

Homework Assignment 5

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April 11, 2016

Objective Statement: This homework assignment introduces the development and interaction of raster data. Rasterized data is critical to data analysis in field of land ecology, and in many fields in general. In this assignment, we will be developing a predictive model that will characterize the amount of biomass in the northern California riparian habitats that we've been studying. Through our analysis, we've come to the realization that we do not possess enough data to properly characterize the carbon stocks; however, through the use of a predictive model we can properly inform field scientists which data are assumed to be the best indicator.

Methods In this assignment, we will be learning about building predictor models and applying them to a data-set that has missing information. We will then compare the predicted values to those found in the larger data-set from previous homework assignments.

Data Three sources of data are utilized in this lab. The first is the riparian data-set from the previous assignments. The second are three rasterized maps of California containing elevation, mean temperature for August and precipitation levels for August. These first two sets of data are used to develop the predictive linear model, after which we will introduce the third source of data that contains latitude, longitude, DBH and Genus.

Code We begin by reading in the data-set from the csv file, and adding the parameter for height in the units of centimeters, as well as project location.

```
# Note: or Mac: Open Terminal.app and execute `R CMD INSTALL [path to library]`.
# This will then install the downloaded package from source.
# An error was encountered when attempting to install the source package for
# rgdal with automatic compiling,
# thus the binary version was downloaded and installed.

# Load Ripdata and place into a dataframe
rip <- read.csv("riparian_cleaned.csv", sep = ",", header = TRUE)
# Add an object that scales the value of height from meters to centimeters
rip$htcm <- rip$Woody_Height_m*100

ProjLoc <- aggregate(cbind(Longitude, Latitude) ~ ProjCode, data=rip, mean)
```

We use the following two commands to read the data from *.tif files and then store the data as a projected raster:

```
# Load the DEM
gdal_grid = readGDAL("DEM.tif")

## DEM.tif has GDAL driver GTiff
## and has 1137 rows and 1233 columns

dem = raster(gdal_grid) #use data as a projected raster
plot(dem)

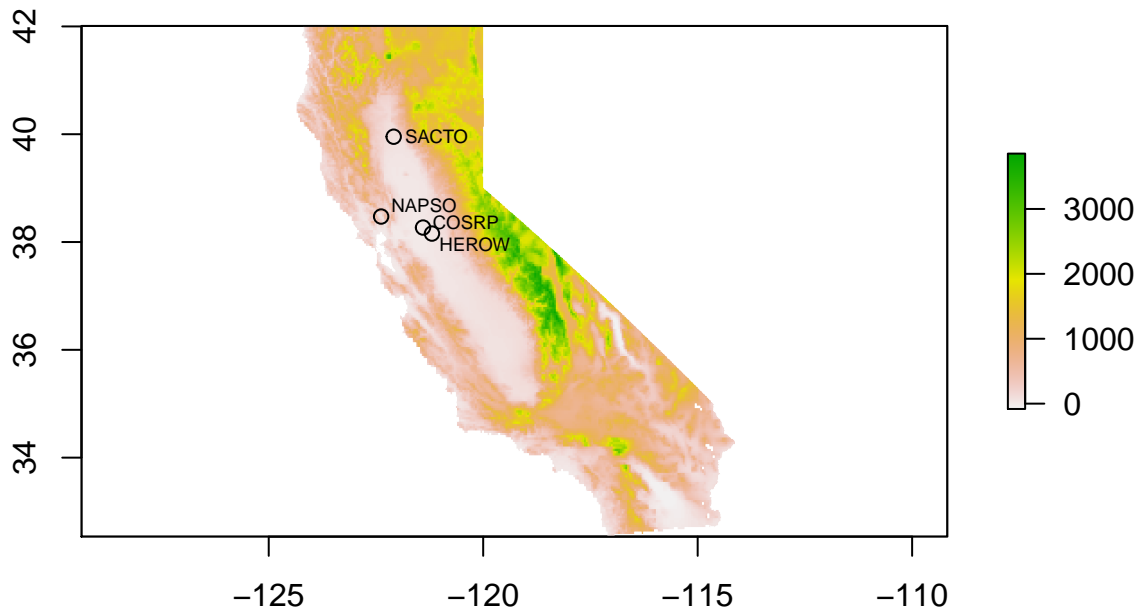
# Create a vector to aid in plotting text for ProjLoc$ProjCode
```

```

xtext = ProjLoc$Longitude+1
ytext = ProjLoc$Latitude
ytext[1] = ytext[1]+.1
ytext[2] = ytext[2]-.2
ytext[3] = ytext[3]+.2

# Plot the ProjLoc over the DEM
points(ProjLoc$Longitude,ProjLoc$Latitude)
text(xtext,ytext,labels=ProjLoc$ProjCode,cex=.6)

```



“ After plotting the DEM, plot the project locations based on the project codes and make small adjustments to the location of the text. We repeat the process with the rasterized precipitation and temperature data:

```
gdal_grid = readGDAL("precip_8.tif")
```

```

## precip_8.tif has GDAL driver GTiff
## and has 862 rows and 744 columns

```

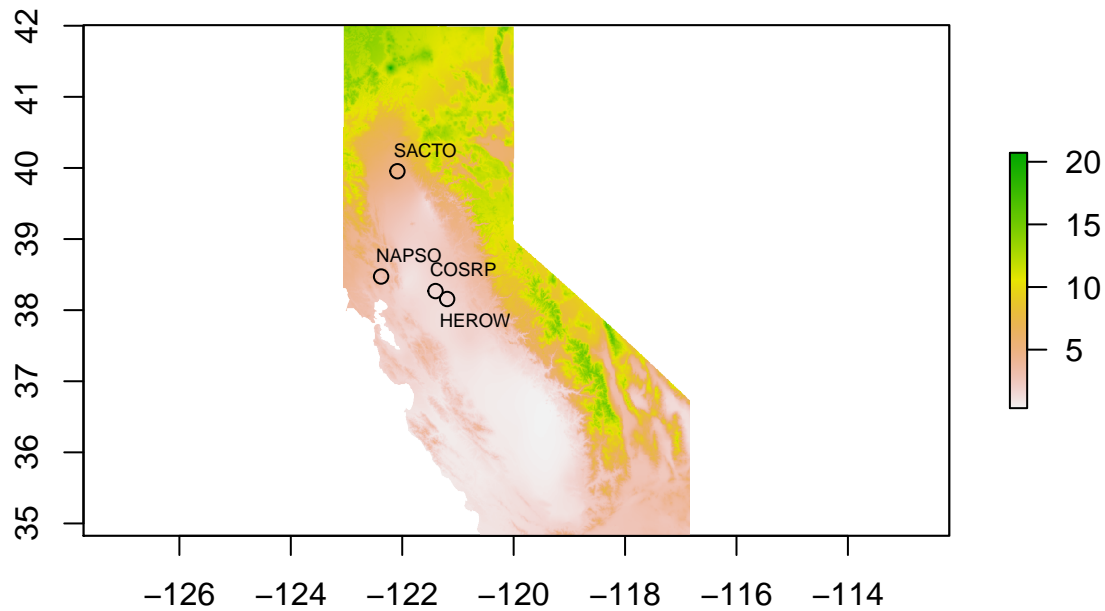
```

precip = raster(gdal_grid) #use data as a projected raster
plot(precip)

# Create a vector to aid in plotting text for ProjLoc$ProjCode
xtext = ProjLoc$Longitude+.5
ytext = ProjLoc$Latitude
ytext[1] = ytext[1]+.3
ytext[2] = ytext[2]-.3
ytext[3] = ytext[3]+.3
ytext[4] = ytext[4]+.3

# Plot the ProjLoc over the DEM
points(ProjLoc$Longitude,ProjLoc$Latitude)
text(xtext,ytext,labels=ProjLoc$ProjCode,cex=.6)

```



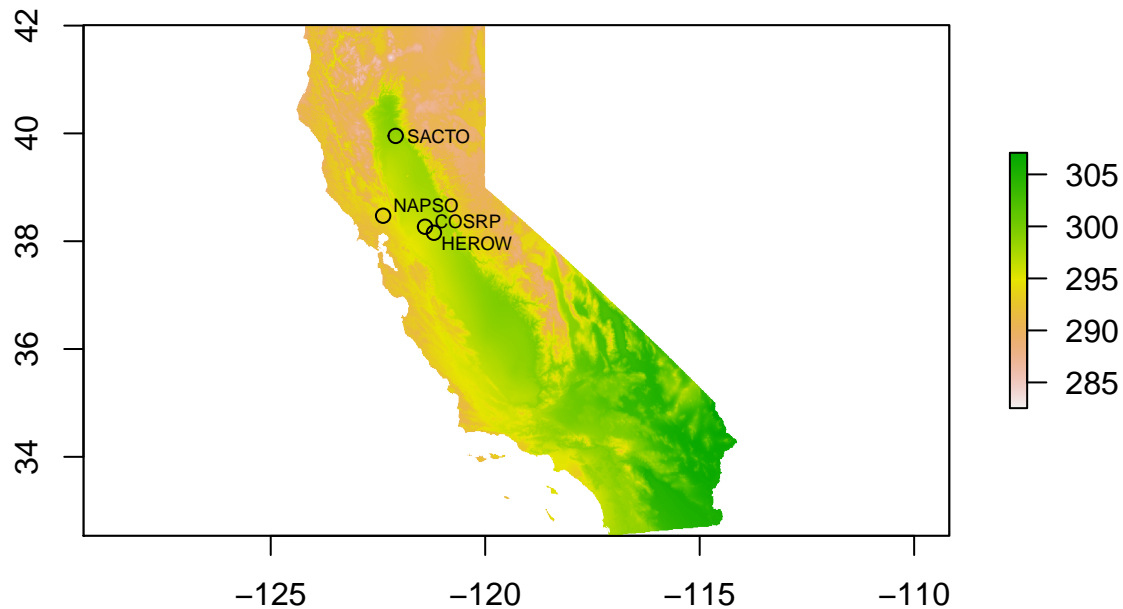
```
gdal_grid = readGDAL("tmean_8.tif")
```

```
## tmean_8.tif has GDAL driver GTiff
## and has 1137 rows and 1233 columns
```

```
tmean = raster(gdal_grid) #use data as a projected raster
plot(tmean)

# Create a vector to aid in plotting text for ProjLoc$ProjCode
xtext = ProjLoc$Longitude+1
ytext = ProjLoc$Latitude
ytext[1] = ytext[1]+.1
ytext[2] = ytext[2]-.2
ytext[3] = ytext[3]+.2

# Plot the ProjLoc over the DEM
points(ProjLoc$Longitude,ProjLoc$Latitude)
text(xtext,ytext,labels=ProjLoc$ProjCode,cex=.6)
```



We now extract the values pertaining to the areas of interest in our riparian dataset:

```
# x,y locations
xy = cbind(rip$Longitude,rip$Latitude)

# extract the values from the dem dataset
evals = extract(dem,xy)

# extract the values from the dem dataset
tvals = extract(tmean,xy)

# extract the values from the dem dataset
pvals = extract(precip,xy)

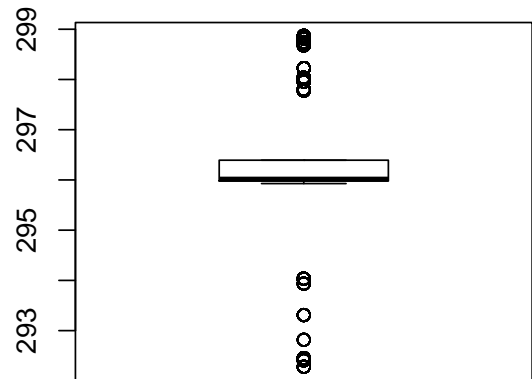
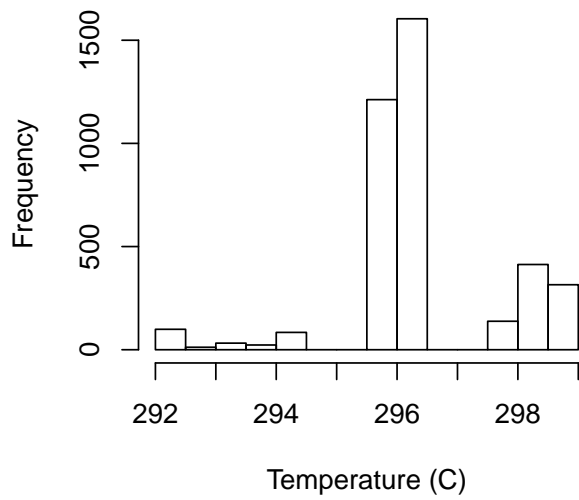
# Combine all new data into the dataframe. Attempted to use melt(),
# but the data type was always indicated to be "values" rather
# than "numeric"
rip$Elevation <- evals
rip$Temp_aug <- tvals
rip$Precp_aug <- pvals
```

Step 1 - Adding Covariates to the Mix

The first step when receiving a new set of data is to perform an exploratory data analysis. Here we have chosen to use histograms, boxplots and a scatter matrix to get a feel for these data.

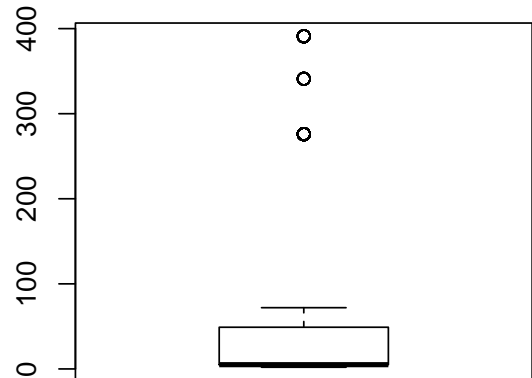
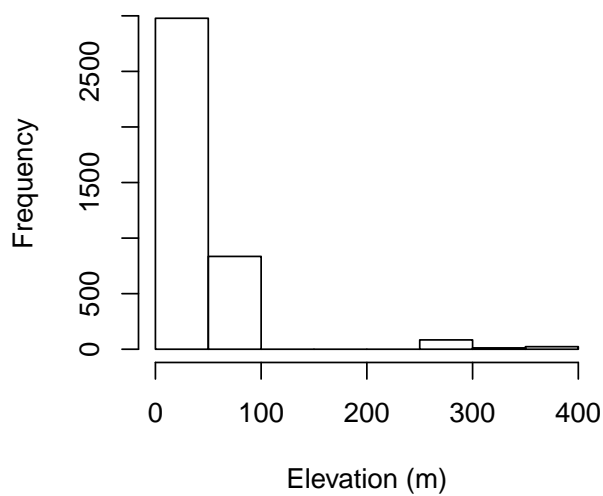
```
# Exploratory data analysis
layout(matrix(c(1,2), 1, 2, byrow = TRUE))
hist(rip$Temp_aug, xlab="Temperature (C)",main="Histogram of August Temperature")
boxplot(rip$Temp_aug)
```

Histogram of August Temperature



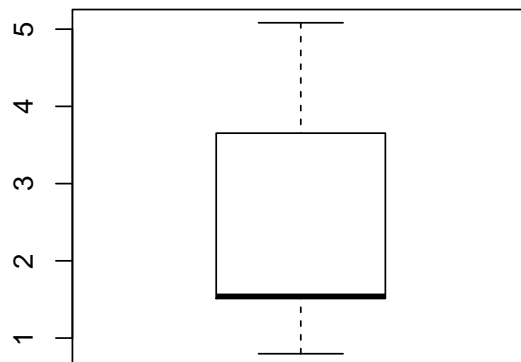
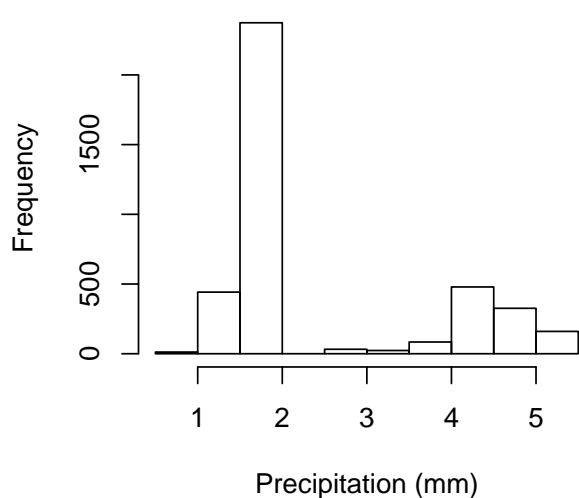
```
hist(rip$Elevation,xlab="Elevation (m)",main="Histogram of Elevation")
boxplot(rip$Elevation)
```

Histogram of Elevation

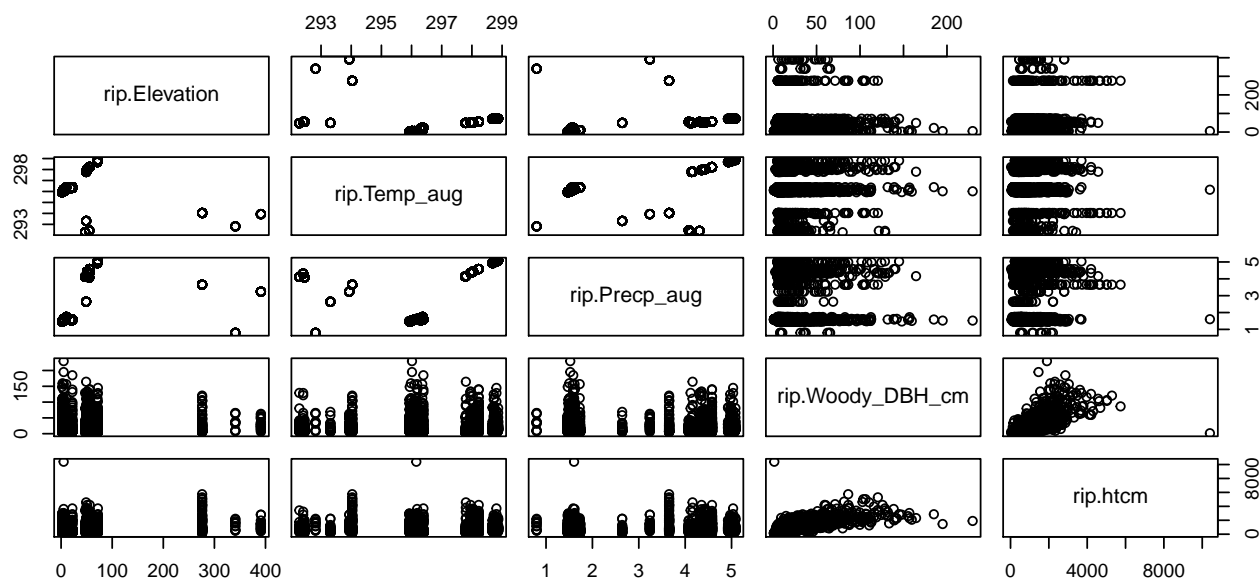


```
hist(rip$Precp_aug,xlab="Precipitation (mm)",main="Histogram of Precipitation")
boxplot(rip$Precp_aug)
```

Histogram of Precipitation



```
eda <- data.frame(rip$Elevation,rip$Temp_aug,rip$Precp_aug,rip$Woody_DBH_cm,rip$htcm)
pairs(eda)
```



```
summary(rip)
```

```
##      SurveyID      ProjectID
## Min.   : 6    Cosumnes River Preserve :2427
## 1st Qu.: 48    Heritage Oak Winery     : 320
## Median : 85    Napa_Sonoma             : 319
## Mean   :380    Sacramento R. Red Bluff to Hwy 32: 866
## 3rd Qu.:776
## Max.   :857
##
##      LocationName      Date
## Tall Forest           : 320  3/20/2012 : 304
```

```

## Merrill's Landing : 242    9/26/2012 : 179
## Denier            : 213    7/25/2012 : 166
## Accidental Forest : 212    9/1/2013  : 165
## Shaw Forest       : 192    9/13/2012 : 157
## Intentional Forest: 163    10/14/2013: 152
## (Other)           :2590    (Other)   :2809
##
## Collectors      Longitude
## M. Vaghti, M. Read      : 345    Min.    :-122.9
## M. Vaghti, K. MacMillen : 311    1st Qu.: -122.0
## M. Vaghti, J. Kattenhorn, L. Breed, E. Butler: 144    Median :-121.4
## All                   : 134    Mean    :-121.6
## Liz, Hayawen, Melissa, Jackie, Mehrey      : 109    3rd Qu.: -121.4
## RH,DB,AS,CK           : 102    Max.    :-121.2
## (Other)                :2787
##
## Latitude      SurveyTypeID      Plot.Name      SpeciesVarietalCode
## Min.      :36.46    Plant:3932    CRP09      : 112    POFR      :824
## 1st Qu.:38.26      6      : 102    QULO      :698
## Median :38.27      CRP75      : 100    FRLA      :468
## Mean      :38.65      RIP06      : 93    ACNE      :451
## 3rd Qu.:38.52      Crp2013_509: 81    JUHI      :316
## Max.      :40.12      CRP51      : 80    SAGO      :314
##
## (Other)      :3364    (Other):861
##
## SpeciesVarietalName      Measurement      CanopyID
## Populus fremontii :824    Min.      : 1.00      :3288
## Quercus lobata      :698    1st Qu.: 7.00    5      : 36
## Fraxinus latifolia:468    Median : 15.00    1      : 35
## Acer negundo        :451    Mean      : 24.26    12     : 35
## Salix lasiolepis    :344    3rd Qu.: 33.00    2      : 34
## Juglans hindsii     :316    Max.      :156.00    8      : 27
## (Other)             :831    (Other): 477
##
## Woody_DBH_cm      Woody_Height_m      ProjCode      Genus
## Min.      : 0.90    Min.      : 0.300    COSRP:2427    Populus :824
## 1st Qu.: 7.30    1st Qu.: 5.300    HEROW: 320    Salix   :789
## Median : 12.00    Median : 8.000    NAPS0: 319    Quercus :703
## Mean      : 18.71    Mean      : 9.406    SACT0: 866    Fraxinus:468
## 3rd Qu.: 21.73    3rd Qu.: 11.800      Acer      :457
## Max.      :229.50    Max.      :104.000    Juglans   :318
##
## (Other)      :373
##
## htcn      Elevation      Temp_aug      Precp_aug
## Min.      : 30.0    Min.      : 2.00    Min.      :292.3    Min.      :0.797
## 1st Qu.: 530.0    1st Qu.: 5.00    1st Qu.:296.0    1st Qu.:1.512
## Median : 800.0    Median : 5.00    Median :296.0    Median :1.542
## Mean      : 940.6    Mean      : 28.44    Mean      :296.4    Mean      :2.348
## 3rd Qu.: 1180.0    3rd Qu.: 49.00    3rd Qu.:296.4    3rd Qu.:3.653
## Max.      :10400.0    Max.      :391.00    Max.      :298.9    Max.      :5.083
##

```

Based on the histograms, we can see that the data isn't normally distributed by any means. It seems that the new data-set is highly variable. By analyzing the scatter matrix, we may be able to come to the conclusion that temperature and precipitation are correlated, but there doesn't seem to be enough data to solidify this notion. There is a large amount of variability in the height and DBH when plotted against the three predictors as well. In the next step, we develop linear models utilizing each one of these predictors.

Step 2- Final Model Selection

We begin by building the sets of linear models including our predictors: elevation, precipitation, temperature and latitude. Additionally, we include our “base” model to test against, in which we do not include any predictors: `Height~DBH*Genus`.

```
# Build Linear models for each predictor
lm.prede <-lm(htcm~Woody_DBH_cm*Genus+Elevation,data=rip)
lm.predp <-lm(htcm~Woody_DBH_cm*Genus+Precp_aug,data=rip)
lm.predt <-lm(htcm~Woody_DBH_cm*Genus+Temp_aug,data=rip)
lm.predl <-lm(htcm~Woody_DBH_cm*Genus+Latitude,data=rip)
lm.base <-lm(htcm~Woody_DBH_cm*Genus,data=rip)

esum <- summary.lm(lm.prede)
psum <- summary.lm(lm.predp) # Best model
tsum <- summary.lm(lm.predt)
lsum <- summary.lm(lm.predl)
bsum <- summary(lm.base)

psum

##
## Call:
## lm(formula = htcm ~ Woody_DBH_cm * Genus + Precp_aug, data = rip)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -2718.0  -224.4   -27.3   186.2 10032.1
##
## Coefficients: (2 not defined because of singularities)
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)    299.7646    34.8965   8.590 < 2e-16 ***
## Woody_DBH_cm     30.5897     1.7059  17.932 < 2e-16 ***
## GenusAcsculus   -70.3303     94.8356  -0.742 0.458373
## GenusAilanthus -255.5827    223.5832  -1.143 0.253059
## GenusAlnus      346.7955    160.9523   2.155 0.031251 *
## GenusArbutus   -477.2212    414.4605  -1.151 0.249627
## GenusBaccharis -312.0209    396.4585  -0.787 0.431318
## GenusCephalanthus -467.7483   1686.7740  -0.277 0.781562
## GenusCornus     19.1084   1227.0574   0.016 0.987576
## GenusFraxinus    30.4907    41.4509   0.736 0.462027
## GenusJuglans    211.7283    47.5999   4.448 8.91e-06 ***
## GenusMaclura   -370.5170    389.1029  -0.952 0.341037
## GenusPaulownia  -83.0980    396.3551  -0.210 0.833948
## GenusPlatanus    37.8591    93.4320   0.405 0.685350
## GenusPopulus    664.4376    36.3350  18.286 < 2e-16 ***
## GenusPrunus     52.5906    144.0834   0.365 0.715131
## GenusPseudotsuga 148.6995    107.0114   1.390 0.164740
## GenusQuercus    149.0919    37.2867   3.999 6.49e-05 ***
## GenusSalix      189.8985    38.3095   4.957 7.47e-07 ***
## Genussambucus   249.7548    99.1240   2.520 0.011788 *
## GenusSambucus   -23.3206    781.5075  -0.030 0.976196
## GenusSequoia    395.1396    93.1401   4.242 2.26e-05 ***
## GenusUmbellaria  14.3112    486.0651   0.029 0.976513
```



```
## GenusVitis -478.2472 466.1116 -1.026 0.304938
## Precp_aug 0.7669 6.1436 0.125 0.900671
## Woody_DBH_cm:GenusAcsculus -17.8205 4.9691 -3.586 0.000340 ***
## Woody_DBH_cm:GenusAilanthus 41.0792 18.4123 2.231 0.025733 *
## Woody_DBH_cm:GenusAlnus -15.5476 5.3745 -2.893 0.003839 **
## Woody_DBH_cm:GenusArbutus 5.1124 18.6368 0.274 0.783857
## Woody_DBH_cm:GenusBaccharis NA NA NA NA
## Woody_DBH_cm:GenusCephalanthus 58.8553 280.6483 0.210 0.833904
## Woody_DBH_cm:GenusCornus -30.5897 168.1483 -0.182 0.855654
## Woody_DBH_cm:GenusFraxinus -4.6091 2.6309 -1.752 0.079873 .
## Woody_DBH_cm:GenusJuglans -7.7816 2.1941 -3.547 0.000395 ***
## Woody_DBH_cm:GenusMaclura 26.3233 27.3180 0.964 0.335313
## Woody_DBH_cm:GenusPaulownia NA NA NA NA
## Woody_DBH_cm:GenusPlatanus -8.3130 3.3993 -2.445 0.014510 *
## Woody_DBH_cm:GenusPopulus -14.6740 1.7761 -8.262 < 2e-16 ***
## Woody_DBH_cm:GenusPrunus -10.9822 12.5220 -0.877 0.380523
## Woody_DBH_cm:GenusPseudotsuga 14.2842 2.5472 5.608 2.19e-08 ***
## Woody_DBH_cm:GenusQuercus -10.0901 1.8178 -5.551 3.03e-08 ***
## Woody_DBH_cm:GenusSalix -5.8398 2.4754 -2.359 0.018368 *
## Woody_DBH_cm:Genussambucus -23.4073 6.5290 -3.585 0.000341 ***
## Woody_DBH_cm:GenusSambucus -23.9211 115.0945 -0.208 0.835366
## Woody_DBH_cm:GenusSequoia -7.6632 2.5452 -3.011 0.002622 **
## Woody_DBH_cm:GenusUmbellaria 19.9679 20.8758 0.957 0.338874
## Woody_DBH_cm:GenusVitis 106.4036 51.2808 2.075 0.038060 *
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 395.8 on 3887 degrees of freedom
## Multiple R-squared: 0.6188, Adjusted R-squared: 0.6145
## F-statistic: 143.4 on 44 and 3887 DF, p-value: < 2.2e-16
```

The final model chosen is the one including the precipitation predictor. While all the linear models yielded for similar r-squared values and p-values, the intercept of the precipitation variate resulted in a low standard error and high Pr value.

Step 3 - Predicting Carbon

We apply the linear model chosen above to predict the height of the new data-set of trees given their genera, height in centimeters and precipitation values at the locations. We begin this process by extracting the data from the comma-separated-values file into a dataframe and then binding it with the precipitation values based on the latitude and longitude location. Finally, we apply the `predict()` function on the new data using the precipitation-as-predictor linear model.

```
# Load new data to compare to predicted model
data <- read.csv("new_data.csv",sep = ",",header = TRUE)

# x,y locations
xy = cbind(data$Longitude,data$Latitude)

# extract the values from the dem dataset
Precp_aug = extract(precip,xy)

# Combine all new data into the dataframe
```

```
data$Precp_aug <- Precp_aug
```

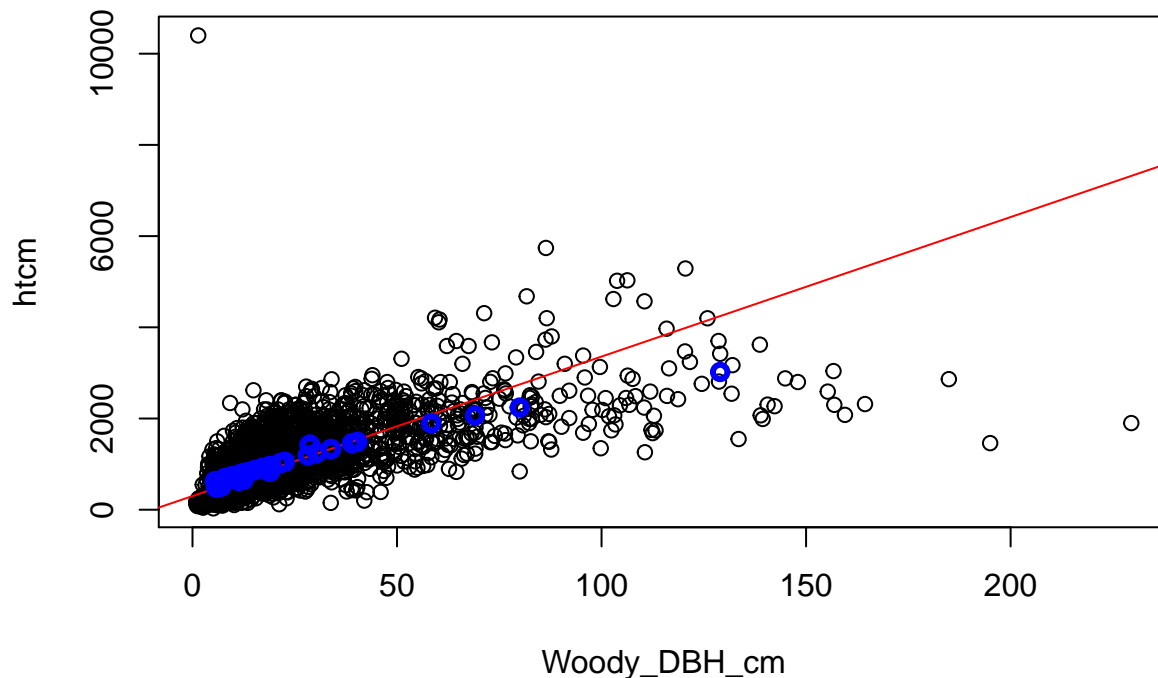
```
# Plot the scatter plot from the original data-set
with(rip,plot(Woody_DBH_cm,htcm))
# insert a trend line based on the precipitation predictor linear
# model
abline(lm.predp,col="red")
```

```
## Warning in abline(lm.predp, col = "red"): only using the first two of 47
## regression coefficients
```

```
# Apply the linear model to predict the height in cm of the new trees
lm1.pred.y <-predict(lm.predp,data)
```

```
## Warning in predict.lm(lm.predp, data): prediction from a rank-deficient fit
## may be misleading
```

```
# Plot these points over the old data
points(data$Woody_DBH_cm,lm1.pred.y,col="blue",lwd=3)
```



Results: We can see from above scatter plot that the predicted values fit quite nicely into our original data, reassuring us that the model chosen was appropriate. We further utilize this model to calculate the Mg of C per hectare of the new data-set. We know that one hectare is equivalent to 10,000 squared meters. We extrapolate our calculation from 100 squared meters to estimate the volume of trees at one hectare. This is then multiplied by the density of carbon in order to calculate the Mg of C per hectare.

```
# Calculating the carbon
```

```
C = 705*(0.0000334750*data$Woody_DBH_cm^2.33631)*lm1.pred.y^0.74872 # Calculate the Volume for each ind
TV = sum(C) # Calculate the sum of the tree volume
```

```
TVpH = (TV/(100))*(10000/1)
MgCpH = (TVpH*.6)*.50/1e6 # The density of wood is about 0.6 g/cm^3 []
```

The estimated biomass for the new site is approximately 44.560 Mg of C per hectare.

Discussion: This exercise of developing a linear model based upon factors and predictors is key in developing predictive model sets and validating models developed for data analytic. We began this assignment by first interpreting raster files that contained elevation, precipitation and temperature overlain on a map of California. We then plotted the four main study areas from the running data-set used in this course on each one of these maps. From there, we extracted the data from the raster files and utilized them for development of a predictive model, which was ultimately used for the prediction of tree height based on location, genus, DBH and precipitation.

Limitations: As with any model, the limitation is almost always resolution. Little is known regarding the source of the raster data utilized in this assignment, and is most likely data extracted from multispectral imagery collected via stallites. Finally, the use of an allometric estimation yields it's own set of limitations, and many assumptions had to be made in order for it to be considered for this analysis. Two of these assumptions are that all the genera in this study utilize the same formula as a Valley Oak and the biomass is approximately 50% of the total volume.