MULTI-VARIATE ANALYSIS OF BIOMASS PRODUCTION RELATIVE TO WEATHER AND CLIMATE ACROSS THE WESTERN UNITED STATES

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ABSTRACT
The production of vegetation biomass is a key parameter toward understanding wildfire fuels. This study sought to identify the primary drivers of biomass production throughout the hydrologic water year (October through September) across the western United States between 2001 and 2019. National Oceanic and Atmospheric Administration (NOAA) monthly minimum temperature, maximum temperature, and cumulative precipitation data were used as explanatory variables, along with growing degree months (derived from temperature data), to model maximum Normalized Difference Vegetation Index (NDVI) using a multi-variate ordinary least squares (OLS) analysis. The results of this study indicate the relationship between biomass production and the explanatory weather variables used in this study is not linear. Furthermore, while the general outcomes of this study illustrate promising spatio-temporal trends, none of the results from OLS were statistically significant. Additional research using non-parametric and non-linear modeling is necessary to accurately characterize the interaction between weather variables and vegetation production.

KEYWORDS: *NDVI, temperature, precipitation, growing degree, wildfire*

INTRODUCTION
Since the 1950's, the frequency and size of wildfires across the western United States has increased substantially (Weber and Yadav 2020). In order for a fire to burn, three criteria must be met, the presence of (1) fuel, (2) oxygen, and (3) a source of ignition. Without any one of these fire triangle components (https://www.nps.gov/articles/wildlandfire-facts-fuel-heat-oxygen.htm) a fire cannot exist. With this understanding, we asked what changed to allow for the current fire regime?

Since the availability of oxygen has been more or less constant over the past centuries, we dismissed this as a driver variable behind this phenomenon. An ignition source that provides sufficient heat to allow a fuel to combust is not as readily dismissed. While the prevalence of lightning --the primary ignition source of wildfire-- has likely been relatively constant, the co-occurrence of rainfall along with lightning is not well understood. For example, if a thunderstorm produces both lightning and precipitation, the likelihood of a wildfire ignition is relatively low compared to a dry-thunderstorm. If dry thunderstorms are more common today than they were just a few decades ago, then the changing ignition regime could help explain the increase in wildfire frequency seen today. In addition, the role of man in both managing the landscape and either accidentally or intentionally starting fires may also help explain the change in fire frequency observed over the past few decades (Balch et al. 2017). In essence, an increase in human population increases the probability for human-caused wildfires (Radeloff et al. 2005).

However, even if a change in the ignition regime could be demonstrated, this would not readily explain the increase in fire size currently observed. In a previous paper, we found the mean fire size increased from 1,204 acres in the decade of the 1950s to 3,474 acres for the decade between 2010 and 2019 (Weber and Yadav 2020). Thus, a reasonable explanation for this change points to the final portion of the fire triangle, fuel.

Wildfire fuels include both live and dead biomass that must be dry enough to combust. Weather (precipitation, heat, and humidity) is the key driving factor influencing fuel moisture. In addition, fuels must be continuous to carry a fire across the landscape. Areas of sparse vegetation can and will burn but the likelihood of a fire growing into a 100,000+ acre megafire is extremely low. Thus, fuel load, availability, and continuity are very important components which may be affected by changing climate as well as land management policies and practices (e.g., long-term fire suppression leading to fuel stockpiling).

In a previous paper (Weber and Walz 2021), another fuel related variable was explored, namely length of the growing season. In that study, the hypothesis was that a longer growing season would likely --though not absolutely-- lead to a longer fire season and the potential for more wildfires. However, the results of that study found the length of the growing season has been quite stable since the year 2000. Still, these results do not fully answer the question due to the temporal limitations of that study (2001-2019). Furthermore, these results highlight the need for a similar study using a broader temporal scope.

The current study sought to identify the primary drivers of biomass production throughout the hydrologic water year (October through September). The results of this study will allow for an increased understanding of wildfire fuel production and ultimately, improved land management decisions.

METHODS

Study Area

The study area is a region covering approximately 3 million km^2 and 11 western states (Arizona, California, Colorado, Idaho, Montana, Nevada, New Mexico, Oregon, Utah, Washington, and Wyoming) (**Figure 1**). The study area contains numerous vegetation types and ecosystems including coniferous forests, grasslands, shrublands, sparsely vegetated areas, hardwood forests, and riparian areas. The conifer, grassland, and shrubland vegetation types together comprise 78% of the study area (**Figure 2).**

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

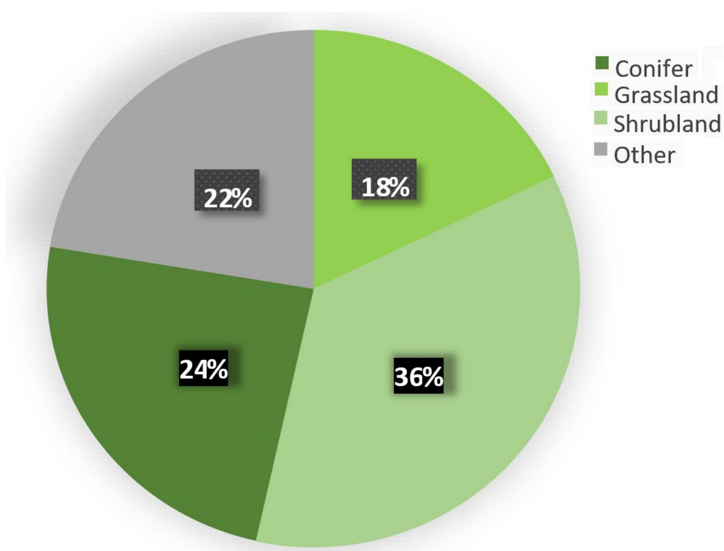

Figure 2 *Percent cover by vegetation type for the study area. Conifer, grassland, and shrubland make up 78% of the land cover.*

Spatial Data

Land cover and vegetation biomass

Moderate Resolution Imaging Spectroradiometer (MODIS) 16-day composite NDVI data (MOD13) were used to identify vegetation production across the study area. This dataset contained 23 composite NDVI images annually (2001-2019) or 414 data layers in total and has a 250-meter x 250-meter spatial resolution. These data were organized by hydrologic water year (HWY); for example, NDVI data beginning in September 2001 and ending in August 2002 became the first HWY explored in this study and is referred to as the 2002 HWY NDVI dataset.

Weather

Weather data, specifically monthly minimum temperature (T_{min}), monthly maximum temperature (T_{max}), and monthly cumulative precipitation (Precip), were acquired from the NOAA National Centers for Environmental Information (NCEI)[1] in netCDF format. These data were extracted for the years 2001-2019 and converted into raster TIF files, projected into the Albers Equal Area spatial reference system (WKID: 102039), and finally clipped to the study area polygon. The spatial resolution of these data was approximately 5-km (4,700-meter x 4,700 meter).

Sample points

To ensure only data describing conifer, grassland, and shrubland vegetation types were used in this study, 7,180 sample points were carefully digitized in ArcGIS Pro using the aerial imagery base map (Table 1). This time-consuming process was necessary to avoid sampling NDVI in developed areas (cities and agricultural areas). These sample points were used to extract NDVI, T_{min}, T_{max}, and Precip data from the underlying pixel values using the *Extract Values to Table* tool in ArcGIS Pro. All resulting tabular data were exported to Microsoft Excel and organized by HWY.

Table 1. *Distribution of sample points across vegetation types found in the study area*

Vegetation Type	Sample Point	
	Frequency	Percent
Coniferous forest	2,379	33%
Grassland	1,380	36%
Shrubland	2,616	19%
Other	805	11%

Derived Growing Degrees

In addition to the data extracted by sample point, monthly growing degree fields (columns) were derived using corresponding T_{min} and T_{max} data. Typically growing degree is calculated using daily temperature data. However, since these data were not readily available across the study area, existing monthly temperature data was used to approximate cumulative growing degree and provide a relative comparison between years. Growing degree was calculated following:

$$GDD = \frac{T_{\max} + T_{\min}}{2} - T_{\text{base}}$$

Where 2.8° C was used for $T_{base.}$ Cheatgrass (*Bromus tectorum*), a common invasive plant with a strong relationship to wildfire (D’Antonio and Vitousek 1992) germinates across a

[1] URL = https://www.ncei.noaa.gov/data/nclimgrid/

wide range of ambient temperatures with 2.8° C noted as one of the lowest germination temperatures yet with relatively high germination rates (Martens et al., 1994)

Prior to creating any data visualizations or descriptive statistics these data were reviewed and all null data values were deleted. In addition, null identifiers (e.g., -1 for precipitation) were also deleted.

Statistical analysis

Vegetation productivity is a complex problem driven by numerous, interacting variables such as precipitation, temperature, soil fertility, solar radiation, topography, etc. This study used NDVI as an indicator of vegetation production and both precipitation and temperature (weather) as driver variables. No allusion is made suggesting the results of this study comprehensively describe vegetation productivity. Rather, the focus of this study was simply to better understand the influence of weather on biomass production.

Using the assembled dataset described above, exploratory regression was run for each HWY. Exploratory regression is a data mining tool that evaluates all possible combinations of explanatory variables (i.e., monthly T_{min}, T_{max}, Precip., and Growing Degrees) to model vegetation productivity (i.e., peak NDVI). Exploratory regression results were used to inform an ordinary least squares (OLS) analysis. Four iterations of OLS were completed using data for the hydrologic water years 2002, 2005, 2012, and 2019. These years were selected and used in previous parts of this particular study due to the somewhat extreme and contrasting temperatures and/or precipitation occurring in those years.

RESULTS AND DISCUSSION

The results of numerous exploratory regressions (n = 18) produced a substantial amount of data. To condense and summarize these results, only those variables with significance ≥ 98% were further examined (**Figure 3**).

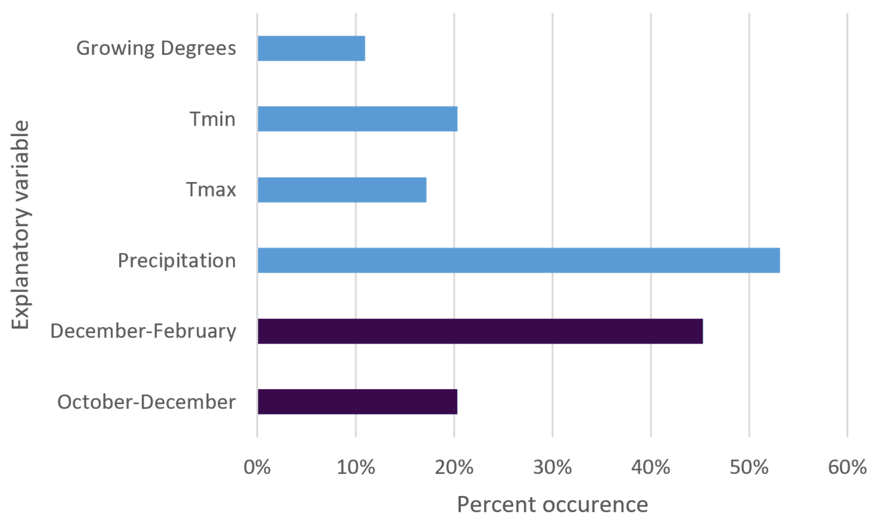

Figure 3. *Summary of exploratory regression results for all 18 hydrologic water years examined in this study. Specific weather variables are shown in blue while more general temporal variables are shown in purple. The variables with the highest frequency of significance (monthly precipitation and any weather variables from December-February) were used to inform the ordinary least squares (OLS) analysis.*

The explanatory variable having the highest frequency of significance was precipitation. This is reasonable as precipitation is the primary driver of vegetation production in arid and semiarid ecosystems (Thomas and Squires 1991; Miranda et al. 2011, Yan et al. 2015). It is interesting that the remaining weather variables did not have a higher frequency of significance but when combined and summarized temporally, the weather variables for December, January, and February revealed a high frequency of significance in predicting maximum NDVI through the peak of the growing season. This latter observation needs additional research but suggests the trajectory of a growing season may be set relatively early. That is not to say that an extreme drought will in early summer will not affect plant growth but that biomass production appears to be highly dependent upon winter and early spring precipitation.

Ordinary Least Squares

The results of explanatory regression were used to select input variables for ordinary least squares (OLS) analysis. OLS effectively calculates a multiple linear regression using the provided explanatory or driver variables (X-axis) to predict the dependent variable (Y-axis) (**Figure 4**). The results of this analysis show that while these data follow a normal distribution, they also exhibit a high degree of redundancy and spatial autocorrelation. The latter should be expected in accordance with Tobler's first law of geography (Tobler 1970). A problem with this analysis is it assumes a linear relationship between the driver variables and response variable exists. Realistically, this may not be the case and a better suited statistical analysis may be required to understand and model the relationship between weather and vegetation productivity throughout the growing season. Furthermore, an analysis subset by vegetation type and ecological region may also improve model results. While the results of OLS analysis were not significant, it is of interest to note the clear spatial clustering shown in figure 4.

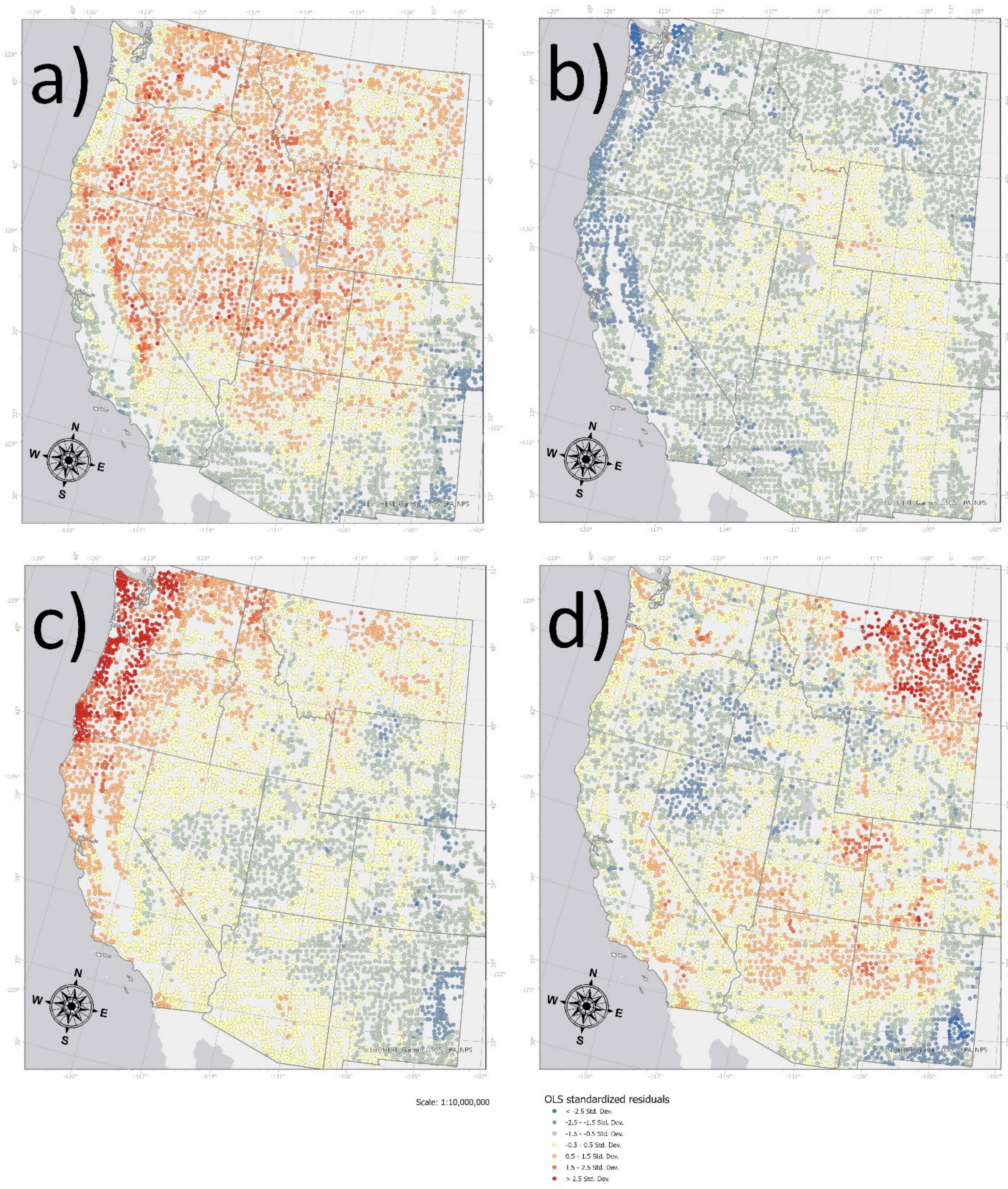

Figure 4.*Results of OLS spatial analyses for years (a) 2002, (b) 2005, (c) 2012, and (d) 2019. The spatial clustering of these data merits additional research.*

CONCLUSIONS

This study sought to explore and model vegetation productivity across the western United States using temperature, growing degrees, and precipitation. The results of this study demonstrate the importance of precipitation as a primary driver variable and suggest weather events early in the hydrologic water year (i.e., December through February) may be more important than previously thought.

Furthermore, the results of this study indicate the relationship between vegetation production and any single weather variable (e.g., maximum temperature) is not linear. While the general outcomes of this study are promising, none of the results were found to be statistically significant. Additional research using non-parametric and non-linear modeling is necessary to better understand the interaction between weather variables (driver variables) and vegetation productivity. This course of research is particularly important to characterize and understand wildfire fuels.

ACKNOWLEDGEMENTS
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