ANALYSIS OF VEGETATION PRODUCTIVITY RELATIVE TO THE PALMER DROUGHT SEVERITY INDEX (PDSI)

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ABSTRACT
Wildfire management is an issue of safety for the entire western United States and understanding how weather and climate affects vegetation production (fuel) is an important component of both forecasting and management of fire. In this study we sought to better understand temporal fluxes in plant production across the western United States relative to wildfire. The LANDFIRE Existing Vegetation Type (EVT) product was used to identify three dominant vegetation types in the study area (conifer, grassland, and shrubland) and the normalized difference vegetation index (NDVI) was used to estimate plant productivity within each vegetation type. A threshold NDVI value of 0.30 was used to indicate actively growing vegetation (AGV). The Palmer Drought Severity Index (PDSI) was treated as a composite of existing weather parameters and used to examine correlations between AGV and PDSI. ANOVA results indicate a difference in the percent of actively growing vegetation in the years 2002 and 2012. Results of regression analyses revealed a significant relationship between PDSI and AGV for all but two annual comparisons. While drought is frequently considered a driver of plant production, PDSI only explained a small part of the variability observed in the AGV dataset. To better visualize these results, maps were made of percent AGV for each vegetation type. These maps show the majority of the western United States exhibited a peak of only 20% actively growing vegetation between 2001 and 2019. This is likely due, at least in part, to our choice of 0.30 as the NDVI threshold for AGV indicating the NDVI threshold needs to be reviewed to develop a better indicator of AGV.

KEYWORDS: *biomass, LANDFIRE, NDVI, climate, wildfire*

INTRODUCTION
In order for a fire to burn, three criteria must be present: fuel, oxygen, and a source of ignition. Wildfire fuels include live and dead biomass that must be dry enough to burn. Weather is the key driving factor influencing fuel moisture. Different vegetation types respond differentially to weather and climate. For example, coniferous forests tend to exhibit a more static photosynthetic pattern throughout the year while higher inter-annual variability is observed in grassland ecosystems. Realizing the variable effect of weather and climate on vegetation production, a study was developed using LANDFIRE Existing Vegetation Type (EVT) data, MODIS composite NDVI data, and Palmer Drought Severity Index (PDSI) data to better understand temporal fluxes in plant production across the western United States (**Figure 1**).

The study area is a region covering approximately 3 million km^2, including 11 states (Arizona, California, Colorado, Idaho, Montana, Nevada, New Mexico, Oregon, Utah, Washington, and Wyoming). The study area contains many different vegetation types and ecosystems including conifer, grassland, shrubland, sparsely vegetated, hardwood, and riparian areas. However the conifer, grassland, and shrubland vegetation types make up 78% of the study area (**Figure 2).**

Conifer and shrubland ecosystems consist of a wide variety of species depending on latitude, elevation, and precipitation. Conifer ecosystems can be dominated by one species or a mix of several species. For example, the conifer vegetation type (VT) in Wyoming is predominantly Lodge Pole Pine (*Pinus contorta*), while the same VT in the Cascades is a mix of Fir (*Abies spp.*), Douglas fir (*Pseudotsuga menziesii*), Arborvitae (*Thuja spp.*), and Pine (*Pinus spp.*). The shrubland VT in Idaho is mostly Sagebrush (*Artemisia tridentata*) and Rabbit brush (*Ericameria spp.*), while California's chaparral shrublands consists of chamise (*Adenostoma fasciculatum*), several variety of Oaks (*Quercus spp.*), Manzanita (*Arctostaphylos spp.*), Sagebrush (*Artemisia californica*), Buckbrush (*Ceanothus megacarpus*), and Sumacs (*Rhus spp.*). The diversity of species communities in our VT classifications and the large size of the NOAA Climate Divisions presents a challenge to characterize these data statistically.

In this study we set out to determine the relationship between drought (PDSI data) and the timing and extent of vegetative biomass production across the western United States, using three vegetation type classifications: conifer, grassland, and shrubland. Understanding how drought effects plant production will be important for future studies on the effect of weather and climate on wildfire fuels.

Figure 1. *The study area is a region including 11 states (Arizona, California, Colorado, Idaho, Montana, Nevada, New Mexico, Oregon, Utah, Washington and Wyoming). A substantial number of wildfires in the conterminous United States occur in this region.*

METHODS

The LANDFIRE program produces nearly two dozen geospatial data products derived principally from the Landsat sensor, and thus each data product has a 30-meter x 30-meter spatial resolution. The LANDFIRE Existing Vegetation Type (EVT) product maps assimilated complexes of plant communities following the NatureServe terrestrial ecological system classification (Comer et al. 2003). Using the current, 2016 EVT layer, six discrete raster layers were created for the western U.S. study area; conifer, grassland, shrubland, hardwood, riparian, and sparsely vegetated. Each Boolean layer contained pixels with a value of one (1, true) where that pixel represents an area containing the specific vegetation type (e.g., shrubland) and a value of zero (0, false) for all other pixels.

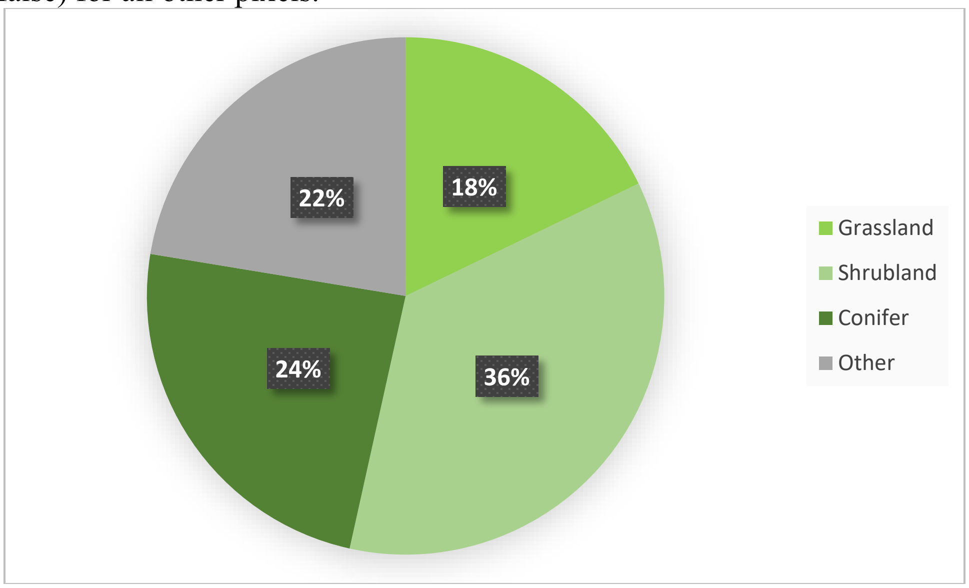

Figure 2 *Percent cover by vegetation type for the study area. Conifer, grassland, and shrubland make up 78% of the land cover.*

MODIS composite NDVI data were used to estimate vegetation production across the study area. This dataset library contained 23 composite NDVI images annually (2001-2019) and has a 250-meter x 250-meter spatial resolution. The ArcGIS Raster Calculator was used to identify those pixels describing healthy, actively growing vegetation (i.e., pixels with NDVI values $\geq$ 0.30). All pixels that satisfied this criterion were assigned a value of one (1, true). The resulting layers were henceforth referred to as Actively Growing Vegetation (AGV) to distinguish these data from the original NDVI source data. The specific NDVI value ($\geq$ 0.30) was chosen based on observations described by Myneni (1995) and Al-doski (2013). Together, these 23 data layers characterize the spatio-temporal extent or the "green wave" and allow for the visualization of the growing season throughout each year.

The Palmer Drought Severity Index (PDSI) was used to describe drought conditions across the study area (NOAA 2021). Tabular PDSI data were joined to NOAA Climate Division polygons (n = 84) (**Figure 3**) and used to map drought severity across hydrologic water years (HWY). The HWY is a 12-month period beginning October 1st on a given year and ending September 30th of the following year. Thus, the HWY ending September 30, 2019 is referred to as the "2019 hydrologic water year". The temporal resolution of these PDSI data is monthly. Thus, to facilitate comparison with AGV data --having a 16-day temporal resolution-- the AGV data representing vegetation conditions latest in each given month was selected for use in this study. As a result, the number of annual AGV layers was reduced from 23 to 12.

Each Boolean Vegetation Type (VT) layer (e.g., shrubland) (n = 6) was multiplied by each Boolean AGV layer (n = 12) resulting in 72 discrete AGVxVT layers annually (n = 1,296 layers in total for the 18 year study period). The raster attribute tables were exported to Microsoft Excel spreadsheets where each column provided AGV data (0 or 1) for a given month in the HWY.

To examine the correlations that might exist between AGV (or AGVxVT) and PDSI, the Zonal Statistics as Table tool was used to extract AGV data within each climate division polygon. This resulted in a table with 84 records (one for each climate division polygon) and attributes describing the frequency of AGV pixels within each polygon as well as the sum, mean, and median statistics. These data were similarly organized following HWY. The climatic zone/AGV layers were further subset using the EVT layers. The resulting data for both PDSI and AGV were weighted by the area of the corresponding climatic zone and normalized to facilitate meaningful comparisons. Excel spreadsheets were similarly created from these data containing monthly HWY values (n = 12 columns). Each spreadsheet contained 1,008 data values (12 monthly value column for each of 84 climatic division rows).

Figure 3. *NOAA Western Climate Divisions used throughout this study (n = 84).*

Analysis of Variance (ANOVA) tests were used to compare annual growing season data (the percent area considered to have actively growing vegetation) across time (2002-2019 HWY). Matrices of all ANOVA results were compiled and are summarized below. Regression analyses were used to determine the relationship between AGVxVT data and PDSI. These results are also summarized below.

RESULTS AND DISCUSSION

Results of ANOVA testing indicated a difference in percent AGV for the years 2002 and 2012 in both the grassland and shrubland vegetation types (**Table 1**). In contrast, vegetation types with closed canopies (e.g., conifer and hardwood) or sparse vegetation showed no difference in AGV between years. This is understandable as a coniferous forest canopy tends to show much less change over time and masks most changes that may have occurred in the understory. Lastly, sparse vegetation areas do not have enough vegetation present to reliably detect change in AGV over time as each pixel is typically dominated by bare soil or rock.

Table 1*. Summary table of P-values comparing actively growing vegetation trends for grassland (first value) and shrubland (second value) across the western United States between 2001 and 2019. Results with significant values (C.I. = 0.05) are highlighted in yellow. Those years where no P-value was considered significant (i.e., P > 0.05) were excluded from the table.*

YEAR	2001	2002	2003	2005	2008	2012
2005	0.26/0.02	0.03/0.00	0.17/0.02		0.25/0.04	0.01/0.00
2008	0.93/0.93	0.34/0.16	0.82/0.77	0.25/0.04		0.20/0.41
2010	0.26/0.16	0.04/0.01	0.17/0.13	0.93/0.44	0.24/0.20	0.02/0.04
2011	0.81/0.25	0.20/0.02	0.59/0.21	0.40/.030	0.76/0.32	0.11/0.08
2012	0.14/0.45	0.62/0.50	0.30/0.62	0.01/0.00	0.20/0.41	
2014	0.20/0.13	0.02/0.00	0.13/0.10	0.87/0.31	0.19/0.18	0.01/0.02
2015	0.10/0.04	0.01/0.00	0.06/0.03	0.59/0.67	0.10/0.06	0.00/0.01
2016	0.13/0.08	0.01/0.00	0.08/0.06	0.70/0.69	0.13/0.10	0.01/0.01
2017	0.21/0.06	0.02/0.00	0.13/0.05	0.85/0.87	0.19/0.08	0.01/0.01
2018	0.32/0.23	0.04/0.02	0.21/0.18	0.94/0.30	0.30/0.29	0.02/0.06
2019	0.08/0.03	0.01/0.00	0.05/0.02	0.44/0.87	0.07/0.04	0.00/0.01

Based upon these results, maps were made of mean PDSI for the years 2002 and 2012, along with two additional years (2007 and 2019) for comparison and data visualization purposes (**Figure 4**). The year 2019 was specifically chosen as it had above average precipitation across much of the study area as can be seen in the PDSI map (**Figure 4d**).

AGV data for each of the four years (2002, 2007, 2012, and 2019) were graphed to facilitate visualization of the growing season over time (**Figure 5**). The height or amplitude of each growing season curve indicates the percent area considered to exhibit actively growing vegetation. The width of each curve describes the period between the onset of the green wave and the later senescence of plant productivity. In effect, this illustrates the duration of the growing season across each year. It is interesting to note the two years found to be consistently different in the ANOVA test results (2002 and 2012) also exhibited the lowest amplitude in the AGV curves shown in **Figure 5**.

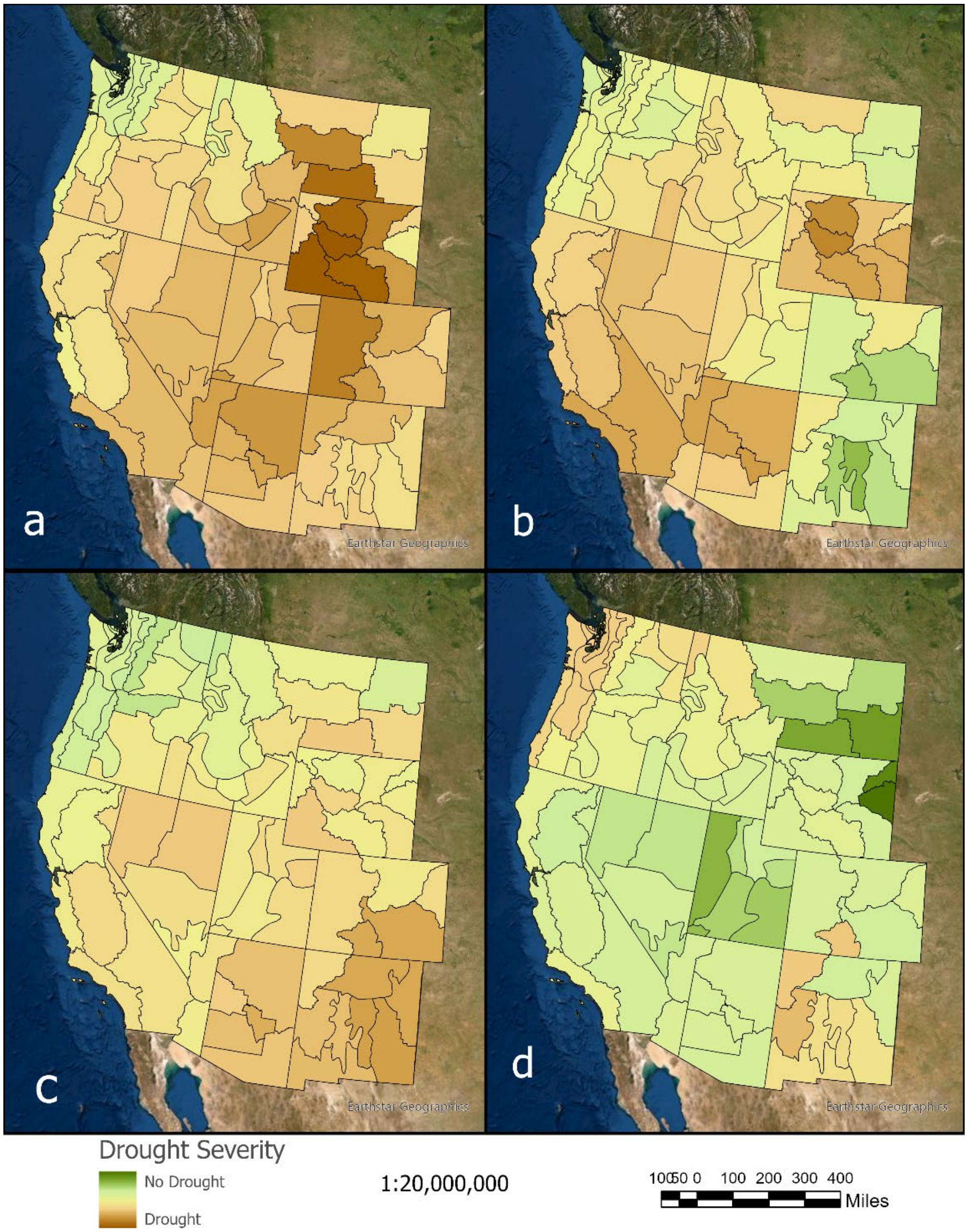

Figure 4. *Mean Palmer Drought Severity Index (PDSI) for the years 2002 (a), 2007 (b), 2012 (c), and 2019 (d). Years 2002 and 2012 exhibited very low biomass production as suggested by NDVI and Actively Growing Vegetation (AGV) data. In contrast, 2007 and 2019 AGV data suggested much higher biomass production. Figure 3a shows widespread drought (2002). Figure 3c also depicts drought conditions in 2012 but not as severe or widespread as seen in 2002. Figure 3b (2007) shows drought in the southwest but much less severe conditions across the rest of the study area. Figure 3d (2019) was an exceptionally wet year overall.*

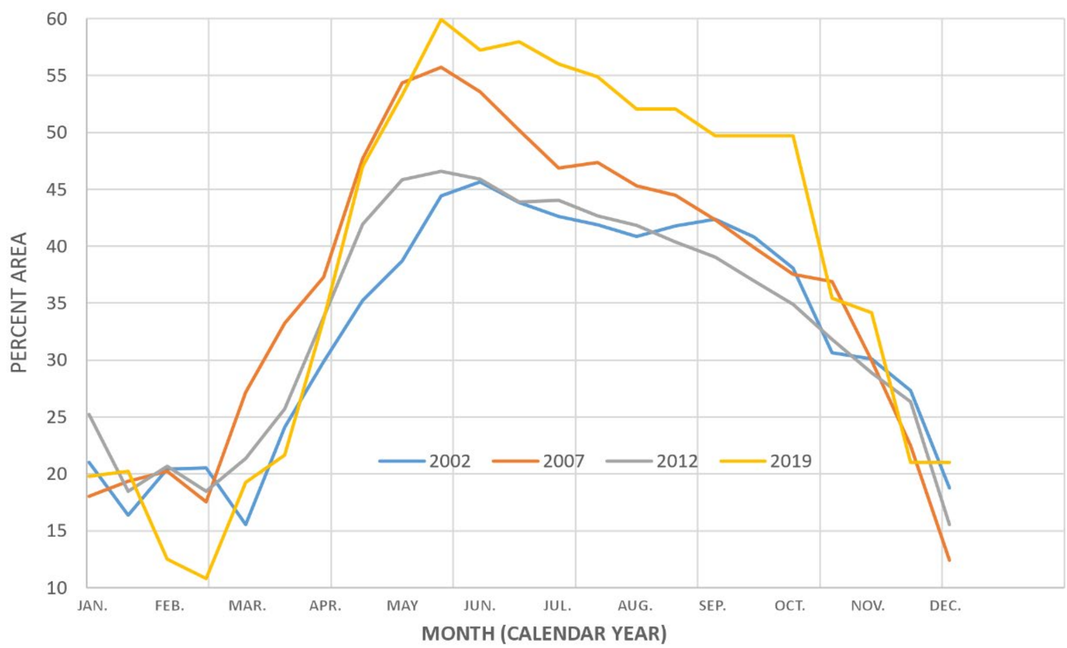

Figure 5*. Percent of the study area exhibiting actively growing vegetation (AGV) across a calendar year. Years 2002 and 2012 never achieved the overall productivity seen in 2007 and 2019 based upon the height or amplitude of each curve. However, the length of the growing season appears approximately the same based upon the width of each curve.*

These data were also used to map the percent of actively growing vegetation by vegetation type (AGVxVT) within each climatic zone for the months of March, April, and May. Peak biomass production was typically seen in the May datasets used in this study (note: June is commonly cited as the month of peak biomass production but since we selected the later MODIS NDVI/AGV date in each month, June values frequently exhibited a decline in productivity). The months of March and April were also selected as they showed the steepest or most rapid increase in AGV each year (**Figure 5**). The conifer vegetation type showed the highest percent activity for all months and all years (**Figures 6**), while the grassland (**Figure 7)** and shrubland (**Figure 8**) vegetation types showed very little activity overall. This result inspired further research that indicated the NDVI threshold value of 0.30 may not be a good threshold value in non-forested vegetation types. Paruelo and Lauenroth (1995) showed shrublands and grasslands exhibit significantly different NDVI curves during active growth. The results of their study reveal most shrublands do not reach an NDVI value of 0.30 even during the peak of their growing season (**Figure 9**). The maps of percent AGV (**Figures 6-8**) show the majority of the study area for all three vegetation types contains only 0-20% actively growing vegetation when using the NDVI threshold value of 0.30.

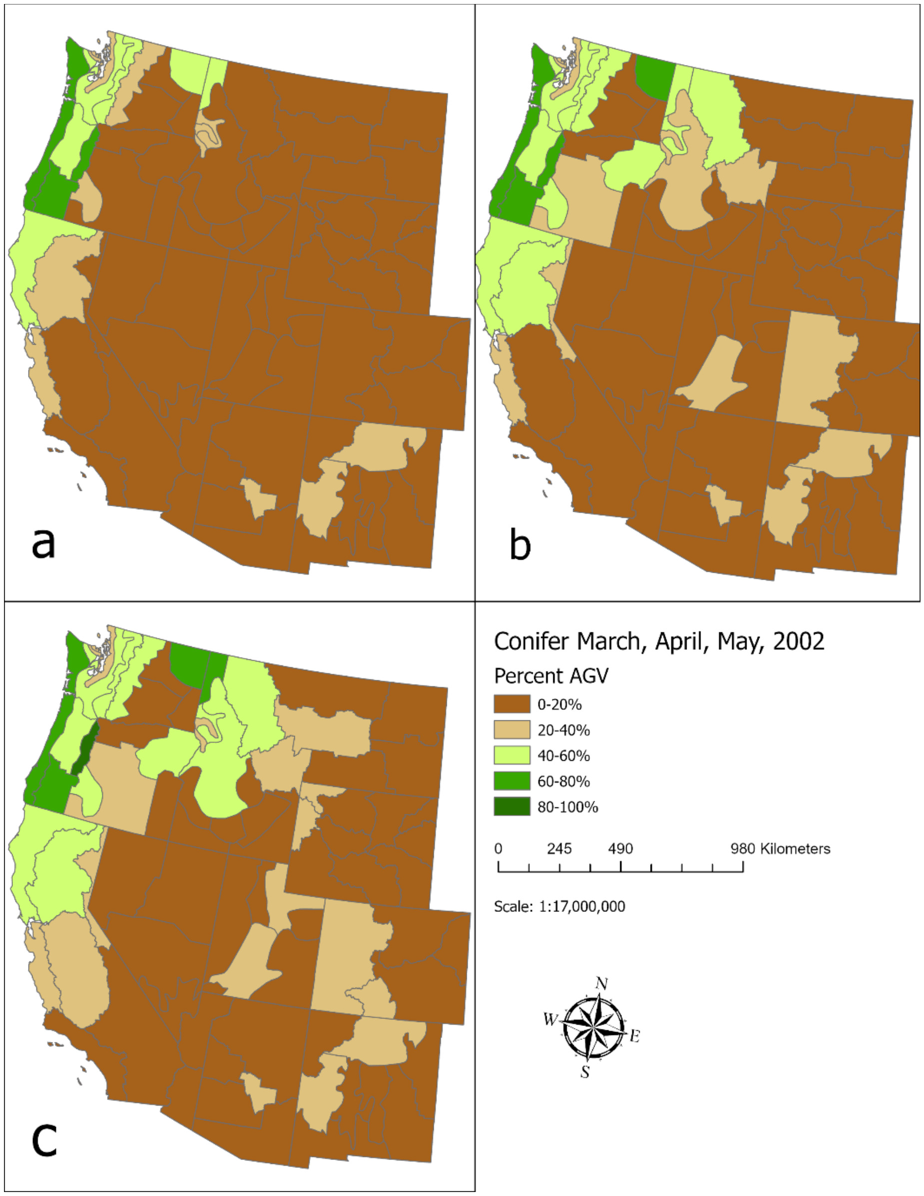

Figure 6*. Percent of AGV in 2002 for conifer during the months of March (a), April (b), and May (c). Polygons follow NOAA Climate Divisions.*

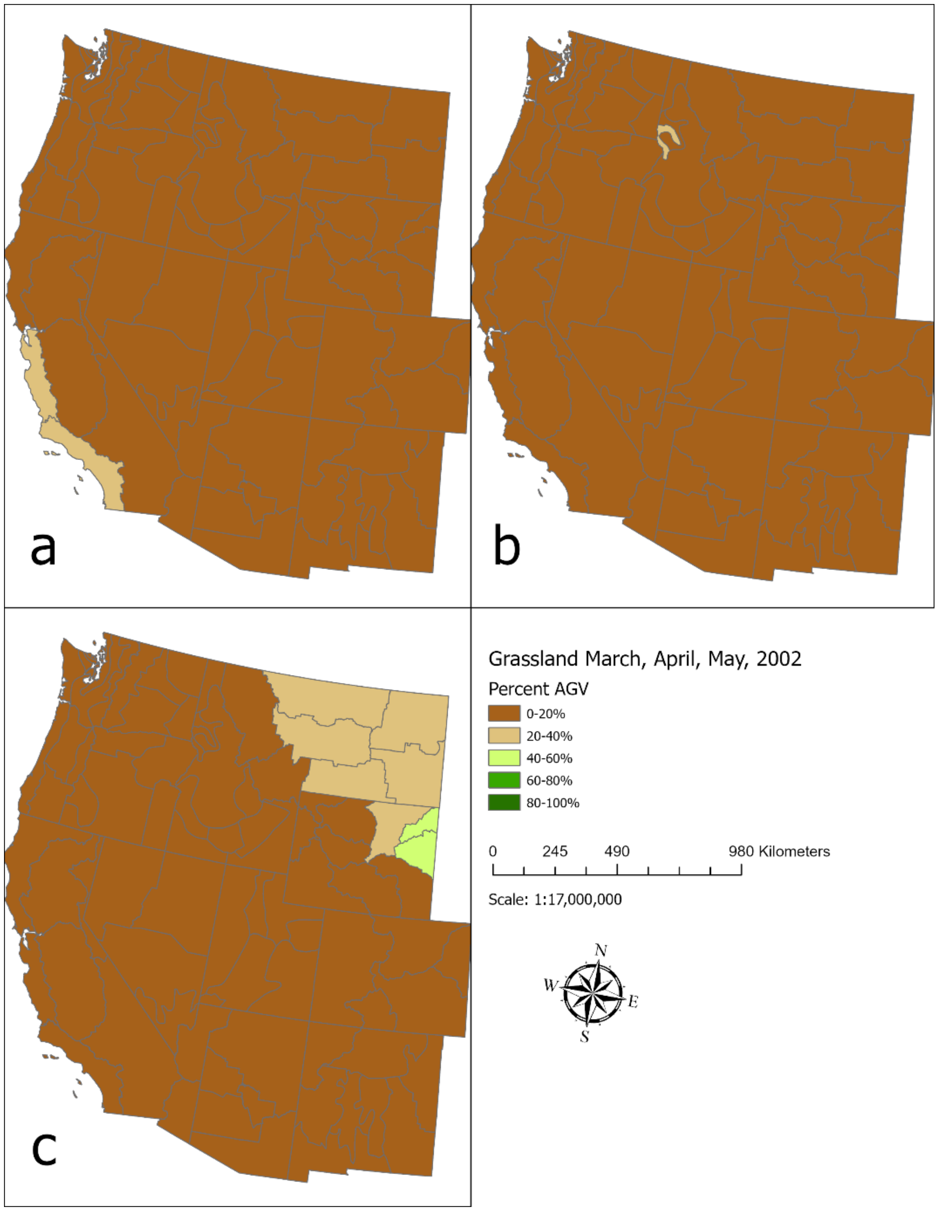

***Figure** 7. Percent of AGV in 2002 for grasslands during the months of March (a), April (b), and May (c). Polygons follow NOAA Climate Divisions.*

Figure 8 *Percent of AGV in 2002 for shrubland during the months of March (a), April (b), and May (c). Polygons follow NOAA Climate Divisions.*

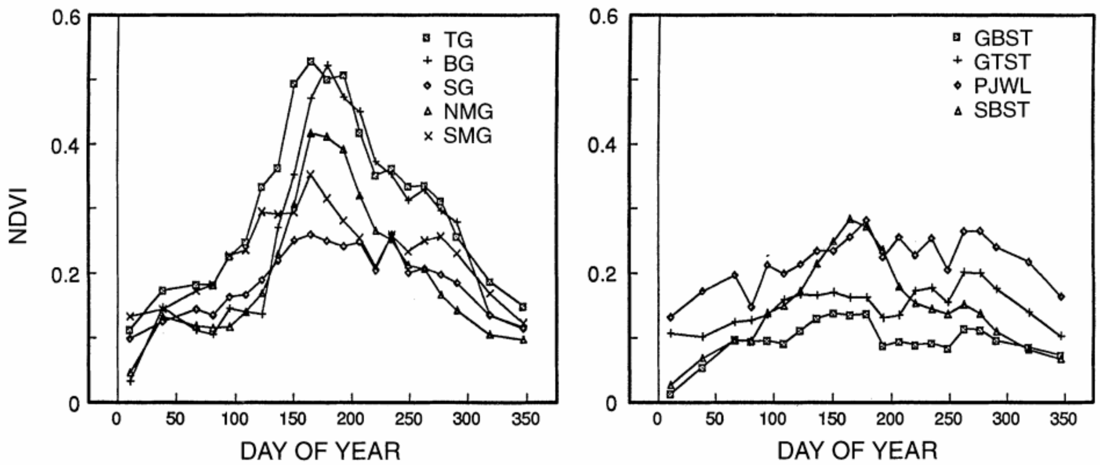

Figure 9. *Paruelo and Lauenroth (1995) reported the seasonal course of NDVI in grassland (left) and shrubland (right) vegetation types. Each curve is an average of the study sites corresponding to this type. Grassland vegetation types: NMG = Northern mixed-grass prairie, SG = Shortgrass steppe, BG = Bunchgrass steppe, TG = Tallgrass prairie, SMG = Southern mixed-grass prairie. Shrubland vegetation types: SGST = Sagebrush steppe, GTST = Gramma-tobosa shrubsteppe, PJWJ = Pinyon-Juniper woodlands, GBST = Great Basin sagebrush steppe. The values for shrublands show that an NDVI value of 0.30 may be too high to properly detect AGV and suggest a threshold of 0.10 may be better.*

Results of regression analyses revealed a significant relationship between PDSI and AGV for all but two of the comparisons (**Table 2**). The two results that did not show a strong relationship were grasslands in 2007 ($P = 0.43$) and conifers in 2019 ($P = 0.95$). It is interesting that while a significant relationship was observed across most of these comparisons, the R^2 values were quite low. This indicates that while drought is considered a significant driver of vegetation production, its effect explains only a small portion of the variability observed in vegetation production. For example, only 22% of the variability in vegetation production as indicated by AGV data can be explained or attributed to drought as indicated by PDSI data. We note that an exceptionally large sample size almost always shows a significant difference in statistical tests (Sullivan & Feinn 2012). According to Sullivan & Feinn (2012), if the sample size were large enough only a difference of zero would be non-significant. With a sample of 1008, our study had a sample size that merits careful interpretation and when coupled with the extremely low R^2 values, suggests the relationship between the Palmer Drought Severity Index and Actively Growing Vegetation data is quite small.

Table 2. *Regression analysis between AGV and PDSI data. All were significant save for grassland in 2007 and conifer in 2019. Total observations for each record (n=1,008).*

Hydrologic Water Year	Vegetation Type	R^2	P-value
2002	Conifer	0.33	0.00
2002	Grassland	0.16	0.00
2002	Shrubland	0.22	0.00
2007	Conifer	0.31	0.00
2007	Grassland	0.00	0.43
2007	Shrubland	0.08	0.00
2012	Conifer	0.07	0.00
2012	Grassland	0.11	0.00
2012	Shrubland	0.15	0.00
2019	Conifer	0.00	0.95
2019	Grassland	0.22	0.00
2019	Shrubland	0.06	0.00

CONCLUSIONS

The hydrologic water years of 2002 and 2012 were shown to be less productive growing seasons (**Figure 10**) relative to 2007 and 2019. While a significant relationship was observed between drought (PDSI) and actively growing vegetation (AGV) (**Table 2**), one can conclude the differences are due only in small measure to drought. PDSI explains only a small portion of the variability seen in AGV data as suggested by the overall low R^2 values. The small P-values indicate a significant relationship, but this is influenced by the large sample size used in this study (*n*=1008). Effect size may be a more accurate way to describe these data and P-values in this case do not give an accurate representation of ecosystem dynamics. Several additional factors could have contributed to these results as the response of vegetation to drought is controlled by landscape level factors such as soil water movement and retention, groundwater interactions, evaporation, plant community composition, and the ability of particular species to handle stress (Cartwright et al. 2020).

The maps of percent AGV show little variation across the study area for grassland (**Figure 7**) and shrubland (**Figure 8**) vegetation types. This is likely due to our initial choice to use an NDVI threshold value of 0.30 which, in hindsight, may not capture actively growing vegetation accurately in these ecosystems. Additional research is needed to determine the proper NDVI threshold value to characterize actively growing vegetation.

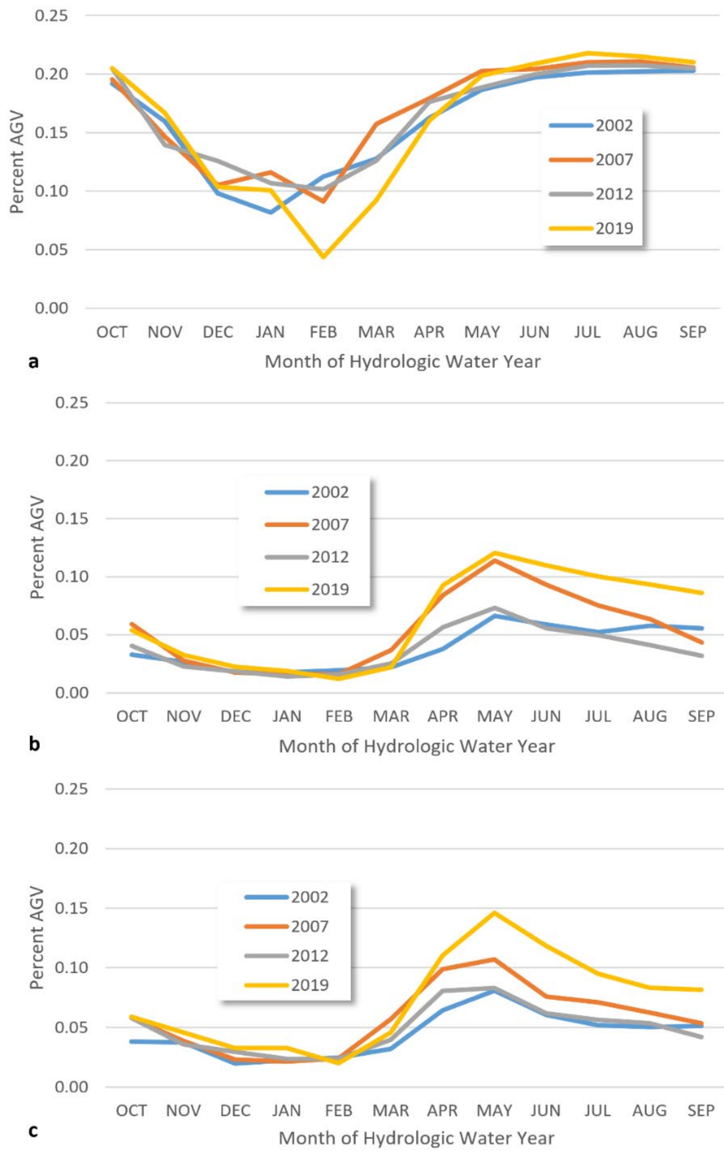

Figure 10 *Percent area of AGV for conifer (a), grassland (b), and shrubland (c) for the years of 2002, 2007, 2012, and 2019.*

The shrubland vegetation type exhibited the most sensitivity to drought. This concurs well with a study by Cartwright et al. (2020) who found drought sensitivity was generally greater in shrub-steppe areas than in forests. This is perhaps best visualized in 2019, where wetter than normal conditions existed across the study area (**Figure 10**) resulting in a substantial rise in AGV for shrublands. The response of shrublands to drought could be due to the heterogeneous composition of shrubland where understory grasses exist alongside various woody shrubs and occasional tree species (e.g., Juniper). In addition, shrubland ecosystems typically exhibit a substantial bare ground component resulting in a more "mixed pixel" composition relative to forested ecosystems.

In this study we set out to determine the relationship of the PDSI drought data to the timing and extent of vegetation production across the western United States. Understanding how drought effects plant production will be important for our future studies on the effect of weather and climate on wildfire fuel production. Vegetation production and vegetation characteristics drive wildfire fuel load and fuel continuity. All wildfire fuels are ultimately derived from vegetation and are typically classified into four groups: grasses, brush, timber, and slash (Anderson 1982). Knowing vegetation productivity and potential in a given year is important to understanding wildfire behavior.

This study found vegetation production can vary significantly between years. Furthermore, while significant, vegetation response to drought indicated by the Palmer Drought Severity Index (PDSI) has little direct effect on percent actively growing vegetation. Future research will focus on more direct weather factors, such as precipitation and temperature, as well as the development of a reliable NDVI threshold indicator of actively growing vegetation.

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