Regression model building followed a stepwise forward selection pattern guided by preliminary data exploration that involved graphing and correlation. For the satellite data, only data from the Landsat satellite were used and plot data were restricted to those plots where Landsat data were available for both seasons. Models were then applied to geographic data by building ENVI/IDL functions from the relevant variables and their coefficients. Numerous models can be found with similar statistical power, but many of these can result in inappropriate maps. Thus many likely models were geographically applied and evaluated by field experience. Lastly, to fill the 'cloud gaps' in the landsat data, the final model for the Landsat data was used but with newly calculated coefficients for the MODIS data. This resulted in a model for the MODIS data with several statistically insignificant variables; however, lack of significance is believed to be a result of the heterogenous landscape contained within each 250 m pixel, and the mapped result of the model is highly compatible with the Landsat-only map.

Several cleanup processes were then run on the map. For instance, even with the high resolution of Landsat data, heterogeneity within and between pixels may cause undue variations in the annual grass estimates. Also, variations in reflectance on water may even result in the statistical model predicting grass cover on lakes. After merging the Landsat and MODIS based maps, a conservative smoothing kernel was passed over the map with each pixel recalculated as a weighted average of it and its eight neighbors (focal pixel weighted equal to the total of all eight neighbors). The map was zeroed in areas with liquid water and snow as detected by the formulae in Table 2 applied to each seasonal image separately and from further edits 'by hand' utilizing the polygon 'grow' function in ENVI to detect the water edges. The water detection formulae also detected some strong shadows from cliffs that were left in for the zeroing, since annual grass estimations in such dark areas of the satellite data would be unreliable. Areas of very high vegetation cover (primarily wetlands) were also zeroed, using the formula in Table 2. Lastly, the map was clipped to the Owyhee Uplands plus a 25 km (15.5 mi) buffer.

Assessment Data

Assessment data were obtained from two independent projects: the Southwest Regional Gap Analysis Project covering Nevada (SWReGAP; Lowry et al. 2005) and the Shrubmap project (U.S.G.S. 2005b) covering Oregon and Idaho, in which the data appear to have been collected separately for each state and will be treated as separate data sets here. In all three data sets, cover values are given in 5% increments, over a non-specific plot area, and only for the primary species present. Peterson (2006) found that the SWReGAP did generally incorporate annual grass cover data when ground-cover was 5% or greater and the data provided a robust examination of error in the Nevada Annual Grass Index map. Since the shrubmap data collection intended to follow the same protocol as SWReGAP, it was presumed that the data would be of similar value. SWReGAP field data were collected primarily during the summer of 2003, but some were collected in late summer of 2002. Shrubmap data for both Oregon and Idaho were collected during the summer of 2003. For additional comparison, a circular assessment using the same field data collected to develop the model (training data) was performed.

RESULTS

Field Data Collection

During field work from May 15 through August 15, 2006, data were collected for a total of 412 plots: 165 plots had no annual grass cover, 24 had only a trace, and 223 had one percent ground cover or more (Figure 6). The mean of total annual grass ground cover was 11.4 % with a standard deviation of 18.7 percent.

Satellite Data

Table 1 provides the dates for the satellite scenes used. Most Landsat data contained little or no clouds over the Owyhee Uplands; the exception being scenes in path 43 for the early season. Scenes for this area were heavily obscured by clouds, but preview images showed at least some clearing over the north-western boundary of the Owyhee. Unfortunately, after the imagery purchase much of the apparent clearing did contain thin clouds and haze. Nevertheless, the scenes obtained did add to the total area mapable with the Landsat data. MODIS data of appropriate timing was available for the entire area with 250 m pixel resolution.

Modeling Process

Of the 412 field plots, 407 were in locations where Landsat data were available for both seasons. All 412 field plots were in locations where MODIS data were available. The final statistical models for Landsat and MODIS data are provided in Table 3. The original (early scene) NDVI and the ΔNDVI form the core of the model. Further calibrating these measures are the average minimum temperature, brightness of the satellite data band for the blue portion of the visual spectrum, and an interaction between the average minimum temperature and ΔNDVI. These will be discussed below.

As with Peterson (2006), the model under-predicts high cover values (Figure 7) and thus should be regarded as providing an annual grass index rather than predictions of actual cover. Additionally, knowing that annual grass cover fluctuates from year to year suggests that an estimation of actual cover for a time in the past may be of limited value beyond the information provided by an index. The final index map, after post-modeling cleanup, is presented in Figure 8. Full-resolution GIS data will be available at http://heritage.nv.gov/gis.

The final map provides the annual grass index across the entire region without gaps from clouds. This is an area of about 7.5 million ha (18.4 million acres) with the 25 km buffer included, or 4.1 million ha (10.2 million acres) within the Owyhee Uplands specifically. For a detailed breakdown of the geographic extent for cover index values classified at 5 unit intervals, see Table 4. Of the entire area mapped (including the buffer area), which includes agricultural fields that have not been masked from the analysis, 48.6 % (3.6 million ha or 9.0 million acres) has an index of zero (no detectable invasion); 11.8 % (883 thousand ha or 2.2 million acres) has an index from 1 through 5 (low invasion); 9.3% (690 thousand ha or 1.7 million acres) has an index from 6 through 10 (moderate invasion); 18.9 % (1.4 million ha or 3.5 million acres) has an index from 11 through 25 (heavy invasion); and 11.3 % (845 thousand ha or 2.1 million acres) has an index of 26 or greater (severe invasion). Restricting figures to the Owyhee Uplands specifically, which includes rather few agricultural fields, 51.5 % (2.1 million ha or 5.2 million acres) has an index of zero; 13.5 % (558 thousand ha or 1.4 million acres) has an index from 1 through 5; 10.6 % (438 thousand ha or 1.1 million acres) has an index from 6 through 10; 18.9 % (781 thousand ha or 1.9 million acres) has an index from 11 through 25; and 5.4 % (223 thousand ha or 551 thousand acres) has an index of 26 or greater.

Accuracy Assessment

Table 5 provides a number of assessment statistics from the three assessment datasets. Some problems with the data were identified that cause uncertainty in the assessment (see discussion) so an assessment using the data collected for modeling is also given. Using this training data first to build the models, then again to assess the map results in a logical error of circularity, but can provide some insight into model accuracy. This too, will be covered in the discussion.

DISCUSSION

Accuracy of the Map

The greatest analysis of accuracy will likely be a qualitative evaluation over the upcoming field season as biologists working in the field compare the map to their observations. Until then, quantitative comparisons with the data sets available will provide a preview of map accuracy. Measures of accuracy reported in Table 5 are variable. The SWReGAP field data suggest an RMSE (9.7%) very much in line with previous annual grass maps (Peterson 2003, 2006), and the amount of error within 50 and 75 percentiles seems exceptionally good with 75 percent of plots estimated to within 2 % of measured cover. However, the correlation between estimated values and SWReGAP field data suggests a rather noisy relationship. Given that much of the Owyhee Uplands within Nevada are very low in annual grass cover, the low errors for 50th and 75th percentiles are to be expected, and ideally the RMSE should be lower. However, plots that fell within the 25 km buffer were included and these add many sites on the periphery of the Owyhee where annual grasses are abundant. The tendency of the model to under-predict high-cover values may be responsible for the high RMSE and for the low correlation statistics.

Shrubmap data from Oregon suggest reasonable, but somewhat higher, RMSE (14.8 %) and error for 50th and 75th percentiles of plots. Given the generally greater abundance of annual grasses in the Oregon portion of the Owyhee Uplands and the under-estimation at high-cover sites, those statistics should be expected to be a little higher than the SWReGAP based statistics.

The correlation statistics are rather poor, and again the under-estimation at high-cover sites is most likely responsible.

Shrubmap data from Idaho provide highly irregular assessment statistics. There are several problems with these data and I suggest that they are not quite appropriate for assessment. First, few plots are actually within the Owyhee Uplands boundary (except to the east of highway 51) so the assessment relies primarily on the 25 km buffer. Second, most of the field plots appear to have not recorded annual grasses unless they were dominating the plots. The result is that an exceptionally large number of plots exist with no measure of annual grasses but with high predicted cover. Oddly, the correlation statistics look fairly strong for these data, probably due to a large number of plots at either end of the distributions: accurately modeled zero-cover sites and reasonably modeled very-high cover sites where annual grasses were actually recorded. It is also possible that annual grass expansion during the period between Shrubmap sampling in 2003 and the satellite imagery acquisition for this map in 2006 may account for some of this discrepancy.

One more source for concern with using these independent data is that they were collected in 2003 while field data and imagery for this project were all collected in 2006. Two intervening winters have been relatively wet and field experience in Nevada across those years suggests that annual grass densities have changed and the distribution has expanded notably in some areas.

Given the troubles with the Idaho data and the time disparity between assessment data collected mainly in 2003 versus the map for 2006, the comparison between modeled values and the training data collected to produce the model is worth more discussion (statistics under ‘Circular’ in Table 5). It is important to note, however, that this comparison involves a logical error of circularity and thus could provide an unduly optimistic assessment. On the other hand, sources of error will be discussed below which could inflate apparent error even in this circular assessment. The RMSE (16.2 %) is higher than in previous annual grass maps (Peterson 2003, 2006) and similar to the value given by the Oregon Shrubmap field data. Error percentiles are also similar. Correlation statistics are acceptable, though not great, hovering around 0.5.

It is difficult to draw hard conclusions given the variation between these assessments. Actual error values and correlation statistics are probably within the range of values suggested by the SWReGAP, the Oregon Shrubmap, and the training data. A comfortable assertion is that the mostly absent or low-cover of annual grasses in the southeasterly half of the Owyhee Uplands is mapped to a high degree of accuracy. Also, for the northwestern half and the transition to the Snake River Plains, overall patterns appear to be reasonable though accuracy for actual cover values be weaker, particularly due to under-estimation of high-cover sites by the model.

Sources of Error

All remote sensing projects are vulnerable to numerous sources of error, starting from the field data collection, but extending on to the numerous influences on the remotely sensed data from sensor accuracy to atmospheric variations. Many of these have been discussed at length in previous annual grass mapping reports (Peterson 2003, 2006) and are reprised in Appendix A.

There are three sources of error that are new with this project or of particular interest, which I will discuss in brief as they may contribute to this apparent decrease in accuracy or influence accuracy somewhat differently than previously discussed.

First, there is a possible additional component to observer error and bias in ocular estimates of cover during field work. Although this was discussed in previous reports, those projects had a single person (the author) performing all estimates. Field work in the Owyhee involved two field crews with three people performing estimates. Crews were brought together for mutual plots numerous times throughout the field season in an attempt to minimize differences in bias. If observer bias is influential on the accuracy, then it could be causing less accuracy for the model *or* less accuracy for the circular assessment (or both).

Secondly, the Owyhee Uplands has a lot of variation in annual grass densities over a relatively uniform surface. Much of the region may be quite vulnerable to invasion but the grasses have simply not arrived yet. The model is largely based on spectral data received by satellite which one might think could 'see' where the grasses have invaded and where they have not. However, the involvement of temperature data (or elevation in previous projects) as a covariate to improve model accuracy demonstrates that the spectral data are not perfect. With a relatively uniform surface where the covariate data change slowly over the landscape, some local variations in annual grass cover might easily be missed.

Lastly, there is the influence of *Poa secunda* on the statistical model. In past mapping efforts, *P. secunda* has caused inflated estimates of annual grasses due to its relatively early phenology. However, *P. secunda* phenology seems to not be very uniform, so its influence on the annual grass model is patchy. Peterson (2003) found *P. secunda* to have caused a dramatic over-estimation in the Owyhee Uplands in Nevada west of the Bull Run Mountains, however that is not a large problem in the present map. Instead, an area in Oregon seems to have been problematic, particularly to the south of Big Grassy Mountain as discussed below. Thus it appears that the patchiness of error from *P. secunda* may vary geographically from year to year.

Patterns of Invasion

<u>Overview.</u> The map shows the bulk of the southern and eastern Owyhee Uplands is lacking strong invasions of annual grasses. However, the buffer retained in the map provides a context for the Owyhee Uplands and reveals some threats. There appears to be an invasion front rising from the Snake River Plains in Idaho. Another, more dissected, invasion front appears to be encroaching into the Owyhee Uplands from the Lahontan Trough in western Nevada and portions of eastern Oregon. The northwestern portion of the Owyhee Uplands already seems to be well invaded and has two centers of heavy colonization within Oregon: one south of Rome near Jacks Butte and upper Rattlesnake Creek, and one to the north, near the southern end of Lake Owyhee from the Jordan Craters area through the Owyhee Breaks.

<u>Bordering the Snake River Plains.</u> The lowlands of the western Snake River Plain are the most heavily invaded areas. Since cultivated fields have not been removed from this map, some of the area mapped as annual grass in that highly agricultural area may be early-season crops, erroneously inflating the coverage of annual grasses for that portion of the map. However, anyone with an eye for landscape condition who has driven along highway 78 in southwestern Idaho will know that the area is indeed thickly infested with invasive annual grasses, especially *Bromus tectorum*.

<u>Bordering the Lahontan Trough.</u> The Lahontan Trough in the Winnemucca area of Nevada, northward into the Pueblo Valley of Oregon, is well known to be heavily infested, particularly on alluvial fans and toe-slopes of the numerous block-faulted mountains of the Great Basin. Prevailing winds can easily lead wildfires from these infestations to the northeast directly into the Owyhee Uplands. Thus the potential for invasion is high within Nevada and southernmost Oregon where the adjacent Owyhee Uplands currently are lacking heavy invasions

of annual grasses. Some of these areas, including significant portions within the Owyhee, did experience severe wildfires over the summer of 2006.

Northwestern Owyhee Uplands and the Big Grassy Mountain Area. The northwestern portion of the Owyhee Uplands, where annual grass populations are frequent and often have high cover, is generally lower in elevation and experiences warmer minimum temperatures than the less invaded southern and eastern portions of the Owyhee. Also the topography is more varied and soils tend to be deeper and more developed. In places around the northwestern Owyhee, the annual grass cover may be somewhat exaggerated by the model. In particular the appearance of low to moderate cover in Oregon south of Big Grassy Mountain and west of Three Forks is a substantial overestimation. Fieldwork there produced almost no annual grass observations either at plots or along the roads. The area had been burned in the recent past and had extensive perennial grass cover that included *Poa secunda*. The influence of *P. secunda* on model accuracy is discussed above near the end of the section, Sources of Error.

Southern and Eastern Owyhee Uplands. The vast plateau of the southern and eastern Owyhee Uplands, along with the mountain ranges within the Idaho portion, appear to be largely free from annual grass invasion at present. Patches exist in scattered sites and detection of them with the model was variable. Field work detected scattered sites particularly in southern Idaho and in Nevada west of the Bull Run Mountains. The annual grass index map frequently shows some level of annual grasses in these areas, though sometimes omitting the sites where field plots measured annual grass presence. These anomalies may suggest that the landscape-level pattern detected by the model may be more accurate than the site-specific prediction. Assuming that average minimum temperature is a limiting factor in annual grass distribution (see below), some of the high-cover sites in this region missed by the model might be sheltered in some way from temperature effects at a scale that is missed by the resolution of the climate data used in the model.

The effects of temperature that might be missed by the scale of PRISM temperature data might be particularly problematic for southerly-facing slopes where soil heat gains during spring days may carry into the night, buffering seedlings from low air temperatures. Southern exposures along canyon slopes commonly host stands of *Bromus tectorum* throughout this otherwise lightly invaded portion of the Owyhee Uplands. Indeed, a model was run to test the influence of the heat index derived from topographic data on the final model for this project. The heat index variable revealed the heavy infestations on these steep southerly slopes quite well, and the model had slightly more statistical power than the final one used. While improving estimations for some slopes, over-estimations of cover on many canyon slopes became unacceptably large. In the end, the model without the heat index variable was chosen due to the lower frequency of over-estimation and the detection of at least some annual grasses in many of the canyons where annual grasses were observed.

Notably, many of the wildfires in Nevada over the summer of 2006 both within and outside the Owyhee Uplands burned through areas where annual grasses were sparse. Such large scale wildfires in Nevada are often presumed to be a result of annual grass infestation. However, these fires may have been carried by a build-up of native grass litter and dense sagebrush overstories.

Diversity of Exotic Annual Grasses. *Bromus tectorum* (cheatgrass) is the dominant invasive annual grass throughout most of the Owyhee Uplands, but two others warrant mention. *Taeniatherum caput-medusae* (medusahead) dominates a great deal of the area in Oregon between highways 95 and 20. The annual grass index map does not distinguish between species of annual grasses, which would be difficult to detect in satellite imagery. However, the phenology of *T. caput-medusae* is also early relative to most native perennials (generally senescing shortly after *B. tectorum)* and thus is well captured by the modeling method. The other noteworthy species is *Bromus arvensis* (field brome; a.k.a. *Bromus japonicus*) which occurs in small patches along roads in the southernmost portion of the Owyhee Uplands (with disturbing frequency). This is the area where large wildfires burned over the summer of 2006 through otherwise native vegetation. This species should be monitored closely over the next few years. It was also seen in more northerly parts of the Owyhee in Oregon. This species appears to have a later phenology than *B. tectorum* or *T. caput-medusae* and may be poorly detected by the statistical model.

Temperature: a Possible Limitation on Invasion

One intriguing result of the statistical analysis of field data is that average minimum temperature correlates more strongly with annual grass cover than does elevation. Previous annual grass maps by Peterson (2003, 2006) have utilized elevation as a covariate to improve model accuracy. Temperature data were briefly examined by Peterson (2006) but found to be an inadequate covariate for modeling annual grasses in state of Nevada, possibly due to the more coarse resolution of temperature data available at that time.

Does minimum temperature limit or restrict annual grass invasion? Clearly it depends on the species and the results reported here are most applicable to *Bromus tectorum*. However, this is an observational, correlative study and has no power to determine causal relationships. Additionally, the temperature data used are themselves based on statistical models created by the PRISM Group (2006). A closer examination of the field data used for the annual grass index map in conjunction with climatological data may be warranted to confirm the correlation strength of minimum temperature relative to elevation and possibly elucidate the timing of temperature limitations. Experimental studies should be performed to establish causality.

If further analysis indicates that minimum temperatures do limit the cover or distribution of *Bromus tectorum* or other annual grasses, then there may be important implications for land management in light of climate change. The gradual warming over the last few decades already may have increased the extent of invasion in the intermountain west and the spread of *B. tectorum* into previously cooler climate zones such as higher mountain slopes and salt deserts under air mass inversions. Future climate trends may exacerbate ecological degradation from these exotic species.

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Table 1: Landsat 5 data purchase. "Use" indicates if a scene was used for the early (E) or late (L) season.

Path	Row	Date	Use
40	31	3 May 2006	E
41	30	10 May 2006	E
41	31	10 May 2006	E
42	29	1 May 2006	E
42	30	1 May 2006	E
42	31	1 May 2006	E
43	29	22 April 2006	E
43	30	8 May 2006	E
40	31	20 June 2006	L
41	30	27 June 2006	L
41	31	27 June 2006	L
42	29	18 June 2006	L
42	30	18 June 2006	L
42	31	18 June 2006	L
43	29	25 June 2006	L
43	30	25 June 2006	L

Table 2: Cleanup algorithms applied to map post-modeling. Bands refer to original Landsat data values (digital number values). Equations result in boolean values (1 if the equation is TRUE; 0 if it is FALSE).

Character	Equation
Water and Shadow =	(BAND7 < BAND4) and (BAND4 < BAND1) and (BAND1 < 20) and ((BAND7 + BAND4) < 70)
Shallow Water and Snow =	(BAND7 < 20) AND ((BAND1/BAND4) > 1.1)
Wetlands =	(BAND 4 > (BAND1 + BAND7)) and (BAND 4 > 100)

Table 3: Statistical Models for Landsat 5TM and MODIS Terra data. NDVIE = early season NDVI; NDVID = ΔNDVI; TMIN = average minimum temperature; and LL1 and MLA1 = late season band for the blue portion of the spectrum.

LANDSAT (*n* = 407):

Parameter	Value	Std. Error	z	p
Intercept	54.2022	17.8060	3.044	2.33e-03
NDVIE	22.2737	30.4038	0.733	4.64e-01
NDVID	111.3461	26.9516	4.131	3.61e-05
TMIN	0.0572	0.0147	3.905	9.42e-05
LL1	-0.7137	0.1820	-3.921	8.83e-05
NDVID*TMINE	0.3225	0.1554	2.076	3.79e-02

Loglik(model)= -1193.9 Loglik(intercept only)= -1269.2

MODIS (*n* = 412):

Parameter	Value	Std. Error	z	p
Intercept	-9.4831	16.1039	-0.589	5.56e-01
NDVIE	39.9413	34.4409	1.160	2.46e-01
NDVID	58.8408	24.4824	2.403	1.62e-02
TMIN	0.0624	0.0140	4.457	8.29e-06
MLA1	-125.1069	141.9871	-0.881	3.78e-01
NDVIDA*TMIN	0.3416	0.1243	2.749	5.97e-03

Loglik(model)= -1231.1 Loglik(intercept only)= -1288.7

Table 4: Breakdown of area mapped to annual grass index values in five percent increments.

Index	Buffer				No Buffer			
	Pixels	Percent	Hectares	Acres	Pixels	Percent	Hectares	Acres
0	44637994	48.636	3625721	8955531	26162566	51.517	2125054	5248884
1 – 5	10870178	11.844	882930	2180838	6868227	13.524	557872	1377943
6 – 10	8499949	9.261	690408	1705309	5395249	10.624	438229	1082426
11 – 15	7330959	7.988	595457	1470779	4432374	8.728	360020	889248
16 – 20	5783310	6.301	469749	1160281	3147178	6.197	255630	631405
21 - 25	4250956	4.632	345284	852851	2030440	3.998	164922	407359
26 - 30	2999257	3.268	243615	601728	1237257	2.436	100496	248226
31 - 35	2061551	2.246	167449	413600	705650	1.389	57316	141572
36 - 40	1434764	1.563	116539	287851	396033	0.780	32168	79454
41 - 45	1022677	1.114	83067	205175	218029	0.429	17709	43742
46 - 50	741392	0.808	60220	148742	107319	0.211	8717	21531
51 - 55	545838	0.595	44336	109509	47007	0.093	3818	9431
56 - 60	409266	0.446	33243	82109	19752	0.039	1604	3963
61 - 65	312510	0.341	25384	62698	8894	0.018	722	1784
66 - 70	242723	0.264	19715	48696	4371	0.009	355	877
71 - 75	182620	0.199	14833	36638	2201	0.004	179	442
76 - 80	138520	0.151	11251	27791	1030	0.002	84	207
81 - 85	104157	0.113	8460	20897	475	0.001	39	95
86 - 90	74826	0.082	6078	15012	256	0.001	21	51
91 - 95	56260	0.061	4570	11287	122	0.000	10	24
96 - 100	79553	0.087	6462	15960	32	0.000	3	6

Table 5: Accuracy assessment statistics from 4 data sources: Southwest Regional GAP field data, Shrubmap data from Oregon, Shrubmap data from Idaho, and the modeling data collected for this project (commits error of circularity in using the same data to build the model as to assess the results). Statistics are comparisons of measured values at field plots versus estimated values mapped by the statistical model and subsequent processing. Correlation statistics include Pearson's R, Kendall's Tau, and Spearman's Rho (the later two being based on ranks). Percentile can be read as a confidence interval, for example "75 % of SWReGAP plots are predicted to within 2 percent of the field plot value."

Data	n	RMSE	Correlation			Percentile		
			R	Tau	Rho	50	75	95
SWReGAP	828	9.7%	0.33	0.36	0.39	0%	2%	20%
Shrubmap OR	662	14.8%	0.28	0.19	0.24	6%	14%	30%
Shrubmap ID	276	22.3%	0.60	0.40	0.50	11%	25%	52%
Circular	412	16.2%	0.55	0.45	0.56	3%	13%	35%

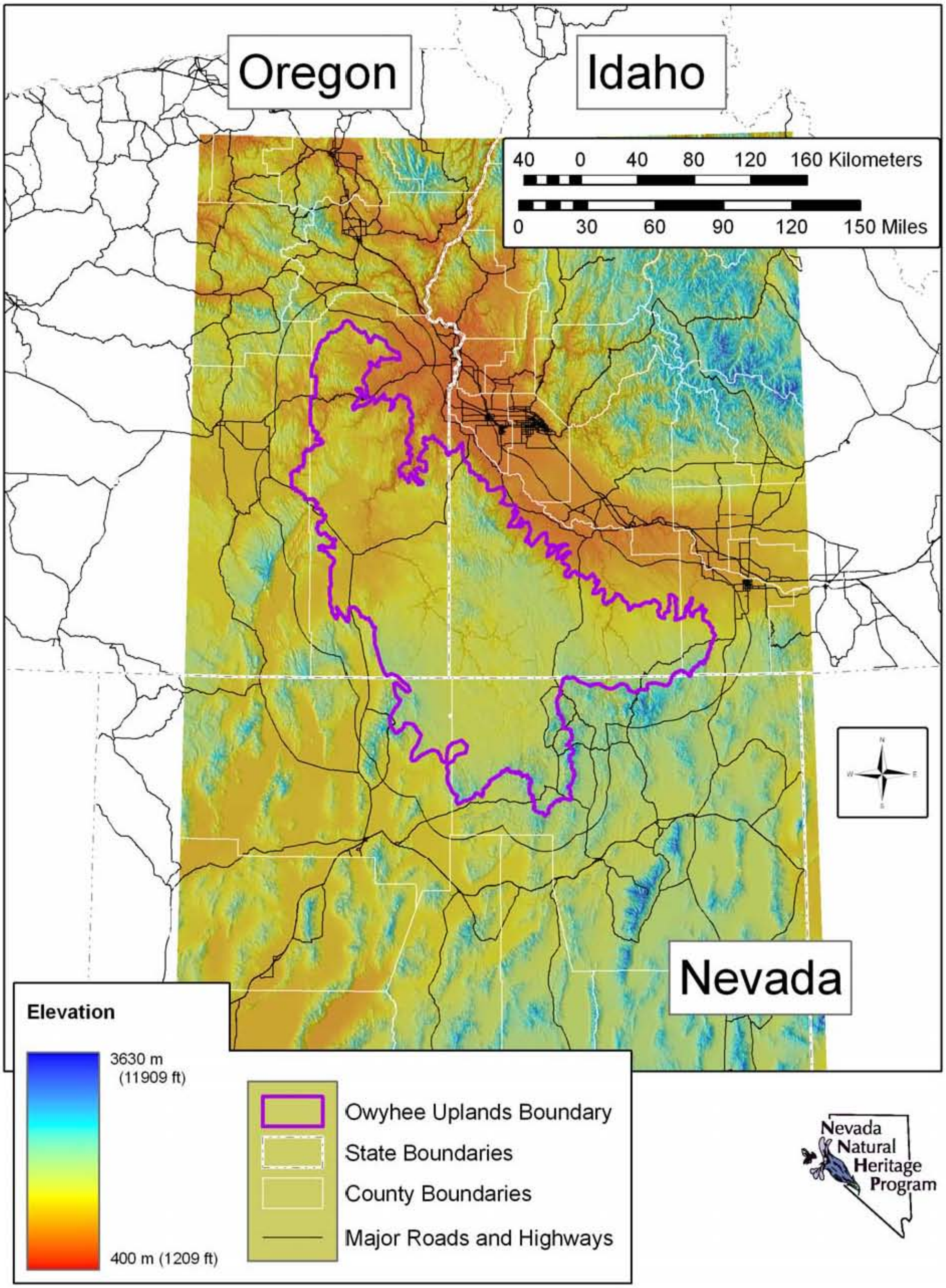

Figure 1: Landscape context of the Owyhee Uplands – a region within the intermountain west of relatively flat topography at moderate elevation.

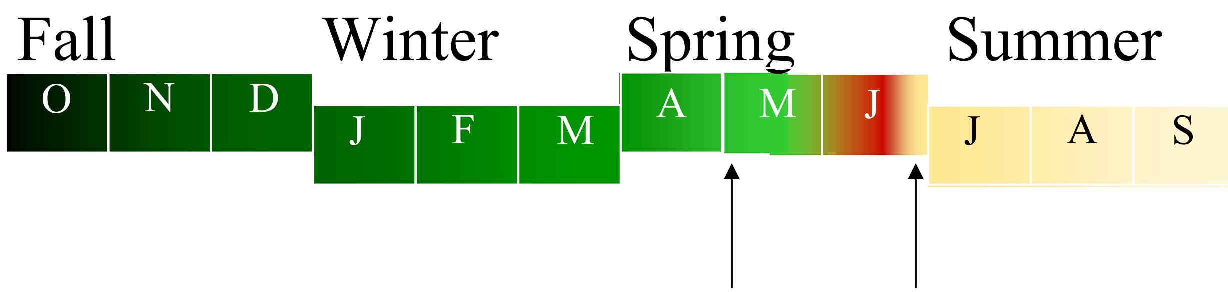

Figure 2: Illustration of the general phenology pattern for *Bromus tectorum* in the Owyhee Uplands. Letters refer to months of the year. *B. tectorum* can germinate after fall rains and over-winter, or germinates in early spring. Then it is ready for rapid growth as temperatures warm in the spring. By the end of May, it usually begins to senesce, first turning purplish-red, then drying out to straw-yellow. Arrows indicate optimal timing for satellite sensor data (imagery) with the first data collection during optimal growth and the second data collection just after yellowing, while most other vegetation remains active.

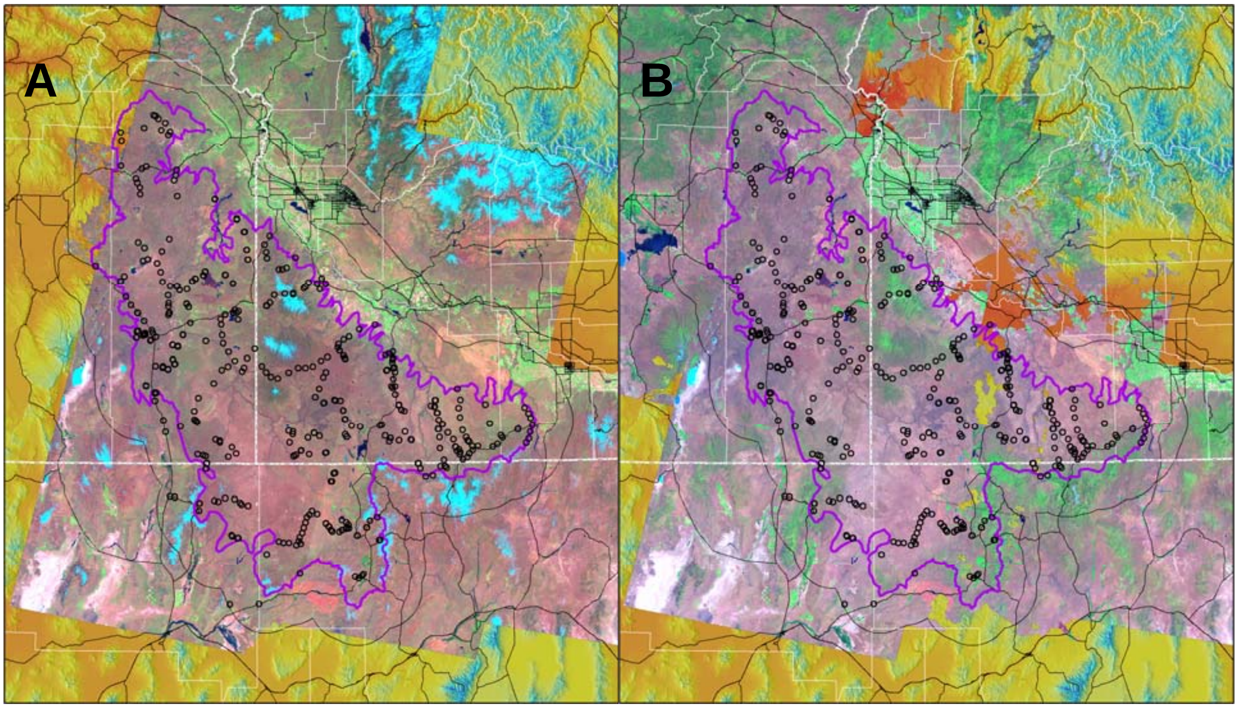

Figure 3: Landsat imagery with clouds removed, displayed with RGB channels referenced to bands 7, 4, and 1, respectively (this exaggerates greenness, while snow and shallow lakes take on a light-blue color). (A) Early season image set. (B) Late season image set.

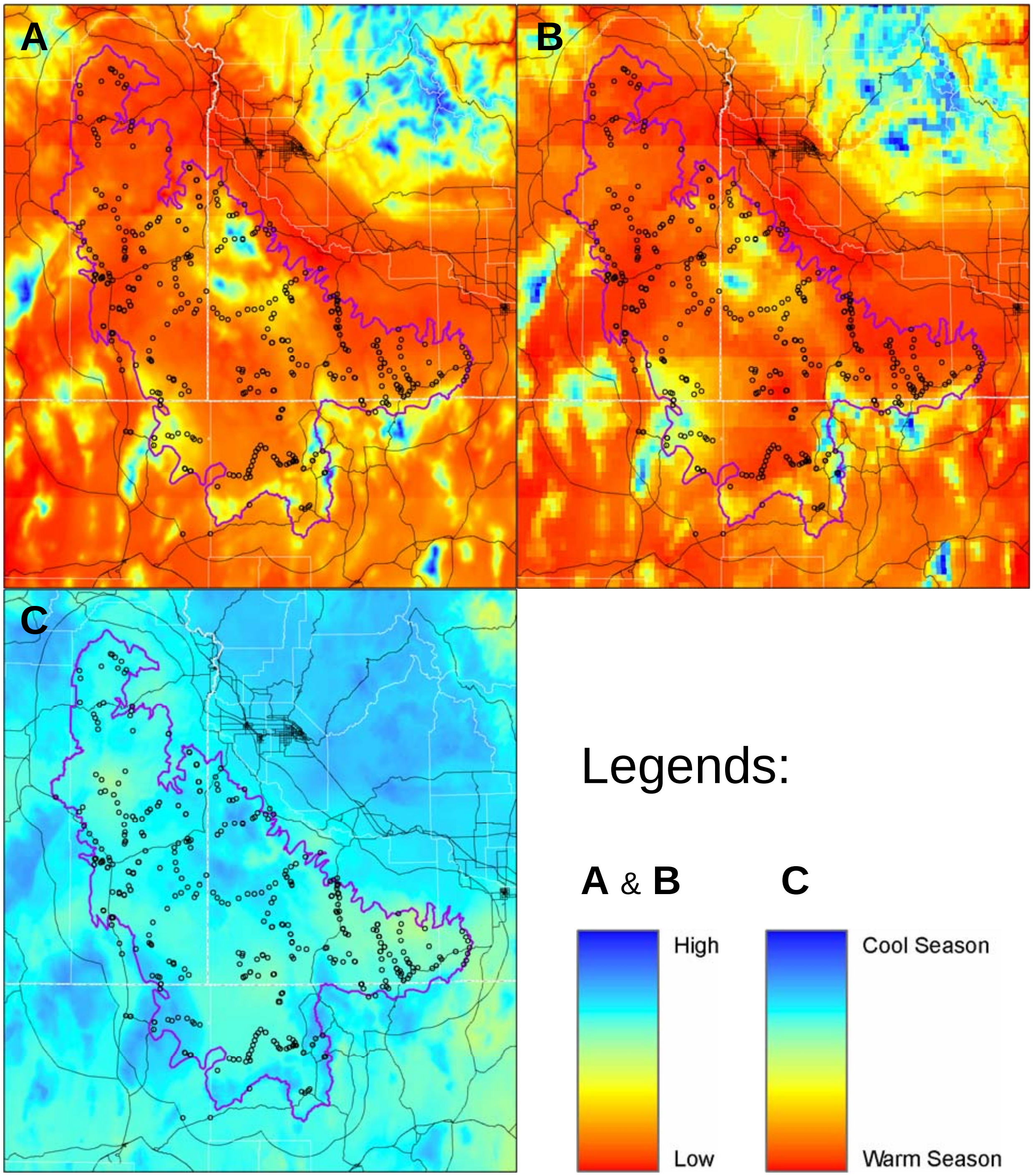

Figure 4: Precipitation data from, or derived from, PRISM Group models. (A) Average annual Precipitation years 1971-2000. (B) Water-year total (October 2005 through April 2006). (C) Timing of precipitation calculated as the normalized difference of precipitation falling January through April versus July through October.

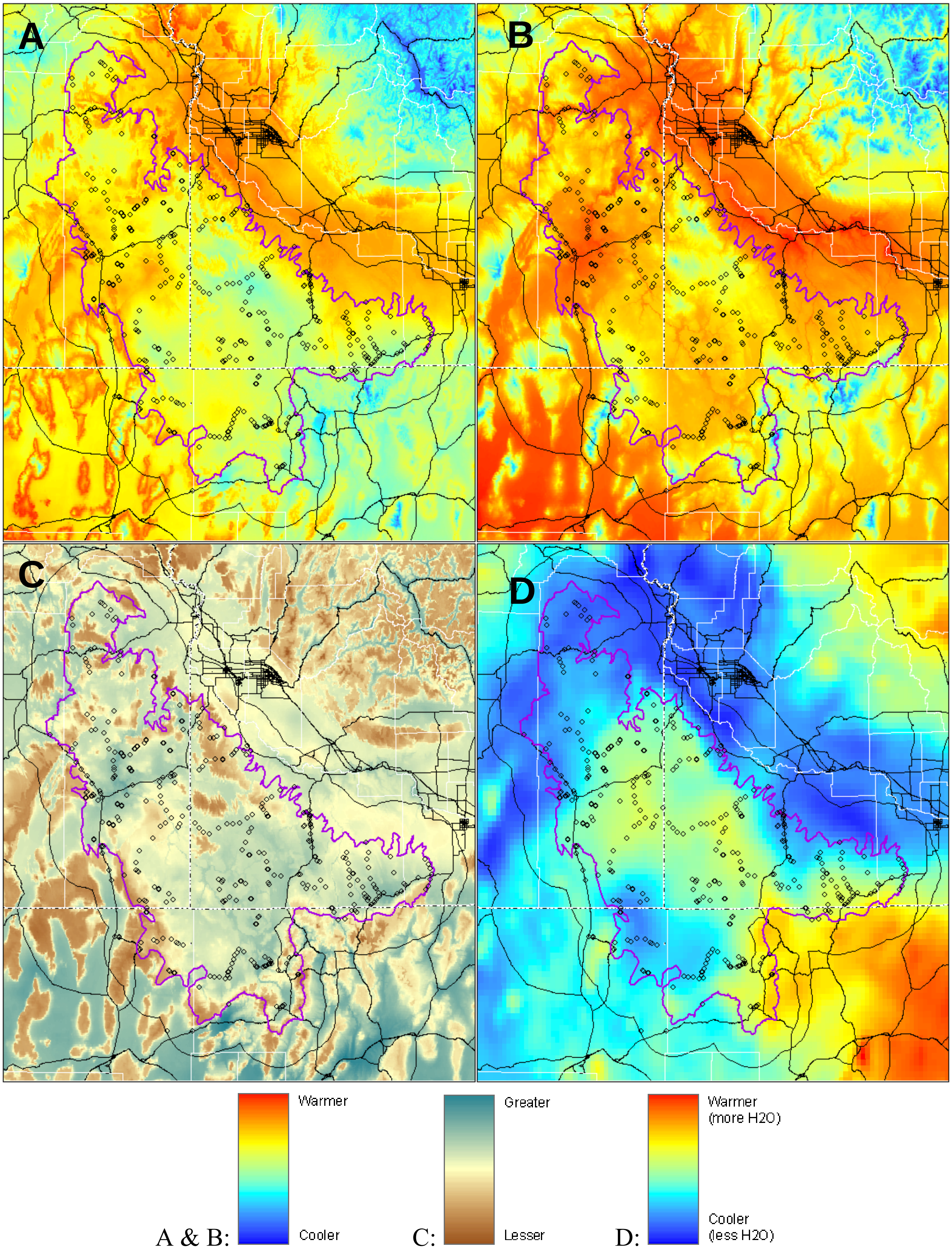

Figure 5: Temperature and dew-point data from, or derived from, PRISM Group models of year-round averages. (A) Minimum temperature. (B) Maximum temperature. (C) Difference between maximum and minimum temperatures. (D) Dew-point temperature.

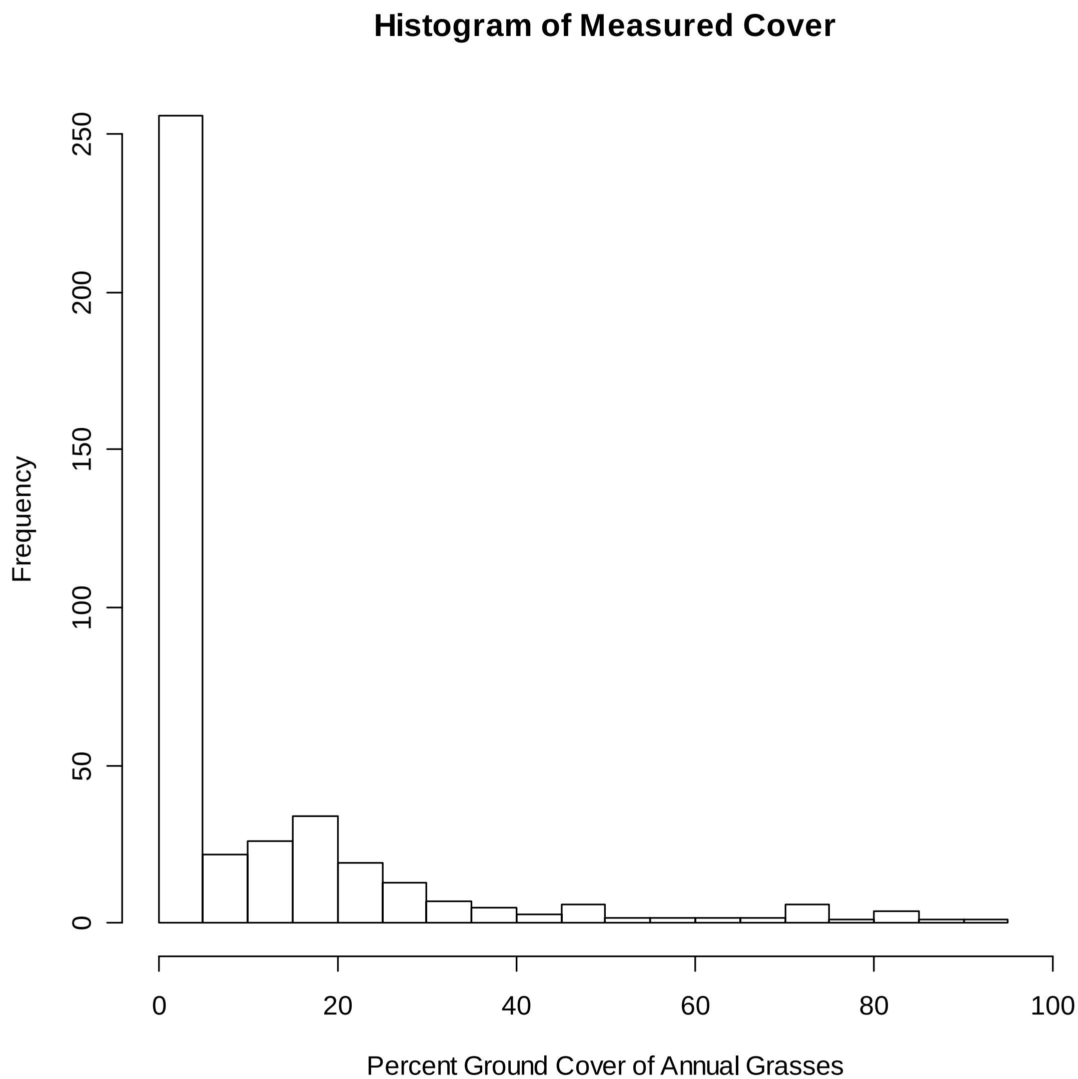

Figure 6: Histogram of percent ground cover values in 5 % increments for total annual grass measurements at 412 field plots.

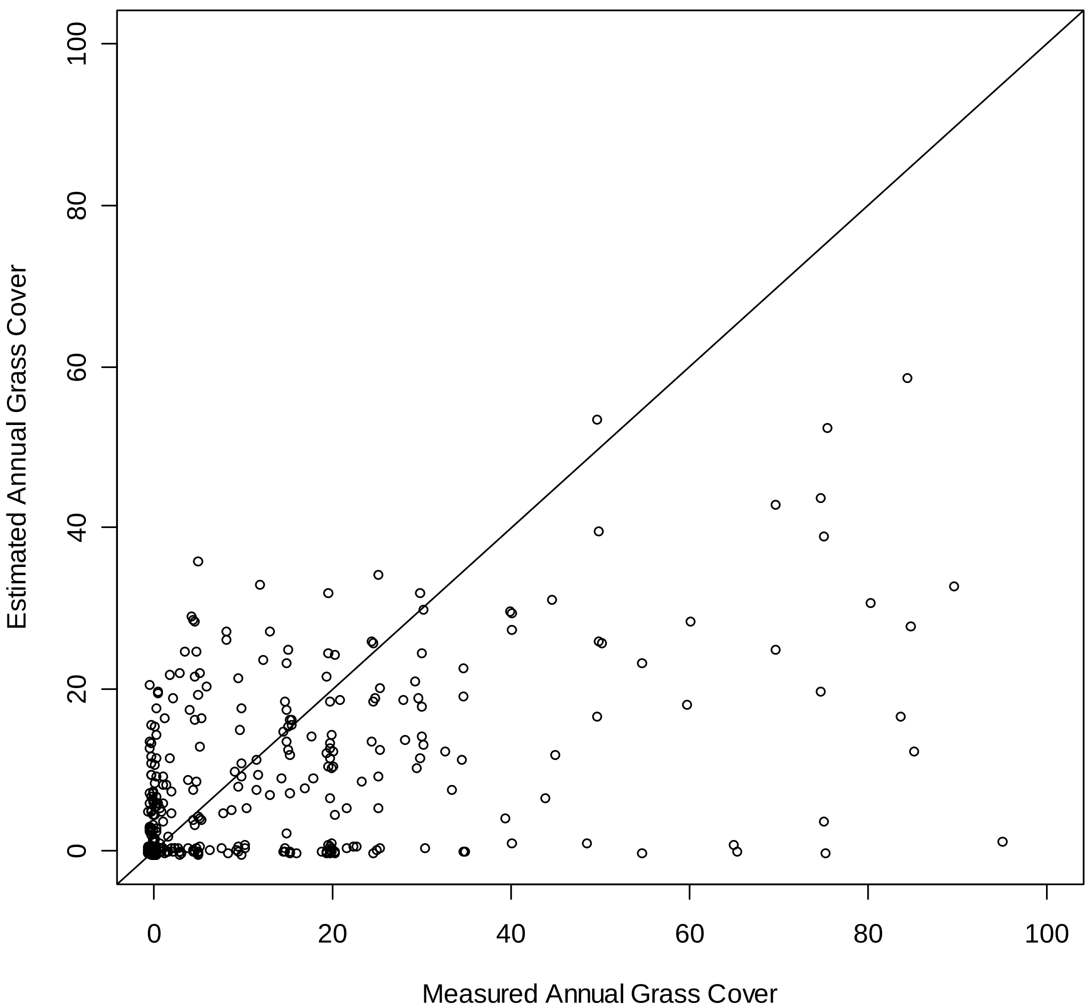

Figure 7: Plot of actual values from field data plots versus predicted values for the plots. Diagonal line represents the ideal 1:1 relationship. Data are jittered up to 0.5 in percent cover to better view overlapping data.

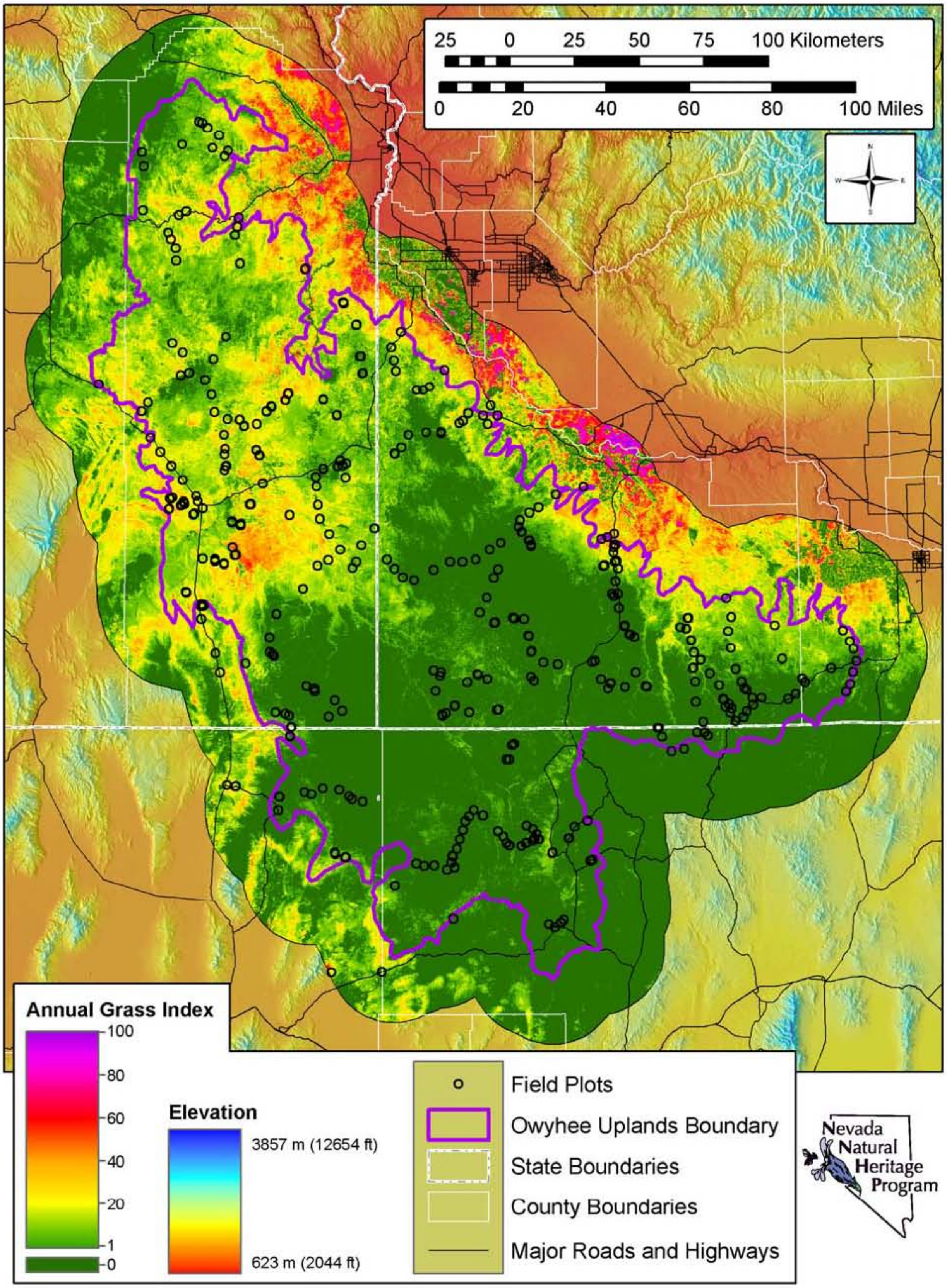

Figure 8: Annual Grass Index Map for the Owyhee Uplands plus a 25 km (15.5 mi) buffer.

APPENDIX A:

Discussions on sources for error from previous annual grass maps (Peterson 2003, 2006). Discussions are quoted here directly from the reports and relevant citations are included. Tables and Figures are omitted; complete reports are available online at http://heritage.nv.gov – google searches on content from these quotes should also reveal download locations.

Peterson 2003:

"Little published research is available for evaluating what constitutes a 'good' error rate. However, I believe the error rates reported for this map are quite good. Most remote sensing of vegetation components involve classification into categories. Reported accuracy for classification maps generally range ca. 70 - 90 % (or 10 - 30 % error). The GAP landcover map for Nevada reports 64 % correctly classified pixels (Homer 1998). The GAP landcover map for Utah has a substantially higher reported accuracy of 83 % (Edwards et al. 1998). The map of *Bromus tectorum* estimated percent cover is fundamentally different from those classified maps in that percent cover is a continuous variable rather than a categorical one. Comparison to categorical maps requires categorizing the *B. tectorum* map by setting arbitrary break-points in percent cover. Viewing only the presence versus absence of *B. tectoru*m in the map presented here, 64 % of the accuracy assessment sites were properly classified (Table 3). However only a one percent error (from 0 to 1 percent or 1 to 0 percent) could cause miss-classification and one might expect such low quantities would be difficult to detect by satellite. Considering a more detectable break-point, below 10 % cover versus 10 % and above, the number of accuracy assessment sites correctly classified jumps to 85 % even though a one percent error (i.e. 9 % versus 10 %) could still cause misclassification.

Very few cases of deriving continuous biological variables from remote sensing imagery are discussed in the literature. Most cases involve estimations of Leaf Area Index (LAI) or forest volume characters. White et al. (1997) estimated total vegetation LAI from Landsat-5 TM (an earlier version of the satellite I used) imagery for Glacier National Park (within a single satellite image) with R2 = 0.97 and no RMSE figure was given. Hyyppä et al. (2000) compared various sensors, including Landsat TM for estimating forest mean height, basal area, and stem volume with R2 values ranging from 0.03 . 0.77 across all sensors and 0.26, 0.31, and 0.31 respectively for the Landsat TM values. Those performing better than Landsat were higher in resolution, including the Spot satellite and 3 airplane mounted sensors. Stem volume has also been estimated in small areas by Lidar, an exceptionally precise laser scanning system, with R2 = 0.90 but that corresponded to RMSE = 22 % (Holmgren et al. 2003). Perhaps most relevant to the *B. tectorum* map, Cohen et al. (2002) measured total canopy cover at agricultural sites within a 25 km^2 area with R2 = 0.67 and RMSE = 10.41 %.

The 9.14 % RMSE of the B. tectorum map also seems good in light of the potential error sources. One major source of error is the ocular estimation method used for determining B. tectorum cover in both training and accuracy assessment plots. While many experienced plant ecologists can distinguish between 0, 5, or 10 % cover, consistently distinguishing, say 6 % versus 8 % is near impossible. Such error may be even greater at higher covers, such as in distinguishing 30 % versus 35 %. Where estimations in this work were above 20 % cover, the estimations tended to be rounded to the nearest 5 or 10 %. Thus some error is inherent to the data. It should also be noted that ocular estimations are open to bias through consistently over or underestimating cover. Since the accuracy assessment plots were performed in the same way, I have no measure of such bias. However, since the ocular estimations were always performed by me, any bias in the ocular estimations should at least be fairly uniform. While this potential error and bias could be controlled by using different cover estimation methods for the sampled plots, such methods would be significantly more time consuming. In the trade-off between fewer, more accurate plots versus numerous, less accurate plots, the latter is preferable for this project as it allows for capturing more of the variation present in a large landscape.

Another major source of error is from temporal variation in *B. tectorum* cover. The satellite imagery was from the year 2001, most training plots were examined in 2002 with a few more in 2003, and all accuracy assessment plots were examined in 2003. Many of the high density *B. tectorum* stands were initiated after the 1999 summer fire season and may be still increasing in density each year. Other recently invaded areas are also probably still increasing in density. For areas where *B. tectorum* density has maximized, annual variation in rainfall or other environmental factors will still cause year-to-year variation. In the creation of this map, training and accuracy data were all from locations that had not been significantly disturbed since 2001. The model fitted the training data to the phenology signal from the 2001 imagery. Then the model was separately run on the 2001 imagery. Thus, the map is effectively an estimation of the B. tectorum cover in the year 2001. Accuracy assessment plots were from 2003 so the error measure includes any further invasion over 2 additional growth seasons.

Locations where this map is most clearly dated to 2001 is in failed greenstrips that were initiated during the previous year (barren of *B. tectorum* in the 2001 imagery and mapped as such). Several of these greenstrips were observed during the fieldwork, where the land had been disk plowed then seeded. The planted seeds had largely failed to germinate or establish, allowing dense stands of *B. tectorum* to form by the summer of 2003, even though adjacent recently-burned areas seeded without disking had great establishment of native grasses and crested wheat with near-exclusion of *B. tectorum*. The frequency of these failed greenstrips on the landscape is quite discouraging. There seems to remain a leaning in land management agencies to solve revegetation problems with industrial agriculture techniques such as disk plowing even to the acknowledged detriment of other ecosystem components. This is demonstrated in a discussion of advantages of mechanical treatment in a recent sagebrush management guideline publication (U.S.D.I. 2002):

> ‘The potential to damage biological crusts, however, must be weighed against the potential consequences of a failure to act. Irreversible dominance by annual species such as cheatgrass can prevent the return of even well-developed biological crusts.’

Soil crust communities in sagebrush ecosystems require decades to establish and more to mature (Belnap et al. 2001). They are valuable for erosion control and soil quality (Belnap & Gillette 1998; Eldridge & Greene 1994), and may even inhibit B. tectorum germination (Kaltenecker et al. 1999; Larsen 1995). Given the failure of many greenstrips, I suggest that the potential damage to biological soil crusts combined with the risk of failure outweighs any advantages on land with moderate to high cover of soil crusts and, following adaptive management philosophy, suggest that greenstripping with disk plowing should be reexamined and continued only with caution. Perhaps drill seeding could be favored over disking as a less soil-disturbing method that still plants the seed (Hilty et al. 2003).

A third major source of error is that phenology is not a perfect predictor of *B. tectorum* cover. The phenology as detected by the satellite is integrated over all vegetation within the 30 m X 30 m pixel. Plants other than *B. tectorum* within the pixel with different phenologies will alter the phenology measurement. But what appears to be most relevant is that certain plants have similar phenology to *B. tectorum*, causing over-estimates of *B. tectorum* where they are abundant. From field experience, two plants cause such error at scales that are visually noticeable: *Lepidium perfoliatum* L. and *Poa secunda* J. Presl. *L. perfoliatum* is an annual nonnative weed that is often abundant in highly disturbed areas. It is known to have caused over Battle Mountain peak, just southwest of the town of Battle Mountain and in Buena Vista Valley on the lower alluvial fans from the Stillwater Range. *P. secunda* is a widespread perennial native grass with tremendous genetic and ecotypic variation, which has been considered to include multiple species in the recent past. *P. secunda* appears to have only inflated estimations of *B. tectorum* cover in a few portions of the map suggesting that only a portion of the variants have early enough phenology to cause noticeable error in the *B. tectorum* estimations. Over estimations caused by *P. secunda* are in a small area at the north end of Jersey Valley, and over much of the eastern Owyhee Plateau. The latter is by far the most extensive noticeable error in the map.

The final major source of error is in the limitations of the statistical model. Although Tobit Regression overcomes the zero-truncation problem, it is still a linear modeling method. The plot of predicted versus measured cover of *B. tectorum* (Figure 11) indicates overestimation of low cover values and underestimation of high values, suggesting that the true relationship between phenology and *B. tectorum* cover is non-linear. The inclusion of phenology in the model in a quadratic form reduces this problem (the discrepancy shown in Figure 11 is even greater without the quadratic term), but the problem cannot be eliminated while using Tobit Regression. A non-linear modeling method which has potential to solve this problem, Nonparametric Multiplicitive Regression, a multivariate kernel technique (Peterson 2000; McCune et al. 2003), is currently under development but was not available for geographic mapping in time for this report.
Potential sources of minor error are numerous and cannot be discussed exhaustively. Notable sources include any agricultural cultivation and human habitation areas not masked as ‘urban’ or ‘cultivated’. Such areas often include vegetation removal, crop irrigation, landscaping, and other alterations to the plant-life on the land that result in changes to phenology and thus affect estimations of *B. tectorum* cover. Another potential source of error are thin clouds and haze that are not distinct enough to have been masked out of the map, or clouds and cloud shadows erroneously not masked. Positional error resulting in improper alignment of the sampling plots with the imagery may have resulted from both the quality of GPS receiver used, and from the geometric correction of the images.

Given that RMSE = 9.14 % and that the parameters used in the model, particularly the measure of phenology from the satellite data, were statistically significant (p-values < 0.05), I do not reject my first hypothesis, .that the early phenology of *B. tectorum* can be used to distinguish it from other vegetation, using satellite imagery from two separate dates.. There may be some issues of reliability for distinguishing *B. tectorum* from *Lepidium perfoliatum* and *Poa secunda*, and I would recommend land managers do some reconnaissance prior to making decisions based on this map. But errors from those species appear to be localized. There is little doubt that this map provides a strong overview of the invasion of *B. tectorum*.”

Relevant Citations:

Belnap, J. & D. A. Gillette. 1998. Vulnerability of desert soil surfaces to wind erosion: impacts of soil texture and disturbance. Journal of Arid Environments 39: 133-142.

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Peterson 2006:

"*Sources of Error:* There are countless sources of error in any remote sensing project; any imaginable natural or human-caused variation in the spectral reflectance or accessory modeling can reduce the quality of a map. Here I will focus only on major sources of error.

The training data were collected through ocular estimation. This method was necessary for rapid gathering of a large number of plots. However, the method is subject to observer bias. This was discussed thoroughly by Peterson (2003) and will not be discussed further here.

Annual grasses are known to have substantial inter-annual variation in biomass (Bradley & Mustard 2005). There is little doubt that such variation causes some degree of error in the

ANGRIN map, as data collection was from the years 2002 through 2005 and included both relatively dry and wet years. For this reason in addition to the poor estimation of high-density annual grass sites, I suggest that the map be treated as an index of annual grass cover rather than an estimation of actual cover. Nevertheless, some assumptions of increased annual grass cover after wet winters in the Great Basin deserve review. The data shown in Figure 12 might suggest the opposite. Those data are not conclusive, however, in that observer bias may have changed between the initial plot sampling and the repeat. Still, the NNHP has photographs of most of these plots from both sampling dates and reduction in *Bromus tectorum* is quite visible in some and my personnel observation is that while *B. tectorum* certainly grew taller after the wet winter, it did not necessarily occupy more ground-cover. On an anecdotal note, one plot near the south end of the Sonoma Range in Pershing County in particular has had impressive growth of *Poa secunda*. The plot was near an area that burned in 1999 and may have been receiving tremendous input of *B. tectorum* seed when first sampled in 2002, but for whatever reasons (land management?) *B. tectorum* has reduced in the burned area and *P. secunda* has occupied much of the ground space at the plot.

Inter-annual variation in annual grass cover is much more substantial toward the south, particularly in the Mojave. Many places that might seem devoid of herbaceous plants in dry years were thickly carpeted with *Schismus barbatus* in April and May of 2005. The discrepancy histogram for the MOJAVE data (Figure 22) is skewed opposite of the REGAP discrepancies; for the MOJAVE data, ANGRIN values were generally *higher* than measured ground cover. This is presumably the result of using 2005 satellite data for the ANGRIN map (following a wet winter), while MOJAVE data were collected in relatively dry years. The inclusion of other early-season annual plants in the Mojave may also contribute to the higher values in the ANGRIN map.

This method requires a clear and relatively uniform phenology pattern. The senescence of *Bromus tectorum* in the relatively dry years of 2001 to 2003 appeared to be quite uniform across the region mapped by Peterson (2003, 2005). The spring of 2005, following a relatively wet winter and spring, had geographically variable timing of senescence, possibly due to variation in late-spring rainfall. For that reason, and for problems with clouding of imagery, 2005 satellite sensor data was not used in the north. Instead, 2004 data was used on the assumption that having been a relatively dry year, it would have a relatively geographically uniform senescence pattern like the previous years. It is difficult now to roll back the clocks and properly assess this, but it is possible that senescence was geographically variable in that year, which would add noise to the phenology signal. Additionally, a larger and more ecologically variable area was mapped from the 2004 satellite sensor data than was mapped in the previous project, adding to the potential for geographic variation in senescence. Also supporting more heterogeneity in senescence timing, ΔNDVI was not really significant when modeling with the spatially chunky MODIS data (Table 4).

Possibly the most problematic source of error in the southern area is a compression of growth and senescence seasons. There is little, if any, time difference between senescence of annual grasses and senescence of other annual vegetation. Given that the annual grass signal in satellite imagery for the Mojave may be trivial during dry years and may be flooded with noise during wet years, it may not be practical with current remote sensing technology to map annual grass cover specifically on a regional basis. Hyperspectral imagery may provide alternative avenues to explore for mapping of annual grasses, but at present, such imagery is simply not available for such vast areas and would be expensive to collect even at the scale of a county.

Even in the northern portion of the state, some other species may have similar phenology as that of the annual grasses. The predominant ones on the landscape are the invasive annuals *Lepidium perfoliatum* and *Ranunculus testiculatus*, and the native perennial *Poa secunda*. In the previous mapping effort (Peterson 2003, 2005), *P. secunda* caused substantial error in the Owyhee Uplands just west of the Bull Run Mountains. That error does not appear as significant in the ANGRIN map, though the precise reason has not yet been sought. For further discussion of this source of error, see Peterson (2003).

For the southern analysis (LL05), a number of the rejected models showed ΔNDVI to be statistically insignificant. When significance was found, the slope turned out to be negative: opposite of what is expected if senescence is being measured. There are two possibilities for this. One is that the early season imagery has a low sun angle, thus the imagery is dark. Although the normalization of NDVI attempts to prevent error from variable brightness, this may still be a cause of early season NDVI being lower than late season NDVI even where annuals are senescing. The second possible reason is that the growth season is much compressed in the Mojave relative to other parts of Nevada; growth happens quickly, as does senescence, and there is little time between senescence of annual grasses and other vegetation. Both the annual grasses and other annual vegetation had fully senesced over much of the landscape by the time of field sampling in the Mojave during early May, 2005 so late April was targeted for satellite sensor data. However, much of the Landsat data suggests that these annuals, including the grasses, were still photosynthetically active through much of April. Thus much of the late-season imagery for southern Nevada may have been from too early in the season.

There was a lot of variation in the date of the satellite sensor data that may have also added noise to the phenology signal. Although the date, or time between early and late season dates, did not account for much variation in the data and was of limited significance (Table 4), the effect of differing imagery dates on the ANGRIN map is obvious and widespread in Clark and southern Lincoln counties. In fact, the variable for the number of days between acquisitions was left in the LL05 model despite a lack of statistical significance because retaining it made a visual reduction in this error. Despite the coarse resolution, the MODIS derived map may be more useful in this area for understanding relative quantities of annual grasses from one place to another. Moderate to high resolution satellite sensors such as Landsat are limited in timing of data acquisition and clouding will frequently be problematic.

Modeling annual grasses over the entire state of Nevada with just a few equations has been surprisingly successful given the ecological variation in the state. However, people with field experience will notice regions where ANGRIN values seem generally low or generally high. The ecoregion data was constructed as an attempt to reduce this problem and did help substantially to improve accuracy for most regions. The eastern great basin, however, appears to be substantially underestimated. This may be due in part to less geographic spreading of annual grasses to present, and consequently a larger proportion of training data plots with zero annual grass ground cover. The high valleys in the central part of the state are also underestimated, showing only a few areas with low cover. While the geographic extent of annual grasses is limited there, cover can be high at times. To the west and North, the ecoregion variables performed well. Initially, the Owyhee Uplands were separated from the rest of the Columbia Basin, but this distinction made little difference so they were ultimately combined. There may be some underestimation of annual grasses along the southern edge of the Owyhee Uplands (roughly from Midas to Tuscarora) and perhaps the ecoregion boundaries should have been altered there to prevent the reduction in estimates used for the Columbia Basin in general.

Although the intent of this project was to map annual grasses *within* Nevada, the models were allowed to run geographically beyond the border to the end of the Landsat data footprint. Geographic extrapolation of an annual grass model was found to yield valid results when to a limited degree and mostly within a single ecoregion by Peterson (2003). It is likely that the ANGRIN map provides useful information in portions of all states included. However, map users should be wary in Arizona, California, and Utah where it crosses into the Sonoran Desert, the Colorado Plateau, and (especially) California's Central Valley as the project never intended to map annual grasses within those regions.

Similarly, this project was intended only for wildlands, not for urban and agricultural lands. Peterson (2003) masked over these intensively manipulated lands. These have not been masked in the ANGRIN map, partly due to lack of project time. However, such masking would also cover greenspace and other open sites within populated areas, so perhaps there is reason to leave them unmasked. Nevertheless, these areas will often show very high values in the ANGRIN map. Particularly when agricultural fields are irrigated early in the growing season, but left to dry later in the season; to the modeling method, their phenology signature will appear similar to dense annual grasslands and they will be incorrectly mapped as such.

Tobit regression has a strong advantage over many modeling methods in it's handling of censored data (limited to zero and positive values). However, it is a linear modeling method and distributions of response variables (e.g. annual grass cover) over satellite sensor data variables is generally non-linear (see Figure 13A). This source of error was discussed by Peterson (2003) so I will not dwell on it here, but alternative methods do need to be explored. Multivariate windowing techniques (Peterson 2000) and particularly Nonparametric Multiplicative Regression have potential to provide more realistic models of the data. In fact, I had intended to explore these with the current project. However, the project was conducted on a truncated timetable due to unexpected delays. Current software for those techniques are limited in the size of geographic data files that they can use and considerable time may need to be devoted to reprogramming their data handling capabilities. It is hoped that more robust software will be available for future annual grass mapping projects."

Relevant Citations:

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