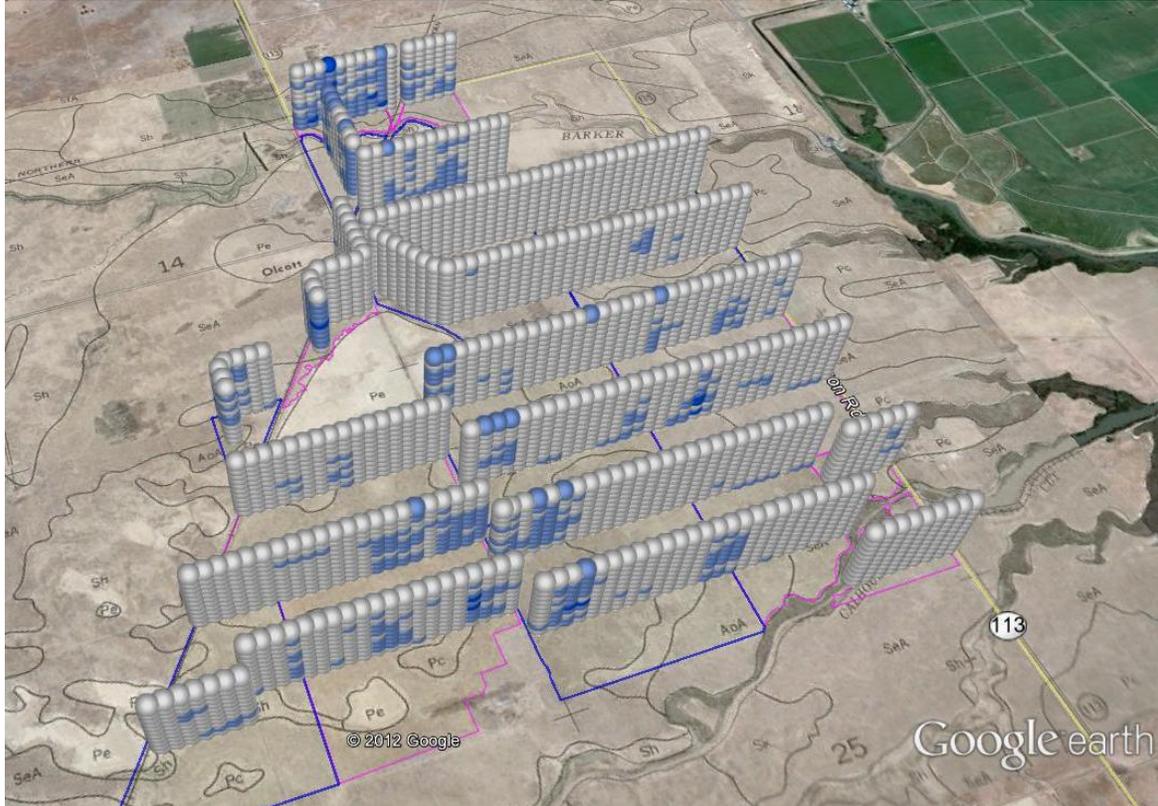


## Jepson Prairie Preserve Vegetation Monitoring Transects: Analysis of data from 2001 through 2011



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Prepared for: Ben Wallace  
Solano Land Trust

Prepared by: Tedmund Swiecki, Ph.D.  
Elizabeth Bernhardt, Ph.D.



**PHYTOSPHERE RESEARCH**

1027 Davis Street, Vacaville, CA 95687-5495

707-452-8735

email: [phytosphere@phytosphere.com](mailto:phytosphere@phytosphere.com)  <http://phytosphere.com>

Introduction.....	3
Methods .....	4
Outcome variables .....	4
Predictor variables .....	4
Soils and microtopography .....	4
Weather variables .....	5
Fire.....	6
Grazing .....	7
Types of analyses used .....	7
Limitations.....	8
Results and Discussion .....	8
Overall repeated measures analyses .....	8
Analyses for selected species.....	10
<i>Nassella pulchra</i> .....	10
<i>Achillea millefolium</i> .....	14
<i>Viola pedunculata</i> .....	15
<i>Taeniatherum caput-medusae</i> .....	16
<i>Centaurea solstitialis</i> .....	21
Effects of reducing sample size or data collection frequency .....	21
Using fewer transects.....	21
Monitoring in alternate years.....	25
Effect of Monitoring Date .....	28
Conclusions.....	29
Changes over time .....	29
Factors associated with vegetation changes .....	30
Altered data collection scenarios .....	30
Literature cited.....	31

## Introduction

In 2001, we developed a transect-based monitoring system for assessing changes in exotic and native plant cover at Jepson Prairie Preserve (Figure 1). The monitoring system was designed to detect significant changes in cover and distribution of selected species across the entire preserve. The monitoring system is based on permanent transects that are assessed annually in the spring, near the time of peak bloom of many native spring annuals. Transects pass through every pasture unit at the preserve. The basic data unit is a 0.1 ha strip transect, 50 m long by 20 m wide.

Within each transect segment, the cover of selected species is estimated in one of four cover classes (0 = not observed, 1 = up to 1% cover, 2 = 1-10% cover, 3 = more than 10% cover). The cover classes were selected to allow for rapid, repeatable assessments of cover and to optimize detection of the spread of exotic species with low absolute cover. The cover classes are also useful for detecting changes in the cover of native and exotic species that have relatively low absolute cover overall or in specific areas. The rating system was not designed to track changes in cover of species that have uniformly high cover levels.

Because the position of transect segments are fixed, repeated annual measurements for any given segment ideally show how plant cover has changed over time in that segment. This assumes that observers follow the established protocols consistently over time, and that the positional errors associated with relocating transect segments are minimal. These potential sources of error may lead to a recorded change in cover when no change has actually occurred. The importance of random errors associated with these factors is reduced by the large sample size within and across years. Systematic errors, such as a consistent observer bias, have the potential to bias the data for the affected segments and years.

We have undertaken an analysis of the data collected using this system for the 11 years from 2001 through 2011. The primary objectives of our analysis were to:

- identify directional trends indicating long-term increase or decrease in the cover of any monitored species;
- identify significant patterns of change over time that may not have resulted in net changes in cover from the beginning to the end of the observation interval;
- determine whether environmental, management, or other factors are associated with observed changes over time and space.

In addition, we assessed whether reducing either the frequency of data collection or number of transect segments would affect our ability to discern trends and assess the influence of predictive factors.

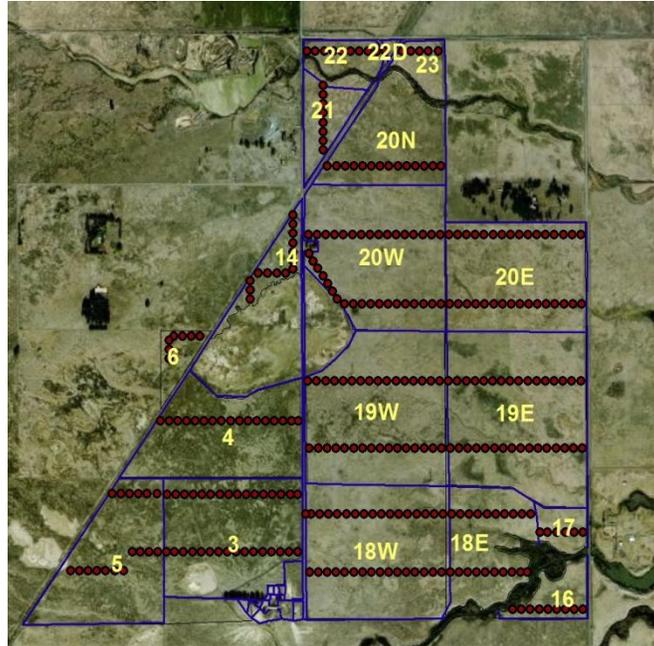


Figure 1. Transects used for monitoring vegetation in Jepson Prairie Preserve. Red dots represent transect segments. Pastures are outlined in blue. Pasture numbers are shown in yellow.

## Methods

### OUTCOME VARIABLES

For each species monitored, two basic outcome variables were used in our analyses. For repeated measures models and graphical data visualization, the cover ratings (0-3) were used. These ratings can be used directly where the repeated nature of observations is directly considered.

For models that do not account for this data structure, we used the difference in the cover ratings for each pair of consecutive years as the primary outcome variable. This variable has a potential range from +3 to -3, where positive values indicate an increase in cover, negative values indicate a decrease in cover, and zero represents no change across the two year period. This was calculated for each segment as:

$$\text{cover rating}_{\text{year } n} - \text{cover rating}_{\text{year } n-1}$$

for pairs of years where one or both cover ratings are nonzero. If both years have a cover rating of 0 (species not observed either year), a missing value code was assigned. This was done because a zero change in the cover rating for a segment where a species occurs is intrinsically different from a zero change that results because the segment lacks the species of interest.

### PREDICTOR VARIABLES

#### Soils and microtopography

Soils and microtopography are the primary fixed factors that influence vegetation composition at Jepson Prairie. These factors are fixed for each transect segment and only contribute to variability between segments, not within segments over time.

In 2011, ratings were taken in most segments to characterize the relative amount of microtopographic features within the segments. To create variables for analysis, we used cluster analysis to group transect segments based on the percentage of the transect segment classified in each of the five microtopography categories (upland, mound, channel side, pool/swale, damp terrace). We defined five clusters, each dominated by one of the five microtopography categories, which were used as a categorical analysis variable ( $M$ ). We also created a second continuous variable ( $M_{dry}$ ) by adding the percentages for the three drier categories (upland + mounds + channel sides) within a given segment. For some analyses, the actual percentages in each microtopography category were used as predictors.

Microtopography data were not collected in pastures 4, 6, 14, and portions of pastures 3 and 18E. Due to the amount of missing data, the microtopography variables were not used in all analyses. In addition, after most analyses had been completed, Ben Wallace reported that the microtopography data for about 10 segments in transects 8 and 9 (pastures 19 E and W) were suspect. This was based on a comparison between the vegetation in these segments and their microtopography classifications. The data in these transects had been collected by an observer who may have not been applying the rating criteria in the same manner as other observers. Our own data summaries suggested that some microtopography categories had not been distinguished consistently, particularly upland vs. damp terrace.

Errors associated with misclassification of microtopography in the segments have the potential to add noise to the data, which would reduce the significance of these variables. Although the integrity of the variable is less than optimal, the microtopography data available for our current analyses do provide an opportunity to investigate whether this factor could be a useful predictor of vegetation outcomes.

Soil type information for each segment was available from the NRCS Soil Surveys, but the resolution of this data is rather coarse. We used the predominant soil type shown in the Soil Survey for each transect segment as a predictor variable. The soil types represented are Pescadero clay loam (Pc), Solano loam (Sh), San Ysidro sandy loam (SeA), and Antioch - San Ysidro complex (AoA). In addition, because only the Pc and Sh soil types are described as slightly to highly saline ( $EC_e=4-8$  and  $2-10$  dS/m, respectively), we created a binary variable that contrasts these two saline soil types with the two nonsaline types.

### **Weather variables**

Rainfall is probably the most important variable that influences the vegetation at the preserve on an annual basis. Rainfall interacts with soil and topography to produce the prolonged periods of ponding that give rise to vernal pools. Effects of rainfall are related to both the amount and the timing of precipitation. After reviewing rainfall data for 2000 through 2011, we calculated the rainfall variables shown below for use in analyses. Because cover ratings were made in April, variables only included seasonal rainfall totals for the months from September of the previous year (start of the rainy season) through April of the rating year. In some analyses, we used a simplified ranking variable ( $P_{rank}$ ) based on Sep-Apr precipitation. The levels of this rank variable were based on the first and fourth quartiles of precipitation for the data period:

- 1: <14 inches (35.6 cm);
- 2: 14 - 18 inches
- 3: >18 inches (45.7 cm)

Precipitation period	Variable abbreviation
Sep-Oct	P <sub>9-10</sub>
Dec-Feb	P <sub>12-2</sub>
Dec-Mar	P <sub>12-3</sub>
Feb-Apr	P <sub>2-4</sub>
Mar-Apr	P <sub>3-4</sub>
Sep-Apr	P <sub>9-4</sub>
Sep-Apr	P <sub>rank</sub>

Temperature also influences vegetation, mainly by interacting with rainfall to affect the rate at which pools dry down. In addition, early season temperatures can affect the rate at which various plants grow. We used potential evapotranspiration data (ETo), which integrates temperature, humidity, and solar radiation effects, to serve as a general temperature-related predictor. The two variables tested in most models are shown below.

Cumulative ETo period	Variable abbreviation
Feb-Apr	E <sub>2-4</sub>
Dec-Jan	E <sub>12-1</sub>

### Fire

Fire is a major driver of vegetation change that is subject to manipulation, though unplanned fires also occur at Jepson. Effect of fires on annual vegetation are typically most pronounced in the year immediately after a fire, but residual effects persisting up to several years are possible. The number of repeated fires occurring over a given time interval may also affect vegetation outcomes. Based on these and several other considerations, we defined the fire-related variables shown below for use in analyses. Each of the variables was recalculated for every segment for each year's data. Since all fires occurred during the dry season after plot ratings were made, fires occurring in a given year were considered to affect only subsequent years (e.g., effects of a 2007 fire were only included in analyses of 2008 and later data).

Based on historical fire information, the last probable fire year for plots not burned since 1995 was set at 1966 for the variable B<sub>y</sub>. For repeated measures models, we also created a categorical variable (burn years) that described each of the burn regimes. This variable had 12 levels, based on the years that fires had occurred in various segments since 1995. Most segments (227) had burned at least once over this period. Only one segment had burned as many as three times, and 97 had not burned.

Fire history	Variable abbreviation
Years since last burn	<b>B<sub>y</sub></b>
Burned previous year	<b>B<sub>.1</sub></b>
Burned both of last 2 years	<b>B<sub>2</sub></b>
Number of burns between 1995 and the current year	<b>B<sub>t</sub></b>

### Grazing

Grazing is the primary management input used to influence vegetation at Jepson Prairie. A number of grazing variables can be defined for any given pasture and the values of these variables change each year. In defining grazing variables, we looked at grazing periods that have been shown to be of interest in our previous study (Swiecki and Bernhardt 2008). These included periods of grazing through April of the current season as well two variables related to previous season grazing. Stocking rates in AMU/acre/month were used for all calculated variables to correct for differences in field size.

Grazing history	Variable abbreviation
Previous year grazing	<b>G<sub>.1</sub></b>
Previous year May-Aug grazing	<b>G<sub>5-8</sub></b>
Current year Jan-Feb grazing	<b>G<sub>1-2</sub></b>
Current year Mar-Apr grazing	<b>G<sub>3-4</sub></b>

Because all pastures have unique grazing histories, pasture number was used in some analyses to screen for an overall effect related to grazing history. We also created a pasture × fire history variable that subdivides pastures into units with the same fire history. The pasture × fire variable has 27 discrete levels because 7 of the pastures had two or three separate fire history regimes represented in different transect segments.

### TYPES OF ANALYSES USED

The data structure of the monitoring data is quite complex. Seventeen species are represented in the data set, but several weed species (purple starthistle, bull thistle, milk thistle, and wild fennel) were too uncommon in the data to allow for meaningful analyses. As noted above, data consist of repeated measurements on individual transect segments, each of which has its own combination of soil and microtopographic characteristics. Within fields, all transect segments are assumed to have the same grazing regime, which changes from year to year. We know from other research that this is an oversimplification and that grazing intensity within a field can vary greatly due to microtopography, flooding, species composition, and other factors (Swiecki and Bernhardt 2008). Fire histories also vary spatially in burned areas that sometimes, but not always, coincide with pasture boundaries. Weather variables are assumed to be uniform across the preserve, but both amounts and patterns of precipitation vary each year.

We used various types of modeling techniques to identify those variables that have the greatest influence on outcomes. Some techniques are better than others are for

modeling the effect of time and various interactions between factors. Analyses that we used included:

- Repeated measures multivariate analysis of variance (MANOVA)
- Partition (regression tree) models
- Stepwise linear models
- Eureqa II Formulize models (models created using an artificial intelligence technique known as genetic programming)

These models are all correlative in nature and attempt to maximize the goodness of fit between the observed data and the predictions of the model.

We also created graphical representations of the data over time using ArcGIS and Google Earth Pro. Successive years of data are shown at successively higher elevations above ground level. This allows for visual detection of patterns that may not show up in other analyses.

### Limitations

Even with 11 years of data, the data set is fraught with various singularities and confounding between variables. For example, because fires have been relatively uncommon and restricted in area, certain combinations of grazing, fire, and weather occur in a limited number of transect segments. If such combinations are associated with particular changes in outcome variables, it is difficult to determine which of the factors may be contributing to the outcome, or whether the unique combination of factors may be responsible.

## Results and Discussion

### OVERALL REPEATED MEASURES ANALYSES

Repeated measures MANOVA models were developed for all monitored species except for the most uncommon weedy species. These models indicate overall whether cover values changed significantly over the 11 years of monitoring and whether certain variables (fire, soil, microtopography) were associated with these changes over time. However, the repeated measures MANOVA does not indicate whether there has been an overall increasing or decreasing trend over time across the preserve. To ascertain trend direction, we regressed the least squares means for cover by species (from the repeated measures model) over time. Least square means are adjusted for factors in the repeated measures model that might otherwise obscure an overall trend. Regressions over time were fitted with and without rainfall variables, to determine whether changes seen over time depended on rainfall.

For native species, all repeated measures models showed significant effects of time and significant interactions for time  $\times$  soil type and time  $\times$  fire history variables (Table 1). Time  $\times$  microtopography variables were also significant for all species other than *Achillea millefolium*. Using these significant models to adjust the average annual cover ratings for these factors, three perennial species (*Nassella pulchra*, *Viola pedunculata*, and *A. millefolium*) showed significant negative trends in average annual cover over time (Table 1). Precipitation variables for these three species were not significant, suggesting that the downward trend observed over time for these species was unrelated to precipitation (Table 1).

In contrast, precipitation variables were significantly correlated with the observed variation in cover over time for the four annual species: *Deschampsia danthonioides*, *Pleuropogon californicus*, *Triphysaria eriantha*, and *Lasthenia spp.* For *D. danthonioides*, a downward trend in cover ratings over time was apparent if the effect of precipitation was accounted for in the model. The other three species do not show a directional trend over time when adjusted for precipitation.

Table 1. Overall repeated measures multivariate analysis of variance (MANOVA) model parameters and regressions of adjusted least squares means by year from the MANOVA for native species.

Species	Repeated measures, interactions: P level	Regression on LS means by year (P level)	Regression on LS means by year and best precipitation variable. Positive and negative correlations are indicated by (+) or (-)
<i>Nassella pulchra</i>	Time: 0.0002 T × soil type: 0.0496 T × burn years: <0.0001 T × M: <0.0001	R <sup>2</sup> =0.783, P<0.001	R <sup>2</sup> =0.807, P=0.001 Year (-) P=0.001 P <sub>9-11</sub> NS
<i>Deschampsia danthonioides</i>	Time: <0.0001 T × soil type: 0.0013 T × burn years: <0.0001 T × M <sub>dry</sub> : <0.0001	NS	R <sup>2</sup> =0.573, P=0.033 Year (-) P=0.036 P <sub>3-4</sub> (+) P=0.029
<i>Pleuropogon californicus</i>	Time: <0.0001 T × soil type: 0.0005 T × burn years: <0.0001 T × M <sub>dry</sub> : <0.0001	NS	R <sup>2</sup> =0.781, P=0.002 Year NS P <sub>9-4</sub> (+) P<0.001
<i>Triphysaria eriantha</i>	Time: 0.0003 T × soil type: <0.0001 T × burn years: <0.0001 T × M: <0.0001	NS	R <sup>2</sup> =0.547, P=0.042 Year NS P <sub>9-4</sub> (+) P=0.019
<i>Viola pedunculata</i>	Time: 0.0288 T × soil type: <0.0001 T × burn years: <0.0001 T × M: <0.0001	R <sup>2</sup> =0.617, P=0.004	R <sup>2</sup> =0.741, P=0.005 Year (-) P=0.006 P <sub>2-4</sub> NS
<i>Achillea millefolium</i>	Time: <0.0001 T × soil type: <0.0365 T × burn years: <0.0001	R <sup>2</sup> =0.733, P<0.001	R <sup>2</sup> =0.755, P=0.004 Year (-) P=0.003 P <sub>9-11</sub> NS
<i>Lasthenia spp.</i>	Time: <0.0001 T × soil type: <0.0001 T × burn years: <0.0001 T × M <sub>dry</sub> : <0.0001	NS	R <sup>2</sup> =0.453, P=0.089 Year NS P <sub>9-4</sub> (+) P=0.033

Significant effects of time were also seen in all repeated measures models for the most common exotic species (Table 2). Two of the exotic species, *Centaurea solstitialis* and *Lactuca serriola*, showed significant negative trends in cover over time based on least squares means. Correlations for these trends were weaker than those seen for *N. pulchra*, *A. millefolium* and *V. pedunculata*.

Repeated measures models for all the exotic species showed significant interactions for time × fire history variables (Table 2). The time × soil type interaction was significant for all species except *C. solstitialis*, and time × microtopography variables were significant for all species except *Lepidium latifolium*.

The least squares means for many of the species showed some correlation with precipitation variables. Precipitation effects were most pronounced for *Taeniatherum caput-medusae*. This species tended to show higher cover in years with greater Feb-Apr

precipitation levels, based on a regression of the overall least squares means. *Carduus pycnocephalus* also showed a positive correlation with rainfall (Table 2). The variable P<sub>9-4</sub> can be substituted for P<sub>12-2</sub> with nearly identical results. Cover levels of *C. pycnocephalus* peaked in 2005 and 2006, which were relatively wet years with late spring rains. Cover levels dropped off quickly in the succeeding dry years.

Table 2. Overall repeated measures multivariate analysis of variance (MANOVA) model parameters and regressions of adjusted least squares means by year from the MANOVA for selected exotic species.

Species	Repeated measures, interactions: P level	Regression on LS means by year (P level)	Regression on LS means by year and best precipitation variable
<i>Carduus pycnocephalus</i>	Time: 0.0366 T × soil type: <0.0001 T × burn years: <0.0001 T × M: <0.0006	NS	R <sup>2</sup> =0.457, P=0.087 Year NS P <sub>12-2</sub> (+) P=0.047
<i>Centaurea solstitialis</i>	Time: <0.0001 T × burn years: <0.0001 T × M: <0.0001	R <sup>2</sup> =0.519, P=0.012	No significant precipitation variables
<i>Erodium</i> spp.	Time: <0.0001 T × soil type: <0.0001 T × burn years: <0.0001 T × M: <0.0001	NS	R <sup>2</sup> =0.472, P=0.077 Year NS P <sub>12-3</sub> (-) P=0.039
<i>Lactuca serriola</i>	Time: <0.0001 T × soil type: 0.0003 T × burn years: <0.0001 T × M: <0.0001	R <sup>2</sup> =0.601, P=0.005	R <sup>2</sup> =0.615, P=0.022 Year (-) P=0.012 P <sub>2-4</sub> NS
<i>Lepidium latifolium</i>	Time: <0.0001 T × soil type: <0.0365 T × burn years: <0.0001	NS	R <sup>2</sup> =0.591, P=0.028 Year NS P <sub>3-4</sub> (-) P=0.026
<i>Taeniatherum caput-medusae</i>	Time: <0.0001 T × soil type: <0.0001 T × burn years: <0.0001 T × M <sub>dry</sub> : <0.0002	NS	R <sup>2</sup> =0.672, P=0.012 Year NS P <sub>2-4</sub> (+) P=0.004

## ANALYSES FOR SELECTED SPECIES

### *Nassella pulchra*

Purple needlegrass, *Nassella pulchra* is considered one of the quintessential native upland prairie species at the Jepson preserve. It is found in all pastures at the preserve. A 3-d scatter plot of its distribution shows that its density is lowest on transect segments mapped to Solano loam (Sh) soils that have relatively wet microtopographic relief (pool-swale, damp terrace). Graphically, it is obvious that fields 20N, 20E, and 20W (all previously one field) had the lowest density of *N. pulchra* at the start of the monitoring period. Many of the original gaps in *N. pulchra* cover in these pastures coincide with the location of eucalyptus stands that were subsequently removed (Figure 2). By comparison, the density of the invasive grass *Taeniatherum caput-medusae* shows little correlation with the previous location of eucalyptus trees. The few transect segments in these fields that lack both *N. pulchra* and *T. caput-medusae* are dominated by pool-swale microtopography.



Figure 2. Distribution of *Nassella pulchra* (left) and *Taeniatherum caput-medusae* (right) from 2001 to 2011 relative to the previous location of eucalyptus trees (dark areas in imagery). Data for each year are displayed at progressively higher altitudes above the map surface. Higher levels of cover are shown as progressively darker symbols. Missing symbols (left) or white symbols (right) indicate zero cover ratings. Background image is a 1970 aerial photo from the Soil Survey of Solano County.

Several types of analyses showed that *N. pulchra* has declined over time across the preserve in general, although the loss is clearly more pronounced in certain pastures (Figure 3). As noted above, repeated measures analysis showed a significant effect of time on cover rating, and the regressions of adjusted least squares means showed a strong negative slope. Interactions of time with fire history (or alternatively pasture number) were significant, indicating that changes occurring over time differed among the pastures. We used both cluster analysis and visual analysis to identify pastures that showed a stronger decline in *N. pulchra* cover over time. In addition to 20E, 20W, and 20N, pastures 18W, 19W, 21, and 5 also show significantly stronger declines in *N. pulchra* cover than do the remaining pastures. These seven pastures all show strong downward trends starting in 2006 (Figure 3).

Several different types of analyses point toward factors that appear to be associated with negative changes in *N. pulchra* cover. Among weather variables, higher Sep-Oct precipitation ( $P_{9-10}$ ) was generally associated with year-to-year increases in *N. pulchra* cover in several types of models. Both  $P_{9-10}$  and  $P_{9-11}$  show a general downward trend (with high year-to-year variation) from 2001 through 2011, though the regression lines are not significant. It is also noteworthy that the strongest decline in *N. pulchra* cover readings began in 2006, a very wet season, and continued strongly in 2007, a very dry year. Both positive and negative effects of  $P_{9-4}$  are significant in some models. It is possible that high moisture in 2006 put stress on marginal *N. pulchra* populations (e.g., by favoring annual plant competition, or favoring foliar and/or root diseases) and subsequent drought conditions in 2007 continued to stress these populations by different mechanisms (e.g., drought stress). However, strong negative effects are limited to only some fields, suggesting that fire and/or grazing could also be interacting with weather conditions.

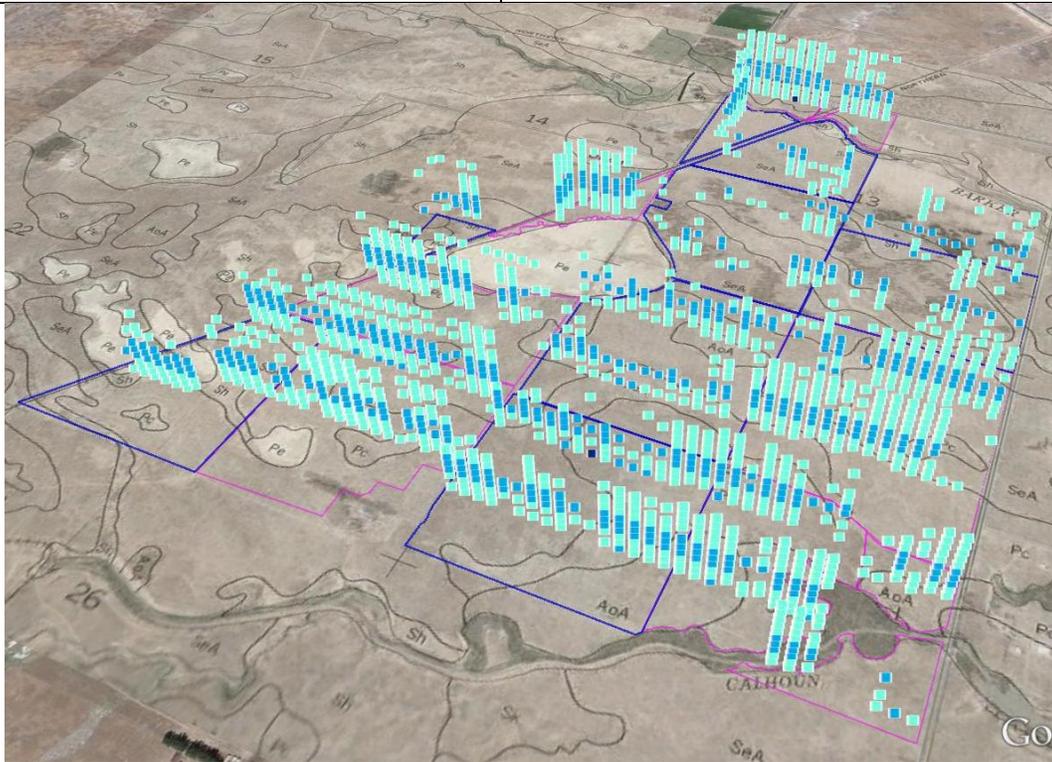
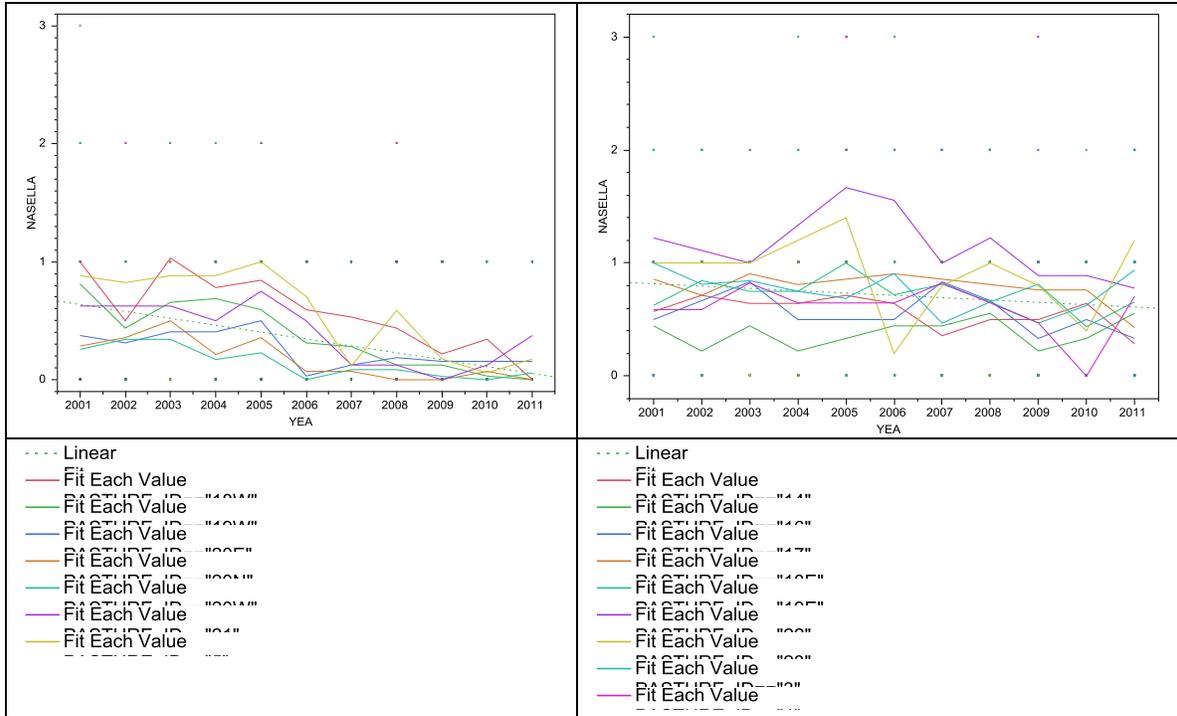


Figure 3. Changes in *N. pulchra* cover from 2001 to 2011 among different pastures. Pastures outlined in blue in the lower image show a steeper decline in *N. pulchra* cover (upper left linear fit dotted regression line) than do remaining pastures (upper right). Lower image shows *N. pulchra* ratings for 2001-2011 displayed at progressively higher altitudes above the map surface. Higher levels of cover are shown as progressively darker symbols. Missing symbols indicate zero cover ratings. Background image is a 1970 aerial photo from the Soil Survey of Solano County.

Several models showed highly interactive, conditional effects of fire and grazing on the change in *N. pulchra* cover. In particular, the 2007 burn, which affected parts of 20W, 19W, and 18W, appears to have contributed to the decline of *N. pulchra* cover within the burned area (Figure 4). However, earlier fires in other pastures do not appear to have had a strong negative effect. Possibly the 2007 fire was more destructive because it followed the combined stresses of the 2006 and 2007 weather years.

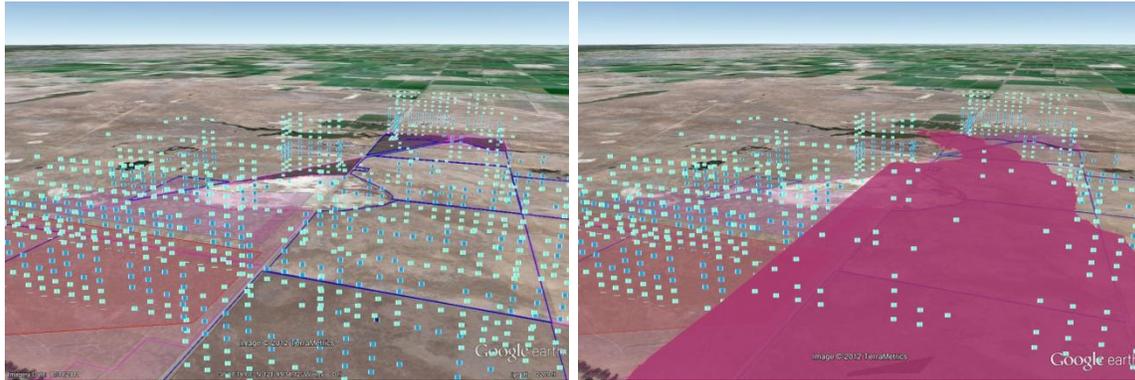


Figure 4. Distribution of *N. pulchra* relative to fire history. Gray, red, and magenta polygons represent areas that have burned at various dates since 1995. Left shows fires prior to 2007, right shows 2007 burn polygon. Note low density and declining density of *N. pulchra* post burn (points visible above plane on right) compared with previous densities visible on left.

All analyses generally showed only weak positive or negative grazing effects that were influenced by other factors. More complex Eureka models and partition models included several grazing variables ( $G_{-1}$ ,  $G_{5-8}$ ,  $G_{3-4}$ ). These models suggest that the effects of grazing were variable and limited by thresholds or dependent on other variables. For example, the most complex Eureka model for change in *N. pulchra* cover indicated that previous year grazing ( $G_{-1}$ ) had no effect below 0.56 AMU/acre, a positive effect up to 0.8 AMU/acre and a negative effect above that level. It also indicated that previous May-Aug grazing ( $G_{5-8}$ ) had a negative effect only if there was precipitation in Sep-Oct. From graphical analysis of the grazing regimes, it appeared that May-August grazing intensity levels have tended to increase over time, which was confirmed by regression analysis (Figure 5). The increases in  $G_{5-8}$  were no higher overall in pastures showing strong negative changes in *N. pulchra* cover. However, if negative effects of grazing are associated with interacting factors such as fire or precipitation, no obvious correlation may be evident between grazing intensity and *N. pulchra* cover.

Although various factors were significant in multiple regression models for the change in *N. pulchra* ratings, these models had poor overall fit. The best multiple regression model was highly significant ( $P < 0.0001$ ), but  $R^2$  was only 0.02. This could be due to various factors: predictor variables tested were suboptimal, factors other than those examined were primary drivers of change, and/or interactions and nonlinear effects were not adequately accounted for in the model. Partition models were somewhat more successful than regression models, but still only explained a small amount of the variation ( $R^2 = 0.055$ ) in the change in *N. pulchra* outcome. However, when the data set was split into the two groups of pastures illustrated in Figure 3, a greater amount of the variation in the change in *N. pulchra* ( $R^2 = 0.15$ ) could be explained among the fields showing the

steeper decline in cover using the partition model. These issues illustrate the difficulty of using any single type of analysis to identify possible relationships within this complex data set.

In summary, monitoring data clearly show a downward trend in *N. pulchra* cover at Jepson Prairie Preserve. The trend is not uniform across the preserve, but is most intense in several pastures that had initially low levels of *N. pulchra* cover in 2001. The decline in cover was accelerated in these fields starting in 2006, a very wet year followed by a very dry year. The decline is only weakly associated with fire and, to a lesser degree, grazing, suggesting that these factors may be functioning only as secondary influences.

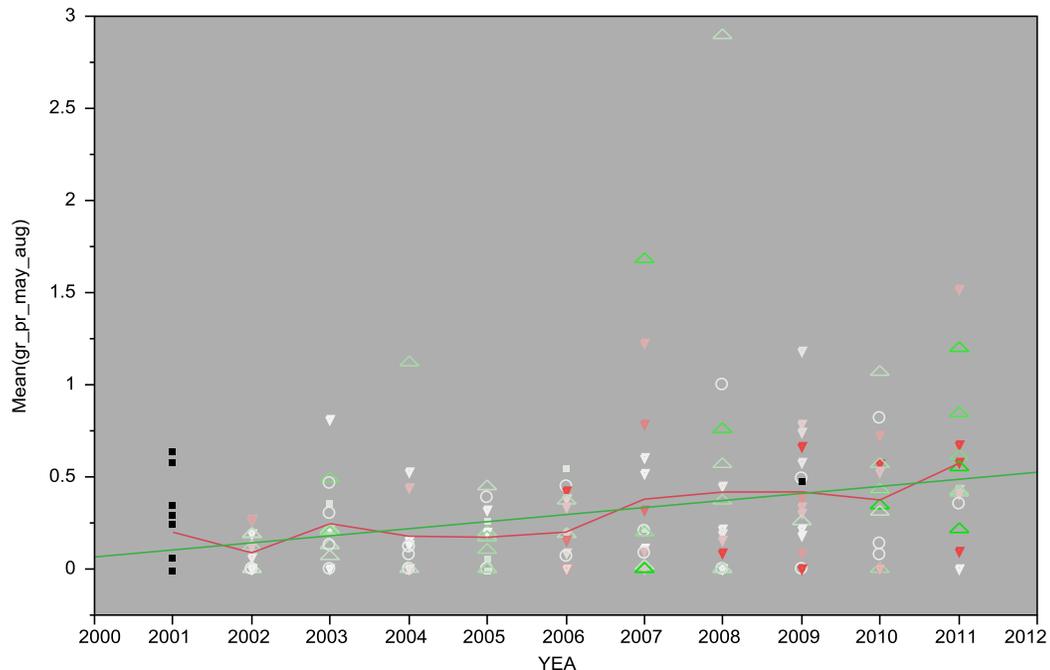


Figure 5. Previous May-August grazing pressure (AUM/acre) for all pastures over time, Red line connects means for each year; green line is the fitted regression line ( $R^2=0.11$ ,  $P=0.0001$ ). Symbols show average change in *N. pulchra* cover for each pasture. White circles indicate no average change; upward arrows indicate an average increase in cover change (greater increases in darker shades of green); downward arrows indicate an average decrease in cover change (greater decreases in darker shades of red), Black squares are used where no average change can be calculated (e.g., 2001).

### ***Achillea millefolium***

This native perennial forb occurs on all soil types that occur in the transects, but has been found in only 12 of the 18 pastures. It has never been observed in transects in pastures 16, 17, 20E, 20W, 22 or 22D. In addition, small populations found within transects in pastures 18E, 21, 23 have apparently died out (Figure 6). This distribution suggests that past cultural practices may have eliminated this species from some areas. For example, the presence of old eucalyptus stands in 20E and W, or operations associated with their removal, may account for the absence of *A. millefolium* in those pastures. As noted above, the lack of *N. pulchra* cover in these pastures is spatially associated with former eucalyptus stands.

Although cover of this species appears to have decreased over the monitoring period, initial analyses did not show clear relationships with fire or grazing variables. Although analyses on the data for this species have been limited, factors associated with its reduced cover over time remain unclear.



Figure 6. Graphical representation of *A. millefolium* cover ratings across all transect segments from 2001 through 2011. Ratings are symbolized as spheres, where successive years are shown at progressively higher elevations. Ratings are shown by sphere color (white=0 rating, ratings 1-3 are progressively deeper shades of blue). Angle of view is from the southeast.

### ***Viola pedunculata***

*Viola pedunculata* is another perennial forb that occurs at low cover levels throughout the preserve. *Viola pedunculata* has never been observed in the transects in pasture 16, or the northern transect in 20E and 20W. Monitoring data suggest that populations of *V. pedunculata* have been declining over much of the preserve (Table 1, Figure 7). As with *A. millefolium*, initial models did not show evidence that declines in *V. pedunculata* are strongly associated with grazing or fire variables. Furthermore, changes in *V. pedunculata* cover are not strongly associated with precipitation variables. Based on only preliminary analyses conducted to date, it is not clear what factors may be associated with the decline in *V. pedunculata* across the preserve.



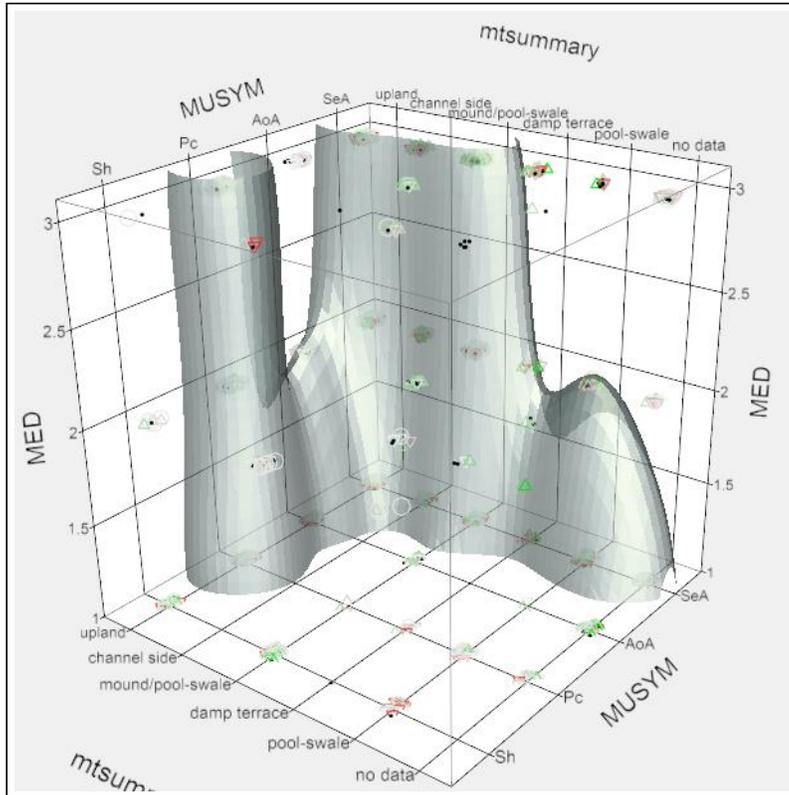


Figure 8. Scatterplot (3-D) showing *T. caput-medusae* cover ratings (MED) for all years by soil type (MUSYM) and microtopography (mtsummary). Nonparametric density contours (shading) are superimposed.

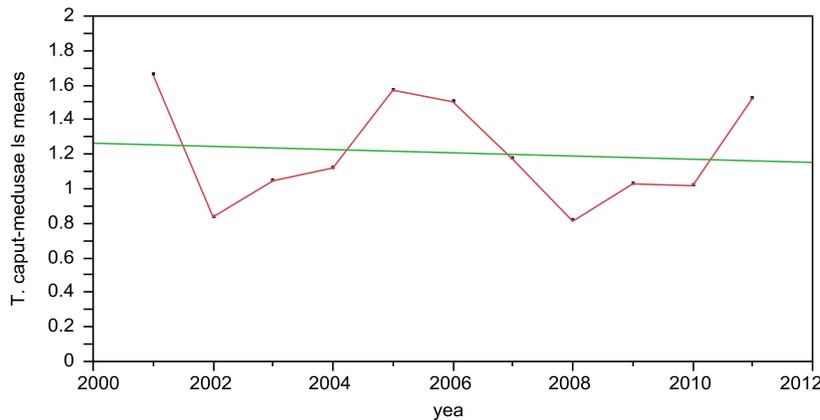


Figure 9. Least squares means from repeated measures MANOVA model for *T. caput-medusae* cover ratings. Cover levels fluctuate over time (red line) but do not show a significant linear trend (green nonsignificant regression line).

Precipitation variables had significant effects on *T. caput-medusae* cover in all models we developed. Models indicate that both  $P_{2-4}$  and  $P_{9-10}$  favor increased *T. caput-medusae* cover. In Eureqa Formulize models for change in *T. caput-medusae* cover, the favorable effect of  $P_{2-4}$  and  $P_{9-10}$  are related to thresholds rather than a linear function.

The thresholds vary between different models but generally separate low rainfall years (below overall mean) from years with higher rainfall.

In multiple regression/general linear models (Table 3), high  $P_{12-2}$  showed a weak but significant negative effect on change in *T. caput-medusae* cover. To validate the model, we tested it against random 50% subsamples using of the data set. In multiple runs, only  $P_{12-2}$  commonly dropped below significance, suggesting that this is the least robust of the predictors in the model.

Table 3. Multiple regression model parameters for change in *T. caput-medusae* cover sorted in descending order of effect significance. Graph shows the t ratio. Blue vertical lines represent 5% significance levels. Pink bars show direction and magnitude of t ratio. A positive effect indicates that cover was more likely to increase as the level of the predictor increased. Overall model  $P < 0.0001$ ,  $R^2 = 0.17$ .

Term	Estimate	Std Error	t Ratio	Prob> t
Feb-Apr ppt+	0.1349085	0.010805	12.49	<.0001 *
Reciprocal(ysinceburn)	-0.676211	0.086444	-7.82	<.0001 *
Sep-Oct ppt+	0.195038	0.027544	7.08	<.0001 *
cumETo dec-jan	-0.280466	0.045033	-6.23	<.0001 *
cumETo feb-apr	0.1044694	0.022286	4.69	<.0001 *
Sqrt(gr_prev_yr)	0.3202401	0.079605	4.02	<.0001 *
Dec-Feb ppt	-0.035775	0.010454	-3.42	0.0006 *

Rain in the early winter is normally associated with greater levels of ponding and flooding in low or flat microtopographic positions. This ponding may have a negative effect on *T. caput-medusae* cover, possibly by directly inhibiting *T. caput-medusae* germination and growth and/or by favoring species that compete with *T. caput-medusae*. Competitors may include both native species and other exotic species, such as *Avena fatua* and *Bromus diandrus*, that germinate and grow more readily in early winter. Although  $P_{12-2}$  probably serves as an indicator of early season flooding, a more direct measure of flooding might be a better predictor in the model.

Effects of competition are also suggested by the significance of ET variables in multiple regression models. Warmer conditions in early winter (higher  $E_{12-1}$ ) were associated with negative changes in *T. caput-medusae* cover, possibly because these conditions favor germination and growth of competing early spring annuals. In contrast, warmer conditions in late winter and early spring (higher  $E_{2-4}$ ) were associated with positive changes in *T. caput-medusae* cover, possibly by favoring germination and early growth of this species.

Fire had strong negative effects on *T. caput-medusae* cover, particularly in the first one to two years after a burn. Most of the better-fitting Eureka Formulize models included the reciprocal of the number of years since the last burn as a predictor. The reciprocal of this variable is greatest at year 1 (year after fire) and rapidly attenuates as the number of years increases. This variable was a better predictor of change in *T. caput-medusae* cover than other fire variables in linear regression models (Table 3). Effects of fire were apparent in graphical spatial analysis of the data (Figure 10), although not all burned transect segments show the same magnitude or duration of *T. caput-medusae* suppression.

Significant grazing effects were seen in multiple regression and partition models suggesting that greater grazing intensity generally favors *T. caput-medusae* cover. In

multiple regression models, higher levels of either previous year grazing ( $G_{-1}$ ) or previous May-Aug grazing ( $G_{5-8}$ ) were associated with increases in *T. caput-medusae* cover. Because *T. caput-medusae* is one of the least palatable species at Jepson Prairie, it is possible that increased grazing suppresses competing species more than *T. caput-medusae*. From the partition model, it appeared that the effect of previous year grazing is stronger in drier years, which are less favorable for *T. caput-medusae* overall. In wet years, a positive effect of Jan-Feb grazing ( $G_{1-2}$ ) on *T. caput-medusae* was also seen in partition models. This could be associated with suppression of early-germinating competitors by early winter grazing.

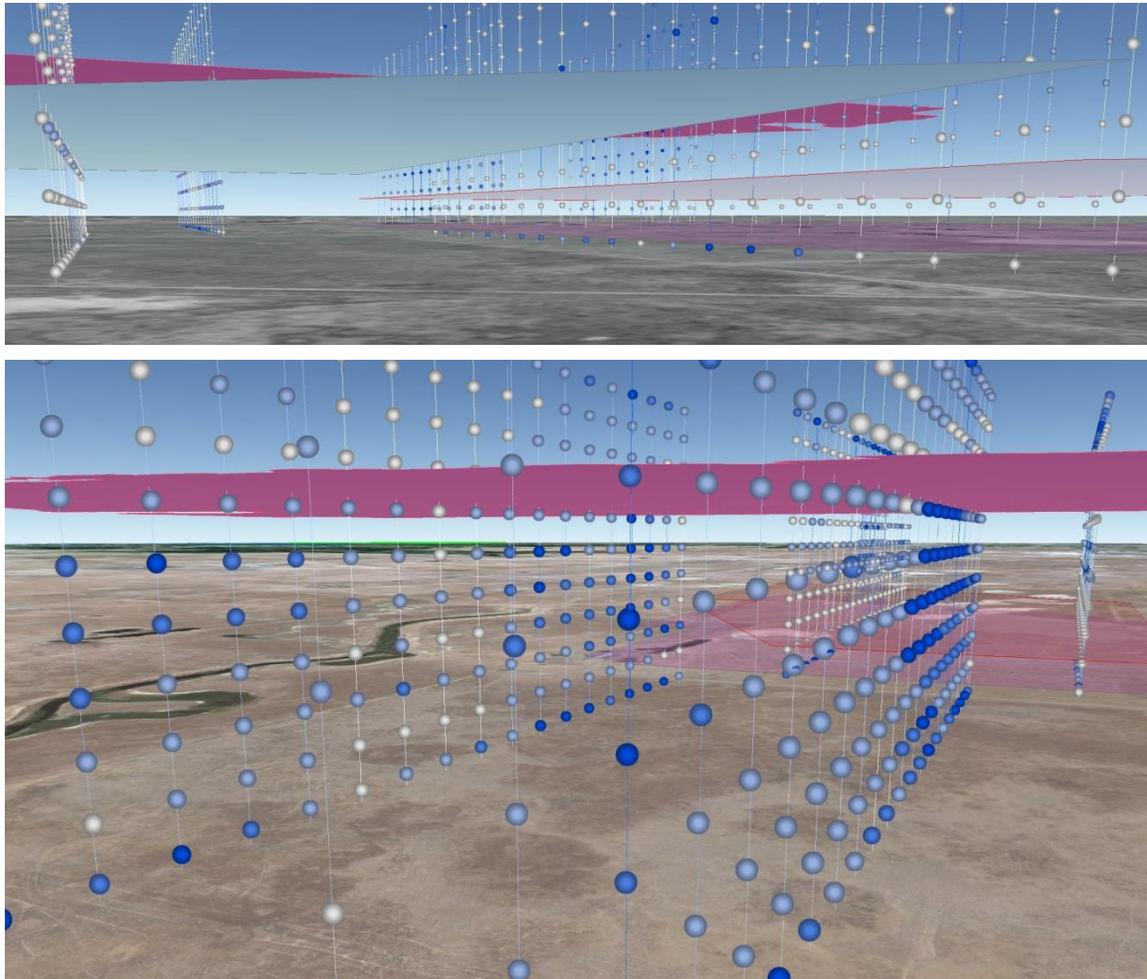


Figure 10. Graphical analysis showing effect of fires on *T. caput-medusae* cover ratings. Ratings are symbolized as spheres, where successive years are shown at progressively higher elevations. Ratings are shown by sphere color (white=0 rating, ratings 1-3 are progressively deeper shades of blue). Burned areas are shown as elevated colored polygons; 2001, 2002, 2003 and 2007 fires are shown at elevations below those of the succeeding year's cover data. Most cover ratings are 0 within burned polygons for one to several years after a fire, whereas adjacent unburned transect segments do not show this change.

The best-fitting Eureka Formulize models for *T. caput-medusae* cover ratings (not change in ratings) included only variables related to precipitation ( $P_{rank}$ ), fire ( $B_t$  and  $B_y$ ),

and microtopography ( $M_{dry}$ ). For example, the following formula was one of several similar formulas with an  $R^2$  value of about 0.32:

$$Tae = \min\left(\max\left(\text{if}(B_t, \max(1.9, P\_rank), 0.715P\_rank), 1.62\right), 0.00336B_tM\_Dry - B_t \geq \left(\max\left(\max(1.82, P\_rank), \frac{0.00336}{M\_Dry}\right)\right)\right)$$

This rather unwieldy formula indicates that:

1. *T. caput-medusae* cover ratings are lowest overall in transect segments with low  $M_{dry}$  (i.e., segments dominated by pools, swales, and damp terraces)
2. *T. caput-medusae* cover ratings increase as the number of years since the last burn increases ( $B_t$ )
3. If  $B_t$  is low (i.e., segment has burned recently), *T. caput-medusae* cover ratings are initially reduced as the number of recent burns increases.
4. *T. caput-medusae* cover increases somewhat as total precipitation ( $P_{rank}$ ) increases, but this effect is largely limited to the wettest years ( $P_{rank}=3$ ) on dry plots microtopographies (high  $M_{dry}$ ) in plots that have not burned for an extended period.

These results are consistent with results from other models and emphasize the interactive effects of these variables.

### ***Centaurea solstitialis***

The regression of least squares means indicates that cover of this species has declined somewhat over time (Table 2). From a graphical presentation of the data (Figure 11), it appears likely that this effect is largely associated with the disappearance or elimination of various spot infestations around the preserve over time. Relatively little directional change in *C. solstitialis* cover ratings are evident in the most heavily infested pastures (14, 22, 23).

Modeling of this outcome is difficult due to the concentrated distribution of *C. solstitialis*. Initial models of various types indicate that precipitation and some grazing variables may influence change, but results may be complicated by effects of any spot eradication efforts.

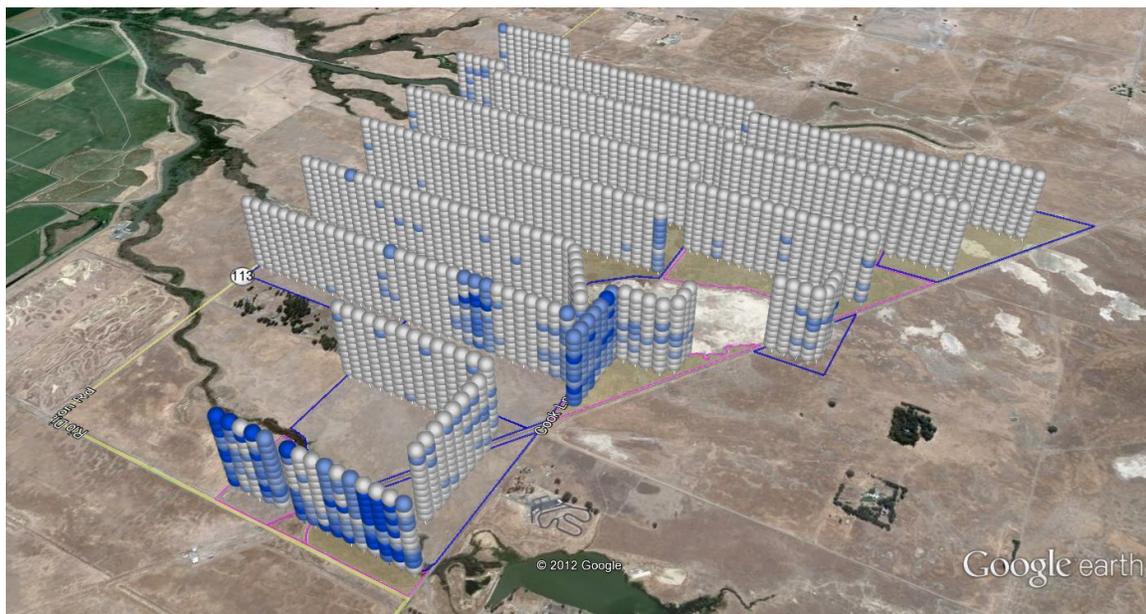


Figure 11. Graphical representation of *C. solstitialis* cover ratings across all transect segments from 2001 through 2011. Ratings are symbolized as spheres, where successive years are shown at progressively higher elevations. Ratings are shown by sphere color (white=0 rating, ratings 1-3 are progressively deeper shades of blue). Angle of view is from the northwest.

### **EFFECTS OF REDUCING SAMPLE SIZE OR DATA COLLECTION FREQUENCY**

Monitoring of the 324 transect segments each year requires a substantial commitment of time and effort. In 2002, three field days (5-6 hours) by two crews (3 or more persons) were required to complete the survey. SLT staff members have expressed interest in knowing how a reduced sampling scheme (fewer segments or alternating years) would affect the quality of the data set. To address this issue, we subsampled the existing data to mimic a reduced sampling plan (fewer segments) or reduced data collection frequency (even or odd years only).

#### **Using fewer transects**

The transect system was designed to both provide a robust sample size and to ensure that all pastures were included. All of the 2001 pastures included at least one transect,

and larger pastures had two or more transects. Due to this sampling intensity, every pasture had at least one transect even after several large pastures (18, 19, and 20) were subdivided into smaller pastures. Approximately 5% of the total area of the pastures was included in the original transect pattern.

### “All pastures” alternative

To develop a reduced sampling plan, we eliminated the second transect from any of the pastures that included two transects and the one diagonal transect leg in pasture 20W (Figure 12). This sampling scheme still leaves one transect in each field, but reduces the number of transect segments by 37%, from 324 to 204. Reading this reduced set of plots would presumably reduce field personnel use by about one third and data entry time by a similar amount. However, other aspects of the monitoring effort, such as coordinating and training field crews, printing datasheets, developing reports, etc., are not likely to be appreciably shortened. Hence, the total time savings associated with reduced sampling will be less than the 37% reduction in transect segments.

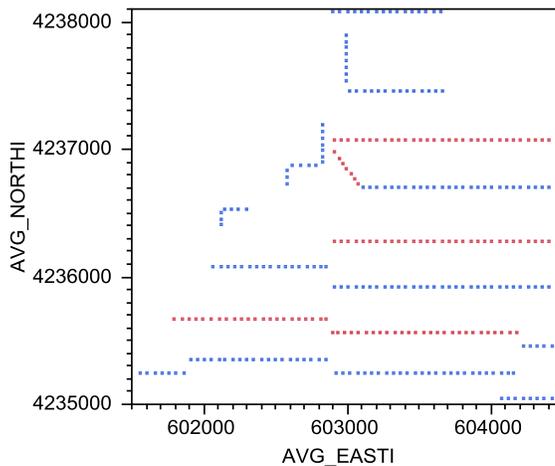


Figure 12. “All pastures” reduced transect sampling plan that eliminates the second transect in all pastures. Deleted transect segments are shown in red, retained segments are in blue.

### “Vernal pools” alternative

After reviewing the above reduced sampling plan, Ben Wallace proposed another reduced sampling alternative. This reduced sampling alternative eliminates transects 1, 2, 3, 7, 10, 12, 13, 14, and 15 (Figure 13). This alternative reduces the number of segments by 114 to 210, a reduction of 35%. It eliminates transects from some of the pastures on the edge of the preserve, which would make the monitoring program less sensitive for weed detection. It also removes the second transect in most pastures that have two transects. The emphasis of this alternative is to emphasize monitoring of the core pastures within the preserve, which have a more “typical” mix of vernal pools and grasslands. As with the above alternative, total time savings would likely be less than the 35% by which the segment count is reduced. However, since several of the excluded transects are more difficult to access, field data collection time should be somewhat shorter than the “all pastures” alternative.

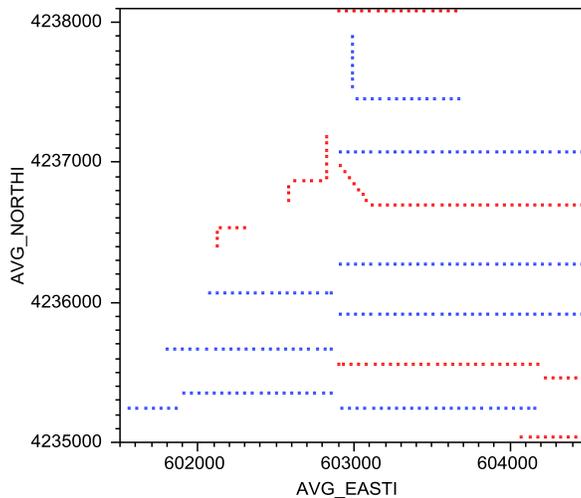


Figure 13. “Vernal pools” reduced transect sampling plan that eliminates transects primarily at the edges of the preserve. Deleted transect segments are shown in red, retained segments are in blue.

### Comparisons between full data set and reduced transect subsets

After excluding the transect segments shown in red in Figures 12 and 13, we checked to see whether models based on the full data set differed from those based on the reduced data sets. As noted above, regression models for change in *N. pulchra* cover were significant but had low predictive power even when the entire data set was used. With both of the reduced data sets, overall model  $R^2$  dropped slightly and one of the factors that was significant in the full data set model ( $P_{9-10}$ ) was no longer significant (Table 4). Regression models for change in *T. caput-medusae* cover were more robust than those for change in *N. pulchra* cover. With both reduced data sets, overall model significance and fit were similar to that of the full data set model (Table 4). All variables in the model were still significant, although the P level for some variables declined.

We also compared partition models for change in cover for the full and reduced transect data sets. For change in *N. pulchra* cover, partition models for both full and reduced data sets had poor fit overall. The initial cutting variable differed for the three data sets, but some variables ( $E_{12-1}$ ,  $P_{2-4}$ ) were used as cutting variables within the first few splits in two or more of the models. As noted above, changes in *N. pulchra* cover appear to be related to various interactions between certain variables. The reduced data sets delete non-random subsets of the data and may eliminate some or all of the segments showing these interactions. Hence, the partition models differed substantially between the full and reduced data sets.

Table 4. Overall regression models for change in cover for selected species using the full data set and two reduced transect subsets shown in Figures 12 and 13. Note that for change in cover variables, the sample size (N) is commonly less than the total number of segments because plots with no cover in consecutive years are defined as missing (see methods).

Species		Full data set	“all pastures” reduced sample set	“vernal pools” reduced sample set
<i>Nassella pulchra</i>	<b>Sample size</b> <b>Overall model</b> Parameters: <b>P</b> <sub>12-2</sub> <b>E</b> <sub>12-1</sub> <b>P</b> <sub>9-10</sub>	N=1952 R <sup>2</sup> =0.020, P<0.0001  P=0.0002* P<.0001* P=0.0091*	N=1267 R <sup>2</sup> =0.015, P=0.0003  P=0.0107* P=0.0002* P=0.1957	N=1334 R <sup>2</sup> =0.018, P<0.0001  P=0.0116* P<.0001* P=0.0555
<i>Taeniatherum caput-medusae</i>	<b>Sample size</b> <b>Overall model</b> Parameters: <b>P</b> <sub>2-4</sub> <b>1/B</b> <sub>y</sub> <b>P</b> <sub>9-10</sub> <b>E</b> <sub>12-1</sub> <b>E</b> <sub>2-4</sub> <b>sqrt(G</b> <sub>-1</sub> <b>)</b> <b>P</b> <sub>12-2</sub>	N=2536 R <sup>2</sup> =0.170, P<0.0001  P<.0001* P<.0001* P<.0001* P<.0001* P<.0001* P<.0001* P=0.0006*	N=1558 R <sup>2</sup> =0.168, P<0.0001  P<.0001* P<.0001* P<.0001* P<.0001* P=0.0115* P=0.0208* P=0.0046*	N=1614 R <sup>2</sup> =0.205, P<0.0001  P<.0001* P<.0001* P<.0001* P<.0001* P<.0001* P=0.0003* P=0.0007*

\*Significant at P≤0.05

For change in *T. caput-medusae*, partition models had higher R<sup>2</sup> values from the initial split. For the full and both reduced data sets, the initial partition was at  $P_{2-4} \geq 5.455$ , but the three models began to diverge at the second split. The effect of fire history was more influential in the full data set than in either of the reduced data subset models. The model derived from the “vernal pools” data set also showed a much greater influence of previous year grazing (G<sub>-1</sub>) than did either of the other data sets. Because grazing interacts with other factors, grazing effects may be more apparent in subsets of the data in which interactions enhance grazing impacts.

Repeated measures analyses were generally less sensitive to reductions in the number of transect segments because of the high significance levels associated with effects in the models. In general, P levels were reduced using both the “all pastures” and “vernal pools” subsets. As shown in Table 5, the effect of time for *V. pedunculata*, which was only moderately significant in the full data set was nonsignificant for both reduced data subsets. For *C. pycnocephalus*, the P level for time was still significant for the reduced data sets, but was not as highly significant.

Based on visual analysis alone, the full set of transect data (Figure 3) presents a more complete and more complex picture of the changes seen in *N. pulchra* cover over time compared with the reduced data sets (Figure 14). Areas with declining *N. pulchra* populations are still discernible from the reduced data sets, but are less clear. In particular, both reduced transect alternatives eliminate one of the transects in pastures 20E and 20W, where the *N. pulchra* populations were especially sparse. An advantage of the full data set is that it can be pared down in various ways if needed to isolate specific patterns. The reduced data sets provide fewer options for visual exploration of the data because it is more difficult to detect patterns when fewer points are available.

Table 5. Overall repeated measures multivariate analysis of variance (MANOVA) model parameters for cover of selected species using the full data set and two reduced transect subsets shown in Figures 12 and 13. Full data set models differ from those in Tables 1 and 2 in that microtopography variables, which were not recorded for all transects, were not considered in the MANOVA models.

Species	Full data set	"all pastures" reduced sample set	"vernal pools" reduced sample set
<i>Viola pedunculata</i>	Time: 0.0374* T × soil type: <0.0001 T × burn years: <0.0001	Time: 0.1151	Time: 0.9572
<i>Carduus pycnocephalus</i>	Time: 0.0002 T × soil type: : 0.0002 T × burn years: <0.0001	Time: 0.0085 T × soil type: 0.0299 T × burn years: <0.0001	Time: 0.0311 T × soil type: 0.0040 T × burn years: <0.0001

One of the priorities considered in the original design of the monitoring system was to provide a way to detect and monitor the spread of new weeds at the preserve. With reduced sampling intensity, this capability would be degraded. The degradation in detection sensitivity would be greater for the "vernal pools" transect subset because invasive species tend to be introduced along roadways such as SR113. As shown in Figure 11, the largest and most persistent populations of *C. solstitialis* are found in pastures 14, 22, and 23, which would be eliminated in the "vernal pools" alternative. In addition, eliminating the second transect in the larger pastures (both reduced transect alternatives) results in wider spacing between adjacent transects. This would reduce the ability to monitor spread of invasive species within the preserve. For example, expansion of the patches of *C. solstitialis* in pasture 20W (Figure 11) would be more difficult to track using either of the reduced transect alternatives.

### Monitoring in alternate years

Reducing monitoring by collecting data only in alternate years would be another way to reduce the costs and time associated with sampling. Since all activities related to monitoring would only be done in alternate years, the reduction in effort by SLT would be very close to 50%. However, changing the monitoring to a biennial activity has a number of significant consequences for data collection and analysis. It is likely to become more difficult to avoid methodological drift on a two-year schedule because of the increased time between monitoring and less overlap in crew members on a two-year schedule.

One of the basic analysis outcomes, change in cover from one year to the next, cannot be calculated without annual data. It is possible to compute a two-year change in cover, but this variable is difficult to interpret. Most of the year-to-year changes are associated with conditions that occurred during the current year's growing season (e.g., precipitation, ET), although some factors have effects that can last into a second year or longer (e.g., fire). By looking only at two-year changes in cover, it is not possible to differentiate between current season influences and influences from the preceding growing season. This effectively eliminates the possibility of doing meaningful analyses to test for the effect of these factors.



data set and reduced data sets using only even or odd years. All of these models differed substantially from each other with respect to the effects that were significant, and in some cases, the direction of the effect (positive vs. negative). The models were also quite different from the model developed using change in cover over a single year.

Repeated measures analyses for *T. caput-medusae* and *N. pulchra* cover showed less sensitivity to alternate year subsampling of the data set. As expected, the significance levels of the time or time by factor (e.g., soil type) interactions were reduced. In some cases, factors that were significant with the full data set were non-significant in the reduced sample.

As with the reduced sampling intensity, strong trends are still evident in graphic analysis of alternate year data (Figure 15). However, the strength of trends over time is more difficult to judge with alternate year data.

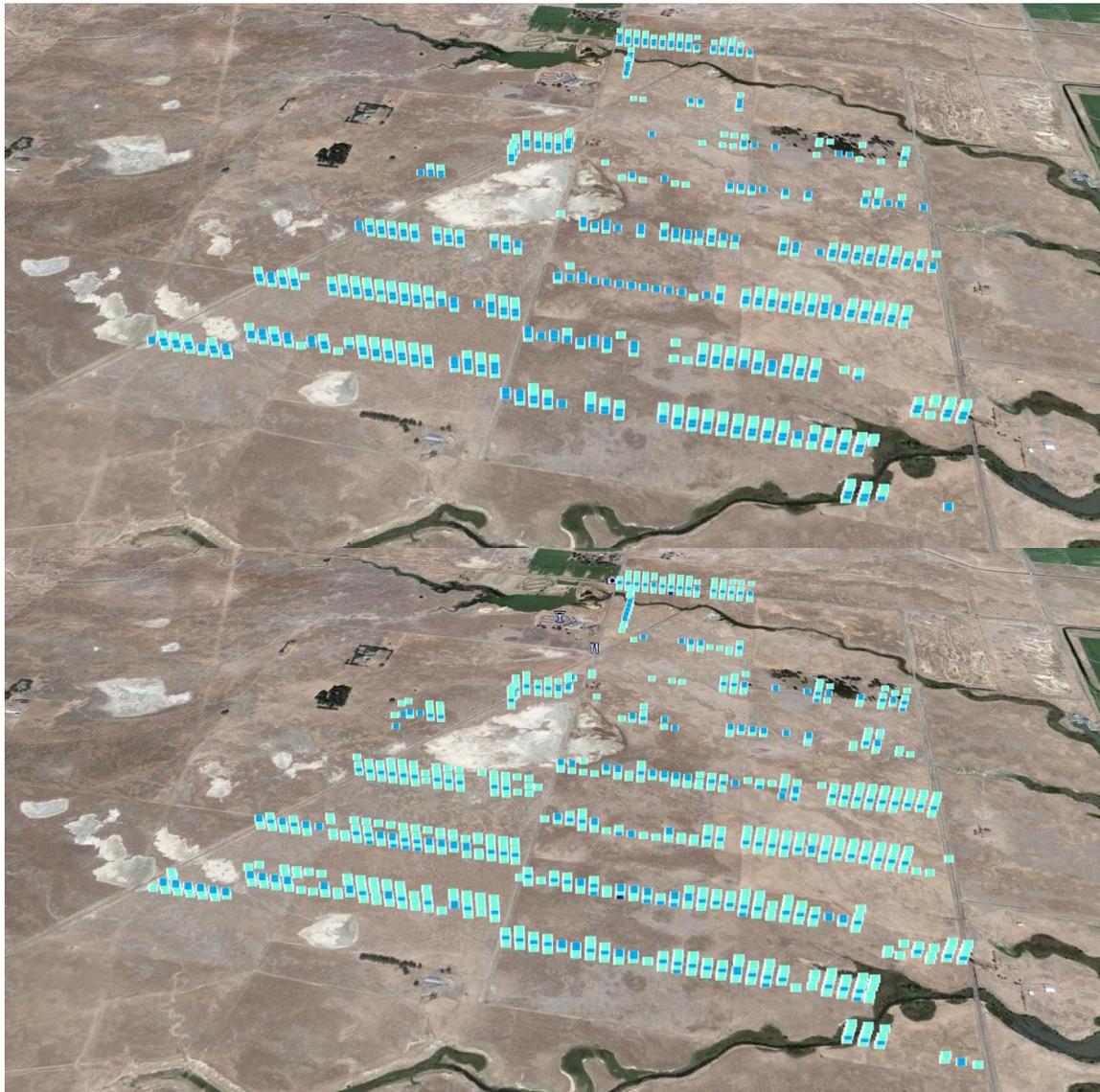


Figure 15. Images showing *N. pulchra* ratings for even (top) or odd (bottom) years between 2001 and 2011. Data for later years are displayed at progressively higher altitudes above the map surface. Higher levels of cover are shown as progressively darker symbols. Missing symbols indicate zero cover ratings. Compare with Figure 2, which shows the same data for all years.

### Effect of Monitoring Date

One question related to the monitoring effort is the extent to which cover estimates are influenced by overall plant growth stage and phenology. The optimal timing is considered to be when *Lasthenia* spp. are at or slightly past peak bloom. At this time, many of the native species are at or somewhat past bloom, whereas various exotics (e.g., *T. caput-medusae*, most thistles) have not bloomed or are just beginning to produce inflorescences. From year to year, some differences in phenology occur depending on the date that the survey is conducted. As previously reported (Swiecki and Bernhardt 2002), small differences arose when 14 transect segments were rated 4 days apart in 2002.

Because many of the monitored exotic species mature later in the season, it is possible that a later assessment date would increase their visibility and cover estimates. Ratings made later in the spring might therefore provide a better estimate of the maximum cover that these species attain in a given growing season.

To test this hypothesis, SLT staff reassessed cover on transects in pastures 3, 14, 22, 22D, and 23 in May 2010. This provided two sets of ratings for 46 transect segments, one taken in mid-April and the other in early May. We used both contingency table analyses and repeated measures MANOVA to assess whether the two sets of readings differed significantly (Table 6). For MANOVA analyses, pasture was included in the model as a predictor. Because pasture 22D (Dozier) had only two transect segments, each segment was assigned to the adjoining pasture (22 or 23) for purposes of this analysis.

Several statistics used to assess differences between the two sets of readings provided similar results (Table 6). Ratings of the exotic species *L. serriola*, *C. pycnocephalus*, *C. solstitialis* and the native species *A. millefolium* and *D. danthonioides* showed good agreement between the two rating dates. In contrast, three species showed highly significant changes between the two ratings. *T. caput-medusae* ratings increased substantially from the April to the May ratings, whereas ratings for the spring annuals *Erodium* spp. and *T. eriantha* were significantly lower in May than April. Several other native species (*V. pedunculata*, *P. californicus*, *Lasthenia* spp., and to a lesser degree, *N. pulchra*) had lower cover ratings in May than April in substantial numbers of segments. Variation in the amount of change seen among the different pastures resulted in a significant time  $\times$  pasture interaction for most of the significant models.

Several factors probably contribute to differences seen between the ratings. For *T. caput-medusae*, plants were likely to be more visible in May because seedheads would have been fully expanded by that point. It is also possible that the actual cover of this species increased somewhat over the interval as it expanded into space occupied by dead or senescent annuals. Most of the species that showed clear declines in cover are annuals that were probably quite dry and difficult to identify from a distance in May. The perennial species *V. pedunculata* would have been inconspicuous in its post-bloom stage, and may have been starting to senesce as well.

It appears likely that cover and incidence of *T. caput-medusae* is underestimated in the existing data set, which is based on April assessments. Nonetheless, detection of this species has been adequate to identify factors that affect its cover, such as fire. Other summer annual exotics (*L. serriola*, *C. pycnocephalus*, *C. solstitialis*) were detected with similar efficiency in April and May. Furthermore, many spring annuals were detected

much less efficiently in May than in April. Based on these results, there appears to be little justification for either shifting to a later evaluation date or rating natives and exotics independently on different dates.

Table 6. Comparisons of ratings for selected species made in April and May 2010 in 46 transect segments. Species highlighted in yellow showed significant differences between April and May ratings based on multiple tests.

Species	Statistical test			Average rating		Number of segments			Largest change	
	Kappa <sup>1</sup>	Bowker/ McNemar P level <sup>2</sup>	Repeated measures time P level <sup>3</sup>	April	May	No change	Higher in May	Lower in May	increase	decrease
<b>Exotic species</b>										
<i>Taeniatherum caput-medusae</i>	-0.0006	<.0001*	0.0002*	0.82	2.33	8	36	2	0 → 3	3 → 2
<i>Erodium</i> spp.	0.06	<.0001*	<.0001*	2.67	1.72	12	2	32	1 → 2	3 → 1
<i>Lactuca serriola</i>	0.30*	0.0588	0.1460	.065	.17	39	6	1	0 → 1	1 → 0
<i>Carduus pycnocephalus</i>	0.47*	0.5062	0.5484	0.48	0.48	33	7	6	1 → 2	2 → 1
<i>Centaurea solstitialis</i>	0.72*	0.8088	0.165	0.56	0.52	39	2	4	0 → 1	2 → 0
<b>Native species</b>										
<i>Triphysaria eriantha</i>	-0.005	<.0001*	<.0001*	1.11	.07	5	0	41	--	3 → 0
<i>Viola pedunculata</i>	0.12	0.0009*	0.0005*	0.26	.02	35	0	11	--	1 → 0
<i>Pleuropogon californicus</i>	0.31*	0.0117*	0.0023*	.37	.11	35	0	11	--	2 → 0
<i>Lasthenia</i> spp.	0.45*	0.0380*	0.0010*	.93	.61	30	1	15	2 → 3	3 → 1
<i>Nassella pulchra</i>	0.33*	0.7667	0.9635	.63	.51	40	6	10	1 → 2	2 → 1
<i>Deschampsia danthonioides</i>	0.69*	0.8013	0.7748	.26	.24	41	2	3	0 → 1	2 → 1
<i>Achillea millefolium</i>	0.86*	0.8013	0.4521	0.11	.09	45	0	1	--	2 → 1

\* Significant at P≤0.05.

<sup>1</sup> Kappa agreement statistic (Cohen's kappa). The statistic is significant if agreement is greater than expected by chance alone. A value of 1 represents complete agreement between the two values, 0 represents a level of agreement based on chance alone. Negative values indicate disagreement that is greater than expected by chance. Values of k indicate the strength of the agreement: < 0.20=Poor; 0.21 - 0.40=Fair; 0.41 - 0.60=Moderate; 0.61 - 0.80=Good; 0.81 - 1.00=Very good (Altman 1991)

<sup>2</sup> The Bowker statistic tests the hypothesis that an observed r x r contingency table contains frequencies that are symmetric and is used to test the null hypothesis that the two sets of ratings do not differ. For a 2 x 2 table (ratings of only 0 and 1), the test is equivalent to the McNemar test. A significant statistic indicates a difference between the two sets of ratings.

<sup>3</sup> P level of the time factor from a repeated measures MANOVA of the two rating dates, using pasture as a model effect.

## CONCLUSIONS

We can draw several conclusions from the analyses presented above.

### Changes over time

All of the monitored species showed year-to-year changes over the monitoring period. Weather, especially precipitation, appears to be the primary driver of many of the observed fluctuations in cover. However, three native perennials (*N. pulchra*, *A. millefolium*, and *V. pedunculata*) and two exotics (*C. solstitialis* and *L. serriola*) showed

general declines in cover over the monitoring period that were not explained by the weather variables tested.

### **Factors associated with vegetation changes**

Detailed analyses of data for *N. pulchra* did not identify strong predictors of change in cover for this species. In contrast, models for *T. caput-medusae* showed that several precipitation variables and fire history account for a substantial amount of the observed variation. Many of the observed vegetation outcomes appear to result from highly interactive relationships between cultural practices (grazing, fire) and environmental predictors (weather, soils, microtopography). Analyses need to account for these possible interactions, the overall repeated measures design, and the spatial distribution of the segments. The analyses reported here represent a first attempt to take this complex data structure into account, and may not represent the best or only ways to assess factors influencing vegetation outcomes.

### **Altered data collection scenarios**

We looked at several scenarios that involved changing the way that monitoring data are collected. One analysis compared the standard mid-April data collection date to a later May date. As expected, cover estimates for several species changed depending on the assessment date, but only *T. caput-medusae* cover estimates were likely to be improved by the May assessment. We conclude that for all other species shifting data collection to May would not be justified.

Reduced data collection scenarios were also examined. For a number of reasons, reducing data collection to alternate years is not recommended. This sampling scenario is likely to obscure trends that develop over time, degrade data collection consistency, and eliminate the possibility of conducting various meaningful data analyses.

We looked at two alternatives for reducing the number of transects monitored on an annual basis by about one third. We concluded that the most robust effects seen in widely distributed species are still likely to be seen in the reduced data sets, although their significance level is typically reduced. Less pronounced effects or those that are associated with specific interactions are less likely to be detected in reduced data sets.

Furthermore, for species with spatially clumped distributions (e.g., *C. solstitialis*), elimination of specific transects can eliminate opportunities to follow changes over time. Assessment of factors associated with spread or decline of such species will not be possible if transects that include these populations are eliminated. Also, the ability of the monitoring system to detect any new infestations of exotic species or localized declines of native species will be degraded under reduced sampling scenarios.

The Jepson Prairie vegetation monitoring data provides a source of long-term data that will only increase in value over time if high quality data can continue to be collected. One aspect of such long-term data sets is that they can often be useful for examining effects that were not anticipated in the original design. However, maintenance of data quality and integrity is critical. If it is possible, we recommend that the monitoring system be maintained in a fashion that will remain fully compatible with the existing data set. The potential savings associated with reduced sampling (about 30% or less

compared with the current efforts) do not clearly justify the resulting losses in the sensitivity and capability of the monitoring system.

**Literature cited**

Altman D.G. 1991 Practical statistics for medical research. London: Chapman and Hall.

Swiecki, T.; Bernhardt, E. 2002. Exotic and native plant monitoring at Jepson Prairie Preserve, 2002. Prepared for Solano Land Trust, Fairfield, CA. 51 pages.

Swiecki, T. J.; Bernhardt, E. A. 2008. Effects of grazing on upland vegetation at Jepson Prairie Preserve, Solano County, CA. Third year (2007) results and final report. Prepared for Solano Land Trust, Fairfield, CA. 76 p.