Evaluating Land Degradation Indicators in Semiarid Ecosystems Relative to Wildfire

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ABSTRACT

Arid and semiarid rangeland ecosystems cover vast areas of the earth's land surface. Current research has placed heightened importance upon these regions because of their role in the carbon sequestration process and related concerns of rangeland degradation. Various approaches have been used to investigate land degradation with several techniques applying remote sensing technology. Most of these techniques use vegetation indices as a surrogate of primary productivity. This study, applied season-long composite NDVI to begin an assessment of degradation in the semiarid sagebrush-steppe rangelands of southeast Idaho following the 2006 Crystal fire. Further refinements on the cNDVI approach were also used including rain-use efficiency, water-use efficiency, and local net primary productivity scaling. These indicators were calculated annually over a 10-year period and a trend in rangeland condition observed. In nearly all cases, the indicators suggest a slight decline in primary productivity. However, trend lines for most observations were not statistically significant ($P > 0.05$) save for several rain-use efficiency indices ($P < 0.05$). Results from this study highlight the importance of long-term observation periods and demonstrate the significance of the seasonality of precipitation in semiarid rangelands.

KEYWORDS: NDVI, desertification, Landsat, SOGS, ET, METRIC, carbon sequestration

INTRODUCTION

Background

Arid and semiarid rangeland ecosystems cover approximately 45% of the earth's land surface (Huntsinger and Hopkinson 1996, Branson et al. 1981; Reid et al. 2008) and represent nearly 80% of the areas grazed by livestock across the globe (Asner et al. 2004). These areas are typically dominated by grass and shrub communities and can be highly productive, though nearly always limited by the availability of water. When the hydrologic cycle (the capture, storage, and release of available water) is disturbed, rangelands desertify and as a result, typically exhibit increasing amounts of bare ground. Chronic disturbance shifts lead to a loss of ecosystem functionality and a reduction in biodiversity (Daubenmire 1959, Schlesinger et al. 1990) with associated social and economic underpinnings (Savory 1999, Arnalds and Archer 2000, Griffin et al. 2001).

Ecosystem productivity is a related and important metric to evaluate and monitor, especially when desertification and the potential effects of global climate change are concerned (Tian et al 2000; Weber et al. 2009). Measures of productivity are less direct however, than measures of bare ground as the latter exists along a horizontal plane and –for the most part—can be measured and expressed as a unit of area or percent exposure. Unlike bare ground, the definition of ecosystem productivity tends to be vague and open to interpretation. Further, measures of productivity tend to be more difficult to quantify with numerous methods available including above ground biomass (Chambers and Brown 1983), percent cover (Canfield 1941; Daubenmire and Daubenmire 1968), and canopy coverage (Gysel and Lyon 1980) to name but three. In most ecosystems, productivity measures are confounded by the fact that herbivores consume vegetation (the product of ecosystem productivity) during the same period in which one is trying to measure productivity.

Productivity estimates are typically made across large landscapes to better account for the high degree of variability in semiarid ecosystems and for this reason, satellite remote sensing has been frequently used. Similar to field based measures; remote sensing estimates have varied with no single algorithm being considered universally applicable. Some of the earliest and most common productivity algorithms use simple band ratios (SBR) that express an index of photosynthetically active vegetation. Vegetation indices (VI's) vary also, but typically leverage a ratio of reflectance in the red band to that of the near infra-red band of a given sensor. Perhaps the best known and most widely applied VI is the normalized difference vegetation index (NDVI) (Rouse et al. 1973; Tucker 1979).

Composite NDVI

Arid and semiarid rangeland ecosystems exhibit strong seasonal dynamics and the use of single-date NDVI may result in an incorrect assessment of ecosystem productivity. To avoid such errors, composite NDVI (cNDVI) can be used to better capture seasonal variability and the flush of grasses and forbs throughout an entire growing season. Stoms and Hargrove (2000) followed a similar approach when they calculated a time-integrated NDVI using the mean of nineteen 14-day cNDVI layers. Similarly, Prince et al. (2009) used the sum of 16-day cNDVI layers acquired throughout the growing season to estimate net primary productivity (NPP), while Weber et al. (2009) used a composite of maximum NDVI throughout the growing season to compare two biophysically similar semiarid regions. While the statistic extracted from each composite varied (mean, sum, and maximum respectively), the use of several NDVI layers to characterize a growing season was critical to the success of each study.

Rain Use Efficiency

The principle factor limiting plant productivity in semiarid rangelands is precipitation or more precisely, soil moisture (Taylor, 1986; Thomas and Squires 1991; Niamir-Fuller and Turner 1999; Booth and Tueller 2003; Hill 2006; Weber and Gokhale 2010). The response in plant biomass to precipitation appears highly correlated and field measurements reported by Studley and Weber (2010) reveal a high coefficient of determination ($R^2 = 0.93$) between June precipitation and average forage availability (kg/ha). Because rangelands exhibit a high degree of inter-annual variability, determining a long-term trend in rangeland condition using cNDVI alone might be misleading. Le Houerou (1984) and Hountondji et al. (2009) argue that since the vegetation in semiarid areas is strongly associated with precipitation, several years of favorable rainfall may lead one to erroneously conclude that rangelands are in good condition or improving from a degraded condition. To avoid this error, Le Houerou (1984) introduced the concept of Rain Use Efficiency (RUE) as the "quotient of annual primary production by annual rainfall". Subsequent applications of RUE have typically used ∑NDVI to estimate above ground biomass. Hountondji et al. (2009) suggest integrating the sum of rainfall throughout the growing season (RR) to estimate RUE (Eq. 1) and observe the trend in integrated-NDVI (iNDVI) to better assess rangeland condition.

$$\text{iNDVI/RR} = \frac{\sum \text{NDVI}_{\text{(growing season)}}}{\sum \text{Rainfall}_{\text{(growing season)}}} \qquad \text{Eq. 1}$$

The direct use of total rainfall is not without problems as this approach does not account for run-off, evaporation, and ground water recharge fractions, each of which detract from the amount of water that is available to and used by plants. Modeling RUE in such a way may be further complicated by the seasonality of rainfall, rate of precipitation, soil type and depth, as well as the interaction with ambient temperature, wind, and humidity as the fraction of what available to plants is not constant in either time or space.

Water Use Efficiency

Water Use Efficiency (WUE) is similar to RUE save that it substitutes total evapotranspired water (i.e., ∑ of actual evapotranspiration [ET]) for the rainfall divisor. While this approach may be more accurate (Floret et al. 1983; Seiny-Boukar et al. 1992; Aronson et al. 1993) it is also more difficult to calculate correctly. Actual evapotranspiration is a very challenging parameter to measure and requires a weighing lysimeter for direct measurement. In addition, a number of environmental factors affect ET including phenology, soil exposure, and wind, further complicating the extrapolation of lysimeter measurements to entire landscapes. One model used to estimate ET is the Surface Energy Balance Algorithm for Land (SEBAL). SEBAL uses energy balance modeling instead of a catchment water balance approach (which relies on estimates or measures of ground water recharge, stream flow, etc) to estimate ET using satellite data. By indexing radiometric surface temperature from Landsat's thermal band, a near-surface temperature gradient can be determined. These data, along with net solar radiation and soil heat flux are then used to calculate actual evapotranspiration.

Allen et al. (2007) modified the SEBAL algorithm using *in situ* reference ET to internally calibrate surface energy balance estimates and thereby determine a more accurate estimate of actual ET. Using either the SEBAL or Mapping Evapotranspiration at high Resolution with Internalized Calibration

(METRIC) model (Allen et al. 2007), WUE can be calculated and used to visualize trends in rangeland condition over time.

Local Net Primary Productivity Scaling

Another approach used to assess rangeland degradation which effectively circumvents the potential errors associated with RUE as well as the computational challenges of accurately quantifying actual ET and hence, WUE, is Local Net Primary Productivity Scaling (LNS) introduced by Prince in 2004. LNS determines potential productivity within biophysically homogeneous areas and then compares site potential to the actual productivity observed at intrinsically similar sites. This method also relies upon NDVI as the fundamental source for estimates of productivity but makes no estimate of RUE apart from the inherent assumption that sites in proper functioning condition will exhibit higher primary productivity as a result of higher RUE and WUE. A potential problem with the LNS approach noted by Prince (*pers. comm.*) is if the entire study area is degraded then no reasonable potential can be identified. As a result, few sites will be identified as degraded when scaled against equally degraded counterparts.

The process of monitoring land degradation or identifying sites of desertification are essentially applications of land cover change analysis (Yuan et al. 1998). The most basic approach uses vegetation index differencing (Perry and Lautenschlager 1984) between two or more imagery dates while the more complex approaches described above, effectively build upon this concept. Trend lines are sometimes applied across datasets exhibiting long-term fluctuations in productivity with the slope of these lines interpreted as indicators of desertification trend (Hountondji et al., 2009). The accurate identification of land cover change, and especially desertification, is an active area of remote sensing research and many papers have been published that question the approach or conclusions of other papers (Hein and De Ridder 2006; Veron et al., 2006). A related, and perhaps equally active area of research, focuses not upon the identification of degraded areas but on identifying the drivers or causes of land degradation in semiarid rangelands. From these debates, three main paradigms have emerged: 1) environmental factors (rainfall) are the primary drivers of ecosystem change (Westoby et al. 1989), 2) anthropic factors (livestock grazing) are the primary drivers of ecosystem change (Le Houerou 1989; Hein and de Ridder 2006), and 3) both environmental and anthropic factors drive ecosystem change and exhibit interesting interactions over time (Briske et al, 2003; Vetter 2005; Hein and de Ridder 2006). One area of interaction relates to wildfire, a source of punctuated and geographically distributed change, as fires can be initiated and/or suppressed by humans. In addition, fuel load, a factor having substantial influence on a fire's effect (specifically fire intensity), can be influenced by humans and their livestock grazing animals (Weber et al. 2004).

This study, while acknowledging the importance of understanding the causative agents of change, focused on comparing four approaches commonly used to assess land degradation status and trend, namely cNDVI, RUE, WUE, and LNS. To accomplish this, 24 Landsat 5 TM scenes (2000-2009) were acquired for the Big Desert study area in southeast Idaho, USA. Analysis emphasized the effect of the 2006 Crystal fire, the second largest fire (890 km^2) documented in southeast Idaho since 1936. This study sought to determine the trend of primary productivity for Big Desert rangelands 1) in areas where no fire had occurred since 2000 and, 2) in areas burned by the 2006 Crystal fire. In addition, this study compared various methodologies used to assess land degradation relative to their agreement, accessibility, and efficacy.

Materials and Methods

Study Area

The Big Desert study area lies approximately 71 km northwest of Pocatello Idaho and the center of the study area is approximately 113º 4' 18.68" W and 43º 14' 27.88" N (Figure 1). The Big Desert is managed by the United States Department of the Interior Bureau of Land Management (USDI BLM) and is a semiarid sagebrush-steppe ecosystem with relatively high proportions of bare ground. The vegetation in the study area consists primarily of native and non-native grasses, forbs, and several shrub species including big sagebrush (*Artemisia tridentata*) and rubber rabbitbrush (*Ericameria nauseosa* [Pall. ex Pursh]). The study area is relatively flat with elevation ranging from 1349 to 2297 m above sea level. The mean annual precipitation is 210 mm (1992-2009) with the majority falling as snow during the winter months (48%) and another 33% falling from April through June (cf. Yanskey *et al*. 1966). Sheep grazing is the primary anthropic disturbance with continuous/seasonal grazing systems used on allotments ranging in size from 1,100 to over 125,000 ha. The stocking rate is low (approximately 19 ha/animal unit [AU]) with only 10% of permitted grazing utilized in most seasons. Wildfire is a common disturbance and 58% of the study area has burned since 2000 with the Crystal fire burning 31% of the Big Desert in 2006.

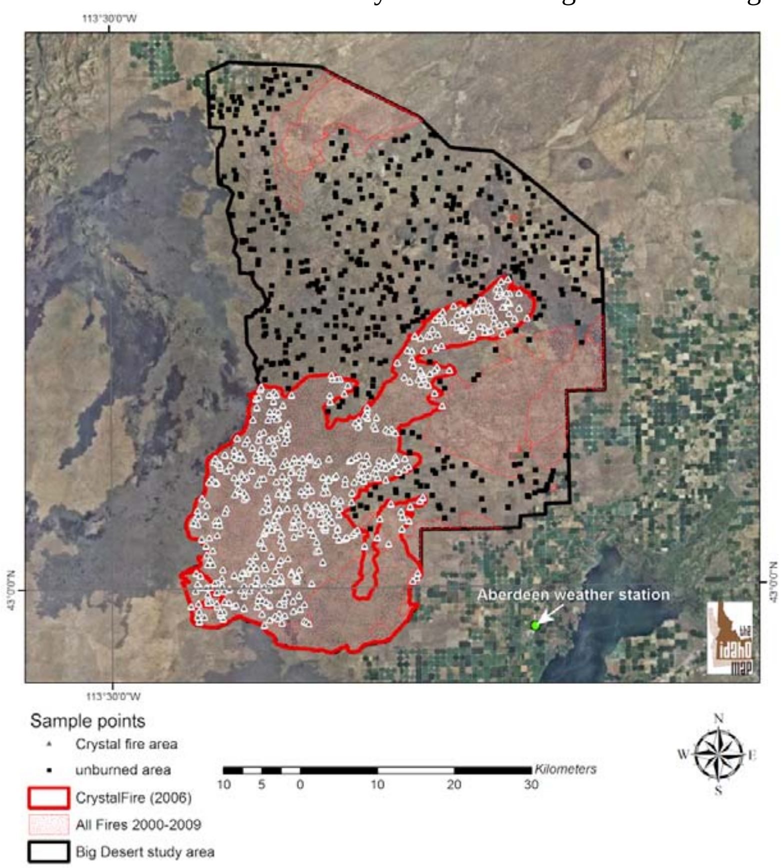


Figure 1. The Big Desert study area in SE Idaho and location of documented wildfires between 2000 and 2009 along with sample sites used in this study (*n* = 600) .

The geology of the Big Desert is typified by shallow soils overlying basalt. Fissures are quite common (approximate spacing of the smallest aperature fractures is 2-4 m [Johannesen 2000]) and water that infiltrates the soil surface can move to a fissure and relatively quickly become inaccessible to plants. As a result, soil water content in the root zone (upper 0.25 m) can drop as low as 5-10% throughout much of the growing season (Kaminsky 1991).

The Big Desert is one of the few remaining large areas (2837 km^2) of contiguous sagebrush-steppe rangelands in the Intermountain West and for this reason is an important conservation area for sagebrush-obligate species like the Greater Sage Grouse (*Centrocercus urophasianus*). In addition, the Big Desert represents an area of importance for livestock production and recreation as well.

The Crystal Fire

The Crystal fire burned approximately 890 km^2 across the Big Desert study area between August 15 and August 31, 2006. This lightning-caused wildfire was the second largest documented in southeast Idaho since 1936 (cf. the DR62 fire of 2007 which burned 1500 km^2). More than 90% of the fire burned land managed by the USDI BLM with another 3% of the fire burning lands managed by the State of Idaho and National Park Service.

Primary Productivity Modeling

Twenty-four Landsat 5 TM scenes (path 039 row 030) were acquired for the Big Desert study area between 2000 and 2009 (Table 1). To capture the phenology and ephemeral productivity periods of the various grasses, forbs, and shrubs in these semiarid rangelands it was advantageous to use numerous scenes collected across each growing season (Weber et al. 2009). Capturing peak photosynthetic activity in this region was accomplished by acquiring one or two scenes in the spring (April or May) and one or two scenes in the early fall (September or October) (Tedrow and Weber 2010). By satisfying these criteria, an increased probability of capturing peak photosynthetic activity throughout the growing season was more likely achieved.

Table 1. Year and date of Landsat 5 TM imagery used in this study (all scenes were acquired for path 039 row 030).

Year	Date of image acquisition
2000	May 27
	June 28
	September 16
2001	May 14
	June 15
	September 19
2002	May 17
	July 4
	September 22
2003	May 20
	July 7
	August 24
2004	May 6
	June 7
	September 11
2005	May 25
	September 14
	September 30

2006	April 26
	May 12
	September 1
2007	May 15
	May 31
	September 20
2008	May 17
	September 6
	October 8
2009	April 18
	September 9
	September 25

All acquired imagery were corrected for atmospheric effects using Chavez' Cos(t) model in Idrisi Taiga's ATMOSC module (Chavez, 1996). The imagery were then tested for georegistration error using National Agricultural Imagery Program (NAIP) aerial orthophotography (1m x 1m pixels) and corrected as needed (RMSE < 0.50 pixel). NDVI was calculated for each scene and used to estimate primary productivity following Prince (1991; 2009). Composite NDVI (cNDVI) layers were created for each year of the study (2000-2009) using the NDVICOMP utility of Idrisi Taiga. cNDVI used maximum NDVI values observed throughout a growing season and in each case, three Landsat scenes were used per year to calculate the respective cNDVI layers. Imagery pairs (e.g., 2004 cNDVI and 2005 cNDVI) were co-registered to eliminate false positive/false negative change detection due to misalignment of features within the imagery. The resulting cNDVI layers were then used as estimates of maximum primary productivity for this study (Pettorelli et al 2005).

Precipitation Modeling and RUE

Precipitation data were used for the development of RUE models and while winter precipitation can be a very important contributor to spring plant growth in areas with deep soils, spring precipitation is also considered important, especially in areas with shallows soils, such as the Big Desert. In this study, five measures of precipitation (PPT) were used; total precipitation accumulated throughout the 1) hydrologic water year (PPT_{hwy} [October $1_{(year\ -1)}$ - September 30]), 2) growing season (PPT_g [April 1 - September 30]), 3) winter (PPT_w [October $1_{(year\ -\ 1)}$ - March 31]), 4) spring (PPT_s [April 1 - June 30]), and 5) winter and spring seasons (PPT_{ws} [October $1_{(year\ -\ 1)}$ - June 30]). These values were determined using data from the Aberdeen weather station (ABEI) located on the southern edge of the Big Desert study area (http://www.usbr.gov/pn/ agrimet/). In addition, surface observation gridding system (SOGS) rasters (1000 m x 1000 m pixels) were used which provided spatially continuous models of meteorological conditions and were acquired through the Numerical Terradynamic Simulation Group (NTSG) at the University of Montana. The specific dataset used in this study described daily precipitation from 2004 through 2009.

Data from the Aberdeen weather station assumed a constant value throughout the study area. To integrate these tabular data into a geospatial format, raster layers were created where all pixels were assigned the value corresponding to the PPT measurement. While SOGS data were considered a better predictor of precipitation across large land areas (Weber et al., 2010) these data were not available for all years included in this study. All raster precipitation layers were projected into Idaho Transverse Mercator

(NAD 83), with 30 m x 30 m pixels, using ArcGIS 9.3.1 and nearest neighbor resampling. These parameters matched those for the Landsat 5 TM imagery described above. All precipitation values were expressed in millimeters. Annual RUE was determined using cNDVI and PPT (Eq. 1) from each of the alternative precipitation models.

Evapotranspiration Modeling and WUE

Actual evapotranspiration (ET) was required to calculate WUE for the Big Desert study area. Data describing actual ET were obtained from the METRIC-ET datasets for 2000, 2002, and 2006. These raster layers estimated the monthly sum of evapotranspired water (mm) across the study area. Total ET for the growing season (ET_g [April 1 - September 30]) was determined by summing each of the monthly estimates. These data, like all raster data used in this study, was projected into Idaho Transverse Mercator (NAD 83), with 30 m x 30 m pixels, using ArcGIS 9.3.1 and nearest neighbor resampling. All ET values were expressed in millimeters. WUE was determined for years 2000, 2002, and 2006 using cNDVI and ET_g.

Local Net Primary Productivity Scaling (LNS) Modeling

Calculating LNS requires two input layers; primary productivity (e.g., cNDVI) and land capability classification (LCC). LCC may be determined using a combination of precipitation, soils, land use, and land cover and is intended to delineate areas with similar intrinsic potential. Prince (2009) described several LCC procedures using k-prototypes clustering techniques (Huang, 1997; Hargrove and Hoffman, 2004) for an LNS study of Zimbabwe. For the Big Desert study area, a similar process was followed by incorporating SOGS precipitation (NTSG, 2010), SSURGO soils (NRCS, 2007), GAP land cover (InsideIdaho, 1999), and southeast Idaho land use/management layers (GIS TReC, 2010). Both land cover and land use layers for the Big Desert study area were constant and had no effect on the stratification of LCC because the entire study area was 1) classified as a basin and Wyoming big sagebrush land cover type (Redmond et al., 1996; Homer et al., 1998) and 2) similarly managed (i.e., livestock grazing allotments) by the USDI BLM Idaho Falls District. Intra-annual precipitation across the study area exhibited little variability (MSE = 0.50 [2004-2009]) and was similarly treated as a constant. As a result of this stratification exercise, LCC was based entirely upon 15 soil associations identified in the SSURGO soils database.

The 15 LCC polygons were rasterized and used as a Boolean mask with each year's cNDVI layer. This procedure produced 15 LNS layers per year, or a total of 120 layers for this study (i.e., 15 layers/yr x 8 years). To specifically examine the effect of the 2006 Crystal fire, an additional Boolean mask was created for the fire area and used as another stratification layer for 2007-2009. The Crystal fire burned parts of seven LCC areas and concomitantly increased the number of total LNS layers. Within each LNS layer, potential productivity was estimated as the cNDVI value at the 90th percentile ($cNDVI_{p90}$). The LNS metric of degradation (LNS_d) was determined using the following equation (Eq. 2).

$$LNS_d = cNDVI_{p90} - cNDVI_{actual} \tag{Eq 2.}$$

where $cNDVI_{actual}$ is the cNDVI value of each pixel assessed against the potential within each LCC area.

The standard deviation for each LNS_d layer was found and used to quantify the area (km^2) within each LCC where primary productivity was >2 standard deviations below the potential. This *below potential* *threshold* was conservatively chosen to allow for natural variability within each LCC and to help eliminate type I and type II errors.

Analysis

To determine the trend in primary productivity and assess rangeland health/land degradation in the Big Desert study area, annual cNDVI, RUE, and WUE was examined at 600 random locations. Half of these locations (n = 300) were within the area burned by the 2006 Crystal fire, but outside other areas of disturbance (i.e., earlier fires). The remaining 300 locations were outside the area burned by the Crystal fire, yet within the Big Desert study area (figure 1). All random sample points were generated using Hawth's tools in ESRI's ArcGIS 9.3.1 using the following criteria: sample points were not located within 70 m of a fire perimeter or within 70 m of another sample point. The value of the pixel at each sample point was extracted from each cNDVI, RUE, and WUE layer using the SAMPLE tool in ArcGIS and saved in a MS Excel spreadsheet. Scatter plots were created with year along the X-axis and the value of the productivity estimator (cNDVI, RUE, or WUE) along the Y-axis. A linear trend line was established for each scatter plot and the line's correlation coefficient, slope and Y-intercept recorded. Regression statistics were calculated for each scatter plot and an ANOVA was used to determine the significance of each relationship.

To assess the trend in primary productivity using LNS_d required a slightly different approach. In this case, the total area (km^2) characterized using the *below potential threshold* was summed for each year and graphed as a scatter plot with year along the X-axis and total area below potential given on the Y-axis. A linear trend line was established for the scatter plot and the line's coefficient of determination, slope, and Y-intercept recorded. In total, ten scatter plots were created, one describing cNDVI, seven describing RUE (five using ABEI data to estimate PPT_{hwy}, PPT_g, PPT_w, PPT_s, and PPT_{ws} [2000-2009], another using ABEI data for PPT_g in years 2004-2009 only to directly compare results with the seventh plot where PPT_g was estimated using SOGS data [2004-2009]), another describing WUE, and finally, one describing LNS_d.

RESULTS AND DISCUSSION

Scatter plots and trend lines of cNDVI calculated for each growing season between 2000 and 2009 initially suggest primary productivity throughout the Big Desert study area declined (Figure 2). The rate of decline, as indicated by the slope of the trend lines, was quite slow for both the Crystal fire (-0.002) and unburned parts of the Big Desert study area (-0.004). In both cases however, large residual values existed due to inter-annual variability. Consequently, the coefficient of determination was quite low (R^2 = 0.01 and 0.04 for the Crystal fire and unburned areas, respectively). The results of ANOVA tests used to determine the significance of the observed trend indicates the relationships were not statistically significant (P = 0.74 and 0.58 for the Crystal fire and unburned areas, respectively). However, the high inter-annual variability in cNDVI did correspond fairly well with variability in precipitation (R^2 = 0.34), serving to empirically validate the work of Le Houerou (1984) and Hountondji et al. (2009), and to illustrate the importance of water in these xeric environments (Niamir-Fuller and Turner 1999; Hill 2006).

RUE metrics (2000-2009) were calculated based upon five different measures of precipitation ($PPT_{hwy,}$ PPT_g, PPT_w, PPT_s, and PPT_{ws} (Figure 3). Results of RUE analysis also suggest primary productivity in the Big Desert declined (Figure 4a-e). However, when plotting data for 2004-2009 only, the results were contradictory (Figure 4f-g), illustrating the need to observe trend over fairly long time periods (~10 years) to gain meaningful and reliable information (Washington-Allen et al., 2006). This observation is supported by an increased coefficient of determination ($\bar{x}$ R^2 = 0.28 [2000-2009] compared with $\bar{x}$ R^2 = 0.05 [2004-2009]). In contrast to the cNDVI results, several RUE metrics revealed a significant trend ($P < 0.05$) including those metrics calculated using PPT_{hwy}, PPT_s, and PPT_{ws} (Table 2).

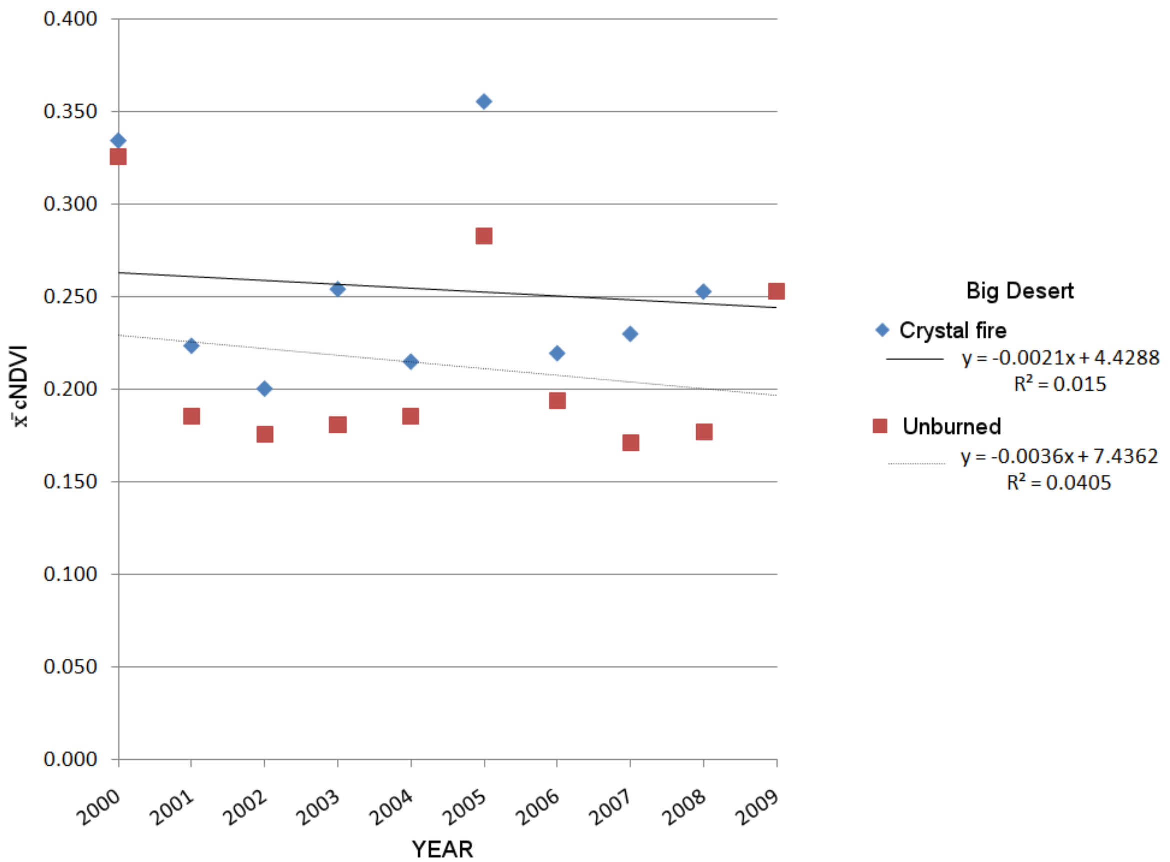


Figure 2. Scatter plot of mean cNDVI values at 600 sample sites in the Big Desert study area (*n* = 300 in both the Crystal fire and unburned regions of the study area).

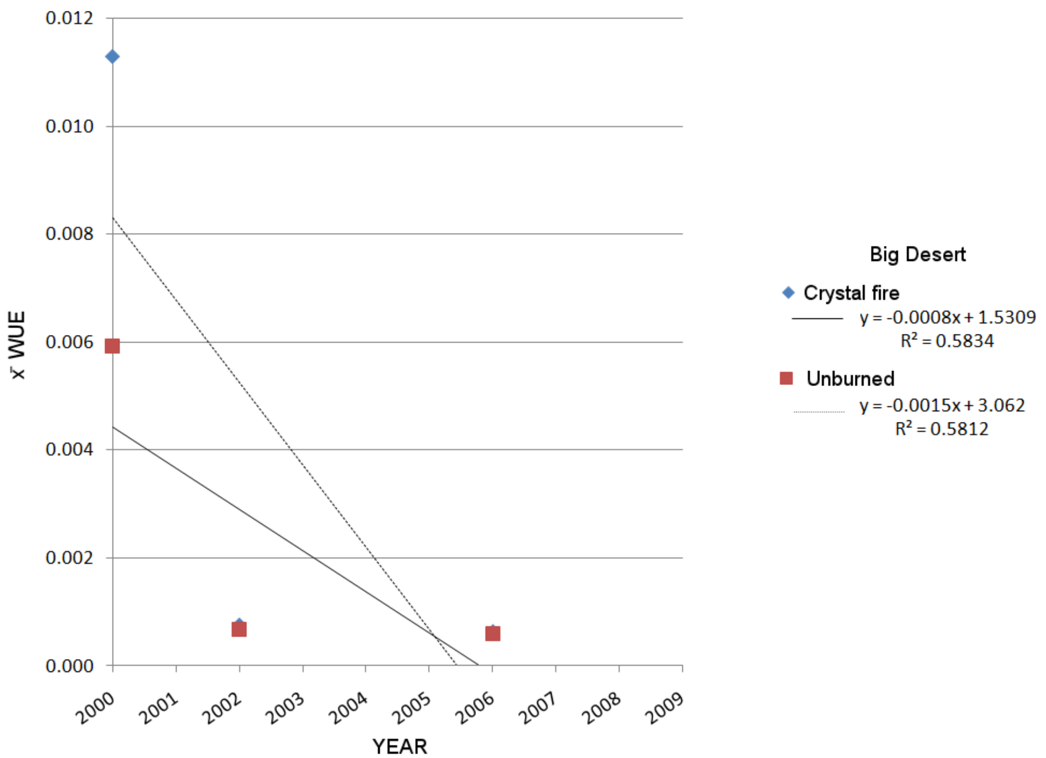
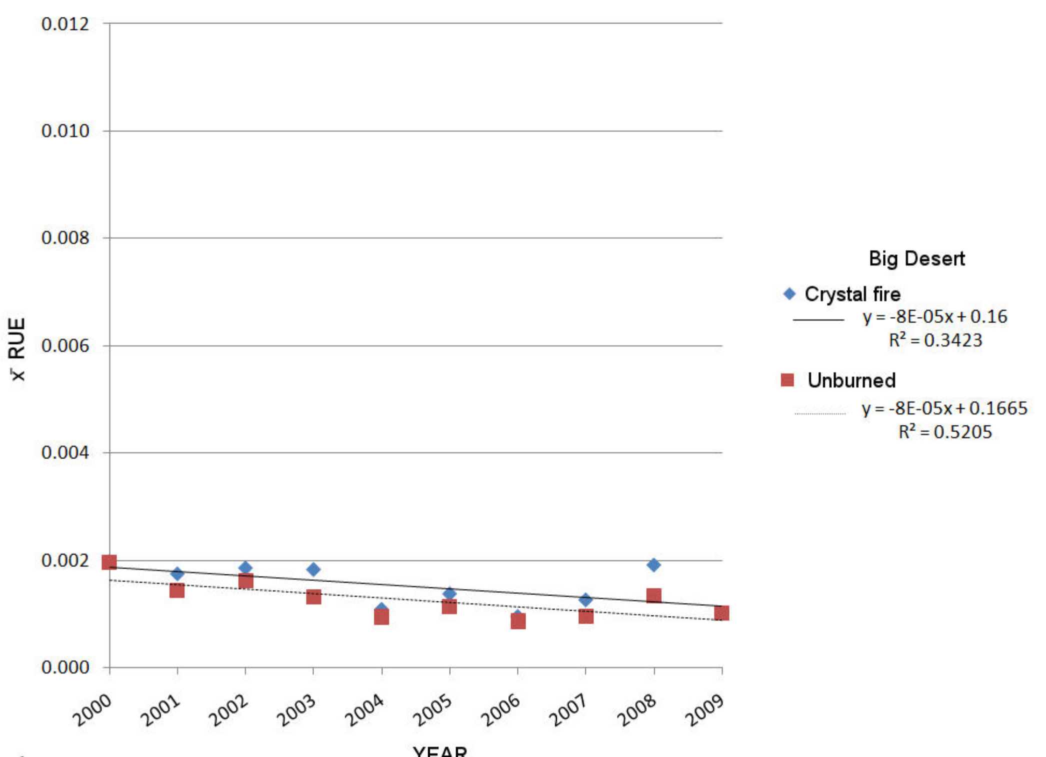
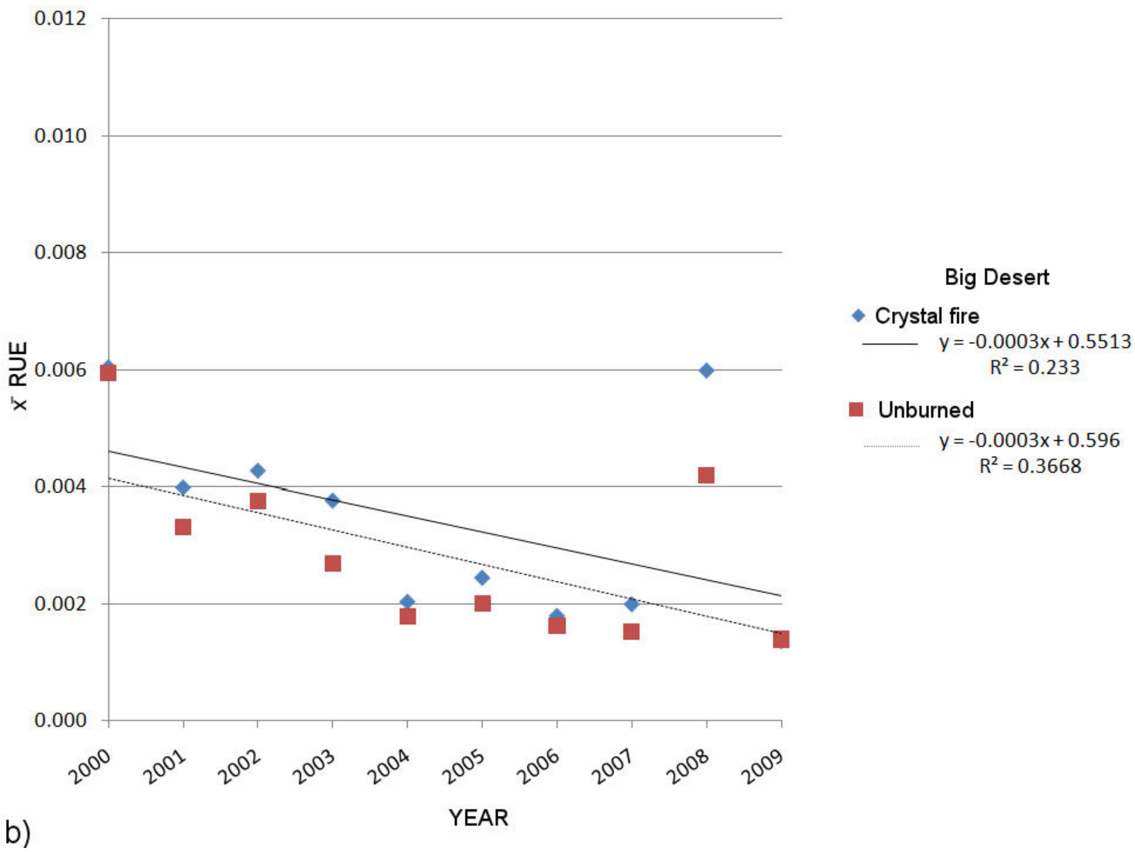


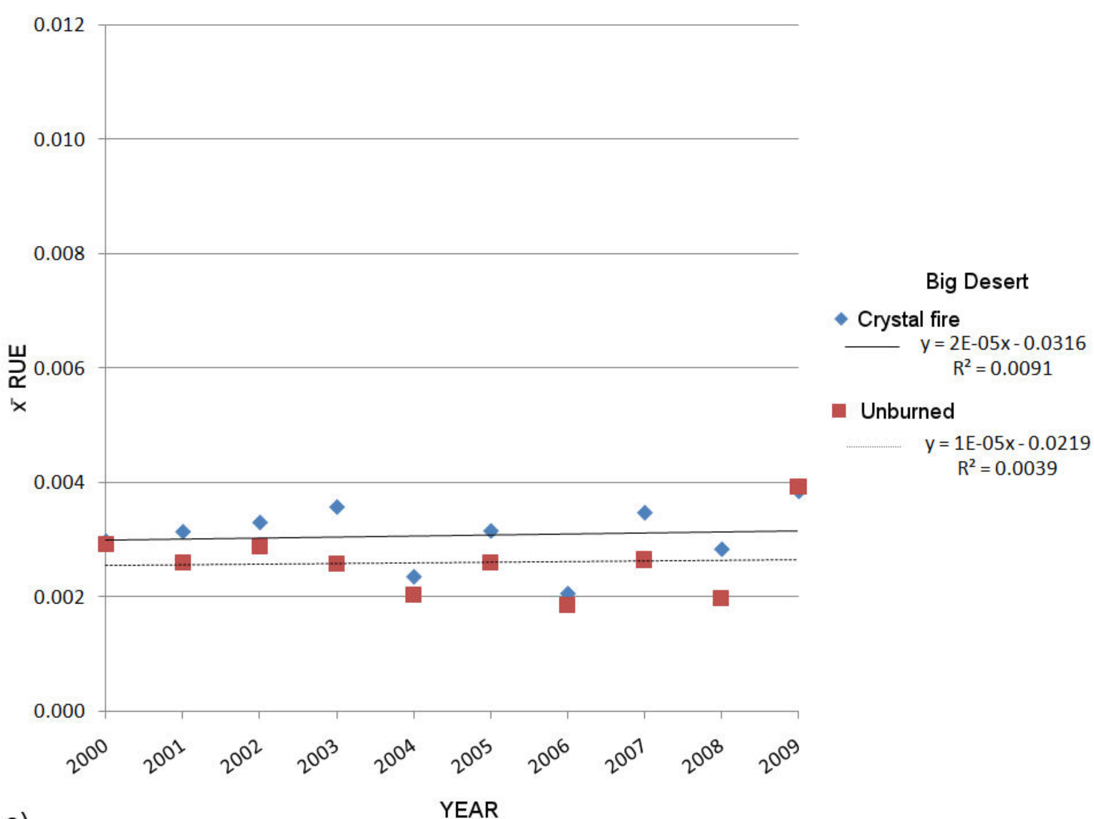
Figure 3. Stack bar chart of precipitation at the Aberdeen weather station (ABEI) for each hydrologic water year (2000-2009) illustrating the portion accumulated during the winter (PPT_w), spring (PPT_s), and other months of the year (PPT_{other}). Mean precipitation is indicated by the dashed horizontal line ($\bar{x}$ = 181.5 mm).



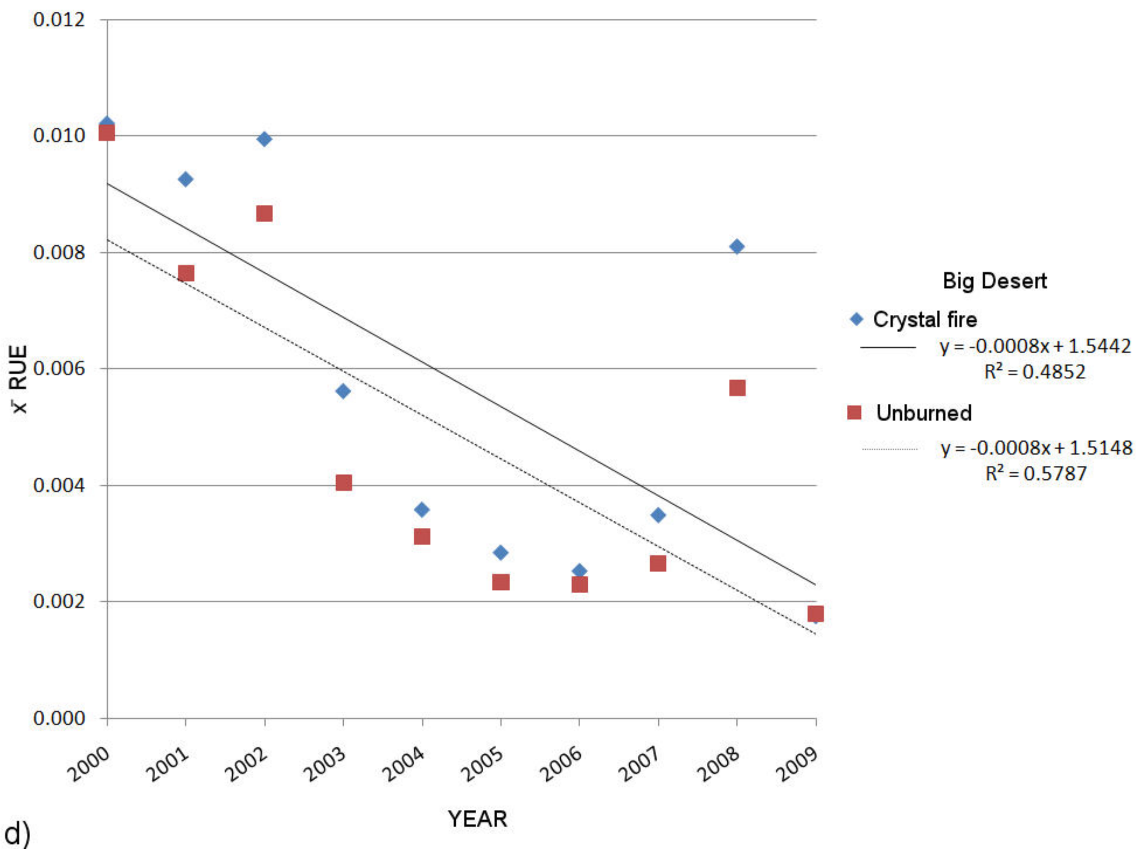
a)


0.012
0.010
0.008
0.006
0.004
0.002
0.000
x̄ RUE
2000
2001
2002
2003
2004
2005
2006
2007
2008
2009
YEAR
Big Desert
Crystal fire
y = -0.0003x + 0.5513
R² = 0.233
Unburned
y = -0.0003x + 0.596
R² = 0.3668

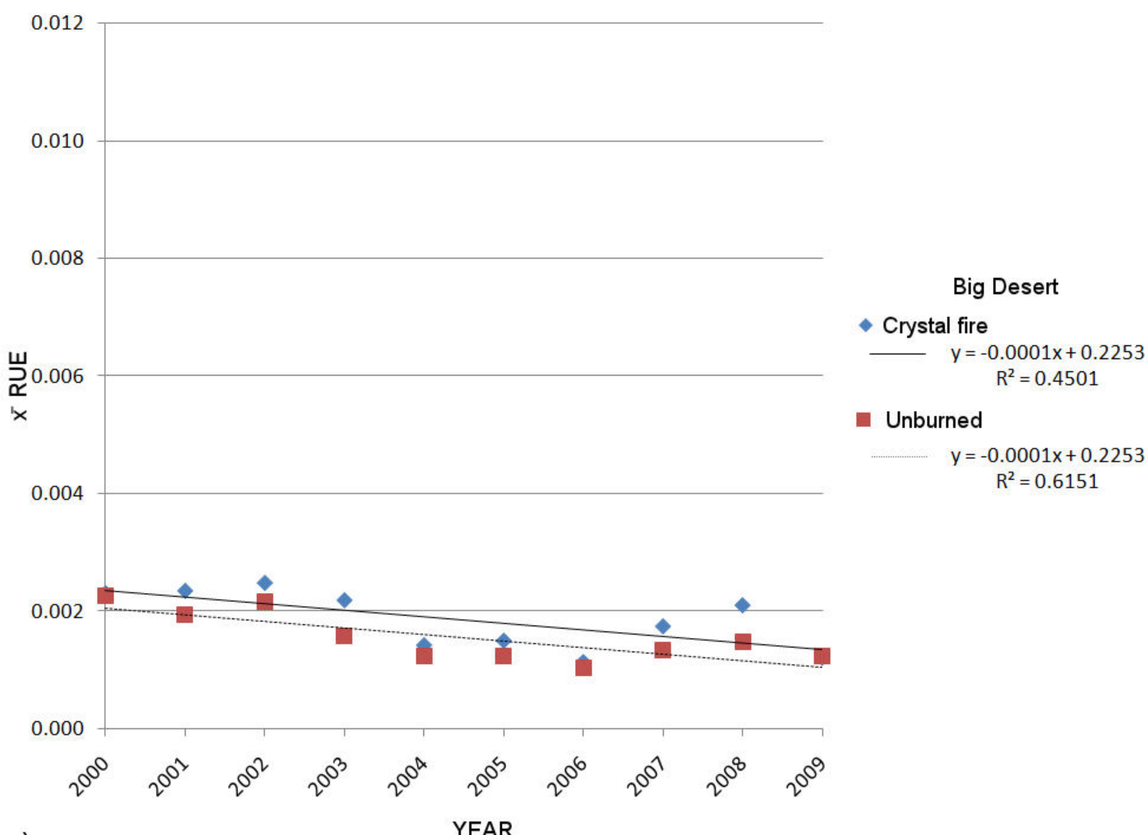
b)


0.012
0.010
0.008
0.006
0.004
0.002
0.000
x̄ RUE
2000
2001
2002
2003
2004
2005
2006
2007
2008
2009
YEAR
Big Desert
Crystal fire
y = 2E-05x - 0.0316
R² = 0.0091
Unburned
y = 1E-05x - 0.0219
R² = 0.0039

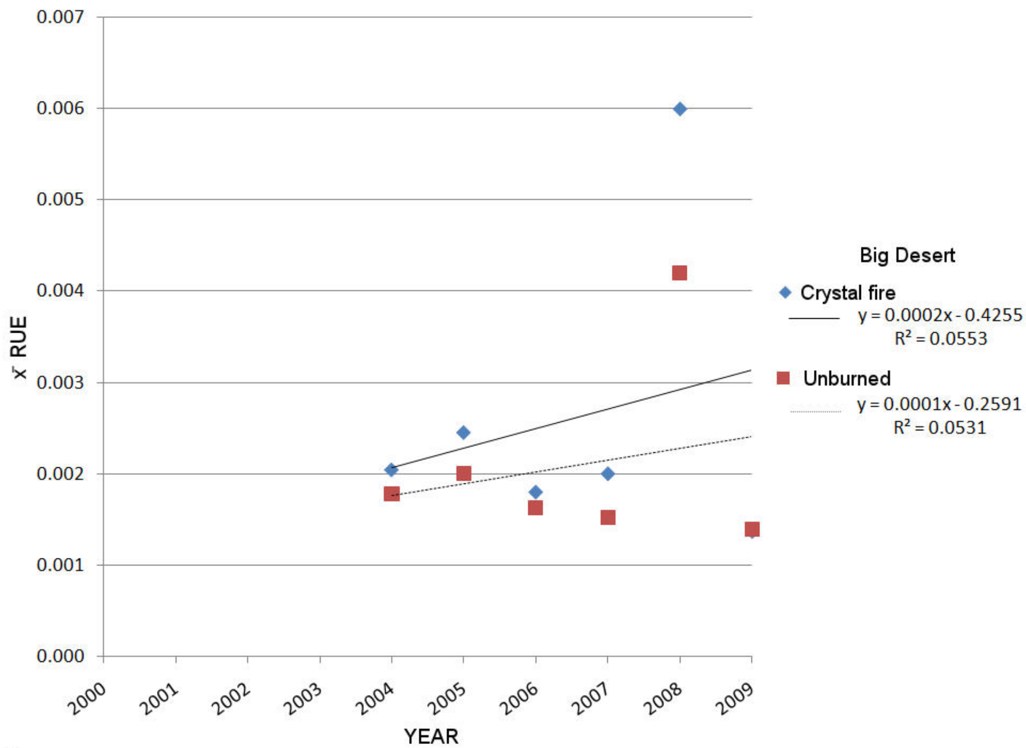
c)


0.012
0.010
0.008
0.006
0.004
0.002
0.000
x̄ RUE
2000
2001
2002
2003
2004
2005
2006
2007
2008
2009
YEAR
Big Desert
Crystal fire
y = -0.0008x + 1.5442
R² = 0.4852
Unburned
y = -0.0008x + 1.5148
R² = 0.5787

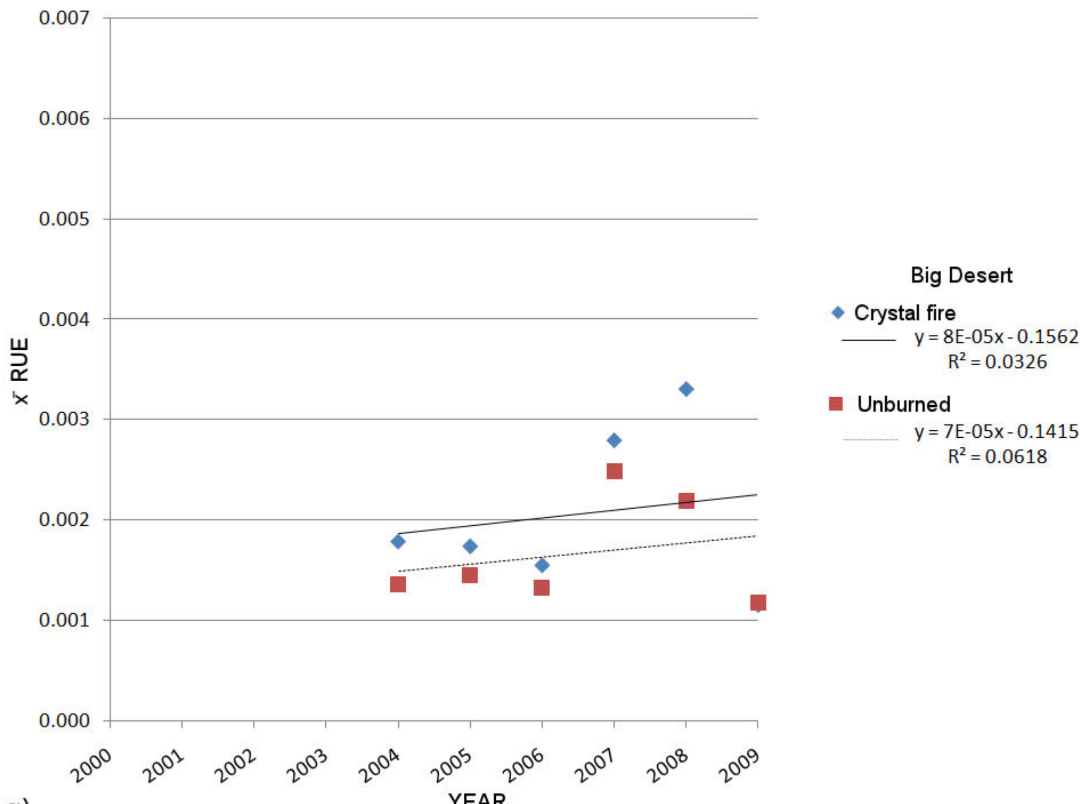
d)


0.012
0.010
0.008
0.006
0.004
0.002
0.000
x̄ RUE
2000
2001
2002
2003
2004
2005
2006
2007
2008
2009
YEAR
Big Desert
Crystal fire
y = -0.0001x + 0.2253
R² = 0.4501
Unburned
y = -0.0001x + 0.2253
R² = 0.6151

e)



f)



g)

Figure 4. Scatter plot of mean RUE values at 600 sample sites in the Big Desert study area (*n* = 300 in both the Crystal fire and unburned regions of the study area) for years 2000-2009 using a) PPT_{hwy}, b) PPT_g, c) PPT_w, d) PPT_s, e) PPT_{ws}, and years 2004-2009 using f) PPT_g from ABEI, and g) PPT_g from SOGS.

Table 2. Coefficients of determination assessed in this study

Analysis Area	R2	Adjusted-R2	Slope	P
cNDVI Crystal fire	0.015	-0.108	-0.0021	0.74
cNDVI unburned	0.041	-0.079	-0.0036	0.56
RUE Crystal fire (PPT_{hwy})	0.342	0.260	-0.0000	0.07
RUE unburned (PPT_{hwy})	0.521	0.461	-0.0000	0.02*
RUE Crystal fire (PPT_g)	0.233	0.137	-0.0003	0.16
RUE unburned (PPT_g)	0.367	0.288	-0.0003	0.06
RUE Crystal fire (PPT_w)	0.009	-0.115	0.0000	0.79
RUE unburned (PPT_w)	0.004	-0.121	0.0000	0.86
RUE Crystal fire (PPT_s)	0.485	0.421	-0.0008	0.02*
RUE unburned (PPT_s)	0.579	0.526	-0.0008	0.01*
RUE Crystal fire (PPT_{ws})	0.450	0.381	-0.0001	0.03*
RUE unburned (PPT_{ws})	0.615	0.567	-0.0001	0.01*
RUE Crystal fire (PPT_g 2004-2009)	0.055	-0.181	0.0002	0.65
RUE unburned (PPT_g 2004-2009)	0.053	-0.184	0.0001	0.66
RUE Crystal fire (SOGS PPT_g 2004-2009)	0.033	-0.209	0.0000	0.73
RUE unburned (SOGS PPT_g 2004-2009)	0.062	-0.173	0.0000	0.63
WUE Crystal fire	0.583	0.162	-0.0008	0.45
WUE unburned	0.581	0.167	-0.0015	0.45
LNS_d Crystal fire	0.019	-0.104	-1.5416	0.71
LNS_d unburned	0.170	0.067	8.6102	0.24

*** statistically significant**

WUE metrics (2000, 2002, and 2006) similarly describe a marginally declining trend of primary productivity throughout the Big Desert study area (Figure 5). However two problems arose which question the validity of this observation if made independent of the previously reported results; 1) the established trend was based on only three observation points and lacks statistical power of analysis and 2) the ET_g values used in the calculation may be erroneous as ET_g exceeded precipitation ($\bar{x}\ \Delta\ (PPT_g - ET_g) = -67.7$ mm). It is recalled that ET_g is a predictor of actual ET, not potential ET, and for this reason it is assumed the METRIC model, which was originally designed for use under irrigated agricultural conditions, incorrectly estimated ET for the semiarid rangelands of Idaho.

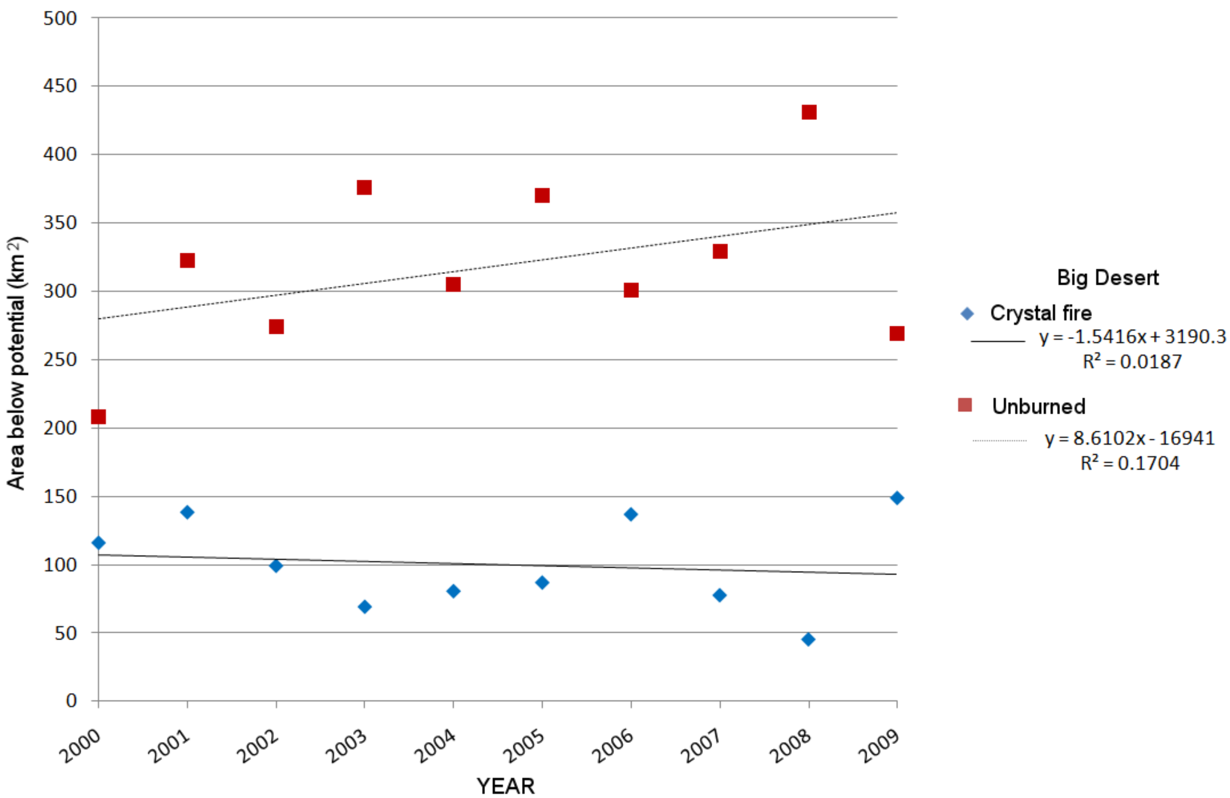


Figure 5. Scatter plot of mean WUE values at 600 sample sites in the Big Desert study area for 2000, 2002, and 2006 (*n* = 300 in both the Crystal fire and unburned regions of the study area).

To explore this potential error, the sum of accumulated precipitation for each Hydrologic Water Year (HWY) was determined using ABEI precipitation data (e.g., $HWY_{2000} = \sum$ precipitation October 1, 1999-September 30, 2000) and compared to ET_g. All precipitation accumulated during the HWY was considered to be available to plants during the growing season (i.e., April 1-September 30) with no soil-water carryover from the previous growing season. ET_g was sampled at the same random locations described previously for this study (n = 600) and differences between HWY and ET_g determined by subtracting ET_g from HWY (e.g., $\Delta_{2000} = HWY_{2000} - ET_{g2000}$). While mean precipitation for the HWY was 169 mm, mean ET_g was 226 mm. The resulting mean difference ($\bar{x}\Delta$) was -67.7 mm or approximately 40% of $\bar{x}$HWY precipitation input. This simple calculation is itself not without error as one may argue the observed difference suggests soil-water carryover from previous growing seasons. This is unlikely however as the soils in the Big Desert typically do not hold water for long periods of time due to the fractured geology underlying this region. The high degree of fissuring in the underlying basalt allows water that infiltrates the soil surface to become inaccessible to plants relatively quickly (Kaminsky 1991). Furthermore, a deep aquifer (50-300 m [IDWR 2010]) coupled with a shallow active root zone (approximately 60-75% of cumulative root distribution occurs in the first 100 mm of the soil surface [Snyman 2009]) suggest the ET_g values used in this study may not be reliable.

LNS_d metrics also suggest primary productivity is declining in areas of the Big Desert outside the Crystal fire as the total area considered *below potential* has increased from 208 km^2 (9% of Big Desert) in 2000 to 269 km^2 (12% of the Big Desert) in 2009 (Figure 6). The relationship however, exhibits much variability and is weakly correlated at best ($R^2 = 0.17$). The trend line for LNS_d metrics within the Crystal fire area is similarly weak with a low coefficient of determination ($R^2 = 0.02$). Upon closer examination, the total area *below potential* has increased from 116 km^2 (7%) in 2000 to 149 km^2 (8%) in 2009. However, the data points quantifying the area *below potential* for the two years immediately following the Crystal fire (2007 and 2008) were atypically low relative to all other years. This suggests entire LCC areas was effectively degraded by the Crystal fire and no reasonable potential could be identified (Prince 2009). Subsequently, very few areas were identified as degraded when scaled against equally degraded counterparts. Neither LNS_d trend line was significant ($P = 0.71$ and 0.24 for the Crystal fire and unburned areas, respectively) (Table 2).

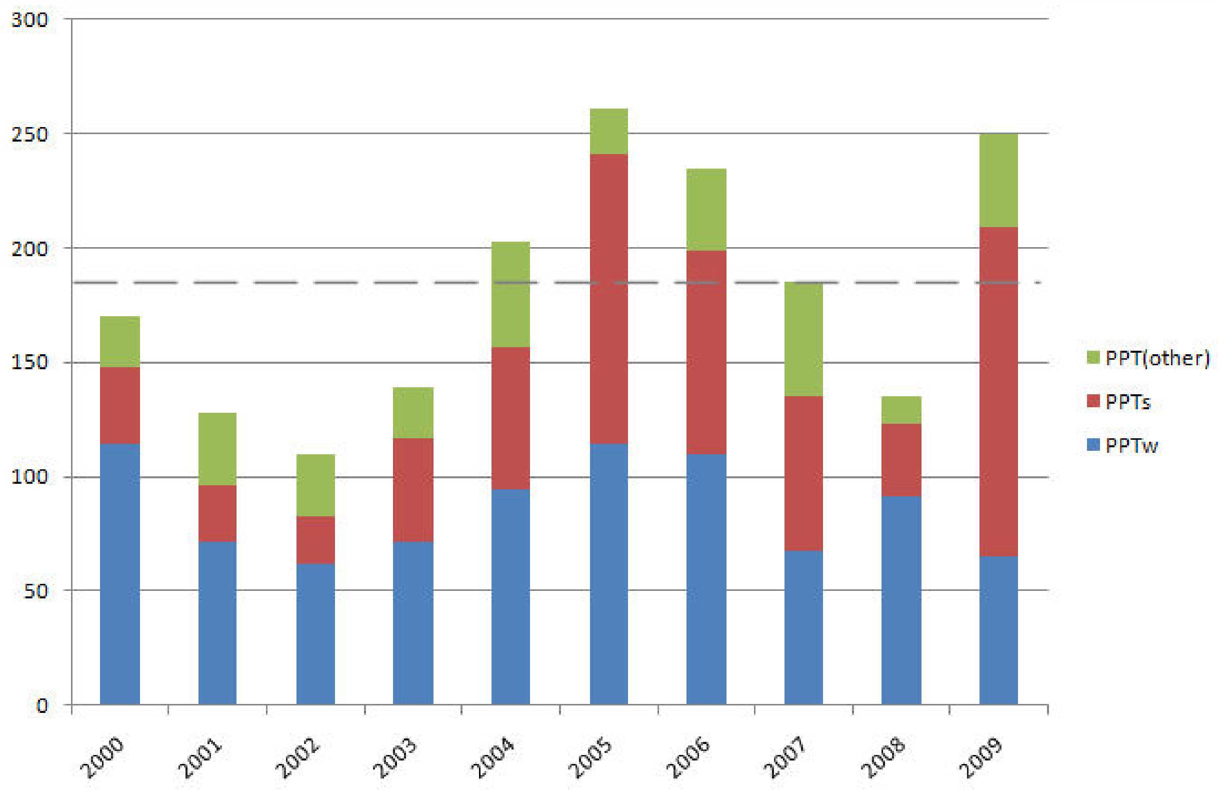


Figure 6. Scatter plot of total area (in km^2) considered below potential ($\leq LNS_{potential}$ - 2SD) using the LNS_d assessment method.

CONCLUSIONS

This study compared four assessments of primary productivity status and trend (cNDVI, RUE, WUE, and LNS) in the Big Desert of southeast Idaho, USA, with emphasis on the effects of the 2006 Crystal fire. Within the area burned by the Crystal fire, all indices, save for the LNS_d metric, suggest primary productivity has been slowly declining since 2000. In areas outside the Crystal fire, all indices and metrics indicated primary productivity in the Big Desert has been similarly declining since 2000 save for short-term RUE evaluations (2004-2009). The consistency among these observations suggest the Big Desert may be degrading or exhibiting a stable state of low primary productivity. The majority of ANOVA tests were not significant ($P > 0.05$) and the only metrics yielding significant results were RUE metrics calculated using PPT_{hwy} (unburned areas only), PPT_s, and PPT_{ws}. These RUE metrics are interesting for several reasons; 1) they suggest the importance of the seasonality of precipitation and specifically, the importance of winter snow fall and early spring rains for the vegetation in the Big Desert, 2) they illustrate that while a relatively strong relationship exists between precipitation and primary productivity, precipitation alone is not a perfect estimator of productivity. For example, in both 2002 and 2008 (figure 4d,e), productivity exceeded what was expected during years of below average precipitation (figure 3). Lastly, these metrics reveal that the Crystal fire and unburned regions of the Big Desert have very similar levels of primary productivity as evidenced by the nearly identical patterns of RUE values (Figure 4d,e) as well as similar slope and y-intercept values.

Each of these methodologies relied upon cNDVI layers derived from Landsat 5 TM as a surrogate for primary productivity (Prince 2009). While the long history of applications using both NDVI and Landsat enhance the qualitative reliability of this study, using cNDVI alone to assess rangeland condition yielded the weakest coefficients of determination ($\bar{x}\ R^2 = 0.10$). RUE, WUE, and LNS_d each produced stronger coefficients of determination and merit additional investigation. RUE is perhaps the simplest to compute of the three derived indices/metrics and when coupled with SOGS precipitation data to better account for spatial variability over long time periods (approximately 10 years), RUE may be one of the best assessment indicators available. In contrast, the difficulty of producing accurate ET models required for WUE estimation nearly negates its use, especially within arid and semiarid ecosystems where it has been well documented that nearly all precipitation (~96%) is returned to the atmosphere through ET processes (Snyman, 1988; Wight and Hanson 1990; Snyman 1998). In this case, WUE could be effectively estimated using RUE.

The LNS_d metric, while time consuming to produce, offers several advantages for rangeland assessment. First, the nature of the methodology ensures that biophysically similar areas are compared to one another through the delineation of LCC regions. This helps eliminate type I and type II errors by ensuring highly productive areas or areas under varying land treatments are not directly compared to one another. Second, degraded areas are readily identified using the *below potential* threshold for each LCC which in turn supports further investigation in the field. In this study however, only 1% of those areas identified as *below potential* were consistently designated as degraded in all ten years. In contrast, nearly 25% were designated as *below potential* only once throughout the ten year period while >36% of the study area was never identified as degraded.

Arid and semiarid rangelands constitute a significant portion of the earth's terrestrial surface. These regions are increasingly being recognized for the ecosystem services they provide and for the role they play in the global carbon cycle (Follett et al. 2001). For these, and other reasons, the long-term sustainability of rangelands is essential and as a consequence, assessing and monitoring the health/condition of rangelands has become equally important. This paper describes a study investigating four assessment methodologies relying upon primary productivity estimates derived through satellite remote sensing. In nearly all cases, the methodologies concur that the Big Desert study area may be degrading. RUE appears to have provided the most reliable results and in all cases the need to use long-term datasets (10 years or more) was apparent. Additional research is merited to better understand and validate the techniques and results.

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