A Map of Invasive Annual Grasses in Nevada Derived from Multitemporal Landsat 5 TM Imagery

Schismus barbatus in *Larrea tridentata* shrubland

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Note:
Portions of this report and related studies will be submitted for publication in scientific journals. A few minor typographical errors were corrected 8 May 2006.

Summary Invasive annual grasses are an ecological catastrophe that we must contend with. The Nevada Natural Heritage Program has developed geographically explicit statistical models and mapped annual grass distribution over the state of Nevada. The models and final map were developed from 806 training sites sampled on the ground, remotely sensed data for two seasons from Landsat 5 TM and MODIS satellite sensors, and accessory geographic data. Accuracy of the final map was analyzed from three independent data sets: Southwest Regional Gap Analysis Project (REGAP) training data (15,318 plots); California Department of Fish and Game vegetation plots from the Mono Lake area (178 plots); and from the Mojave region (939 plots). Data from the Mono area had sparse annual grass cover, therefore summary statistics from that data set may not be appropriate. However, the landscape-level distribution of annual grasses in the plots corresponded reasonably well to the distribution of annual grass in our final map. Root-Mean-Square-Error (RMSE) from the REGAP data was 10.33 %; 75 percent of predictions for gap plots were off by 5 % or less; and 95 percent of predictions were off by 21 % or less. For the Mojave data set, RMSE was 7.48 %; 75 % of predictions were off by 9 % or less; and 95 % of predictions are off by 15 % or less. Accuracy assessment on REGAP data, as well as review of predictions for training data plots, suggest that annual grasses are generally underestimated for sites with high density of annual grasses. Although data were collected that suggest inter-annual variation in the north does not necessarily result in greater cover after wet winters, assessment with Mojave data does reveal strong inter-annual variation in annual grass cover for that region. Due to both the underestimated values for high-density annual grass stands, and the recognition of inter-annual variation, it is recommended that the map presented here be interpreted as an annual grass index (ANGRIN) map, rather than an estimate of actual annual grass cover. Nevertheless, the ANGRIN map clearly reveals the pattern of annual grass invasion across Nevada.

INTRODUCTION

Invasive annual grasses are a blight on the intermountain region and an ecological catastrophe that we must contend with. What has brought on this problem is uncertain, and what the solutions will be are even less known. Ideas on the causes are varied. Among these ideas are simple progressive expansion, that these non-native grasses have found an open niche and will gradually expand until the niche is filled. Another idea is that heavy land use (present or past) has opened native communities to invasion. Some people speak of a threshold being crossed in the 1970's. Prior to that, one of our most pervasive annual grasses, *Bromus tectorum* (cheatgrass), was little more than a roadside annoyance, but during that decade it began to expand in a massive way. Perhaps a threshold of geographic distribution and seed production was achieved, or perhaps weather patterns have been more favorable for the grass since then. Another intriguing idea is that the atmospheric concentration of CO_2 reached during the 1970's was the fulcrum of change; annual grasses have been demonstrated to take advantage of increased atmospheric CO_2 more than some native species (Smith 2000). One reason I find that possibility so interesting is that it points to a solution, though a long term (centuries?) and politically challenging solution: reduction of atmospheric CO_2 to an earlier level. But if the science of ecology has taught us anything, it is that natural systems are complex and problems with single causes are exceedingly rare; some rich blend of causes are probably in action.

Whatever the causes, solutions are not easy to find. Herbicides have been successfully used to treat limited areas, and might be useful in maintaining breaks in the ‘cheatgrass sea’, or toward the south, the 'Schismus sea'. However, treating tens, or probably hundreds, of millions of infested acres throughout the west with herbicides is unrealistic. That does not mean that we should give up! California's Central Valley was nearly completely converted to invasive annual grasses nearly a century ago, yet people maintain hope for small pieces of remnant native grasslands. The intermountain west still retains vast areas of native communities. Furthermore, the region has vast areas maintained by public agencies, which provide potential for landscape-level strategizing against complete transformation of our ecosystems. There is room for optimism, if regional strategies can be sought, found, and employed.

Regional strategies for dealing with invasive annual grasses, as well as strategies for living with them in the mean time, require not just an understanding of annual grass dynamics. It will require a geographic understanding of the problem – the pattern of invasion across the landscape. For this reason, the Nevada Natural Heritage Program (NNHP), which monitors our biodiversity in the state, has taken a large interest in invasive species. The work on mapping invasive annual grasses presented here is but one step toward a more comprehensive understanding and monitoring of native ecosystems, their biodiversity, and their biogeography – past, present, and future.

METHODS & MATERIALS

Annual grasses tend to have a short lifespan, senescing earlier in the season than perennials. Satellite sensor data (imagery) can detect chlorophyll concentration over the landscape (Jensen 1996). Locations with large concentrations of annual grasses should show a marked drop-off in chlorophyll when annual grasses senesce. Thus the change in chlorophyll concentrations as measured by satellite can be correlated with the actual ground cover of annual grasses at training sites, and thus be used to create predictive models of annual grass cover (Peterson 2003, 2005; Figure 1).

The methods used here are very similar to those used to map *Bromus tectorum* previously (Peterson 2003, 2005). 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, used in geographic mapping algorithms and evaluated visually. 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 4.2 (Research Systems Inc. 2005) with nearest neighbor resampling and 100 X 100 triangulation points for reprojections. All statistical analyses were performed with the R statistical package (R Development Core Team 2005)

1. Training Data (Model Calibration): We used 0.1 ha circular plots (17.8 m radius) for vegetation sampling. Geographic position of plot centers was measured with a 12 channel GPS receiver with Root-Mean-Square Error (RMSE) < 15 meters (Garmin GPS12, Garmin eTrex Legend, or Leica GS20). Within the sampling plot, we used ocular estimation of percent cover for each species of annual grasses. For analysis, cover of all annual grass species was summed. Additional data were also collected including slope, aspect, and cover of other vegetation components, including cover for each species of perennially above-ground vascular plant, and cover of biological soil crusts. Data were entered directly into a Geographic Information Systems (GIS) point coverage with ArcPad 6 (ESRI 1995-2005) in order to eliminate transcription error.

Most plots were located strategically in order to incorporate a broad variety of landscape forms and vegetation types into the training dataset. Locations were found by driving roads throughout the state and watching for areas of uniform vegetation of approximately 1 ha or larger. For efficiency, most plots were located within 0.5 km of drivable roads. Plots used for modeling were measured no earlier than the year 2002. Additionally, the randomized plots used for accuracy assessment by Peterson (2003, 2005) were included in the training data for the current project.

2. 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 obscuring by clouds. 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*. Target dates for growing season was the month of March in the south (roughly the Mojave ecoregion), and Mid-April to Early May in the north. Dates for senescence were Mid-April to Early May in the south, and Mid- to Late-June in the North.

The Landsat 7 ETM+ satellite sensor previously used by Peterson (2003, 2005), developed a problem with its scan-line-corrector on 31 May 2003 (USGS 2006b). Data from this satellite are still useful for many projects, though substantial gaps exist near the edges of the scenes (Figure 2). These gaps can be filled with data from alternate scenes, but for a project like this where phenology is critical, use of gap-filled scenes may be unwise. 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, so data from this sensor was used. All Landsat data were purchased from the U.S.G.S. EROS data center in UTM zone 11, NAD 83 projection with terrain-correction and a spatial resolution of 28.5 meters.

There is substantial inter-annual variation in densities of annual grasses, particularly between wet and dry years as measured by total precipitation (Bradley & Mustard 2005). Fieldwork on this project in the years 2002-2005 suggest that phenology of annual grasses is more geographically variable in wet years than in dry years, so a dry year with relatively low cloud cover (2004) was targeted for the northern portion of Nevada. However, during dry years in the southern, Mojave, portion of the state annual grass production is dramatically lower than in wet years, such that annual grasses might be difficult to detect reliably. Thus, a wet year (2005) was targeted for the southern portion of Nevada despite substantial clouding of some scenes. Scenes were overlain and mosaicked to maximize coverage for the two time periods in the two geographic zones (Figures 3 and 4).

Twenty-one scenes are required at a minimum to provide a single coverage of the entire state of Nevada (Figure 5). Landsat satellites capture a given path only every 16 days, so choice of scenes within the time windows is quite limited and clouds were problematic in many scenes throughout the state. Additional (though often sub-optimal) scenes were purchased in many cases to fill-in the 'holes' left by clouds in the optimal scenes (referred to hereafter as 'cloud-holes'). The entire Landsat 5 TM data set of 59 scenes is summarized in Table 1. Even after the inclusion of additional scenes, many cloud-holes remained. Thus data from an additional satellite sensor, MODIS, were obtained. 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, multiple-day data composites are available that greatly reduce the problem of obscuring by clouds, and data can be freely downloaded. For this project, 16-day composite data with included vegetation indices (MOD 13 product; NASA 2005b) for dates that closely matched the corresponding Landsat data sets (table 1) were downloaded from the Earth Observing System Data Gateway (NASA 2005a).

The satellite data were analyzed in 4 distinct sets: the 2004 Landsat data in the north where data exists for both seasons (LL04), the 2004 MODIS data to fill in holes with the prior (MM04), the 2005 Landsat data in the south where data exists for both seasons (LL05), and the 2005 MODIS data to fill in holes (MM05). Raw spectral band values were analyzed, along with derived values: NDVI (for each season), ΔNDVI, a Greenness Ratio (for each season), and ΔGreenness. NDVI (Normalized Difference Vegetation Index; Jensen 1996) is a ratio of a near-infrared spectral band (strongly reflected by chlorophyll) and the red portion of the visual spectrum (strongly absorbed). ΔNDVI was calculated as early season NDVI minus late season NDVI and forms the main measure of phenology. The Greenness Ratio was constructed to represent a greenness of annual grass infestations visible in false-color maps using Landsat bands 7, 4, 2 for red, green, and blue, respectively. The Greenness Ratio was calculated as:

$$GreennessRatio = \frac{B4}{B2 + B7 * 0.5}$$

where B*x* refers to the spectral band number within the Landsat 5 TM data (B4 is the same near-infrared band as used in calculating NDVI. The ΔGreenness was calculated in similar fashion to ΔNDVI using the Greenness Ratios.

3. *Accessory 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 simple geographic coordinates, elevation models and derived land features, estimated precipitation pattern, and ecoregional variation. These are described below.

Elevation and derived land features. 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. 2005; Figure 6a) and reprojected to match the Landsat data. From elevation data, we calculated slope, aspect, heat index, exposure, and aridity indices (Figure 6b-6f) as described in Table 2. Supplementary datasets were calculated from the original un-projected data and subsequently reprojected to match the Landsat data set as completed.

Precipitation. Total annual precipitation corresponds strongly to elevation within the state of Nevada, so total precipitation itself was not analyzed. However, substantial variation exists in the timing of precipitation across the state. Two datasets were constructed to represent normalized seasonality of precipitation (Figure 7), as derived from the PRISM precipitation models (Spatial Climate Analysis Service, Oregon State University 2003). The first contrasted only two months, January versus August (JA) while the second contrasted the total of January to March versus July to September (JFMJAS):

$$JA = \frac{JAN - AUG}{JAN + AUG}$$

$$JFMJAS = \frac{(JAN + FEB + MAR) - (JUL + AUG + SEP)}{(JAN + FEB + MAR) + (JUL + AUG + SEP)}$$

where the three letter abbreviation for each month is the total precipitation for that month according to PRISM models from the years 1971-2000.

Ecoregions. Maps produced by early models indicated a strong geographic trend in error, most noticeably predicted annual grass values were low on the eastern side of the state. One would be surprised if a single equation could uniformly map any vegetative characteristic across the entire state, so to allow for ecoregional variation, an ecoregion map was constructed (Figure 8). The regions are largely based on agglomerations of sub-regions defined by Bryce et al. (2003), but with substantial editing based on field experience and with the intension of mapping boundaries in the behavior of annual grasses. The map construction did not directly utilize a geographic analysis of error from annual grass modeling.

4. Modeling Process: The statistical procedure used by Peterson (2003, 2005) was used here, see those publications for details. In short, a form of survival analysis, specifically Tobit regression (Tobin 1958; Austin et al. 2000; Peterson 2005), was used to construct equations that predict ground cover from satellite and accessory data. Such equations are similar to those that might result from ordinary least squares regression, but the analysis accounts for the limit of ground-cover data to never drop below zero. Separate models were run for each of the four satellite sensor data sets (LL04, LL05, MM04, and MM05). Ground data were subset for these according to the following:

- For LL04, all plots where non-clouded 2004 landsat data exist for both seasons.
- For LL05, all plots where non-clouded 2005 landsat data exist for both seasons.
- For MM04, all plots occurring within Ecoregions 1, 3, 4, 5, and 7.
- For MM05, all plots occurring within Ecoregions 2 and 6.

Once models were chosen, they were used geographically to calculate rough maps of estimated annual grass ground-cover. Maps from LL04 and LL05 were then filtered with algorithms described in Table 3 to reduce error in playas, forests, wetlands and lakes where false positives may result from phenology patterns or water reflection. Filtering options for LL05 were limited by the earlier date of the imagery having a lower sun-angle resulting in less bright images (e.g. north slopes with dark soils were often less bright than lakes).

Assembling the map from these for models was performed by the following manipulations:

1. The maps from MM04 was clipped to the area of the 2004 Landsat scenes (clouds included) *and* to Ecoregions 1, 3, 4, 5, and 7.
2. The map from MM05 was clipped to the area of the 2004 Landsat scenes *and* to Ecoregions 2 and 6.
3. The maps from MM04 and MM05 were mosaicked.
4. The map from LL05 was trimmed to not overlap with L04.
5. The maps from LL04 and LL05 were mosaicked.
6. The MODIS-based map from the MM04 and MM05 mosaic (step 3) was clipped to the

'cloud-holes' in the Landsat-based mosaic from step 5.

7. The clipped MODIS-based mosaic and the Landsat based mosaic were themselves mosaicked together with 0 used as no-data. Even though zero could also be a zero cover value, the mosaic was possible because the MODIS-based maps were already clipped to just the cloud-holes in the Landsat-based map.

Lastly, a conservative smoothing kernel was run over the map identical to that in Peterson (2003, 2005) in which each pixel was revalued by a weighted average of itself and the eight surrounding pixels where the focal pixel was given a weight of eight and surrounding pixels each given a weight of one.

5. Assessment Data (Map Validation): The truncated time table for this project did not allow for collection of assessment data specific to the project. Instead, three independent data sets were obtained for map validation. These were the data collected for the Southwest Regional Gap Analysis Project (REGAP; Lowry et al. 2005), the Mojave Desert Ecosystem Program (MOJAVE; Thomas et al. 2002, 2004), and the vegetation classification of Yosemite National Park which included the Mono Lake area (YOSEMITE; Keeler-Wolf et al 2002). Although the California data is entirely outside of Nevada, sufficient numbers of plots are covered by the satellite data and are in appropriate ecoregions for assessing map quality. Extension of modeling beyond the geographic extent of training data was previously tested by Peterson (2003) and there is no reason to believe that data from the same ecoregion but across a political boundary would be inappropriate for map validation.

REGAP data collected for Nevada were used. In that project, the far northeast corner of Nevada was modeled in that project along with Utah and so REGAP data for that corner were not included here. REGAP data were filtered by using only data with valid UTM zone 11 coordinates and the few plots located well beyond the Nevada border were removed. The remaining 15,318 plots are mapped in figure 9. MOJAVE data were filtered to those with valid coordinates and coverage by the LL05 Landsat data. YOSEMITE data were filtered to those with valid coordinates and placement to the east of the Sierra-Nevada crest.

For all three data sets, cover of annual grasses was summed for each plot. Estimated annual grass cover was extracted for each plot from the final map produced herein. Where appropriate (see results), measures of accuracy were calculated, including Pearson Correlation, Root-Mean-Squared-Error, and 75th and 95th percentile errors.

RESULTS

Training data were collected by the Nevada Natural Heritage Program (NNHP) at a total of 806 plots (Figure 10). The average ground cover of annual grasses is 9.3 percent. Most plots had little or no cover of annual grasses (Figure 11) and 522 plots (64.7 % of the data set) had no annual grasses. Annual grass species observed in plots were predominantly *Bromus tectorum* to the north and *Bromus rubens* and *Schismus barbatus* to the south. *Bromus arvensis*, *Poa bulbosa*, *Taeniatherum caput-medusae*, *Vulpia microstachys,* and *Vulpia octoflora* were also observed at some plots and a few plots included annual grasses not identified to species. For modeling purposes, the cover for all annual grasses in each plot was totaled. Of the annual grass species encountered, only *Vulpia* species are native to Nevada and those constituted a minor fraction of the entire data. They are included here because their phenology is similar to that of other annual grasses, but their abundance is minimal. Thus the maps produced herein effectively target introduced annual grasses.

Of the 806 plots, 30 were repeat plots collected in the years 2002 or 2003 then again in 2005 in order to assess the affect of total seasonal precipitation on annual grass cover. Although fieldwork in 2005 followed a wet winter and was expected to have higher ground cover of annual grasses, mean cover of *Bromus tectorum* among plots was 8.0 % lower and mean cover among all annual grasses was 8.5 % lower while mean cover of the native *Poa secunda* was just 0.9 % lower and biological soil crusts was 1.1 % lower Figure 12). Field sampling in 2002 and 2003 followed relatively dry winters, while sampling in 2005 followed a relatively wet winter. The pattern seen will be discussed below. Since the date of the imagery (2004) lies between these years, both initial, and repeat plots were included in modeling.

Tobit regression modeling proceeded through a step-wise addition of variables guided by experience with annual grass geographic patterns in combination with experience in geographic patterns of satellite and accessory data. Among the four modeling data sets, hundreds of models were tested with more than 50 calculated geographically for evaluation. Final models are provided in Table 4. In general, models included early season NDVI, ΔNDVI, an exponential of ΔNDVI, elevation, and ecoregions. The exponential of ΔNDVI used the power of 4, as a simple square did not seam to distinguish values well enough from the simple ΔNDVI value. Additionally, ΔNDVI, when the exponential was included, was rescaled by adding a value of 2 in order to further distinguish the exponential from the simple variable. The slope of ΔNDVI and its exponential are opposite of those found by Peterson (2003, 2005), and the exponential may reduce estimates for sites with high annual grass cover. However, when the exponential variable is not included, the slope of the simple variable is greatly reduced and the model's fit to the data becomes poor. Ecoregions were included as binary variables and were frequently retained even when not statistically significant because regional patterns in error were more visually obvious without them. Models for MODIS data were initially difficult to develop, possibly due to the low spatial resolution of MODIS data resulting in noisy data. However when models from Landsat data were applied to the MODIS data, but with recalculated coefficients, the resultant models performed well when calculated geographically despite a lack of statistical significance for some parameters. Overall, models appeared to perform reasonably well for lower ground-cover sites, while higher ground cover sites generally received deflated estimates (see below in Results and in Discussion). For this and other reasons (see Discussion) the resulting predictions will be hereafter referred to as an 'annual grass index' (ANGRIN) rather than 'estimated annual grass ground-cover'.

Tobit regression models were calculated geographically within ENVI 4.2 and filtered according to Table 3. Scatter plots of annual grass cover across variables used to guide filter cutoff values are presented in Figure 13. The individual model maps were assembled and smoothed to form the final ANGRIN map (Figure 14). The model maps for MODIS-only data (MANGRIN) was remarkably compatible with the Landsat-based maps that formed the bulk of ANGRIN (Figures 15 and 16).

Although assessment data were not collected specifically for this project, it is worthwhile to note a few statistics for success for comparing ANGRIN to annual grass cover at training plots. It is also worthwhile to note that this commits the logical error of circularity in that the same data are being used to create the map as to evaluate it. Nevertheless, Root-Mean-Squared-Error (RMSE) is 13.26 %, 75 % of predictions are off by 9 % or less, and 95 % of predictions are off by 31 % or less. A scatter plot of measured values versus ANGRIN values demonstrates the poor estimation for sites with high cover of annual grasses (Figure 17).

Evaluation of the ANGRIN map utilizing REGAP data shows that RMSE =10.33 %; 75 % of predictions are off by 5 % or less; and 95 % of predictions are off by 21 % or less. Of the 15318 plots in this dataset, 8909 plots are identical in value between ANGRIN and measured ground-cover, though of those 8848 (99 %) are zero in both datasets. However, correlation between ANGRIN and REGAP data showed weak correspondence (*R* = 0.24). Removal of plots with zero cover measured (which may be up to 5 % cover, or more, see discussion) resulted in even less correlation (*R* = 0.14). The discrepancy between the estimated values in the ANGRIN tends toward underestimation of ANGRIN map (Figure 18) and the measured values at REGAP plots has a geographic pattern (Figure 19).

Evaluating accuracy from California Department of Fish and Game plots in the YOSEMITE data shows that the annual grass map underestimates cover in this area. While 28 of the 178 plots had one percent or more annual grasses, the ANGRIN map shows one percent or more at only two plots. Most of the YOSEMITE plots measured to have annual grasses had only small amounts with just five having ten percent or greater cover, so annual grasses are generally not abundant in this area. The ANGRIN map also represents only scattered, areas with low abundance of annual grasses (Figure 20), thus the general pattern is reasonable for this area.

The California Department of Fish and Game collected over 1200 plots in the Mojave ecoregion of California. Of those, 939 were useful to this project and included in the MOJAVE data set (Figure 21). Comparing the values at those plots from the ANGRIN to the measured annual grass ground-cover shows good correspondence with RMSE = 7.48 %; 75 % of predictions are off by 9 % or less; and 95 % of predictions are off by 15 % or less. A histogram of the discrepancy between measured and estimated values shows that in most cases, the estimated value is higher than the measured value (Figure 22).

DISCUSSION

Overall, early season annuals were well distinguished from other vegetation with satellite imagery. For the northern portion of this mapping project (mainly the Great Basin), modeling performed quite well for annual grasses specifically. Low amounts of annual grasses were clearly detected and accuracy seems to have improved over previous mapping (Peterson 2003, 2005) with less area inappropriately estimated to have annual grasses. For example, considerable cover of *Bromus tectorum* had been estimated for the shores of Walker Lake in the previous map whereas appropriately little area of annual grasses are mapped there in the current effort.

However, there are reasons for not interpreting the ANGRIN map as an estimate of actual annual grass ground cover. Higher densities of annual grasses (especially dense monocultures) were substantially underestimated with ANGRIN. This was demonstrated first in the circular comparison of actual and estimated values for training plots, and was corroborated by the REGAP data. The estimated values for REGAP plots were generally underestimated at sites where annual grasses were present in amounts measured in that project (Figure 18). The geographic pattern of discrepancy at REGAP plots demonstrates that where annual grass cover is low to non-existent, the ANGRIN map is quite accurate. However, where annual grass cover is frequently high, discrepancies increase (Figure 19). Despite the underestimation, I believe the general pattern of no, low, and high density of annual grasses is well represented.

Due in part to this underestimation of high densities, as well as the inter-annual variation in annual grasses (Bradley & Mustard 2005), I recommended that this map be interpreted as an *index* of annual grass ground-cover rather than an *estimation* of annual grass percent ground-cover.

The southern portion of this mapping effort attained less success than the northern portion. While early season annuals are reasonably well represented by the map, grasses are not well distinguished from other annuals. Although much of the non-grass annuals interfering with the annual grass signal may be other invasives, particularly mustards (Brassicaceae), many native annual wildflowers are probably also included.

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.

Success with MODIS: Although statistically, the MODIS data were less clear than Landsat 5 TM data for modeling annual grasses, the resultant map was impressively clear at a regional scale (Figure 15) and compatible with the more statistically secure ANGRIN map (Figure 16). MODIS data acquisitions are repeated daily, and have been used to produce nearly real-time maps of wildfire activity (U.S.D.A. Forest Service Remote Sensing Applications Center 2005-2006). There is potential for a similar modeling effort to map annual grass and other fine fuel production and curing. In such an project, daily imagery may be more vulnerable to obscuring by clouds than the wildfire activity maps, which utilize thermal radiation and is less sensitive to at least to thin clouds. However, the 16-day composite data could prove quite valuable.

A more simple possibility would be to run models similar to the ones presented here for the ANGRIN map each year shortly before the summer wildfire season. These might prove useful to map a 'forecast' of flammability.

Bromus arvensis: Although the data on the invasive species *Bromus arvensis* (field brome) are scant, it was found among the repeated plots just east of Midas, Elko County. In 2002 it was found at a single plot with 5 % ground-cover while in 2005 it was found in the same plot with 10 % ground-cover and an additional plot with 1 % ground-cover. Given the small number of plots and the potential for ocular observation error, nothing can be concluded with certainty. However, there is a suggestion of an increasing trend for this species and a large wildfire occurred in the area during the summer of 2005. It would be worthwhile to explore the area further to gain more understanding of the expansion of the species along the southern edge of the Owyhee Uplands and to see how it responds to the opening of habitat through wildfire.

Conclusion: Despite these sources for error, the ANGRIN map reveals legitimate geographic patterns in annual grass distribution, the vast majority of which are invasive annual grasses, across a large portion of the intermountain west. Accuracy assessment with REGAP data showed that the estimation of where annual grasses do and do not exist was modeled well, however the models do not predict the actual quantity as well and predicted values tend to be low for high density sites. This emphasizes that ANGRIN is really an index rather than a valid estimation of actual cover, but since annual grasses are subject to inter-annual variation, an index may be more appropriate than an attempt to predict a specific density. YOSEMITE data show that for low density areas, the exact location of small quantities of annual grasses can be missed, but the general landscape-level pattern is captured. MOJAVE data show that prediction of presence and absence in the Mojave ecoregion is fairly accurate at least across the border into California, though the data also reflect the difference in cover between dry and wet years. Thus the ANGRIN map forms a worthy foundation for understanding pattern of annual grasses across Nevada.

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LITERATURE CITED

Austin P. C., M. Escobar, and J. A. Kopec. 2000. The use of the Tobit model for analyzing measures of health status. Quality of Life Research 9: 901-910.

Bryce, S. A., A. J. Woods, J. D. Morefield, J. M. Omernik, T. R. McKay, G. K. Brackley, R. K. Hall, D. K. Higgins, D. C. McMorran, K. E. Vargas, E. B. Peterson, D. C. Zamudio, and J. A. Comstock. 2003. Ecoregions of Nevada [color poster with map, descriptive text, summary tables, and photographs]. U.S. Geological Survey, Reston, Virginia.

ESRI. 1995-2005. ArcPad (Versions 6.0.1 to 6.0.3). Environmental Systems Research Institute, Inc.

Lowry, J. H, Jr., R. D. Ramsey, K. Boykin, D. Bradford, P. Comer, S. Falzarano, W. Kepner, J. Kirby, L. Langs, J. Prior-Magee, G. Manis, L. O'Brien, T. Sajwaj, K. A. Thomas, W. Rieth, S. Schrader, D. Schrupp, K. Schulz, B. Thompson, C. Velasquez, C. Wallace, E. Waller and B. Wolk. 2005. Southwest Regional Gap Analysis Project: Final Report on Land Cover Mapping Methods. RS/GIS Laboratory, Utah State University, Logan, Utah.

Jensen, J. R. 1996. Introductory Digital Image Processing: a Remote Sensing Perspective. Second Edition. Prentice Hall, New Jersey.

Keeler-Wolf, T., P. Moore, M. Schindel, S. San, and D. Hickson. 2002. Vegetation classification and description of Yosemite National Park. NatureServe and Environmental Systems Research Institute. Unpublished report on file at Wildlife and Habitat Data Analysis Branch. 265 pp. Sacramento, California.

McCune, B. 2004. Nonparametric multiplicative regression for habitat modeling. Online at http://www.pcord.com/NPMRintro.pdf.

NASA [National Aeronautics and Space Administration]. 2005a. Earth Observing System Data Gateway. Online at http://delenn.gsfc.nasa.gov/~imswww/pub/imswelcome/. Accessed various times from August 2005 through March 2006.

NASA [National Aeronautics and Space Administration]. 2005b. MODIS Web [home page for the MODIS project]. Online at http://modis.gsfc.nasa.gov/index.php. Accessed various times from August 2005 through March 2006.

Peterson, E. B. 2000. Analysis and Prediction of Patterns in Lichen Communities over the Western Oregon Landscape. Ph.D. Dissertation, Oregon State University.

Peterson, E. B. 2003. Mapping percent-cover of the invasive species *Bromus tectorum* (cheatgrass) over a large portion of Nevada from satellite imagery. Report for the U.S. Fish and Wildlife Service, Nevada State Office, Reno, by the Nevada Natural Heritage Program, Carson City.

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

R Development Core Team. 2005. R 2.2.0 - A language and environment. http://www.rproject.org. Accessed 15 November 2005.

Research Systems Inc. 2005. ENVI Version 4.2 – The Environment for Visualizing Images. Boulder, CO.

Smith S.D., Huxman TE, Zitzer SF, Charlet TN, Housman DC, Coleman JS, Fenstermaker LK, Seemann JR, Nowak RS. 2000. Elevated CO_2 increases productivity and invasive species success in an arid ecosystem. Nature 408:79-82.

Spatial Climate Analysis Service, Oregon State University. 2003. PRISM products. Online at http://www.ocs.oregonstate.edu/prism/. Data created in 2003. Accessed 9 March 2006.

Thomas, K., T. Keeler-Wolf, and J. Thorne. 2002c. Central Mojave Field Data. A digital database (MS Access). US Geological Survey and California Department of Fish and Game (available digitally from second author).

Thomas, K., T. Keeler-Wolf, J. Franklin, and P. Stine. 2004. Mojave Desert Ecosystem Program: Central Mojave Vegetation Database. U.S.G.S. Western Ecological Research Center and Southwest Biological Science Center, Sacramento, California.

Tobin, J. 1958. Estimation of relationships for limited dependent variables. Econometrica 26: 24-36.

U.S.D.A. Forest Service Remote Sensing Applications Center. 2005. MODIS Active Fire Mapping Program. Online at http://activefiremaps.fs.fed.us/activefiremaps.php. Accessed 30 March 2006.

U.S.G.S. 2005. National Elevation Dataset. Online at http://ned.usgs.gov/. Accessed various times from August through December 2005.

U.S.G.S. 2006b. SLC-off Products: Background. Online at http://landsat.usgs.gov/data_products/slc_off_data_products/slc_off_background.php. Accessed 24 March 2006.

U.S.G.S. 2006. USGS Global Visualization Viewer. Online at http://GloVis.usgs.gov/BrowseBrowser.shtml. Accessed 24 March 2006.