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DISTURBANCE HISTORIES INCREASE VARIABILITY IN REMOTELY SENSED INDICES OF VEGETATION IN SAGEBRUSH-STEPPE OVER THE PAST CA. 20 YEARS

by

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PREFACE

The combined use of Geographic Information Systems (GIS) and remote sensing has grown in ecological investigations because of their ability to help analyze spatial and temporal data (Cohen and Goward 2004). These tools offer great promise to studies concerning the function of ecosystems across large spatial (regional-level) and temporal (decadal) scales. Prior to the development of remote sensing, it was necessary to deduce ecosystem function based on measurements taken at finer scales. Now, with the availability of remotely sensed data, it is possible to directly discern large-scale patterns in ecosystem function, and to measure large-scale processes as they take place (Roughgarden et al. 1991).

One such application consists of evaluating changes in vegetation across landscapes over time that relate to natural and anthropogenic disturbances (i.e., fire and/or livestock grazing). Ground-based measures for such assessments, by necessity, focus mainly on a limited number of plots ranging in size from one to several square meters (Cohen and Goward 2004), and as a result, may not sample adequately in time and space to capture spatial and temporal changes in vegetation over large areas (Washington-Allen et al. 2004). Remote sensing, however, provides the spatial extent and continuous, long-term data necessary to detect changes in vegetation across landscapes that may be due to fire and/or livestock grazing disturbances.

Of all the remotely sensed data available, those acquired by Landsat satellite sensors have played the most pivotal role in spatial and temporal analyses of vegetation (Cohen and Goward 2004). Landsat has major advantages for regional monitoring applications that rely on temporal data sets. First, with more than 30-years of data collection, it offers the longest-running time series of remotely sensed imagery (Cowen and Goward 2004). Second, the grain of measurement or spatial resolution of the data enables the characterization of vegetation changes associated with the grain at which land management occurs (Cowen and Goward 2004). Third, previous studies have used spectral vegetation indices (SVI's), derived from Landsat data, to examine the abundance of rangeland vegetation (Graetz and Gentle 1982; Pickup and Foran 1987; Graetz et al. 1988; Smith et al. 1990; Pickup et al. 1993; Senseman and Bagley 1996; Elmore et al. 2000; McGwire et al. 2000; Ramsey et al. 2004; Wallace et al. 2004; Washington-Allen et al. 2004). These indices provide estimates of seasonal and inter-annual variations in vegetation in response to natural and anthropogenic disturbances on the environment (Paruelo and Lauenroth 1998) and can be used to detect broad-scale landscape changes related to ecosystem condition, independent of the phenological events of specific plants (Reed et al. 1994). Fourth, when combined with GIS, which was used in this study to incorporate the spatial representation of areas with different histories of fire and livestock grazing disturbances, can be used to examine how disturbance history relates to vegetation changes across landscapes.

Landsat has been used in many ecological applications concerning vegetation, such as characterizing land cover, mapping plant cover change, examining phenological variability, detecting fire or grazing effects on plant communities, characterizing inter-annual variability of shrublands and grasslands, and mapping the spatio-temporal responses of dry season vegetation (ex: Pickup et al. 1993; Reed et al. 1994; Paruelo and Lauenroth 1995; Paruelo and Lauenroth 1998; Qi et al. 2000; Paruelo et al. 2001; Diaz-Delgado et al. 2002; Washington-Allen et al. 2004). While some studies have used

Landsat to examining the separate effects of disturbances, such as fire or livestock grazing (Diaz-Delgado et al. 2002; Washington-Allen et al. 2004), on changes in vegetation over time, few studies have investigated the combination of fire and grazing impacts on long-term vegetation responses.

Examining the combined impacts of fire and grazing disturbances on vegetation relies on change assessment, which, in turn requires an understanding of the natural variability of vegetation over time (Paruelo and Lauenroth 1998). Disturbance impacts can be detected when the variability induced by them becomes larger than the natural variability. One method of characterizing how these factors affect vegetation function at regional or landscape scales (i.e., the Upper Snake River Plain, Idaho) is by analyzing spatial and temporal variability (Magnuson et al. 1991; Paruelo and Lauenroth 1998). This study used a 17-year archive of Landsat imagery in combination with GIS data to examine the effects of fire and livestock grazing on the spatial and temporal variability of sagebrush-steppe rangelands in southeastern Idaho. The study area is located on the Idaho National Laboratory (INL), the largest existing reserve of sagebrush-steppe in the United States.

For clarification, this thesis is comprised of three major sections. The first section addresses the specific GIS and remote sensing methods that were used in this study. The second section consists of a manuscript to be submitted to a peer-reviewed journal, which describes my study and my major findings, and includes an abstract, introduction, methods, results, and discussion. The third section contains the overall conclusions and implications of my study.

GEOTECHNOLOGY METHODS

The geotechnology methods consist of the following sections: 1.) satellite image acquisition, 2.) satellite image pre-processing, 3.) spectral vegetation index (SVI) calculations, 4.) disturbance category selection, and 5.) disturbance category data extraction.

Satellite Image Acquisition

We used multispectral satellite data that consisted of images (path 39, row 30) captured by the Landsat 5 Thematic Mapper (TM) and the Landsat 7 Enhanced Thematic Mapper Plus (ETM+) sensors. The extent of the study area, the Idaho National Laboratory (INL), was characterized by one Landsat 5 TM or Landsat 7 ETM+ image (185 km swath width), with the grain of measurement corresponding to one pixel (30 m) that is defined by the spatial resolution of the Landsat sensors. The Landsat sensors are platforms on space-born satellites that utilize scanning mirror spectrometers and linear array detectors to capture electromagnetic energy reflected from the Earth's surface, while maintaining a 705 km, sun-synchronous orbit on a 16-day revisit cycle.

One cloud-free Landsat image per year was selected for 17 of the previous 20 years from 1984 – 2003, in a 30-day window centered on 27-June (Table 1). This 30-day window consisted of dates ranging from 11-June to 16-July. We were unable to use more sampling dates per year, due to cloud cover or data gaps (Appendix 1); and therefore, adjusted our inquiry to avoid complications due to phenological shifts. The 30-day window was roughly equivalent to the peak summer growing season for sagebrush-steppe, as estimated by Paruelo and Lauenroth (1995 and 1998) using the maximum normalized difference vegetation index (NDVI) derived from Advanced Very High Resolution Radiometer (AVHRR) data. Once all images were obtained, pre-processing steps were performed to ensure the comparisons between pixels and years were due to changes in vegetation (versus sensor and data noise).

Satellite Image Pre-processing

Surface features on the earth are complex and do not lend themselves well to being recorded by remote sensing devices that have constraints such as spatial, spectral, temporal, and radiometric resolution (Jensen 1996). As a result, errors such as data acquisition noise can degrade the quality of the remote sensor data (Duggin and Robinove 1990; Lunetta et al. 1991, Jensen 1996). Consequently, this may impact the accuracy of subsequent image analyses of vegetation change resulting from disturbances. Therefore, satellite image pre-processing was performed on each image prior to performing image analyses. Image pre-processing was performed using ENVI 3.6 software (Research Systems, Inc., Boulder, CO), and consisted of: 1.) conversion of digital number (DN) values per pixel to at-satellite reflectance, 2.) image co-registration, and 3.) multiple-date, image normalization using linear regression.

<u>Conversion of DN values to at-satellite reflectance.</u> It is possible for radiometric errors in remotely sensed data to be introduced as noise from sources such as atmospheric attenuation, changing view and illumination geometry, and instrument errors. A significant portion of this noise can be removed by performing a first order normalization that involves converting the pixel DN values of the original data to at-satellite reflectance values (Huang et al. 2001). At-satellite reflectance images should be more appropriate

for land cover change analysis than DN images (Huang et al. 1998), because the temporal information contained in at-satellite reflectance images is more relevant to ground areas of concern than that contained in DN images (Huang et al. 2001). The three equations used for converting DN to at-satellite reflectance are (Bastiaanssen et al. 2002; Huang et al. 2001):

$$L_\lambda = \text{Gain}_\lambda * DN_\lambda + \text{Bias}_\lambda \qquad (1)$$

$$\rho\lambda = \frac{\pi * L_\lambda * d^2}{ESUN_\lambda * \cos\theta * d_r} \qquad (2)$$

$$L_\lambda = (LMAX - LMIN / 255) * DN + LMIN \qquad (3)$$

Equations (1) and (2) were used for Landsat 5 TM and 7 ETM+ data when the gains and bias information was provided in the header file, where DN is the digital number of each pixel, L and ρ are at-satellite radiance and reflectance, respectively. The subscript λ refers to spectral band λ, $ESUN_\lambda$ is the mean solar exo-atmospheric irradiance for each band ($W/m^2/\mu m$), cos θ is the cosine of the sun elevation angle or solar incidence angle (from nadir), and d_r is the inverse squared relative earth-sun distance. Gains and bias are general terms used to denote an increase in signal power measured by the sensor. An image is captured in low gain mode when surface brightness is high and in high gain mode when surface brightness is lower. Equation (3) was used for Landsat 5 TM and 7 ETM+ data when gains and bias were not provided in the header file, where LMAX and LMIN are calibrated constants for low and high gain that can be found in a look-up table in the Landsat 7 Science Data Users Handbook (Irish 2000; http://ltpwww.gsfc.nasa.gov/IAS/handbook/handbook_toc.html). The majority of the images, which have gains and bias information in the header files, were converted to at-sensor reflectance using the Landsat calibration tool in ENVI 3.6.

Image co-registration. In order to compare pixel values of disturbance sites among and between images, it was necessary to perform image-to-image registration, a geometric correction procedure that aligns corresponding pixels of one image to another. This involves a translation and rotation process by which two images, a base image and registration image, of the same geometry and similar geographic area are positioned in respect to one another so that corresponding pixels appear in the same place on the registered images (Jensen 1996). Prior to co-registration, all images were converted to a common projection and datum, Universal Transverse Mercator (UTM) World Geodetic System 1984 (WGS84), using the convert map projection tool in ENVI 3.6. A spatial subset (resize) of the Landsat 7 ETM+ June 26, 2002 image was used as a base image by which the remaining images were co-registered using 20 ground control points (GCP's). GCP's are points on the surface of the earth where both image coordinates (measured in rows and columns) and map coordinates can be identified (Jensen 1996). GCP's were selected manually using the ENVI 3.6 co-registration tool, and consisted of easily distinguishable ground features, such as road intersections. The accuracy of the co-registration was assessed by the root-mean-square error (RMS_{error}), which is a measure of distortion for each GCP that is calculated by the square root of the squared deviations between the GCP's of the base image and registration image. All images were co-registered at an $RMS_{error} < 0.5$ (Jensen 1996). Additionally, the output parameters for the registered images were changed to correspond to those of the base image so they have the same image size (rows and columns) and upper left X, Y corners.

Image normalization. In addition to correcting for geometric differences between images, it was also necessary to correct for radiometric differences due to non-surface factors, such as sun angle, Earth/sun distance, detector calibration, atmospheric conditions, and sun/target/sensor geometry (Heo and FitzHugh 2000). By reducing the radiometric influence of non-surface factors through image normalization, differences in pixel reflectance values between images from different dates will reflect actual changes on the surface of the Earth (Heo and FitzHugh 2000). The linear regression method described by Jensen (1996) was used. This method uses pseudo-invariant objects (PIO's), which are ground targets that are assumed to be features with consistent reflectance characteristics over time, to normalize multitemporal datasets to a single reference image. Twenty PIO's were selected using the acceptance criteria established by Heo and FitzHugh (2000) where targets: 1.) should be approximately the same elevation so that the thickness of the atmosphere over each target is approximately the same, 2.) targets should contain minimal amounts of vegetation because the spectral reflectance of vegetation can change over time, 3.) must be in a relatively flat area so that increases or decreases in sunlight will be proportional to changes in sun angle from date to date, 4.) should be consistently the same over time or have patterns that do not change over time when viewed on the image display screen, 5.) targets must have a wide range of reflectance or brightness values for the regression model to be reliable. PIO's used in this project consisted primarily of non-vegetation surfaces, such as asphalt or concrete, that were located on roads or building rooftops.

The July 1, 2001 Landsat 5 TM image was used as the reference image because it was atmospherically corrected (prior to when we acquired the image) and, as a result, was likely to contain the least amount of radiometric error due to atmospheric conditions. Linear regressions were performed for Landsat bands three (red) and four (NIR) between the reference image and each image to be normalized using Sigma Plot 2000 v6.0 (SPSS, Inc., Chicago, IL). The resulting normalization equations for bands three and four, or the slopes of relationships between reflectances of the reference and normalization images, were then applied to each corresponding image using the band math tool in ENVI 3.6.

Spectral Vegetation Index (SVI) Calculations

The electromagnetic energy recorded by Landsat is stored into seven spectral bands (channels) ranging from 0.45 – 12.5 μm (Appendix 2 and 3). The spectral designations of the bands were selected to make maximum use of the dominant factors controlling leaf reflectance, such as leaf pigmentation, leaf and canopy structure, and moisture content (Jensen 2000). Previous studies have used spectral vegetation indices (SVI's), derived from remotely sensed ratios of red and near-infrared reflectance, to examine the abundance of rangeland vegetation (Graetz and Gentle 1982; Pickup and Foran 1987; Pickup et al. 1993, Senseman and Bagley 1996, McGwire et al. 2000, Ramsey et al. 2004, Wallace et al. 2004, Washington-Allen et al. 2004). These indices provide estimates of seasonal and inter-annual variations in vegetation in response to precipitation changes and anthropogenic disturbances (Paruelo and Lauenroth 1998; Paruelo et al. 2001; Washington-Allen et al. 2004) and can be used to detect broad-scale landscape changes related to ecosystem condition, independent of the phenological events of specific plants (Reed et al. 1994). SVI's should closely reflect the stability of plant cover because they function as indicators of relative abundance and activity of green vegetation, often including leaf-area-index (LAI), percentage of green cover, chlorophyll content, green biomass, and absorbed photosynthetic active radiation (Jensen 2000). They are dimensionless calculations of radiometric measures of vegetation that rely heavily on the physical ability of vegetation, due to cell wall structures, to reflect high amounts of energy in the near-infrared (NIR) region (0.7 – 1.3 μm) and low amounts of energy in the red (0.6 – 0.7 μm) region of the electromagnetic spectrum. Landsat's Band Three corresponds to red wavelengths and Band Four corresponds to wavelengths in the NIR region. SVI's produce results that range from +1 to –1, with positive values corresponding to higher amounts of vegetation and negative values corresponding to lower amounts of vegetation.

There are more than 20 vegetation indices in use, many of which are functionally equivalent in information content (Jensen 2000), while some provide unique biophysical information (Qi et al. 1995). The most commonly used vegetation index is the Normalized Difference Vegetation Index, NDVI (Jensen 2000). NDVI does not account for differences in soil backgrounds throughout an image, and many studies have shown, that soil background conditions can influence reflectance from vegetation and resulting SVI measures (e.g., Elvidge and Lyon 1985; Huete et al. 1985; Huete and Jackson 1987; Huete 1988). For example, dark soil backgrounds may result in unwanted increases of some SVI measures, while bright soil backgrounds may result in unwanted decreases of some SVI measures. Soil effects may be more prominent in semi-arid environments, where the cover of vegetation is usually low and plant canopies may be sparse or incomplete. Changes in soil background hamper the analysis of reflectance data, recorded by multispectral sensors for vegetation studies, when the vegetation canopy is sparse or incomplete (Williamson 1989). Therefore, in order to get more accurate measures of vegetation across our study area, it was necessary to use a soil-adjusted SVI.

Soil-adjusted SVI's minimize soil background influences resulting from soil-plant spectral interactions by using transformations that shift the origin of reflectance spectra in the NIR and red wavelength space (Huete 1988). One commonly used soil-adjusted SVI, the soil-adjusted vegetation index (SAVI; equation 4), minimizes soil effects by introducing a soil adjustment factor (L) to the NDVI equation (equation 5).

$$\mathrm{SAVI} = \frac{(1 + L)\,(\mathrm{NIR} - \mathrm{red})}{\mathrm{NIR} + \mathrm{red} + L} \qquad (4)$$

$$\mathrm{NDVI} = \frac{\mathrm{NIR} - \mathrm{red}}{\mathrm{NIR} + \mathrm{red}} \qquad (5)$$

Using SAVI can be problematic, however, because defining an appropriate soil adjustment factor for pixels across an entire image, where the quantity and type of vegetation and soil is not constant, is likely to cause non-systematic errors in estimates of variation in SVI's among pixels within or between images. Also, Qi et al. (1994) cites that optimizing the soil adjustment factor in SAVI requires prior knowledge of vegetation amounts within each pixel unless an iterative process is developed. The inductive modified soil-adjusted vegetation index (MSAVI_2; equation 6), a variant of the modified soil-adjusted vegetation index (MSAVI; equation 7a and 7b) avoids this problem by eliminating the need to define a soil adjustment factor (Qi et al. 1994). MSAVI_2 calculates the soil adjustment factor independently, through an iterative process until the soil effects cannot be minimized any further.

$$\mathrm{MSAVI}_2 = \frac{2*(\text{band }4) + 1 - \sqrt{(2*(\text{band }4) + 1)^2 - 8*(\text{band }4 - \text{band }3)}}{2} \qquad (6)$$

$$\mathrm{MSAVI} = \frac{(\mathrm{NIR} - \mathrm{red})}{\mathrm{NIR} + \mathrm{red} + L}(1 + L) \qquad (7a)$$

$$L = 1 - 2\gamma\,(\mathrm{NDVI} * \mathrm{WDVI}) \qquad (7b)$$

This equation increases its sensitivity to vegetation as defined by the “vegetation signal” to “soil noise” ratio by enhancing the red and near-infrared reflectance in low vegetation cover and minimizing soil background influences (Qi et al. 1994). MSAVI has been used to quantify sparse vegetation cover in arid environments, and significantly correlates to field measures of canopy and areal ground cover (Senseman and Bagley 1996; Purevdorj et al. 1998; McGwire et al. 2000). MSAVI_2’s increased sensitivity to vegetation is important for assessing the year-to-year variability of sagebrush-steppe rangelands where the total cover of vegetation is relatively low. In our study area from 1983 to 2001, total cover was 23% +/- 2.4% SD, shrub cover was 19% +/- 3.9 SD, and grass cover was 5% +/- 1.8 SD (Anderson and Inouye 2001; R. Blew, unpublished data). In arid environments with less than 25% vegetation cover, MSAVI had a higher and more constant sensitivity over the full range of cover compared to other soil-adjusted SVI’s (Rondeaux et al. 1996). Soil cover may vary considerably in time and space, especially as a result of fire and/or grazing. Our study was not to examine soil cover *per se*, so it was important to exclude soil effects from our SVI measures, so we used MSAVI_2 as a measure of vegetation in our study.

Disturbance Category Selection

Lands dominated by Wyoming Big Sagebrush (*Artemisia tridentata wyomingensis*) with different fire and grazing histories since 1939, were identified from Bureau of Land Management (BLM) Geographic Information Systems (GIS) data within the Idaho National Lab (INL). We focused our study on lands that burned in 1994, 1995, or 1996 because they encompassed years of significant variation in precipitation, and provided 7 – 9 years of recovery from fire. More current fires occurred on the INL during our 17-year study period, but were too recent to allow for assessment of temporal variation in $MSAVI_2$ following fire. Lands within 1 km buffers of wildfire perimeters were categorized as follows (Fig. 1): 1) *Control*, undisturbed lands where no fires have occurred and livestock grazing has been excluded since 1950; 2) *Grazed*, lands within BLM grazing allotments that have been actively grazed since 1950; 3) *Burned*, non-grazed lands that have been burned once from 1994 – 1996 and not any other time since 1939; and 4) *Grazed/burned*, lands within BLM grazing allotments that have been actively grazed since 1950 and burned once from 1994 – 1996.

GIS data processing was performed using ArcGIS 8.1 and ArcInfo 8.1 software (ESRI, Redlands, CA). All GIS data was projected into a common projection and datum, Universal Transverse Mercator (UTM Zone 12 North) and World Geodetic System 1984 (WGS84), respectively. A shapefile of fire history (1939-2001) was intersected with the grazing history coverage and exported to a Personal Geodatabase to maintain topology. The fire/grazing history layer was then queried to isolate areas within the 1 km buffers of the 1994, 1995 and 1996 fire perimeters that could be categorized as either control, grazed-only, burned-only, or grazed/burned.

Disturbances were selected from within 1 km of wildfire perimeters for two main reasons. First, it was important to exclude any potential bias in our comparisons of disturbance categories that may result from inherent differences between lands, prior to disturbances, due to their spatial locations or lack of spatial dependence. Spatial dependency simply means that lands near to each other are likely to be more similar than lands farther apart. It was important to ensure that this study compared differences due to disturbance effects, and not due to differences between lands because they were on opposing sides of the INL and as a result, not spatially dependent. Second, comparing areas distant to each other could be impacted by the Landsat data quality. In addition to spatial considerations, areas were chosen that did not have albedo effects. There appeared to be an area high albedo in the northern portion of the INL, most likely due to higher amounts of bare ground or non-surface factors that were not possible to minimize with the normalization process. These high albedo areas typically increase the amount of reflectance from the surface and may influence our $MSAVI_2$ measures to some degree.

Disturbance Category Data Extraction

Analyses of inter-annual variability of $MSAVI_2$ for selected lands with different disturbance histories were performed using a multitemporal image stack. An image stack was made by creating an ENVI Standard File of all the co-registered $MSAVI_2$ images. Shapefiles of the disturbance categories were imported into ENVI as vector files and exported as regions of interest (ROI) in the multitemporal image stack. The ENVI ROI tool was used to calculate statistics (mean, min, max, standard deviation) of $MSAVI_2$ values for disturbance ROI's for each image date. The ROI statistics were then exported as ASCII for use in Excel spreadsheet where the coefficient of variation (CV) of mean $MSAVI_2$ was calculated for each image date.

Disturbance histories increase variability in remotely sensed indices of vegetation in sagebrush-steppe over the past ca. 20 years

ABSTRACT

Many studies have investigated the separate effects of drought, fire, or livestock grazing on semiarid rangeland function; however, most sagebrush-steppe rangelands are likely to experience multiple and potentially interacting combinations of these disturbances. Little quantitative information exists over large spatial and temporal scales to help address the effects of multiple disturbances on ecosystem function. Remote sensing and Geographic Information Systems (GIS) were used to investigate spatial and temporal variability of disturbed and undisturbed sagebrush-steppe communities in southeast Idaho from 1984 – 2003. Lands disturbed by livestock grazing and/or wildfire were selected from existing GIS data and combined with modified soil-adjusted vegetation indices ($MSAVI_2$), derived from yearly Landsat data, to examine temporal and spatial responses of sagebrush-steppe to variations in precipitation, grazing, and/or fire. Long-term disturbance effects were most apparent in the spatial variability of $MSAVI_2$ within and between years, rather than in mean responses of $MSAVI_2$. The coefficient of variation (CV) of $MSAVI_2$ among pixels within one sampling date (i.e., within one Landsat image) increased in the first few years following fire. Fire, or the combination of both grazing and fire, resulted in greater correlations and steeper relationships between the CV of $MSAVI_2$ in one image and cumulative annual precipitation, PPT ($r^2 = 0.76 – 0.81$; mean increase of 0.33 in $CV_{spatial}$ of $MSAVI_2$ / mm PPT) than grazed-only ($r^2 = 0.60$; mean increase of 0.08 in $CV_{spatial}$ of $MSAVI_2$ / mm PPT) and undisturbed lands ($r^2 = 0.62$; mean increase of 0.16 in $CV_{spatial}$ of $MSAVI_2$ / mm PPT). These data suggest

that higher levels of disturbance decrease the stability of vegetation indices in sagebrush-steppe ecosystems, primarily by increasing the sensitivity of communities to variability in precipitation. Conversion of vegetation type from shrub to grassland can explain higher variability in $MSAVI_2$ following fire alone, but cannot explain even greater variability in sites disturbed by both fire and grazing. Interactive effects of grazing and fire may cause more fundamental changes in site properties that are more readily detected in spatial and temporal variations rather than mean values of vegetation indices.

INTRODUCTION

Sagebrush (*Artemisia*) steppe ecosystems throughout western North America experience combinations of natural and anthropogenic disturbances, such as altered fire regimes and domestic livestock grazing, in addition to natural variation in precipitation (Anderson and Inouye 2001). Disturbance here refers to events that cause abrupt change in ecosystem processes, or population and community structure, by altering resource availability or other aspects of the physical environment (Pickett and White 1985; Begon et al. 1996). Many studies have investigated the separate effects of disturbance on semiarid rangeland function (Anderson and Holte 1981; Hosten and West 1994; Anderson and Inouye 2001; Wambolt et al. 2001; Diaz-Delgado et al. 2002; Washington-Allen et al. 2004), however most rangeland ecosystems are likely to experience multiple, potentially interacting disturbances (Valone 2003). Additionally, ecosystem responses to disturbance have mostly been studied at the small-scale plot level, ranging from one to several square meters in size (e.g., Anderson and Holte 1981; Hosten and West 1994; Anderson and Inouye 2001; West and Yorks 2002), therefore little quantitative information exists over large spatial and temporal scales to help address the potentially complex effects of multiple disturbances on ecosystem structure and function. Large scale, landscape-level assessments of the separate and combined effects of weather variation, fire, and livestock grazing disturbances are needed to better match the scale at which rangeland management occurs. Evaluations at larger scales are also important because ecological measures have been shown to vary at different spatial scales (i.e., plot vs. landscape scales; Stohlgren et al. 1999; Small and McCarthy 2003). Further, assessments of disturbance impacts are best done in light of comparisons to natural, background variability (Magnuson et al. 1991; Paruelo and Lauenroth 1998).

Remote sensing provides the data necessary to examine large-scale spatial and temporal variability of sagebrush-steppe by obtaining periodic measures of vegetation over areas that exceed the capabilities of traditional ground-based assessments (Washington-Allen et al. 2004). Previous studies have used spectral vegetation indices (SVI's), derived from remotely sensed ratios of red and near-infrared reflectance, to examine the abundance of rangeland vegetation (Graetz and Gentle 1982; Pickup and Foran 1987; Graetz et al. 1988; Smith et al. 1990; Pickup et al. 1993; Senseman and Bagley 1996; Elmore et al. 2000; McGwire et al. 2000; Ramsey et al. 2004; Wallace et al. 2004; Washington-Allen et al. 2004). These indices provide estimates of seasonal and inter-annual variations in vegetation in response to precipitation changes and anthropogenic disturbances (Paruelo and Lauenroth 1998; Paruelo et al. 2001; Washington-Allen et al. 2004) and can be used to detect broad-scale landscape changes related to ecosystem condition, independent of the phenological events of specific plants (Reed et al. 1994).

The modified soil-adjusted vegetation index (MSAVI) enhances the red and near-infrared reflectance ratio in low vegetation cover by increasing the dynamic range of the vegetation signal and minimizing soil background influences (Qi et al. 1994). MSAVI has been used to quantify sparse vegetation cover in arid environments, and significantly correlates to field measures of canopy and areal ground cover (Senseman and Bagley 1996; Purevdorj et al. 1998; McGwire et al. 2000). Other soil-adjusted SVI's require constant, empirically defined, soil adjustment factors to minimize soil influences on canopy spectra. Defining an appropriate soil adjustment factor for pixels across an entire image, where the quantity and type of vegetation and soil are not constant, is likely to cause non-systematic errors in estimates of variation in vegetation indices among pixels within or between images. $MSAVI_2$, a variant of MSAVI avoids this problem by replacing the constant, empirical, adjustment factor for soil with a dynamic, inductive one that varies inversely with the amount of vegetation present in each pixel (Qi et al. 1994). $MSAVI_2$'s increased sensitivity to vegetation is important for assessing the year-to-year variability of sagebrush-steppe rangelands where the total cover of vegetation is relatively low. In our study area from 1983 to 2001, total cover was 23% ± 2.4% standard deviation (SD), shrub cover was 19% ± 3.9 SD, and grass cover was 5% ± 1.8 SD (Anderson and Inouye 2001; R. Blew, unpublished data). In one study conducted in an arid environment with less than 25% vegetation cover, MSAVI had a higher and more constant sensitivity over the full range of cover compared to other soil-adjusted SVI's (Rondeaux et al. 1996).

This study utilized a 17-year archive of Landsat data to determine the interactive effects of fire, grazing, and precipitation change on the spatial and temporal variability of

$MSAVI_2$ in a sagebrush-steppe ecosystem. The Idaho National Laboratory (INL; Fig. 1), situated on the Eastern Snake River Plain, was ideal for this experiment because of its relatively flat landscape and large homogenous management units (livestock grazing allotments) where wildfires have occurred frequently over the last two decades. Some studies have shown a strong relationship between precipitation and variability in shrubland productivity (Le Houerou et al. 1988; Lauenroth and Sala 1992; Milchunas and Lauenroth 1993; Paruelo and Lauenroth 1995; Paruelo and Lauenroth 1998), whereas others detected no relationship (West et al. 1979; Passey et al. 1982; Anderson and Inouye 2001). This study aimed to gain a better understanding of landscape-scale responses of disturbed and undisturbed sagebrush steppe rangelands to variability in precipitation. In addition, this study aimed at testing the sensitivity of remote sensing to evaluate long-term effects of fire and/or livestock grazing disturbances on sagebrush-steppe ecosystem function.

Our research addressed the following questions: 1.) How much spatial and temporal variability occurs in $MSAVI_2$ among lands undisturbed by grazing and fire? 2.) How do natural and anthropogenic disturbances, such as livestock grazing, and/or fire influence spatial and temporal variability in $MSAVI_2$ among sagebrush-steppe communities? 3.) How do spatial and temporal variability of these lands differs during years of precipitation change (i.e., drought years)? We hypothesized that landscapes with histories of multiple disturbances, such as livestock grazing and/or fire, would exhibit relatively higher amounts of variation in $MSAVI_2$ during years of varying precipitation than sites with fewer disturbances. In addition, we hypothesized that burned lands would show increased spatial and temporal variability measured by MSAVI_2 in years immediately following fire.

These hypotheses were based on theoretical predictions that high levels of disturbance decrease biodiversity (Muldavin et al 2001; Ludwig et al 2004), and that resulting decreases in biodiversity should lead to less stability in ecosystem function (Frank and McNaughton 1991; Tilman 1996; Lavorel 1999; Anderson and Inouye 2001; Ludwig et al. 2004). Previous studies have assessed spatial and temporal variability of SVI's to characterize ecosystem function (Paruelo and Lauenroth 1998; Paruelo et al. 2001). In our study, we examined the spatial and temporal variability of MSAVI_2 among lands with different fire and/or grazing disturbances to characterize the effects of disturbances on sagebrush-steppe ecosystem function across our study area. Because studies have shown that the function of sagebrush-steppe ecosystems are directly related to the diversity of vegetation (Anderson and Inouye 2001), the variability we observed in sagebrush-steppe ecosystem function, resulting from disturbances, is likely to indicate overall changes in vegetation due to either losses of vegetation cover/abundance or decreases in diversity.

METHODS

Lands dominated by Wyoming Big Sagebrush (*Artemisia tridentata wyomingensis*) with different fire and grazing histories since 1939, were identified from Bureau of Land Management (BLM) Geographic Information Systems (GIS) data within the INL. Lands within 1 km buffers of wildfire perimeters were categorized as follows (Fig. 1): 1) *Control*, undisturbed lands where no fires have occurred and livestock grazing has been excluded since 1950; 2) *Grazed*, lands within BLM grazing allotments that have been actively grazed since 1950; 3) *Burned*, non-grazed lands that have been burned once from 1994 – 1996 and not any other time since 1939; and 4) *Grazed/burned*, lands within BLM grazing allotments that have been actively grazed since 1950 and burned once from 1994 – 1996. We focused our study on lands that burned in 1994, 1995, or 1996 because they encompassed years of significant variation in precipitation, and provided 7 – 9 years of recovery from fire. More current fires occurred on the INL during our 17-year study period, but were too recent to allow for assessment of temporal variation in $MSAVI_2$ following fire. BLM summer stocking rates of domestic grazers (cattle and sheep) varied little over the last 20 years and ranged from 12.4 to 33.5 acres/active animal unit months (AUM). Grazing was excluded from fire-disturbed areas for two years following fire.

To examine spatial and temporal variability in $MSAVI_2$ among lands with different disturbance histories, we used one cloud-free Landsat 5 Thematic Mapper (TM) or 7 Enhanced Thematic Mapper (ETM+) image per year. Image sampling dates were selected for 17 of the previous 20 years from 1984 – 2003, in a 30-day window centered on 27-June (Table 1). We were unable to use more sampling dates per year, due to cloud cover or data gaps, and therefore, adjusted our inquiry to avoid complications due to phenological shifts. The 30-day window evaluated was roughly equivalent to the peak summer growing season for sagebrush-steppe in North America (including the INL), as estimated by Paruelo and Lauenroth (1995 and 1998) using the maximum normalized difference vegetation index (NDVI) derived from Advanced Very High Resolution Radiometer (AVHRR) data. Pixels (30 m resolution) were converted to at-satellite reflectance, coregistered, and radiometrically normalized with relative corrections for atmospheric attenuation using the empirical, multiple-date, regression method (Jensen 1996). $MSAVI_2$ was calculated from red (band 3, 630-690 nm) and near-infrared (band 4, 750-900 nm) reflectance using the equation developed by Qi et al. (1994):

$$MSAVI_2 = \frac{2*(\text{band } 4) + 1 - \sqrt{(2*(\text{band } 4) + 1)^2 - 8*(\text{band } 4 - \text{band } 3)}}{2}$$

Our analyses focused on calculations of mean $MSAVI_2$, the coefficient of variation (CV) of $MSAVI_2$ among years ("$CV_{temporal}$ $MSAVI_2$"; CV = SD / mean * 100), and CV of $MSAVI_2$ among pixels with a year (i.e., within one image, "$CV_{spatial}$ $MSAVI_2$"). Fire effects on $MSAVI_2$ were determined by using only post-fire $MSAVI_2$ in both burned and non-burned (i.e., control) lands. Distances to livestock watering troughs had no effects on $MSAVI_2$, as assessed by examining variation in $MSAVI_2$ among areas that were either within 30 m, or were 30 m to 100 m, 100 m to 500 m, or 500 m to 1000 m from watering troughs (Fig. 1). Thus, we did not place any qualifiers on which lands to use for assessment of grazing impacts. In addition, the effect of community type on $MSAVI_2$ was examined by comparing mean $MSAVI_2$ between undisturbed areas of sagebrush and grasslands, identified from previous vegetation classifications of the INL (Kramber et al. 1992). One and two-factor analysis of variance (ANOVA) were used to compare mean $MSAVI_2$ and mean CV of $MSAVI_2$ among years, and between pixels with different disturbance histories.

We compared mean and CV of $MSAVI_2$ of lands with different disturbance histories between "wet" and "dry" years with the greatest and least amount of precipitation (PPT) during the study period. Wet years consisted of years when cumulative annual PPT was greater than one SD above the mean PPT over the study period, and dry years were years when cumulative annual PPT was lower than one SD below the mean. These years were determined from sliding, three-year averages of growing season PPT (cumulative from April to image date), which showed higher correlations with $MSAVI_2$ (higher r^2 values) than did water-year PPT (cumulative from October to image date) and yearly PPT (cumulative from January to image date). Precipitation was determined from data obtained from the INL Central Facilities Area station (Western Regional Climate Center, Desert Research Institute, Reno NV). Three-year sliding averages were calculated by averaging precipitation in the current year up to image dates with that in the two preceding years, respectively, to test for lag effects in vegetation responses to precipitation (Anderson and Inouye 2001). Relationships between precipitation and inter-annual mean $MSAVI_2$ and CV of $MSAVI_2$ for disturbance history lands and community types were examined using linear least squares regression. Analysis of covariance (ANCOVA) was used to test for differences between disturbances in responses of inter-annual CV of $MSAVI_2$ to yearly changes in PPT.

RESULTS

Mean $MSAVI_2$ of undisturbed lands fluctuated significantly over the 20-year period, ranging from 0.03 in 1985 to 0.l6 in 1993 (Fig. 2; $F_{16, 84} = 66.57$, $P < 0.0001$). The greatest amount of change in mean $MSAVI_2$ over the 17-years occurred between 1993 and 1994, when mean $MSAVI_2$ decreased by 0.07 (44%).

Grazed/burned pixels had 18% greater mean $MSAVI_2$ compared to undisturbed lands over all 7 – 9 growing seasons following the 1994 fire ($F_{3, 31} = 3.24$, $P = 0.03$), but no differences were observed following the other fires (Fig. 3). However, $MSAVI_2$

increased as much as 61% ($F_{1,71} = 28.32$, $P < 0.000$) in the second growing season following fire, for all fire years in grazed and non-grazed pixels alike, compared to background increases of 20% across the same years, in undisturbed control pixels (Burned: 0.142 ± 0.020 Standard Error (SE); Burned-grazed: 0.140 ± 0.012 SE; Grazed: 0.089 ± 0.008 SE; Control: 0.105 ± 0.010 SE; Fig. 4; $F_{1,71} = 5.21$, $P < 0.008$). For grazed-only lands, there were no differences in mean $MSAVI_2$ as the distance from livestock watering sites increased. Inter-annual variability ($CV_{temporal}$) of $MSAVI_2$ following all fires combined was up to 2-fold greater in pixels of burned and grazed/burned lands compared to control and grazed-only lands (Fig. 4).

Mean $CV_{spatial}$ of $MSAVI_2$ (variation in $MSAVI_2$ among pixels within each image) of increased following fire, especially in the first and second growing seasons (Fig. 5). Specifically, in the first growing season following fire, mean $CV_{spatial}$ of $MSAVI_2$ was 27% higher in burned compared to control pixels and 30% higher in grazed/burned compared to grazed pixels (Fig. 6; $F_{1,71} = 7.55$, $P = 0.008$). In the second growing season, $CV_{spatial}$ of $MSAVI_2$ increased 75% among grazed/burned pixels (CV = 29.6% ± 4.6 SE) compared to among grazed pixels (CV = 16.9% ± 0.9 SE; $F_{1,72} = 4.19$, $P = 0.04$; Fig. 6). $CV_{spatial}$ of $MSAVI_2$ decreased to different extents for all lands during the study period, irrespective of disturbance history, though rates of decrease were at least two-fold greater for sites recovering from fire, and especially for grazed/burned lands (Fig. 6).

$CV_{spatial}$ of $MSAVI_2$ among pixels with no fire or grazing disturbance was correlated with sliding three-year averages of growing season precipitation, PPT (r^2 =

0.62, $P = 0.02$), but the highest correlations occurred in grazed ($r^2 = 0.79$, $P = 0.02$) and non-grazed ($r^2 = 0.81$, $P = 0.002$) lands that burned (Table 2). Following fire, the slope of the relationship between $CV_{spatial}$ of $MSAVI_2$ and PPT in grazed/burned lands (mean increase of 0.33 in $CV_{spatial}$ of $MSAVI_2$ / mm PPT) was over two times greater than burned lands (mean increase of 0.17 in $CV_{spatial}$ of $MSAVI_2$ / mm PPT), and especially undisturbed, control lands (0.16 increase in $CV_{spatial}$ of $MSAVI_2$ / mm PPT), and five times greater than grazed lands (0.08 increase in $CV_{spatial}$ of $MSAVI_2$ / mm PPT). For grassland communities, the slope of the relationship between $CV_{spatial}$ of $MSAVI_2$ and PPT was almost two times higher (mean increase of 0.32 in $CV_{spatial}$ of $MSAVI_2$ / mm PPT) compared to sagebrush communities (mean increase of 0.18 in $CV_{spatial}$ of $MSAVI_2$ / mm PPT). In addition, there was a marginal difference in the interaction between PPT and $CV_{spatial}$ of $MSAVI_2$ between grazed and grazed/burned lands ($F_{15,1} = 3.49$, $P = 0.08$; Table 2 and Figure 7).

Post-fire variability in $CV_{spatial}$ of $MSAVI_2$ increased up to nearly three times in years of high compared to low precipitation (Fig. 8). In drought years, no differences in $CV_{spatial}$ of $MSAVI_2$ were detectable among pixels (Fig. 8). In wet years, post-fire $CV_{spatial}$ among pixels of lands that had been grazed/burned was 20% higher than in control lands, 44% higher than grazed-only lands, and 23% higher than in burned-only lands (Fig. 8; $F_{3,19} = 6.08$, $P = 0.009$). Overall, grazing and fire appeared to have an almost additive, positive effect on $CV_{spatial}$ of $MSAVI_2$ in high precipitation years.

DISCUSSION

Many studies have measured mean changes in plant cover of sagebrush-steppe in response to wildfire and/or grazing disturbances (e.g. Brotherson and Brotherson 1981; Humphrey 1984; Hosten and West 1994; Wambolt 2001; West and Yorks 2002). However, we found that changes in the variability of remotely sensed indices of cover (Fig. 6) were more responsive than mean responses of vegetation indices (Fig. 4) for assessing long-term disturbance effects. Differences in $MSAVI_2$ within a sampling date ($CV_{spatial}$), and between years ($CV_{temporal}$) emerged as more sensitive response variables than mean $MSAVI_2$, over longer time scales. Mean $MSAVI_2$ increased only in the second growing season following fire, but mean $CV_{spatial}$ of $MSAVI_2$ was greater in fire-disturbed lands for nearly a decade (Table 2), most apparently due to greater sensitivity of $CV_{spatial}$ of $MSAVI_2$ to years with above average precipitation (Fig. 7). Greater mean $MSAVI_2$ and mean $CV_{spatial}$ of $MSAVI_2$ observed following fire and grazing/fire compared to undisturbed lands demonstrated that fire and the interaction of fire and grazing can strongly influence the stability or constancy of $MSAVI_2$ measurements in sagebrush-steppe (Figs. 4 and 6).

Although mean $MSAVI_2$ significantly increased among burned and grazed/burned lands the second growing season following fire, mean $MSAVI_2$ appeared to recover to near pre-fire levels by the third growing season after fire. Many studies report that reductions in sagebrush cover due to fire are compensated for in total community biomass/cover by disproportionate increases of perennial and annual grasses and forbs (Humphrey 1984; Hosten and West 1994; West and Yorks 2002). Typically, grassland communities have higher vegetation index measures compared to the sagebrush or other shrub communities (Kremer and Running 1993; Paruelo and Lauenroth 1995; Weiss et al. 2004). In some years, we found MSAVI_2 to be as much as 0.07 higher among undisturbed lands dominated by grasslands compared to sagebrush. Our study provides an indication that flushes of over-compensating responses of herbaceous and grass cover in sagebrush-steppe following fire may not occur until the second growing season following fire.

Grazing has been shown to significantly alter species composition and cover characteristics at the plot level (Brotherson and Brotherson 1981; West and Yorks 2002) and landscape level in sagebrush-steppe (Anderson and Inouye 2001; Washington-Allen et al. 2004). Grazing, along with climate change and fire, is considered to be a primary control of vegetation response in sagebrush-steppe landscapes (Laycock 1991; West and Young 2000; Washington-Allen et al. 2004). We did not detect significant differences in spatial and temporal variability in MSAVI_2 among grazed lands compared to non-grazed lands. However, grazing appeared to interact with fire in a way that increased the heterogeneity of plant cover, resulting in higher post-fire CV of MSAVI_2 among grazed/burned pixels within a sampling date compared to control, grazed-only, and burned-only pixels.

Increases in spatial heterogeneity of MSAVI_2 in disturbed compared to undisturbed lands, and in grassland compared to sagebrush communities, became more evident in wet compared to dry years (Fig. 7 and Table 2). In dry years, CV of MSAVI_2 among lands with different disturbance histories may have decreased because the amount of live cover was relatively low due to decreased growth potential (Lauenroth and Sala 1992). Drought appeared to decrease the vegetation index potential of pixels to common, low values. This is further supported by stronger correlations of spatial variability and growing season precipitation for fire-disturbed or undisturbed grassland pixels compared to non-burned or undisturbed sagebrush pixels. These results indicate that studies seeking to determine fire and grazing impacts should encompass multiple years, and consideration of variation in spatial heterogeneity in sampling among years.

We speculate that increased temporal and spatial variability for pixels with higher levels of disturbance may be partly attributable to increases in abundances of annual and perennial grasses, and forbs, which, compared to sagebrush (evergreen/deciduous), tend to express a tighter linkage of $MSAVI_2$ and variation in PPT (Table 2). Annual grasses tend to be the major cover component on burned sites for at least the first few years following fire, with steady increases of perennial grasses in remaining years up to a decade, as described in nearby sagebrush-steppe (West and Yorks 2002). Wyoming big sagebrush cover appeared to vary less than herbaceous or annual species in response to drought (Passey et al. 1982; West and Yorks 2002). Also, long-term field plots on the INL with higher shrub densities tended to exhibit less variability in cover than plots with low shrub densities over 45 years (Anderson and Inouye 2001). Thus, it is likely that increased temporal and spatial variability (i.e., lower stability) among fire-disturbed lands could be due to reductions of shrub cover and compensating increases in herbaceous and, especially grass cover.

The greater variability in grazed/burned compared to burned-only lands, however, appears to be due to more than conversion of shrubs to grasses alone. Grazing appears to increase the amount of shrub cover relative to herbaceous and grass cover, resulting in higher densities of sagebrush that may persist for long periods (Anderson and Inouye

2001). Indeed, our measurements of less variability in MSAVI$_2$ in grazed-only compared to undisturbed, control lands, could be explained by greater relative abundances of shrubs (Figs. 4 – 7). Greater standing crops of shrubs compared to grasses should raise fuel loads, due to increased shrub cover, amplifying the intensity and severity of fire (DeBano et al. 1998), resulting in greater site alterations (e.g., changes in soil physical properties) rather than just changes in floristics. We speculate that these changes contribute to greater spatial and temporal variability in large-scale satellite-based measurements of vegetation. Interactions of fire and grazing thus appear to affect sagebrush-steppe communities in ways that are not detectable by simple assessments of mean responses, and moreover, cannot be predicted from linear combinations of the separate effects of grazing and fire only.

Table 1. Inter-annual Landsat image acquisition dates from 1984 – 2003.

Image Date	DOY	Sensor Type
07/02/84	183	Landsat 5 TM
07/05/85	186	Landsat 5 TM
06/23/86	174	Landsat 5 TM
06/11/88	162	Landsat 5 TM
06/30/89	181	Landsat 5 TM
07/03/90	184	Landsat 5 TM
06/20/91	171	Landsat 5 TM
06/25/93	176	Landsat 5 TM
06/28/94	179	Landsat 5 TM
07/17/95	198	Landsat 5 TM
06/17/96	168	Landsat 5 TM
06/20/97	171	Landsat 5 TM
07/09/98	190	Landsat 5 TM
06/20/00	171	Landsat 7 ETM+
07/01/01	182	Landsat 7 ETM+
07/12/02	193	Landsat 7 ETM+
07/07/03	188	Landsat 5 TM

Table 2. Correlations of sliding three-year averages of cumulative annual growing season precipitation (from April 1 to image date) and post-fire $CV_{spatial}$ of $MSAVI_2$ among pixels of lands with different disturbance histories. N indicates the number of years prior to 2003.

Disturbance History	r^2	*P*	Slope	N
Control	0.615	0.021	0.160	8
Control	0.378	0.008	0.237	17
Undisturbed Sagebrush	0.183	0.328	0.125	8
Undisturbed Grasslands	0.275	0.214	0.178	8
Grazed-only	0.597	0.025	0.078	8
Grazed-only	0.267	0.034	0.139	17
Burned 1994	0.814	0.002	0.159	8
Burned 1995	0.741	0.006	0.178	7
Burned 1996	0.780	0.009	0.166	6
Grazed, Burned 1994	0.758	0.011	0.238	8
Grazed, Burned 1995	0.787	0.018	0.341	7
Grazed, Burned 1996	0.765	0.022	0.425	6

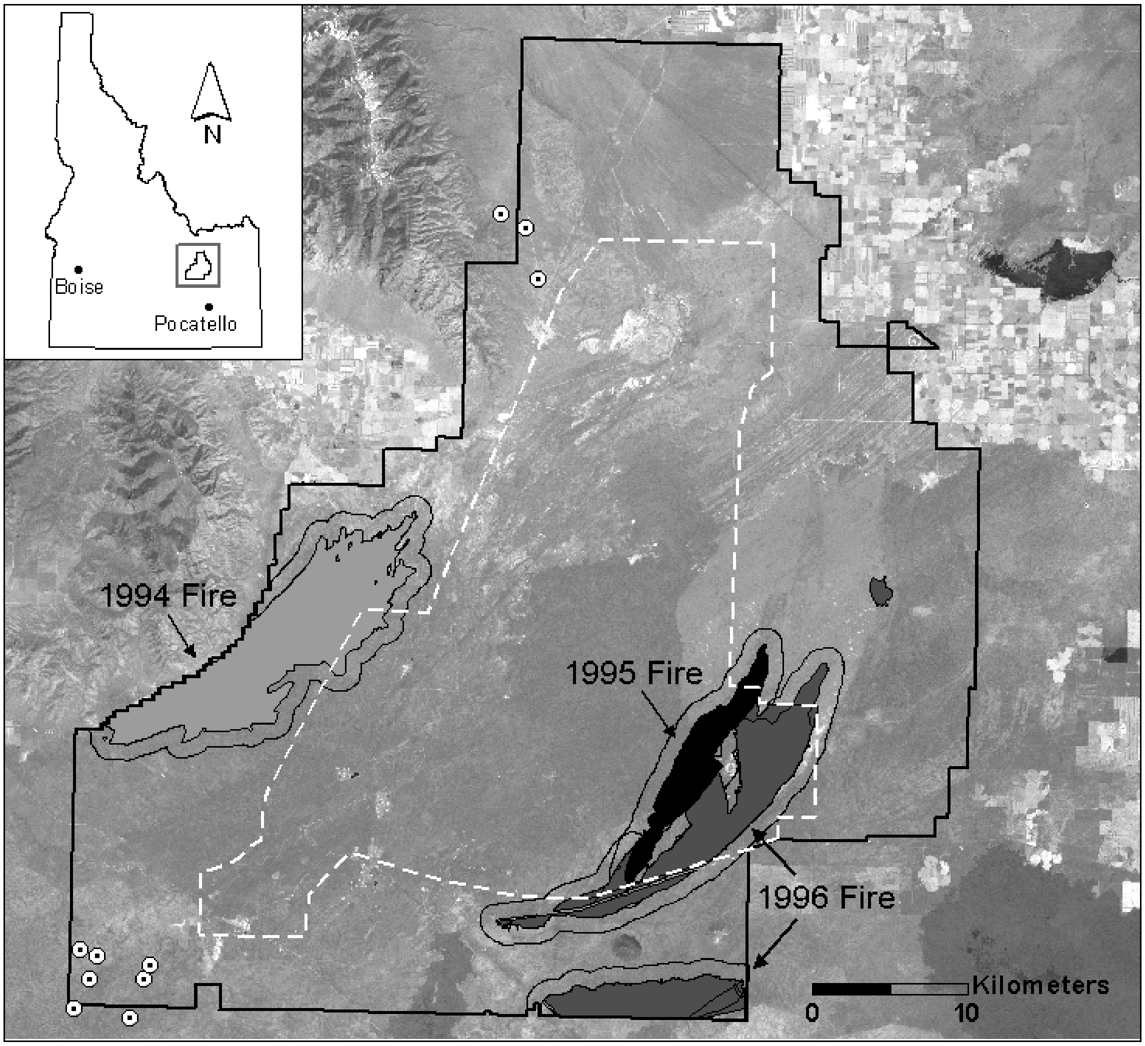


Figure 1. Map of the Idaho National Laboratory (INL) located on the Upper Snake River Plain (Idaho) with disturbance history lands for the 1994, 1995, and 1996 fires indicated. The bold black line indicates INL boundary with lands closed to livestock grazing since 1950 inside the dashed white line. White circles indicate livestock watering sites for two grazing allotments on the INL. The thin black lines around fire perimeters indicate 1 km fire buffers.

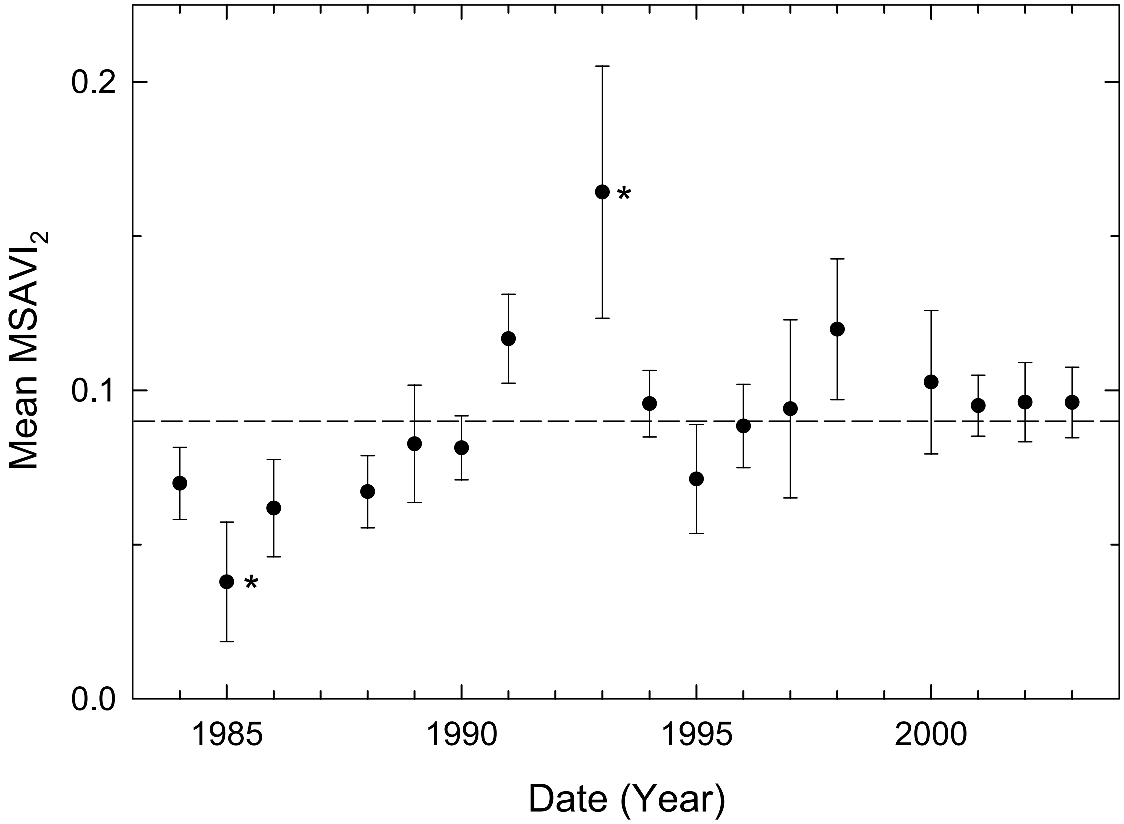


Figure 2. Mean $MSAVI_2$ (± 1 SD) for pixels of undisturbed, control lands on the INL from 1984 - 2003. Dashed line indicates mean of $MSAVI_2$ for all years combined (n = 17 years) and * indicates significant differences from all years (Tukey, *P* = 0.05).

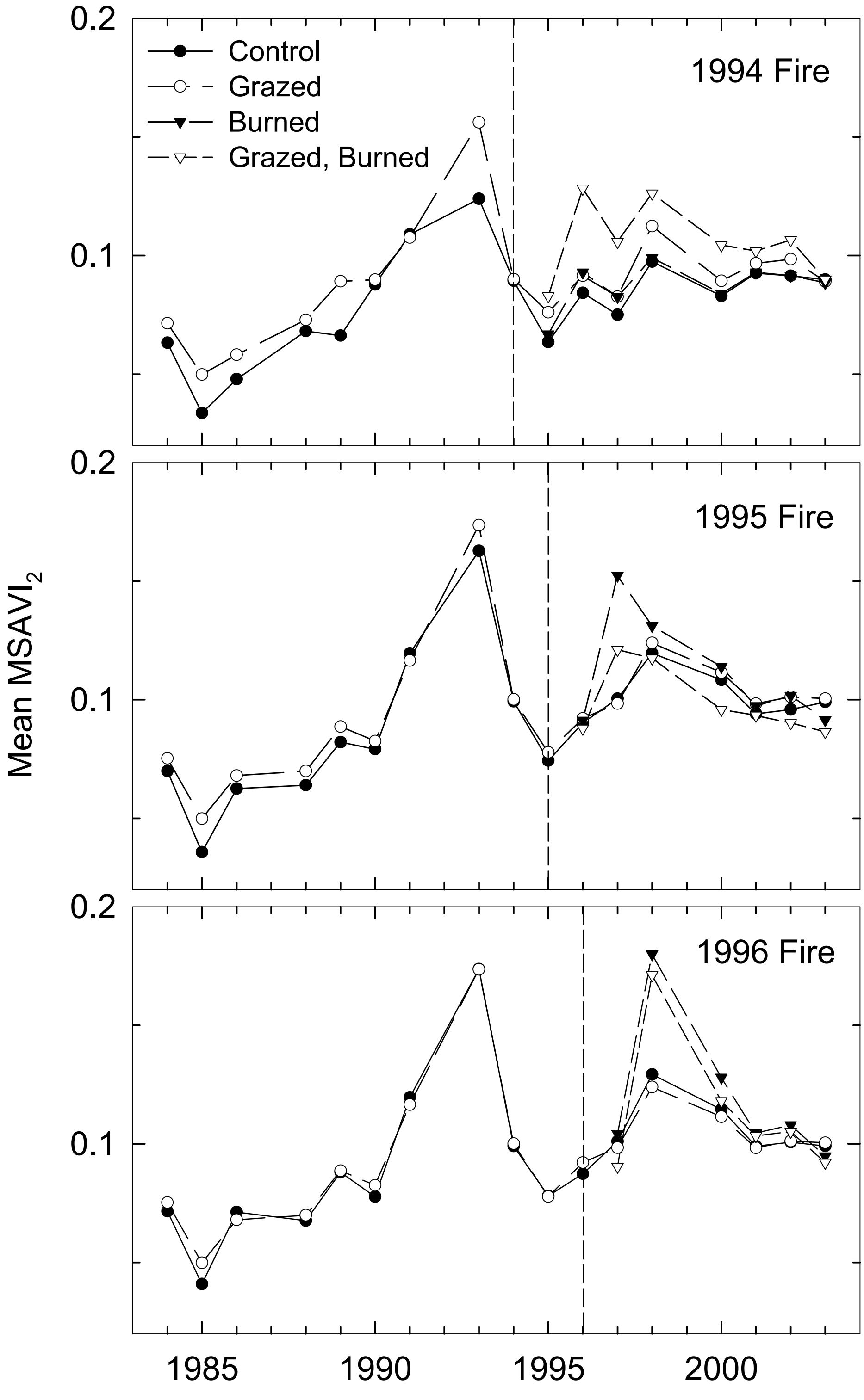


Figure 3. Mean $MSAVI_2$ among disturbance history lands following the 1994, 1995, and 1996 fires. Vertical dashed lines represent the year fires occurred.

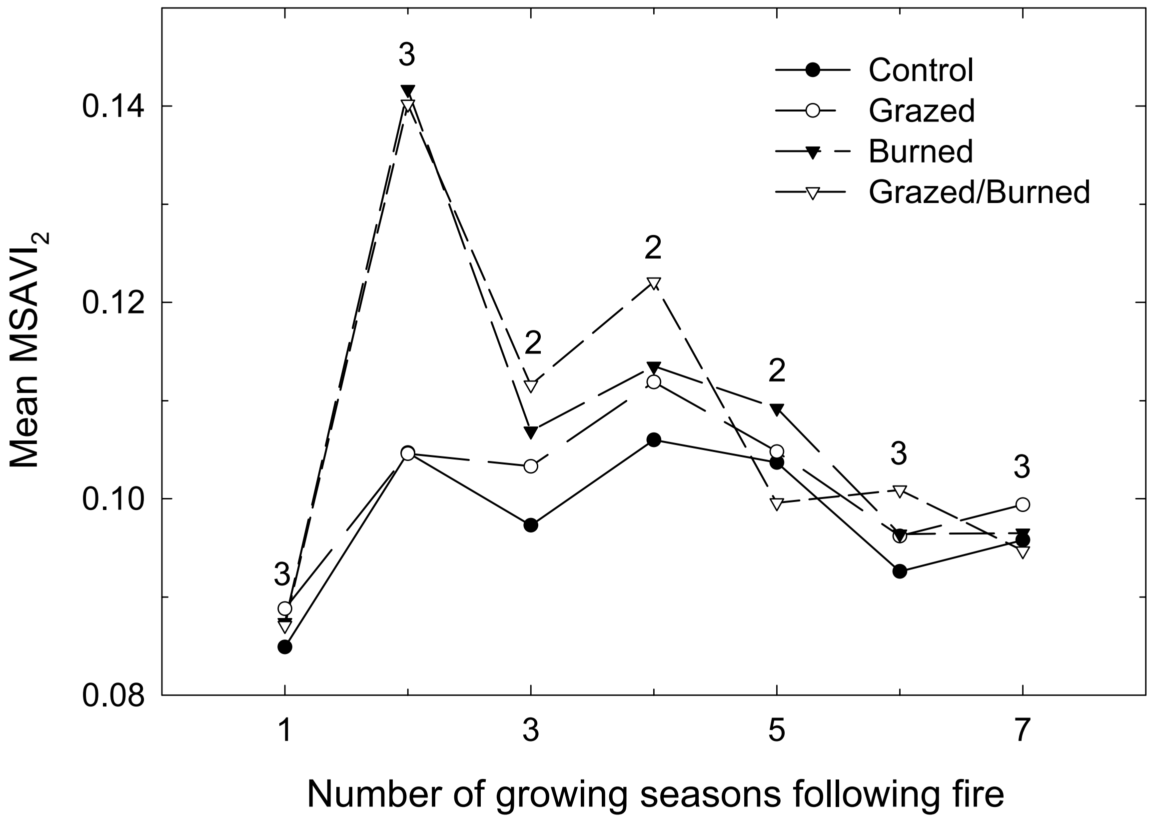


Figure 4. Grouped comparisons of mean $MSAVI_2$ among disturbance history lands following the 1994, 1995, and 1996 fires. The number of burned sites included in grouped post-fire year calculations is indicated above line graphs. Non-grazed (control) and grazed lands are included for reference to fire-disturbed lands. $CV_{temporal}$ of disturbances over these seven growing seasons following fire: control = 14.9%, grazed = 11.9%, burned = 24.3%, grazed/burned = 19.1%.

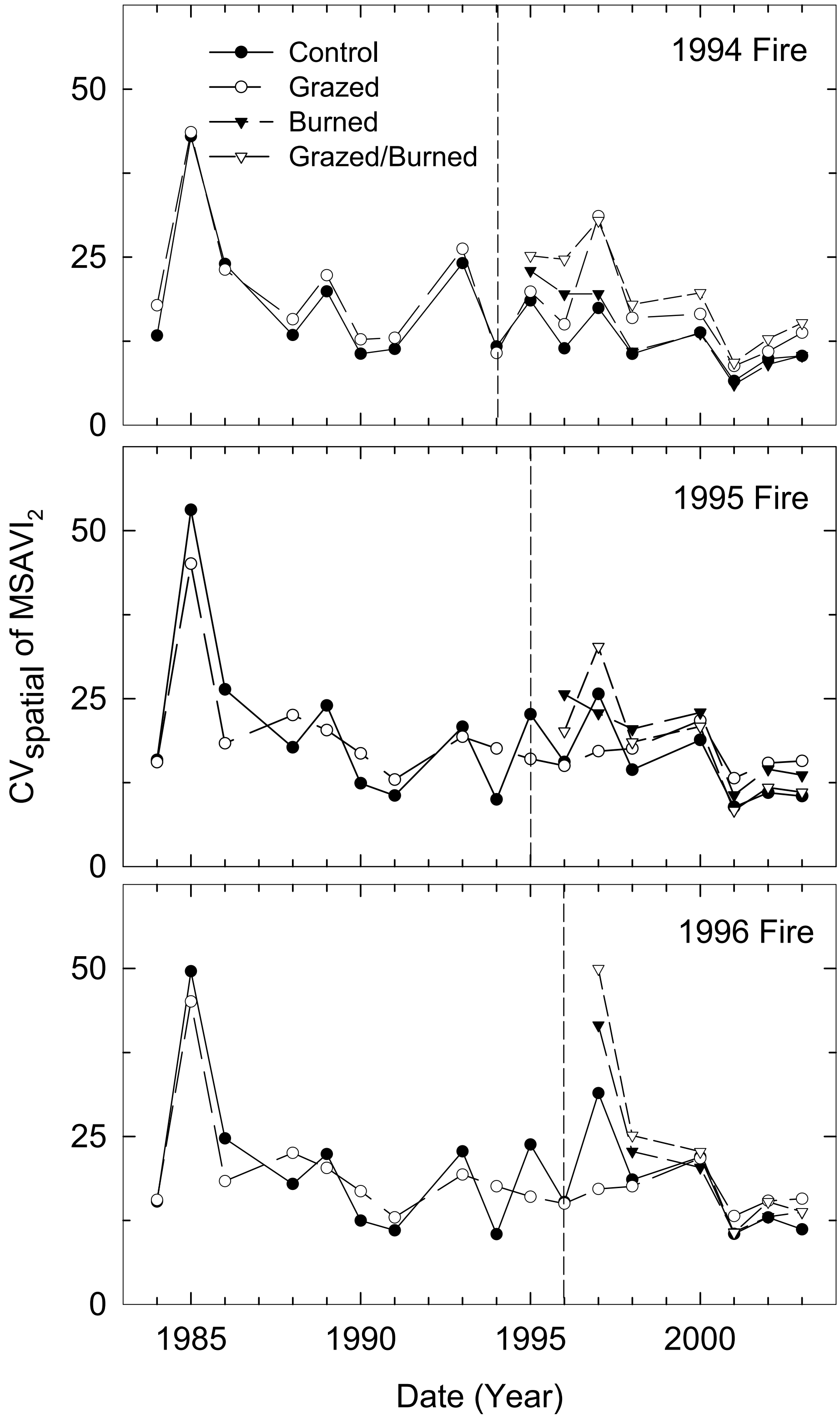


Figure 5. Mean CV of $MSAVI_2$ among pixels for disturbance history lands following the 1994, 1995, and 1996 fires. Vertical dashed lines represent the year fires occurred.

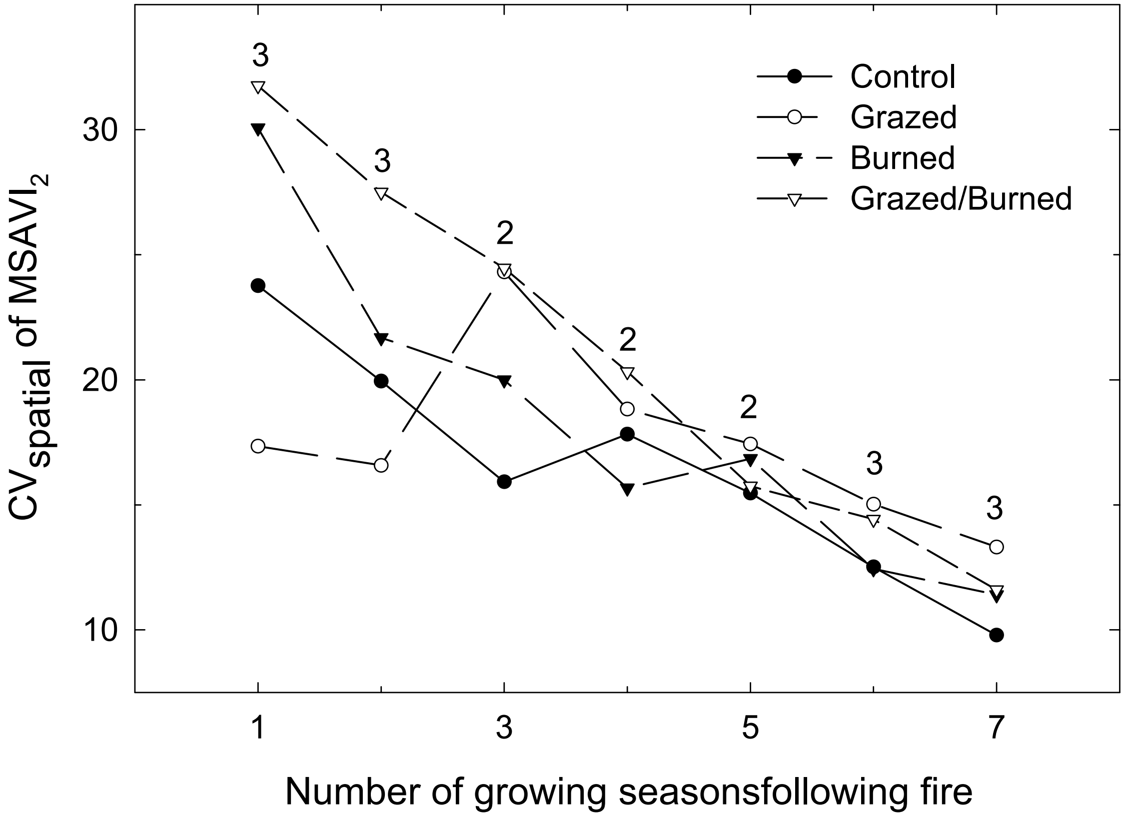


Figure 6. Grouped comparisons of mean CV of $MSAVI_2$ among pixels for disturbance history lands following the 1994, 1995, and 1996 fires. The number of burned sites included in grouped post-fire year calculations is indicated above line graphs. Non-grazed (control) and grazed lands are included for reference to fire-disturbed lands. Mean $CV_{spatial}$ of disturbances in the first growing season following fire: control = 23.8% ± 5.2 Standard Error (SE), grazed = 17.3% ± 1.1 SE, burned = 30.1% ± 4.5 SE, and grazed/burned = 31.8% ± 7.1 SE.

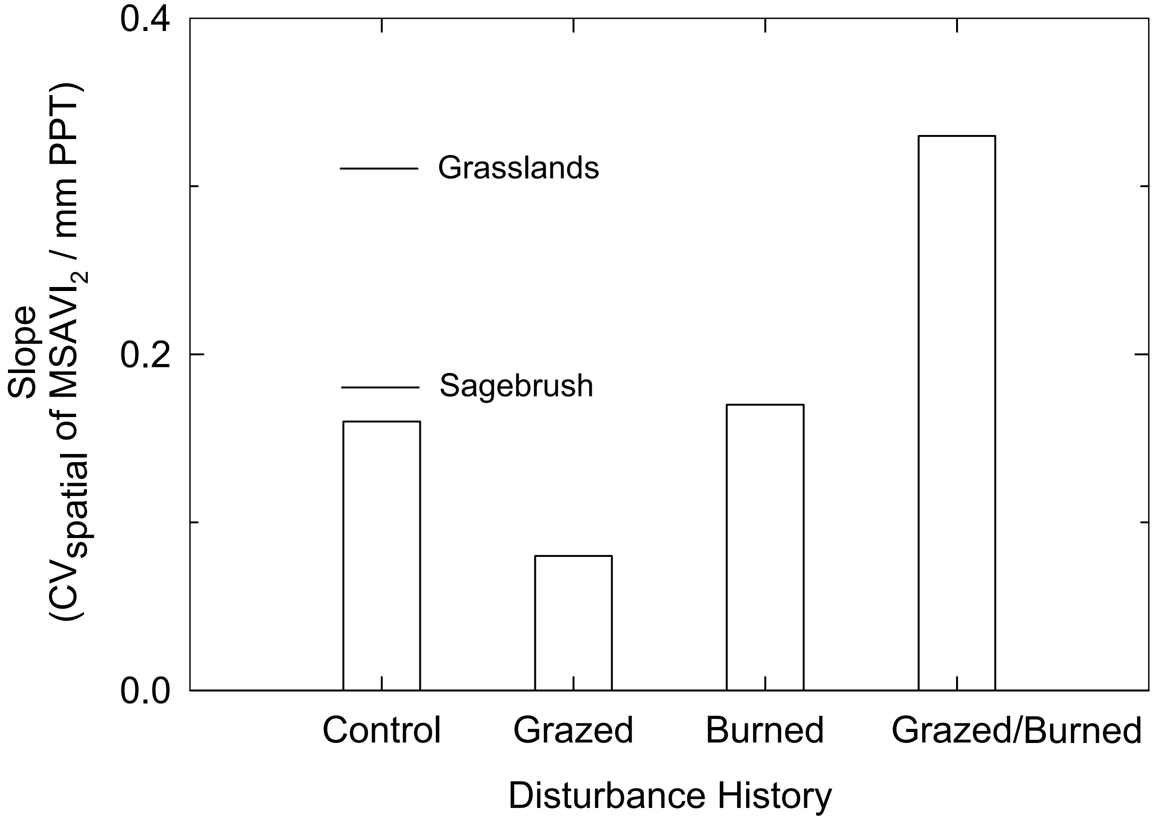


Figure 7. The slopes of the relationships between sliding three-year averages of cumulative annual growing season precipitation, PPT (from April 1 to image date), and post-fire $CV_{spatial}$ of $MSAVI_2$ among pixels of lands with different disturbance histories and undisturbed community types (sagebrush and grasslands). See Table 2 for regression statistics.

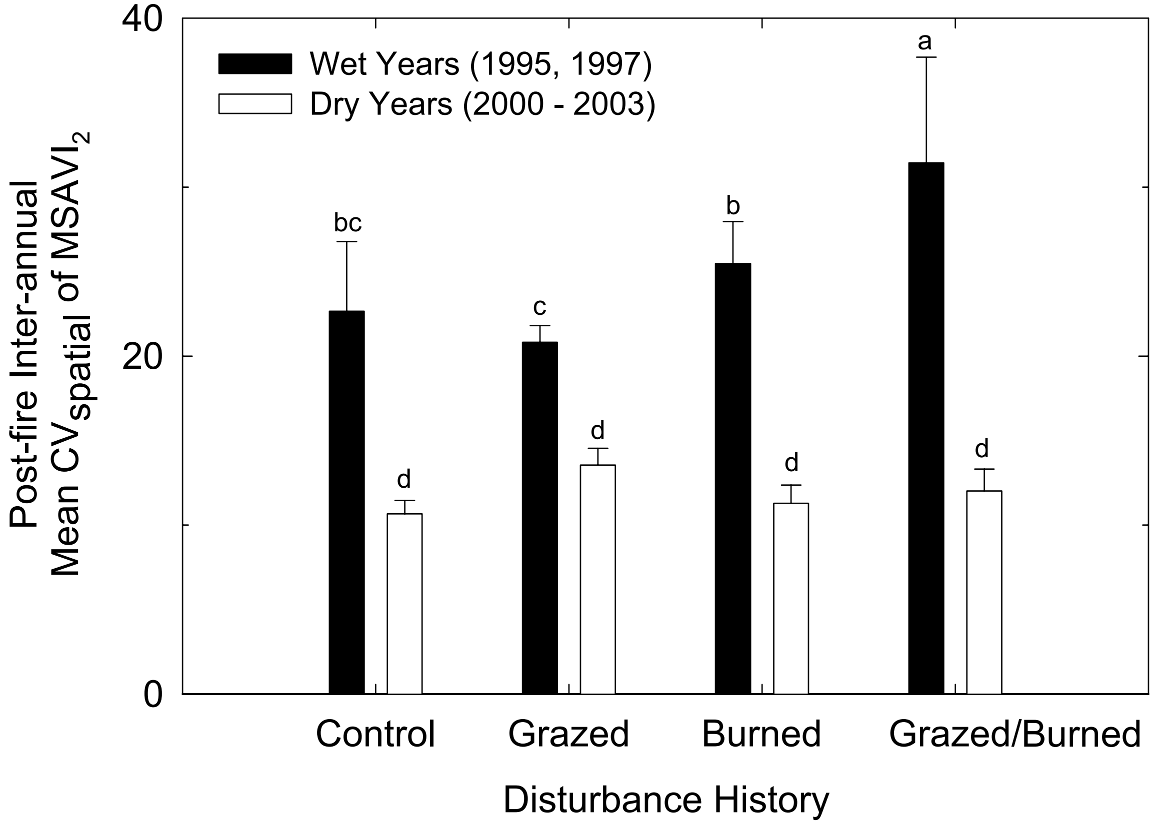


Figure 8. Mean $CV_{spatial}$ of $MSAVI_2$ (± 1 SE) during years of varying precipitation for undisturbed (control), grazed-only, burned-only, and grazed/burned lands. Wet years (n = 2 years) and dry years (n = 3 years) were years when the sliding three-year average of annual cumulative growing season precipitation (mm) was ± 1 SD from the 20-year mean (1984 - 2003). Letters denote significant differences ($P = 0.05$).

CONCLUSION

While studies have demonstrated the utility of remotely sensed SVI's for depicting ecosystem function of North American grasslands and shrublands by examining the spatial and temporal variability of NDVI (Paruelo and Lauenroth 1995 and 1998), no studies have established the utility $MSAVI_2$, for such assessments in sagebrush-steppe shrublands. Theoretically, $MSAVI_2$ should provide a more accurate measure of vegetation throughout an entire Landsat image, compared to NDVI and other SVI's typically used in semi-arid shrublands, because of its ability to account for soil effects and its increased sensitivity to vegetation defined by the "vegetation signal" to "soil noise" ratio. NDVI may be functionally inadequate, compared to $MSAVI_2$, for detecting changes in vegetation that correspond with changes in soil coverage. $MSAVI_2$'s increased sensitivity to vegetation, hence, provides a better representation of sagebrush-steppe ecosystem function in our study compared to other, more commonly used SVI's.

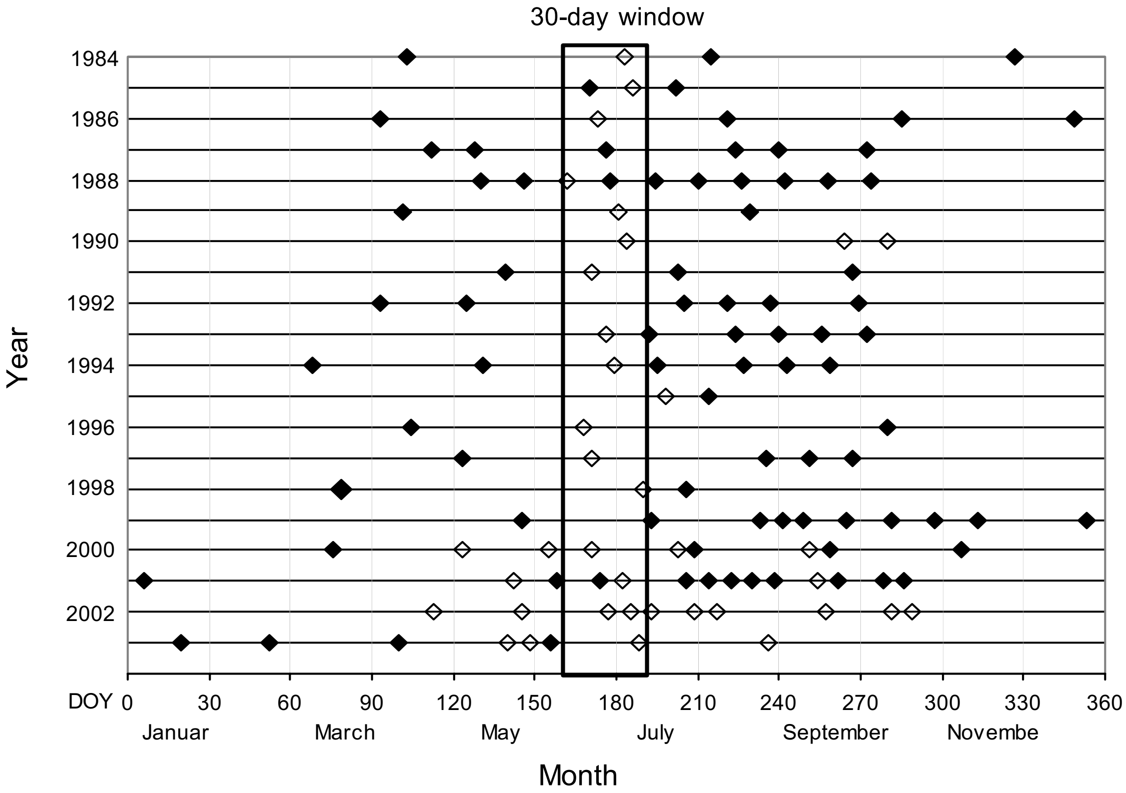
We showed that $MSAVI_2$ was sensitive to long-term changes in sagebrush-steppe vegetation resulting from fire and/or grazing disturbances, in addition to natural variation in precipitation. This demonstrates a significant use of $MSAVI_2$ to sagebrush-steppe ecosystem science applications concerned with examining the effects of disturbances on ecosystem function. However, additional work comparing the detection of such changes measured by $MSAVI_2$ to other soil-adjusted SVI's, and additional remotely sensed measures of vegetation, such as spectral mixture analysis (SMA; Smith et al. 1990; Elmore et al. 2000), may be needed to better assess the suitability of $MSAVI_2$ for such applications. Additionally, assessments regarding the accuracy of $MSAVI_2$ measures, in relation to ground measurements of vegetation cover or abundance, are needed to gain greater confidence in $MSAVI_2$'s use as a surrogate of vegetation abundance or cover, and its ability to characterize spatial and temporal variability of sagebrush-steppe ecosystems in southeastern Idaho.

The analysis of spatial and temporal variability has been shown to provide insight into forces affecting ecosystem function (Magnuson et al. 1991). Our study, which examined forces (i.e., fire and/or grazing disturbances) affecting sagebrush-steppe ecosystem function, further supports the use of such analyses for investigating long-term impacts of disturbances on rangeland vegetation. We found that multiple disturbances, resulting from the combination of fire and grazing, greatly impacted and increased the spatial and temporal variability of $MSAVI_2$ across our study area. In general, we found that the spatial variability of $MSAVI_2$ within and between years, rather than the mean responses of $MSAVI_2$, was most sensitive to disturbance effects. This may be due to the fact that the overall ranges of $MSAVI_2$ values over the entire study period (17 years) are relatively small (0.03 to 0.16) because of low vegetation index potentials resulting from relatively low amounts of vegetation observed in our study area, therefore; the probability of detecting significant changes in mean $MSAVI_2$ resulting from disturbances are more difficult or less likely. However, despite this limitation, we found detectable differences in the amount of variation in $MSAVI_2$ values within and between years when pixels corresponding to lands with different disturbances are compared.

The increased temporal and spatial variability (i.e., lower stability) observed among lands disturbed by fire alone, are likely due to reductions of shrub cover and compensating increases in herbaceous and, especially grass cover. These changes in species composition often have a greater effect on ecosystem processes and function than do the direct impacts of global changes in atmospheric conditions and climate (Chapin et al. 2002). Also, removal of a dominant species, such as sagebrush, from an ecosystem has greater impact on ecosystem processes than does removal of rare species (Chapin et al. 2002).

Greater variability in grazed/burned compared to burned-only lands, however, appears to be due to more than conversion of shrubs to grasses alone. Grazing has been shown to increase the amount of shrub cover relative to herbaceous and grass cover, resulting in higher densities of sagebrush in grazed compared to non-grazed lands. Greater site alterations may exist in these grazed lands following fire due to greater standing crops of shrubs, prior to burning, which raise fuel loads and amplify the intensity and severity of fire. As a result, grazed/burned lands could contribute to greater decreases in species diversity compared to burned-only lands. Higher species diversity is functionally important because it increases the range of organismic traits that are represented in an ecosystem, and consequently the range of conditions under which ecosystem properties can be sustained (Chapin et al. 2002). We speculate that these changes contribute to decreased stability in ecosystem properties, leading to greater spatial and temporal variability in large-scale satellite-based measurements of vegetation in grazed/burned lands.

Our most profound finding is that spatio-temporal variability increases in response to disturbance, and that different disturbances (e.g., grazing + fire) can have synergistic effects on spatial-temporal variability. Greater variability in disturbed sites appears to be due to tighter coupling of vegetation with climate/weather changes. These finding suggest that disturbances, especially combinations of disturbances, lead to greater uncertainty in vegetation and therefore primary productivity of sagebrush-steppe ecosystems. This uncertainty may cause problems for land managers dealing with restoring lands with a history of combined disturbances, such as livestock grazing and fire.



Appendix 1. Landsat 5 TM and 7 ETM+ cloud-free images available by day of year (DOY) from 1984 – 2003 for path 39 row 30. Open diamonds indicate the image dates that were acquired from the ISU GISTreC or INL Ecological and Cultural Resources archives.

Appendix 2. Landsat 5 Thematic Mapper (TM) sensor system characteristics (Jensen 2000).

Band	Spectral Resolution (µm)	Spatial Resolution (m) at Nadir
1	0.45 – 0.52	30 x 30
2	0.52 – 0.60	30 x 30
3	0.63 – 0.69	30 x 30
4	0.76 – 0.90	30 x 30
5	1.55 – 1.75	30 x 30
6	10.40 – 12.5	120 x 120
7	2.08 – 2.35	30 x 30
Sensor Technology	Scanning mirror spectrometer	
Data rate	85 Mb/s	
Quantization levels	8 bit (values from 0 to 255)	
Revisit	16 days	
Swath width	185 km	
Inclination	98.2°	
Orbit	705 km, sun-synchronous	
Launch	March 1, 1984	

Appendix 3. Landsat 7 Enhanced Thematic Mapper (ETM+) sensor system characteristics (Jensen 2000).

Band	Spectral Resolution (µm)	Spatial Resolution (m) at Nadir
1	0.45 – 0.52	30 x 30
2	0.52 – 0.60	30 x 30
3	0.63 – 0.69	30 x 30
4	0.75 – 0.90	30 x 30
5	1.55 – 1.75	30 x 30
6	10.40 – 12.5	60 x 60
7	2.08 – 2.35	30 x 30
8 (panchromatic)	0.52 – 0.90	15 x 15
Sensor Technology	Scanning mirror spectrometer	
Data rate	250 images per day @ 31, 450 km^2	
Quantization levels	8 bit (values from 0 to 255)	
Revisit	16 days	
Swath width	185 km	
Inclination	98.2°	
Orbit	705 km, sun-synchronous	
Launch	April 15, 1999	

Appendix 4. Image-to-image co-registration accuracy (RMS Errors) for Landsat images.

Image Date	RMS Error	Sensor Type
2-Jul-84	0.239	5 TM
5-Jul-85	0.195	5 TM
23-Jun-86	0.291	5 TM
11-Jun-88	0.443	5 TM
30-Jun-89	0.251	5 TM
3-Jul-90	0.327	5 TM
20-Jun-91	0.076	5 TM
25-Jun-93	0.141	5 TM
28-Jun-94	0.185	5 TM
17-Jul-95	0.444	5 TM
17-Jun-96	0.142	5 TM
20-Jun-97	0.486	5 TM
9-Jul-98	0.491	5 TM
3-May-00	0.234	7 ETM+
4-Jun-00	0.450	7 ETM+
20-Jun-00	0.306	7 ETM+
22-Jul-00	0.477	7 ETM+
8-Sep-00	0.441	7 ETM+
22-May-01	0.361	7 ETM+
1-Jul-01	0.403	7 ETM+
11-Sep-01	0.258	7 ETM+
23-Apr-02	0.087	7 ETM+
25-May-02	0.186	7 ETM+
12-Jul-02	0.000	7 ETM+
28-Jul-02	0.000	7 ETM+
28-May-03	0.200	7 ETM+
7-Jul-03	0.444	5 TM
27-Aug-03	0.340	5 TM

Appendix 5. UTM coordinates of the pseudo-invariant objects (PIO's) used for normalization of Landsat bands three and four (with reflectance values).

PIO Number	Easting	Northing	Band 3	Band 4
1	334091.25	4835751.75	0.1778	0.2423
2	332694.75	4834868.25	0.1904	0.2609
3	312288.75	4830878.25	0.1528	0.1827
4	311433.75	4830251.25	0.1904	0.2348
5	366495.75	4828113.75	0.3106	0.3802
6	366495.75	4827857.25	0.3281	0.4063
7	343439.25	4826061.75	0.1929	0.2386
8	343439.25	4825776.75	0.1979	0.2423
9	343211.25	4821444.75	0.2705	0.3206
10	342584.25	4820960.25	0.1904	0.2237
11	334461.75	4818338.25	0.2856	0.3914
12	335060.25	4818053.25	0.4058	0.4399
13	375273.75	4783311.75	0.4033	0.492
14	375188.25	4783169.25	0.2906	0.41
15	369032.25	4752959.25	0.1428	0.1677
16	370913.25	4752303.75	0.0726	0.0783
17	370770.75	4752161.25	0.0701	0.082
18	370485.75	4751876.25	0.0726	0.082
19	380147.25	4748912.25	0.1728	0.205
20	295730.25	4736714.25	0.1603	0.2087

Appendix 6. The number of pixels or replicates (N) and total area for each disturbance category.

Disturbance Category	N (# of pixels)	Area (Ha)
Control (1994 Fire)	9627	781.95
Control (1995 Fire)	14471	1175.41
Control (1996 Fire)	28378	2305
Grazed (1994 Fire)	47370	3847.62
Grazed (1995 Fire)	37812	3071.28
Grazed (1996 Fire)	37812	3071.28
Burned (1994 Fire)	5495	446.33
Burned (1995 Fire)	30494	2476.88
Burned (1996 Fire)	57348	4658.09
Grazed/Burned (1994 Fire)	114797	9324.38
Grazed/Burned (1995 Fire)	3341	271.37
Grazed/Burned (1996 Fire)	51495	4182.68

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