Comparing the Influence of Precipitation, Fire, and Topography on Plant Productivity in the Tallgrass Prairie

Rachel Schwartz

Adapted and excerpted from
https://tiee.esa.org/vol/v3/issues/data_sets/konza/overview.html
and
Briggs, John M. and Alan K. Knapp. 1995. Interannual Variability in Primary Production in Tallgrass Prairie: Climate, Soil Moisture, Topographic Position, and Fire as Determinants of Aboveground Biomass. American Journal of Botany 82: 1024-1030.

Primary production on the prarie

Aboveground plant production in tallgrass prairie has been correlated with several climatic variables (Risser et al., 1981; Towne and Owensby, 1984; Abrams, Knapp, and Hulbert, 1986; Powell, Stadler, and Claypool, 1986). Sala et al. (1988) suggested that variability in grassland primary production at the regional scale can be accounted for by annual precipitation. However, they suggested that, as spatial scale is reduced, additional factors such as fire and soil texture need to be incorporated into predictive models. Fire is considered a necessary component for the preservation and maintenance of the North American tallgrass prairie (Hulbert, 1969; Old, 1969; Vogl, 1974; Axelrod, 1985). Without recurrent fire in the Flint Hills tallgrass prairie, litter accumulates, plant community composition changes, and woody species invade (Abrams, Knapp, and Hulbert, 1986; Knapp and Seastedt, 1986; Gibson, 1988; Hulbert, 1988; Briggs, Seastedt, and Gibson, 1989; Collins and Gibson, 1990; Sea stedt, Briggs, and Gibson, 1991; Briggs and Gibson, 1992; Knight, Briggs, and Nellis, 1994). Several studies have documented that fire can increase aboveground produc tivity in tallgrass prairie (Towne and Owensby, 1984; Abrams, Knapp, and Hulbert 1986; Briggs, Seastedt, and Gibson, 1989).

Hypotheses

1) Plant productivity is impacted by (a) burn frequency, (b) soil depth and type (related to topography), and (c) precipitation.
2) Plant productivity is impacted by the interaction of burn frequency, soil, and precipitation. For example, productivity may be impacted differently by precipitation in different soil types, and burning may have a different impact on productivity in different soil types.

- Uplands are more likely limited by water than lowlands, in which case, tallgrass prairie uplands may respond to variability in precipitation more like the shortgrass steppe (Sala et al., 1988). Burned sites are more limited by water than are unburned sites (Knapp et al., 1993).

3) Different vegetation components (grasses and forbs) respond differently to burning and/or precipitation.

- Forbs (C3 plants) have lower water use efficiency than C4 grasses.

Study location

The Konza Prairie Biological Station (KPBS), located in the Flint Hills of northeastern Kansas, USA (39°05' N, 96°35' W), maintains an interdisciplinary research program documenting the influences of fire, grazing, and climate on the faunal and floral ecology of the mesic prairie. KPBS was established in 1971 with land donated to The Nature Conservancy and is managed by the Division of Biology at Kansas State University. In 1981, KPBS joined the Long-Term Ecological Research (LTER) program funded by the NSF, as one of the original six field stations assembled to document temporal and spatial trends within and across biomes (www.lternet.edu).

KPBS is a 3487 hectares (ha) unplowed tallgrass prairie dominated by a few perennial warm-season grasses (big bluestem, Indian grass and little bluestem), yet supporting a species-rich community of over 500 other species consisting of herbaceous forbs, woody shrubs and trees, and both cool and warm-season grasses (Freeman 1998). KPBS experiences a temperate mid-continental climate characterized by periodic droughts and large seasonal and interannual variability in rainfall. This climate type results in cold, dry winters and warm wet summers with the majority of the annual precipitation occurring between April and September (835mm mean annual precipitation).

Historically, the Flint Hills were not cultivated because the steep hillsides and the rocky, shallow soils of the region prevented conventional tillage practices. For this reason, the region contains the largest remaining area of unplowed tallgrass prairie in North America. Another extraordinary aspect of the KPBS is its experimental design. KPBS is divided into 60 watersheds used to study three factors critical for maintaining the tallgrass prairie ecosystem: periodic fire, ungulate grazing, and a variable climate. KPBS is one of the oldest LTER sites, and experiments with fire and grazing can be carried out over long intervals (e.g., 20 year burns) and with multiple interactions. The focus of this Data Set is to compare the interaction of fire frequency and inter-annual variation in precipitation on the annual production of grasses and forbs.

Data

These data are based on analyses and measurements conducted between 1984 and 1999 at KPBS and archived online at www.konza.ksu.edu. Total aboveground productivity was estimated by quantifying the accumulation of new plant biomass at the end of the growing season along permanent transects in the experimental fire units (watersheds) of KPBS (Briggs and Knapp 1995). In general, prairie plant species in the northern Flint Hills begin growing in early April and have senesced by late September. Plants that use different photosynthetic pathways and annual differences in climate can alter this timeline, but peak biomass is typically reached by late August/early September, the date of biomass harvest each year.

Biomass data

1. Burns were conducted at annual, 4-year, and 20-year intervals at different sites.
2. Data was collected from 1984 to 1999.
3. Biomass was separated into multiple vegetative components that included grass and forb biomass, current year's dead (grass litter), and a minor woody plant component (if present). For this exercise, live grass and grass litter were pooled together.
4. Measurements were taken at upland and lowland sites.
5. Total aboveground productivity was measured using four transects with five 0.1 m2 subplots therein. The clipped subplots were marked so as to avoid subsequent re-sampling for at least four years. This method ensures independence in productivity data between consecutive years. Following sorting, biomass was oven-dried at 60 °C for 48 hours and weighed to the nearest 0.01g (Abrams et al. 1986).

Precipitation data

1. "Precip.g.season"
2. "Avg..Dry.Interval"
3. "Max..Dry.Interval"
4. "Mean.Montly.Precip"
5. "CV.Precip"

6. "SE.Precip"

Data analysis

Make a new project and new script

Load the tidyverse and moderndive libraries

```
library(tidyverse)
library(moderndive)
```

Load data and view it

The data can be found at the following paths relative to your home folder:
"../shared/konza.csv"
"../shared/konza_precip.csv"

```
konza <- read.csv("konza.csv")
rain <- read.csv("konza_precip.csv")
```

How does total productivity vary due to burning?

Total productivity is the sum of the productivity of grasses and forbs. Make a table of total productivity for each Year-Location-Burn type combination.

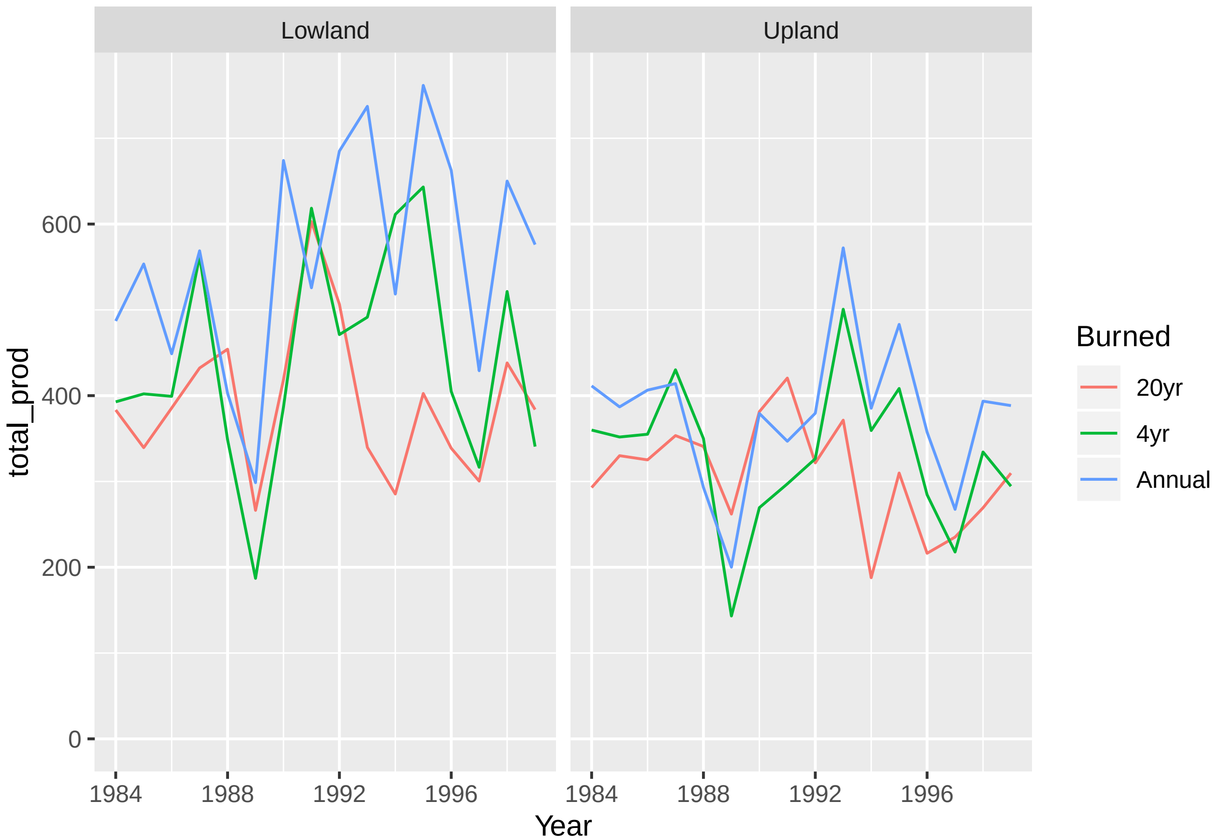
```
total_prod <- konza %>% group_by(Burned, Year, Location) %>%
  summarise(total_prod = sum(Productivity))

head(total_prod)
```

```
## # A tibble: 6 x 4
## # Groups:   Burned, Year [3]
##   Burned  Year Location total_prod
##   <fct>  <int> <fct>         <dbl>
## 1 20yr    1984 Lowland        383.
## 2 20yr    1984 Upland         293.
## 3 20yr    1985 Lowland        339.
## 4 20yr    1985 Upland         330.
## 5 20yr    1986 Lowland        386.
## 6 20yr    1986 Upland         325.
```

Now plot productivity over time for each burn type. You will probably want to separate by upland v. lowland. Use the `facet_grid` layer to create separate graphs based on a variable.

```
prod_max <- max(total_prod$total_prod)
ggplot(total_prod, aes(Year, total_prod, color=Burned))+
  facet_wrap(~Location) + geom_line() + ylim(c(0,prod_max))
```




```r
#lowland seems less than upland
#more burns = higher prod}
```

Make sure to fix your axis labels and make the y-axis start at 0 to avoid misleading your reader.

Because there seems to be a general pattern in the data, average across all years to compare productivity among the three burn treatments using each sample as a replicate. Make a summary table containing the average and standard error of productivity across all sites for each burn treament. Standard error is calculated as `sd(total_prod)/sqrt(n())`. Plotting mean and standard error will allow you to compare results between treatments.

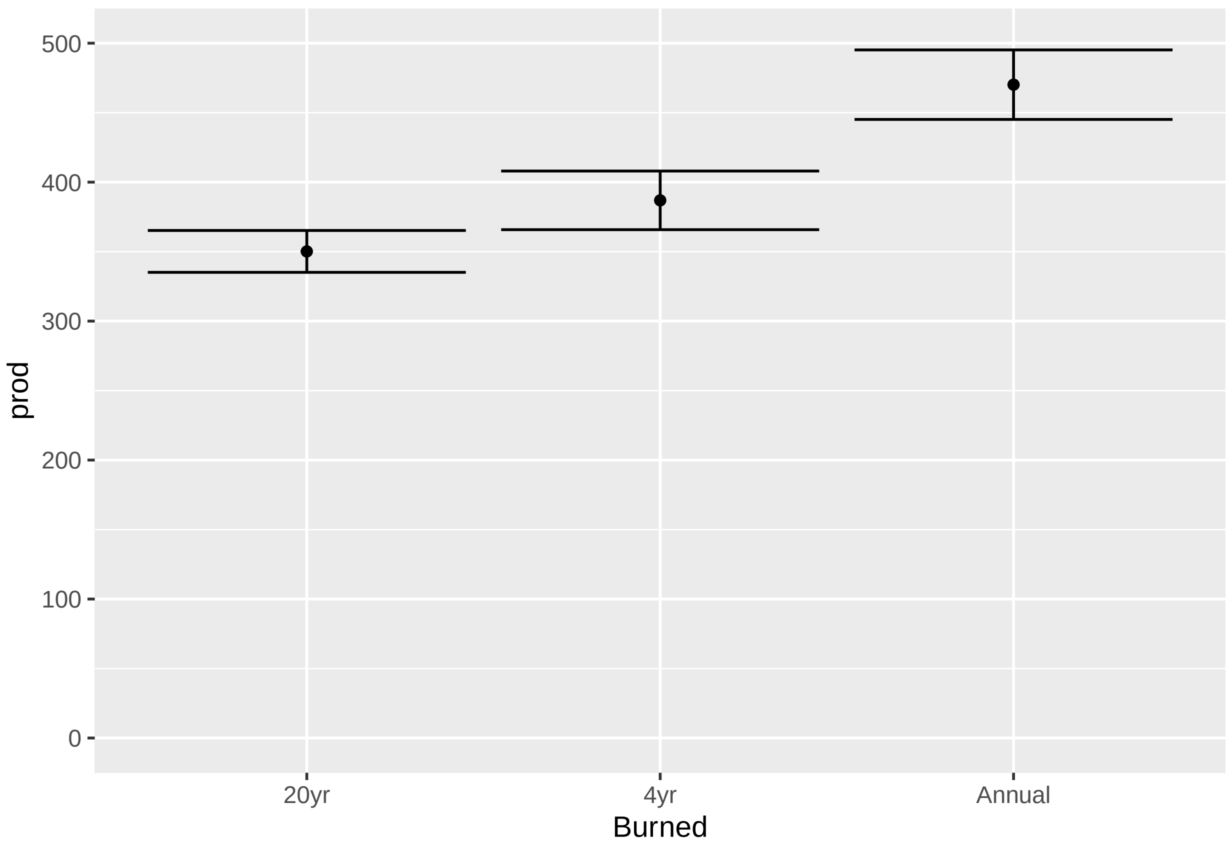
```r
#mean across years and location
total_prod3 <- total_prod %>% group_by(Burned) %>%
  summarise(prod = mean(total_prod), se_prod = sd(total_prod)/sqrt(n()))

head(total_prod3)
```

```
## # A tibble: 3 x 3
##   Burned  prod se_prod
##   <fct>  <dbl>   <dbl>
## 1 20yr    350.    15.1
## 2 4yr     387.    21.1
## 3 Annual  470.    25.0
```

For your plot use the additional layer `geom_errorbar(aes(ymin=prod-se, ymax=prod+se))`.

```r
#Productivity increases with burn rate (total)
ggplot(total_prod3, aes(x=Burned, y=prod)) +
  geom_errorbar(aes(ymin=prod-se_prod, ymax=prod+se_prod)) +
  geom_point() + ylim(c(0,500))
```



Does productivity appear different for the different treatments?

Use an ANOVA to determine whether the three treatments are statistically different. Make sure to use the table with samples not your calculated means.

```
prodAnova <- lm(total_prod ~ Burned, data = total_prod)
anova(prodAnova)
```

```
## Analysis of Variance Table
##
## Response: total_prod
##           Df  Sum Sq Mean Sq F value    Pr(>F)
## Burned     2  241864  120932  8.7337 0.0003343 ***
## Residuals 93 1287733   13847
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
summary(prodAnova)$r.squared
```

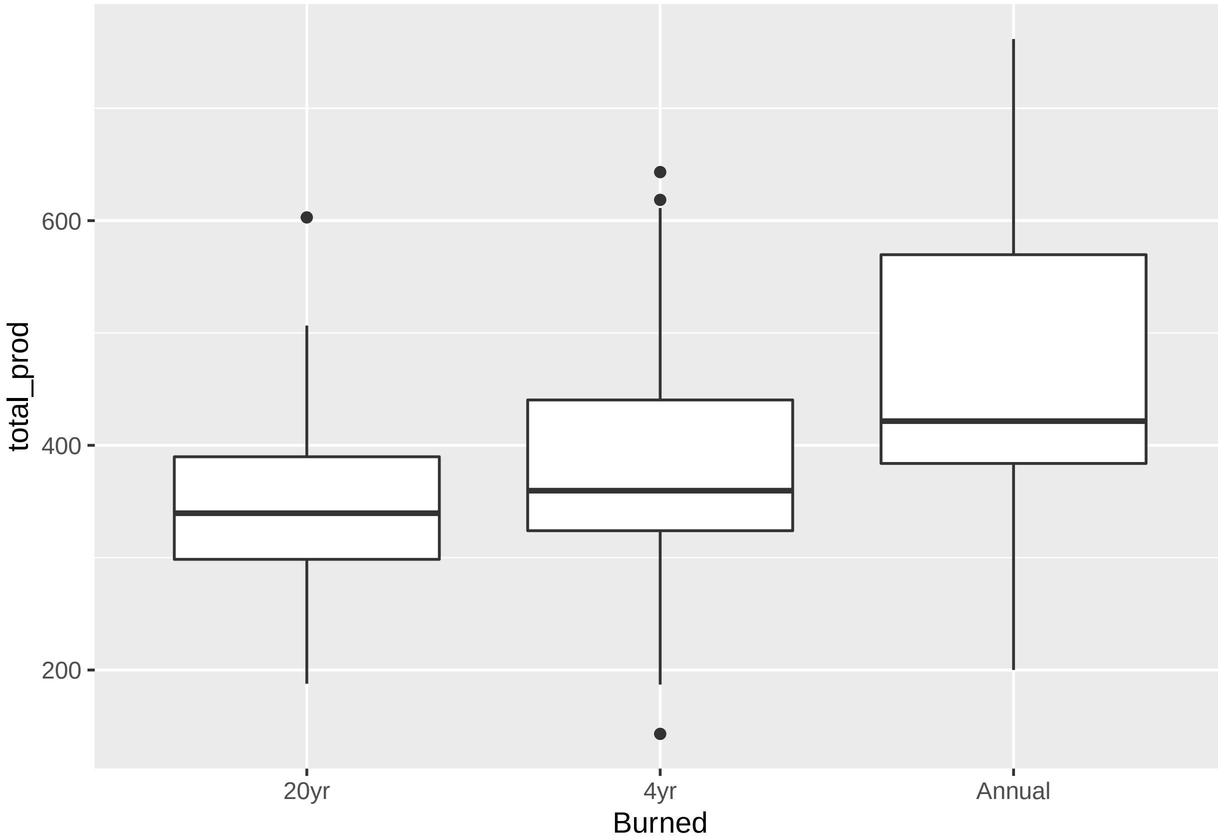
```
## [1] 0.1581226
```

Is productivity statistically different for the different treatments?

How much of the variation in productivity is explained by burning?

Take a look at this variation with a boxplot (use your total productivity table with samples and not mean/se information).

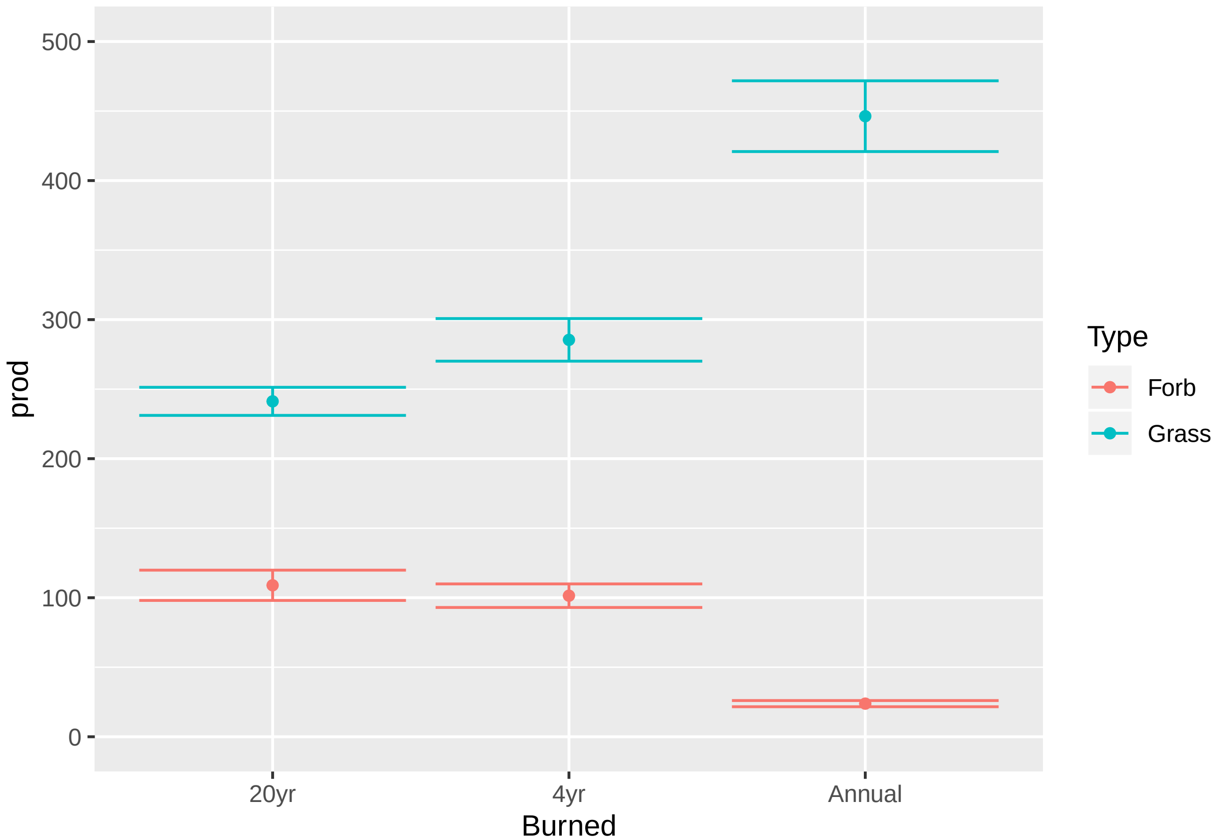
```r
ggplot(total_prod, aes(x=Burned, y=total_prod))+geom_boxplot()
```



Does the pattern you see hold for both forbs and grasses separately? You'll need an additional summary table similar to the one above, but with separate rows by type generated from the original data. Make another mean/se plot but with the forbs and grasses plotted separately.

```r
#but differs for grass/forb
total_prod2 <- konza %>% group_by(Burned, Type) %>%
  summarise(prod = mean(Productivity), se_prod = sd(Productivity)/sqrt(n()))

ggplot(total_prod2, aes(x=Burned, y=prod, color=Type)) +
  geom_errorbar(aes(ymin=prod-se_prod, ymax=prod+se_prod)) +
  geom_point() + ylim(c(0,500))
```



Does burning impact the productivity of grasses and forbs differently?

To test for the significance of both burn treatment and plant type on productivity use a two-way ANOVA with interaction effect. Replace `Burned` with `Burned*Type` and use the original dataset where productivity from different types are separate. Using `Burned*Type` tests for the significant effects of each variable separately and their interaction (which you observed from the graph).

```
prodAnova <- lm(Productivity ~ Burned*Type, data = konza)
anova(prodAnova)
```

```
## Analysis of Variance Table
##
## Response: Productivity
##              Df  Sum Sq Mean Sq  F value    Pr(>F)
## Burned        2  120932   60466   9.6114 0.0001066 ***
## Type          1 2910877 2910877 462.7019 < 2.2e-16 ***
## Burned:Type   2  766827  383413  60.9459 < 2.2e-16 ***
## Residuals   186 1170134    6291
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
summary(prodAnova)$r.squared
```

```
## [1] 0.7645023
```

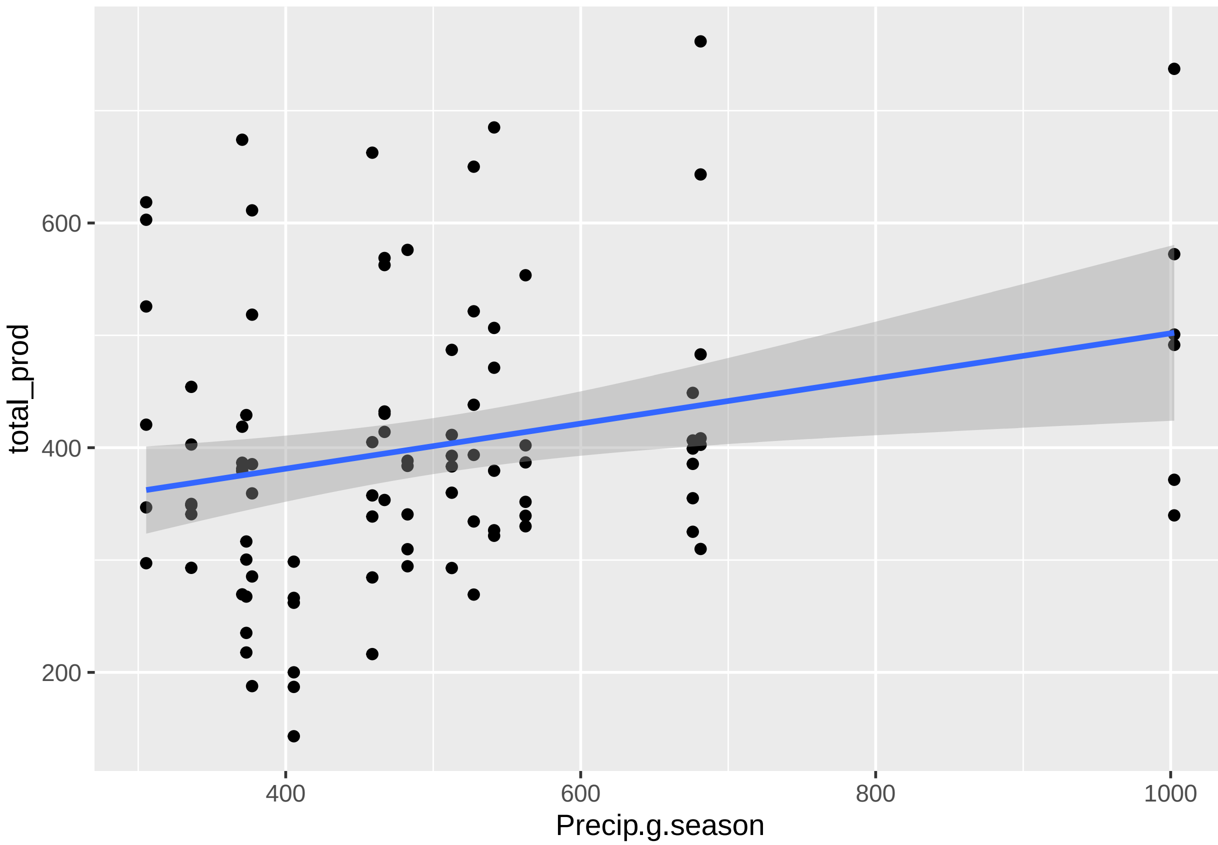
Do burning, vegetation type, and/or their interaction affect productivity?

How much of the variation in productivity is explained by the combination of burning, vegetation type, and their interaction?

Impacts of precipitation

What is the relationship between total annual precipitation (mm) and NPP for all sites on Konza Prairie? Use both a plot (with a regression line) and linear model.

```
total_prod_rain <- left_join(total_prod,rain)
ggplot(total_prod_rain, aes(Precip.g.season,total_prod)) +
  geom_point() + geom_smooth(method="lm")
```




```
precip_prod_lm <- lm(total_prod ~ Precip.g.season, data = total_prod_rain)
get_regression_table(precip_prod_lm)
```

```
## # A tibble: 2 x 7
##   term            estimate std_error statistic p_value lower_ci upper_ci
##   <chr>              <dbl>     <dbl>     <dbl>   <dbl>    <dbl>    <dbl>
## 1 intercept        301.       39.9        7.54   0       222.     380.
## 2 Precip.g.season    0.201     0.075      2.67   0.009    0.052    0.35
```

```
summary(precip_prod_lm)$r.squared
```

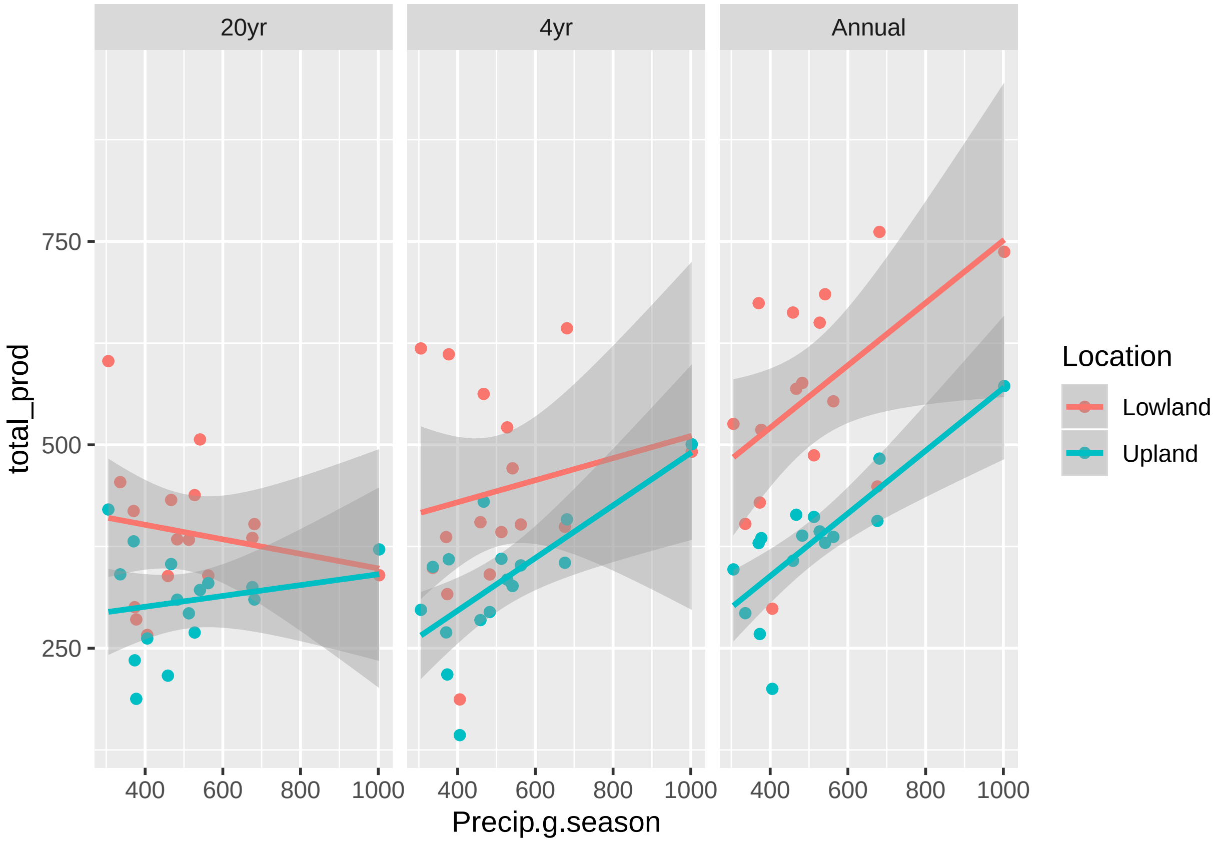
```
## [1] 0.07070738
```

Does precipitation affect productivity?

How much of the variation in productivity is explained by precipitation?

Because there's a lot of variation for any value of precipitation you can examine the effects of location and burn treatment using color and facets respectively. Include regression lines.

```
ggplot(total_prod_rain, aes(Precip.g.season,total_prod,color=Location)) +
  geom_point() + facet_grid(~Burned) + geom_smooth(method="lm")
```



How do precipitation, burn treatment, and location impact productivity?

Use a linear model to examine the relationships you see in your graph. Note: because the interaction of these variables is complicated you should "add" them in the model rather than "multiplying" them as in prior work.

```
lm_prec_burn_loc <- lm(total_prod ~ Precip.g.season+Location+Burned, data=total_prod_rain)
summary(lm_prec_burn_loc)
```

```
##
## Call:
## lm(formula = total_prod ~ Precip.g.season + Location + Burned,
##     data = total_prod_rain)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -243.181  -59.161   -3.611   47.655  229.461
##
## Coefficients:
##                  Estimate Std. Error t value Pr(>|t|)
## (Intercept)     312.09686   34.55034   9.033 2.69e-14 ***
## Precip.g.season   0.20079    0.05705   3.520 0.000677 ***
## LocationUpland -126.67542   19.07259  -6.642 2.21e-09 ***
## Burned4yr        36.74219   23.35905   1.573 0.119205
## BurnedAnnual    119.98250   23.35905   5.136 1.58e-06 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
```

```
## Residual standard error: 93.44 on 91 degrees of freedom
## Multiple R-squared:  0.4806, Adjusted R-squared:  0.4578
## F-statistic: 21.05 on 4 and 91 DF,  p-value: 2.596e-12
```

```
get_regression_table(lm_prec_burn_loc)
```

```
## # A tibble: 5 x 7
##   term            estimate std_error statistic p_value lower_ci upper_ci
##   <chr>              <dbl>     <dbl>     <dbl>   <dbl>    <dbl>    <dbl>
## 1 intercept        312.       34.6        9.03   0      243.     381.
## 2 Precip.g.season    0.201     0.057      3.52   0.001    0.087    0.314
## 3 LocationUpland  -127.       19.1       -6.64   0     -165.     -88.8
## 4 Burned4yr         36.7      23.4        1.57   0.119   -9.66    83.1
## 5 BurnedAnnual     120.       23.4        5.14   0       73.6    166.
```

```
summary(lm_prec_burn_loc)$r.squared
```

```
## [1] 0.4806086
```