The Effect of Climate, Soil, Topography and Species Mixing on Forest Stand Density

STAT517 FINAL PROJECT

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Presentation Overview

- Importance of Density Management
- Forest Measurements
- Data
- Methods
  - Exploratory Data Analysis
  - Supervised – Regression
  - Association
  - Clustering
- Conclusion

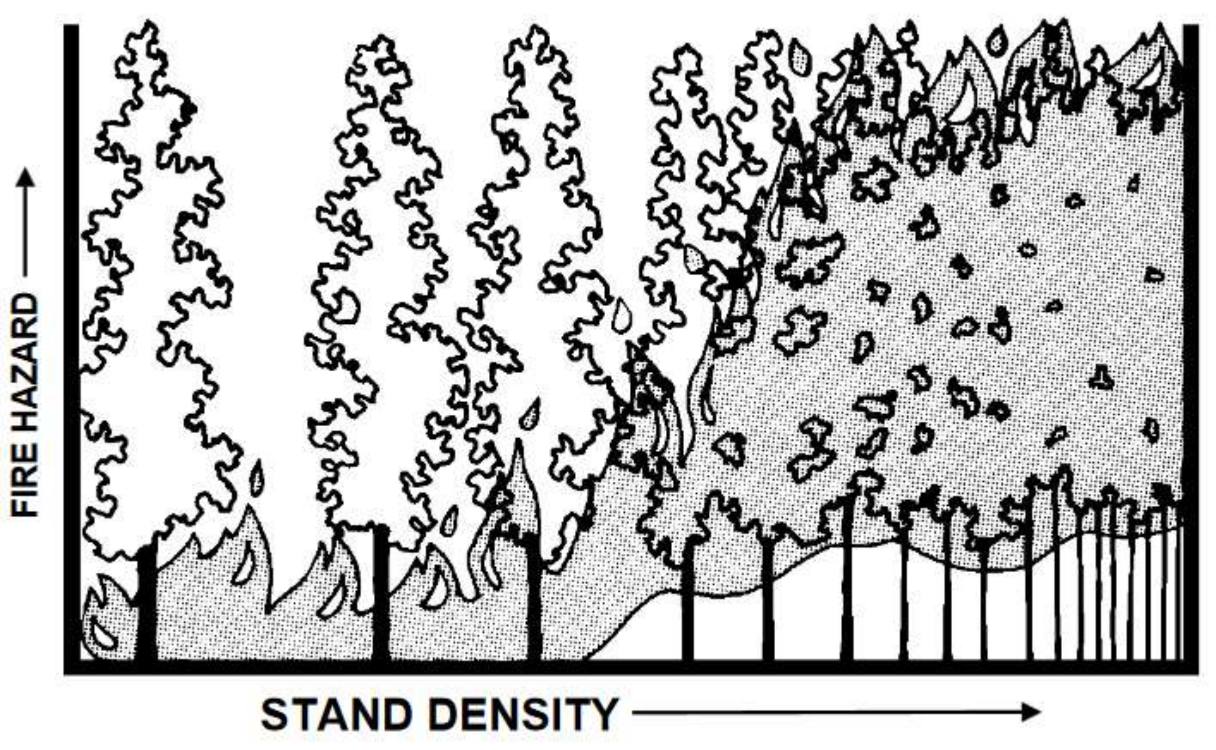
Stand Density Management

- Stand density is a key determinant in the development of a vigorous and productive forest
- Forest management goals

ruffedgroussociety.org

http://nwdistrict.ifas.ufl.edu

https://www.uidaho.edu/news/climate-change/wildfire



"It is clear that forest structure can be manipulated to reduce the severity of fire events."

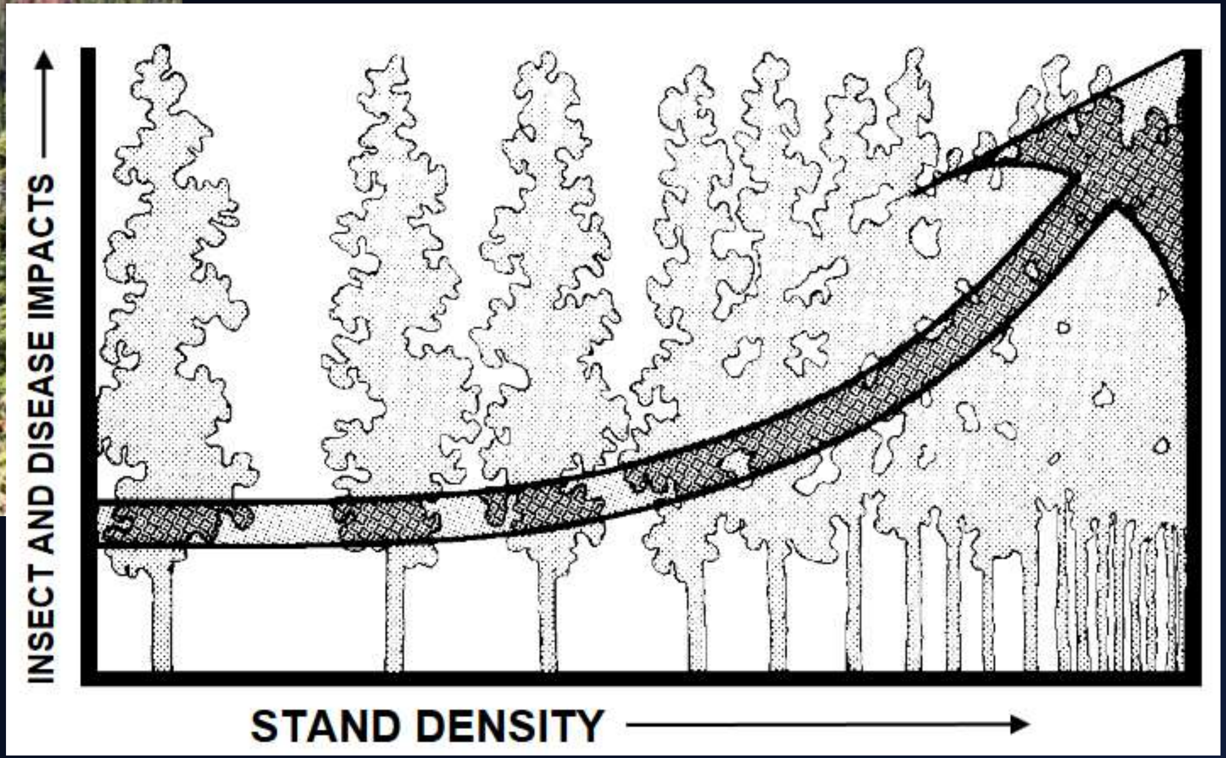
- James K. Agee

The Influence of Forest Structure on Fire Behavior

“Thin out dense stands of trees, leaving the healthiest, most vigorous ones”

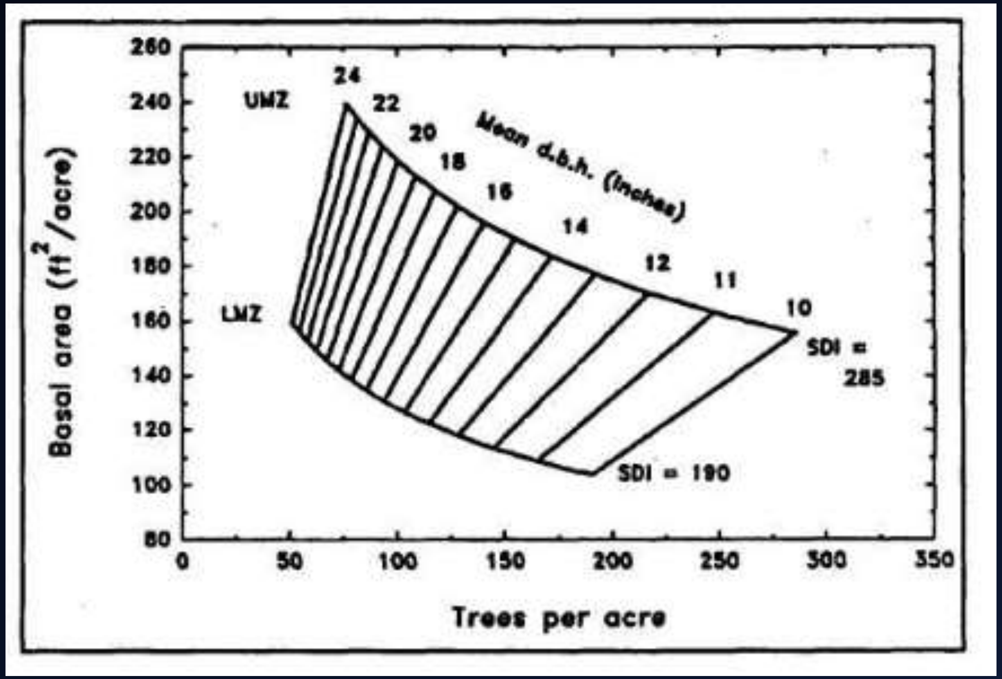
- Idaho Dept. of Lands

https://www.idl.idaho.gov/forestry/forest-health/index.html



TIMBER PRODUCTION

- Density measures guide forest management decisions
  - Growth and yield model inputs
- Optimize growing space utilization to maximize timber production

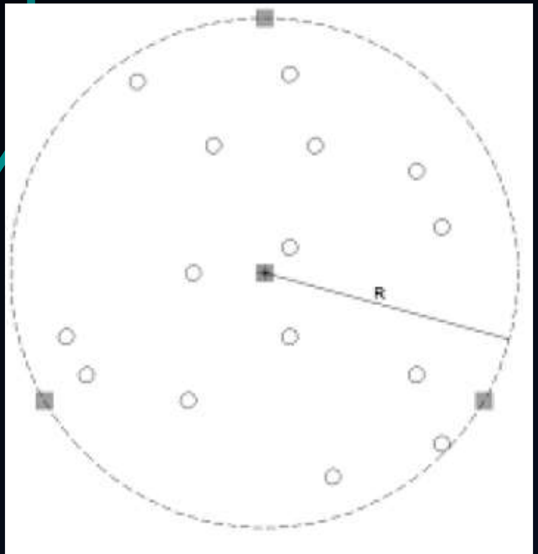


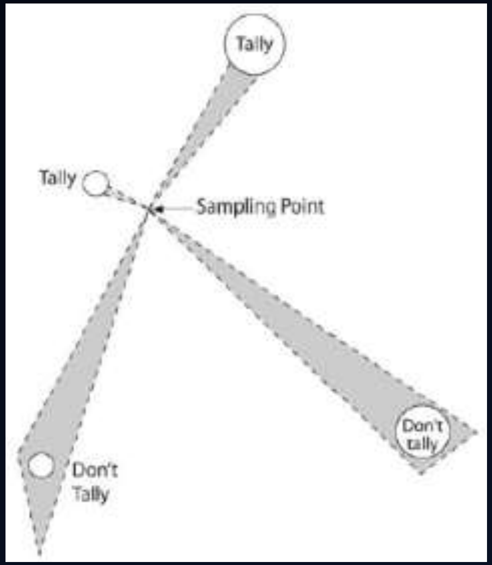
Stocking guide for Douglas Fir

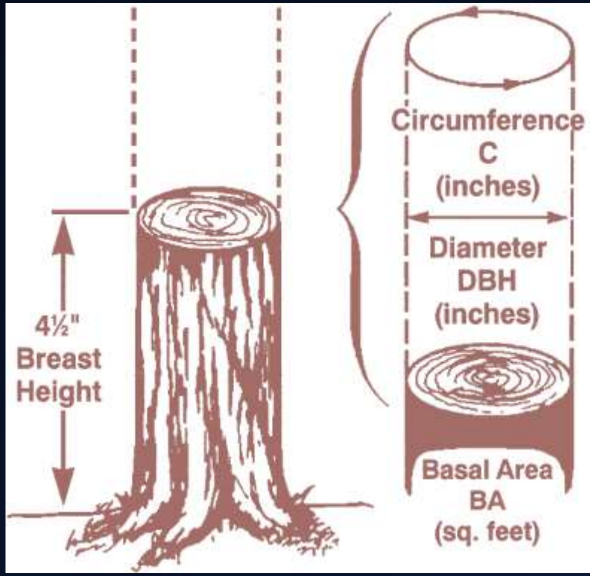
Forest Measurements

- Trees per Acre
- Diameter (DBH > QMD)
- Basal Area

https://andrewsforest.oregonstate.edu

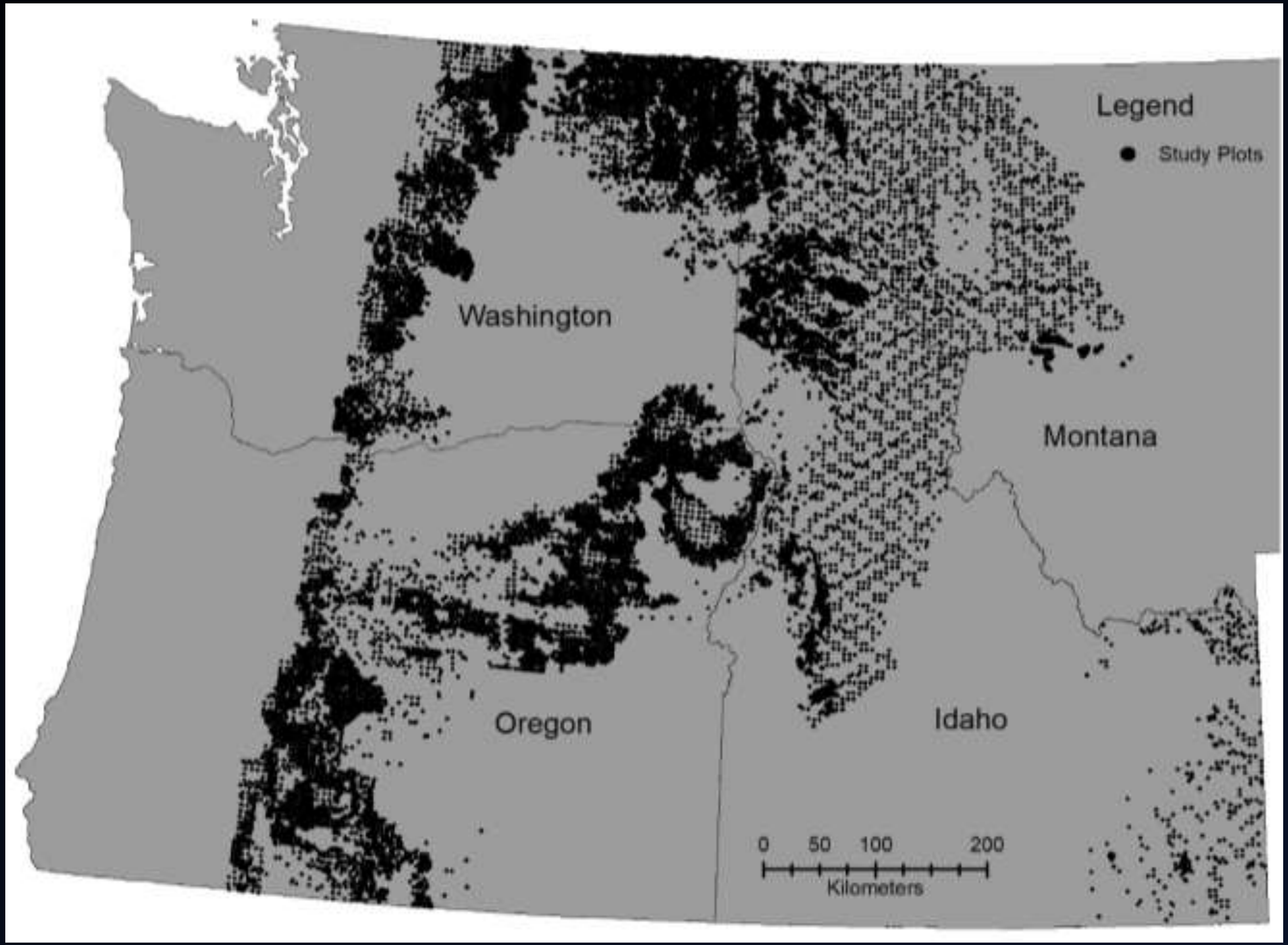






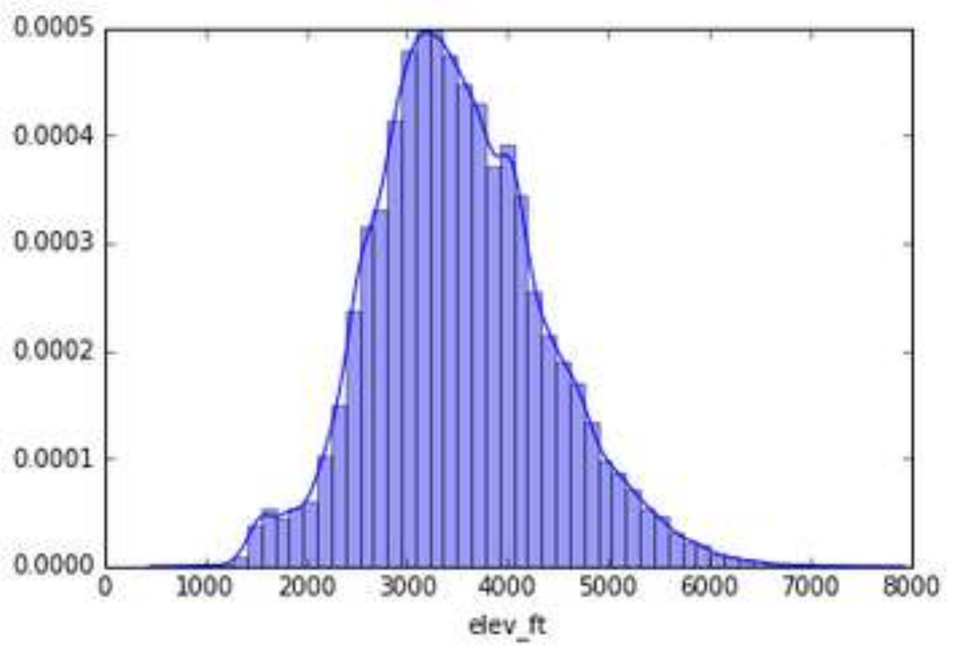
Data – 92,386 records, 42 variables

- Stand level data obtained through a collaborative network of Inland Northwest public and private forest land management organizations, the Intermountain Forestry Cooperative (U-Idaho), and the USFS Forest Inventory and Analysis program.
- Tree Measurements
- Tree Species
  - Douglas Fir
  - Grand Fir
  - Ponderosa Pine
  - Western Larch
  - Other
- Climate
  - Precipitation
  - Temperature
- Topography
  - Aspect
  - Slope
  - Elevation
- Soils
  - Ash Influence
  - Parent Material
- Lat/Long

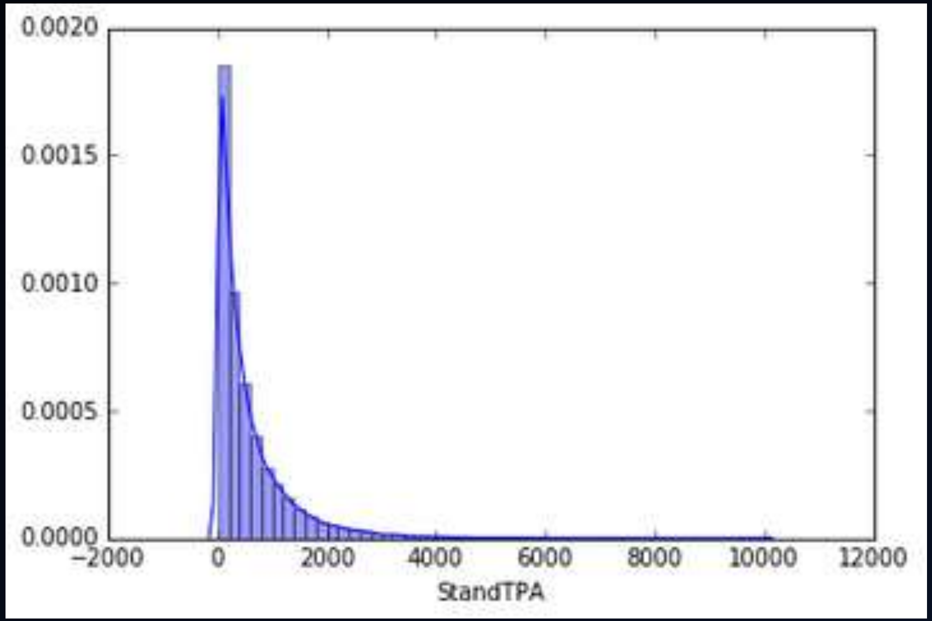

Legend
Study Plots
Washington
Montana
Oregon
Idaho
0 50 100 200
Kilometers

n=110,000

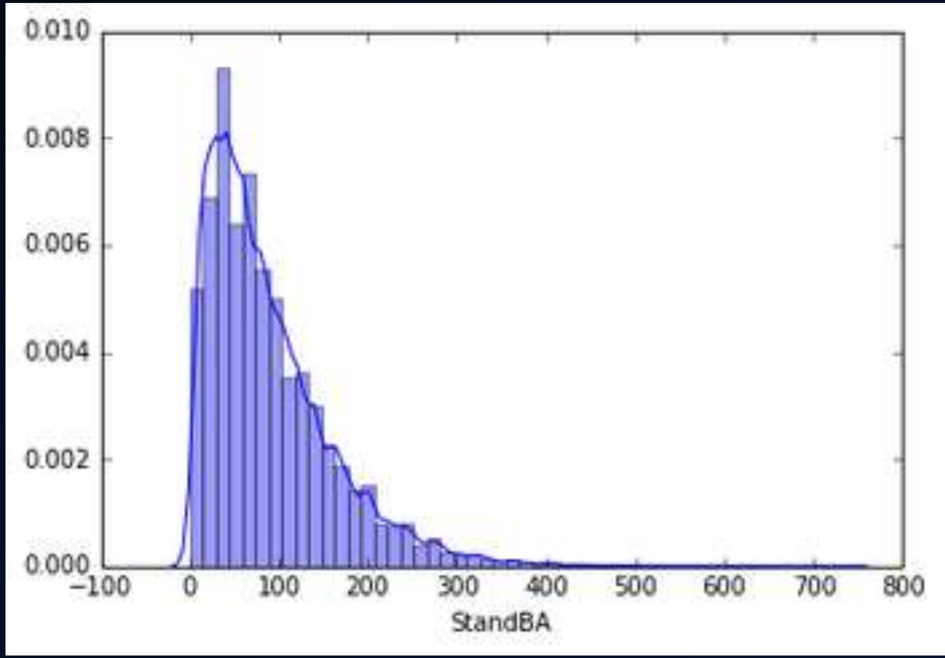
EDA



mean	3518.51
std	855.03
min	715.22
25%	2936.35
50%	3448.16
75%	4049.72
max	7676.65

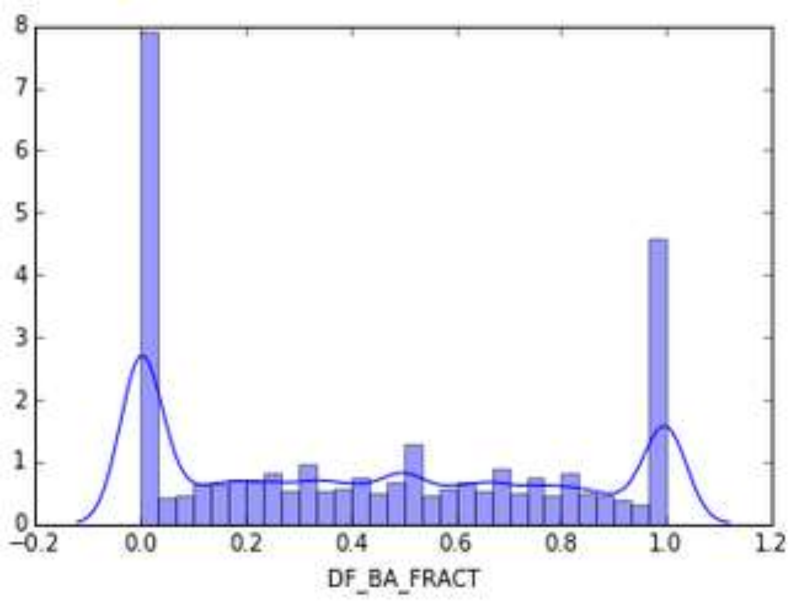


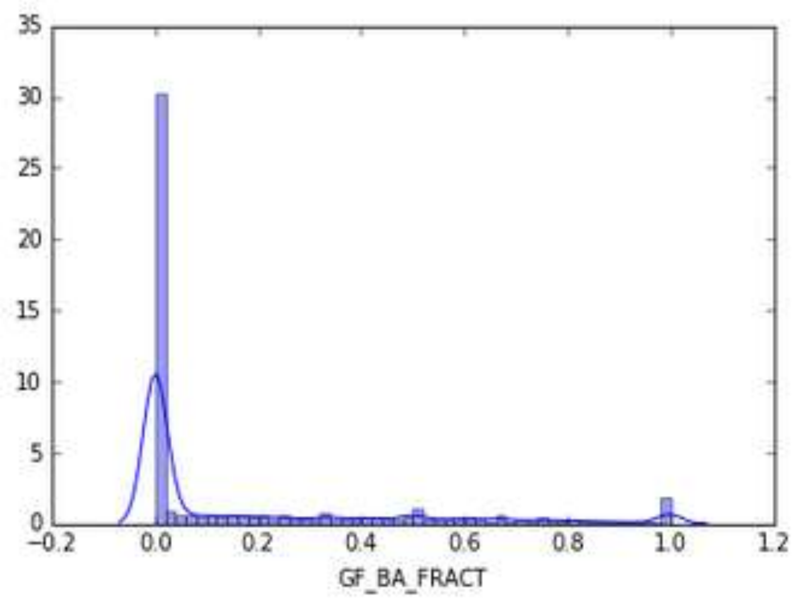
mean	585.75
std	765.01
min	0.21
25%	115.56
50%	321.78
75%	753.58
max	10000.00

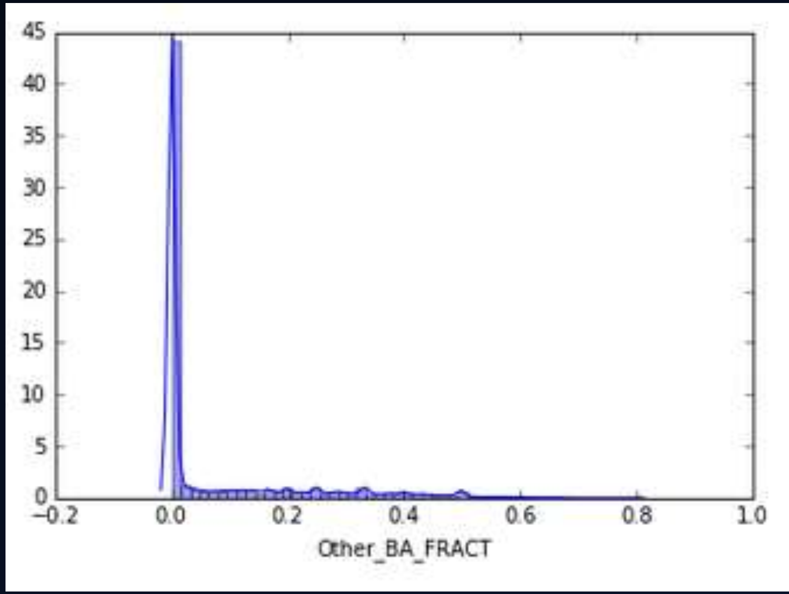


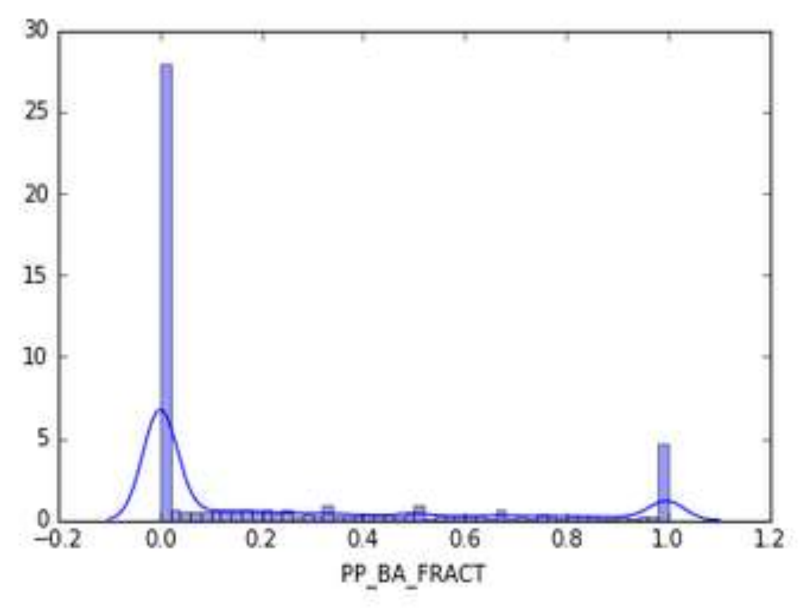
mean	88.94
std	70.16
min	0.12
25%	40.00
50%	70.00
75%	122.05
max	740.00

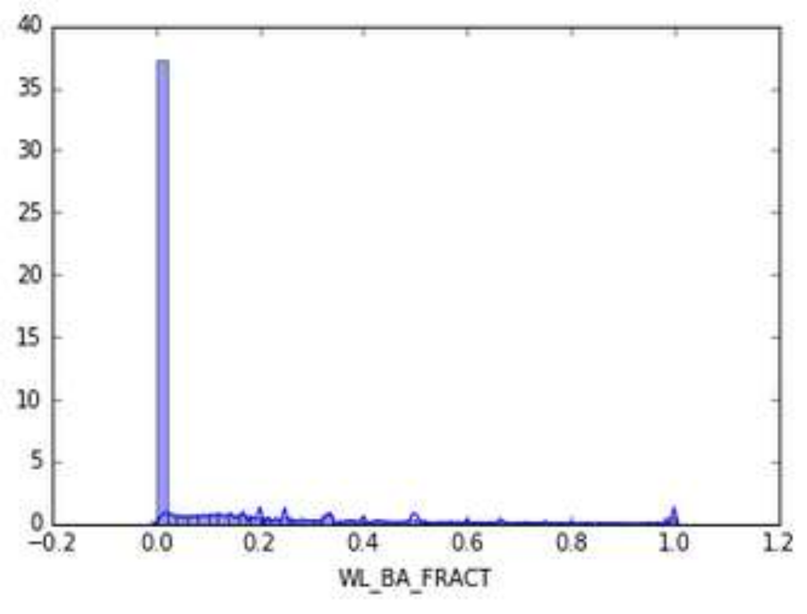
Tree Species BA Fraction



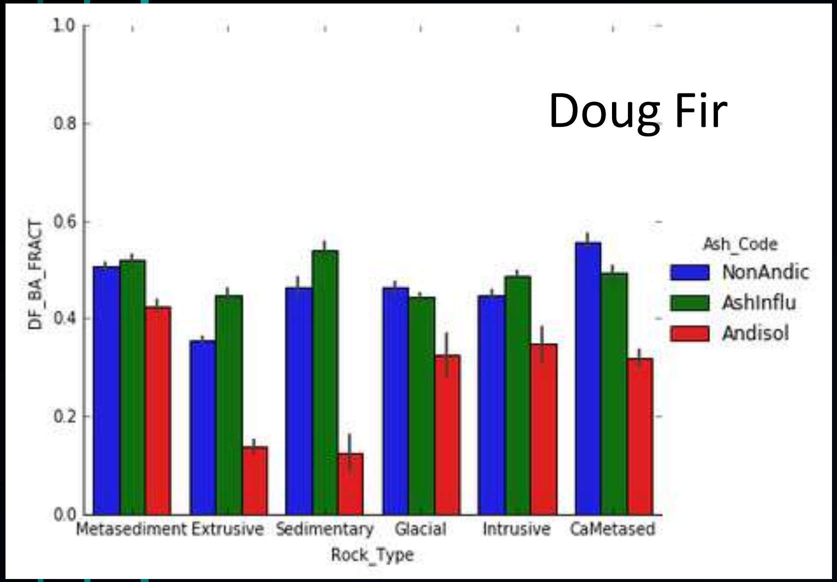


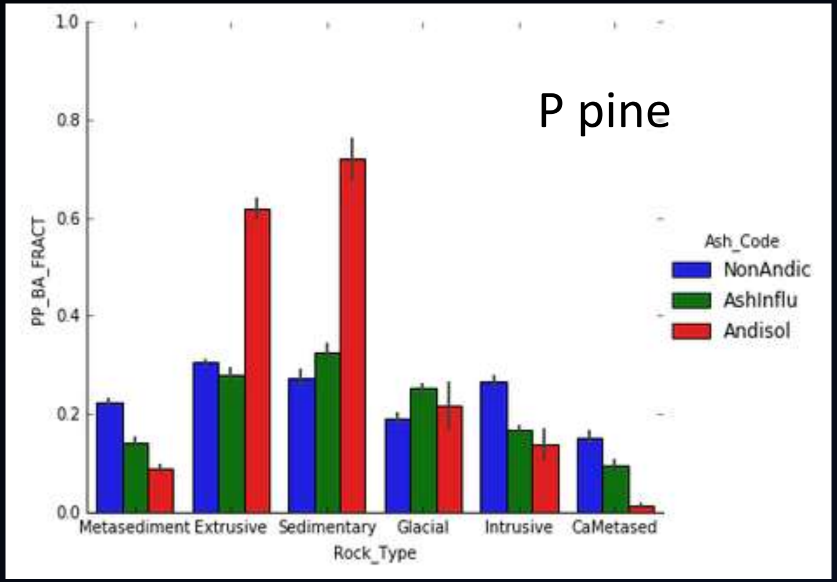


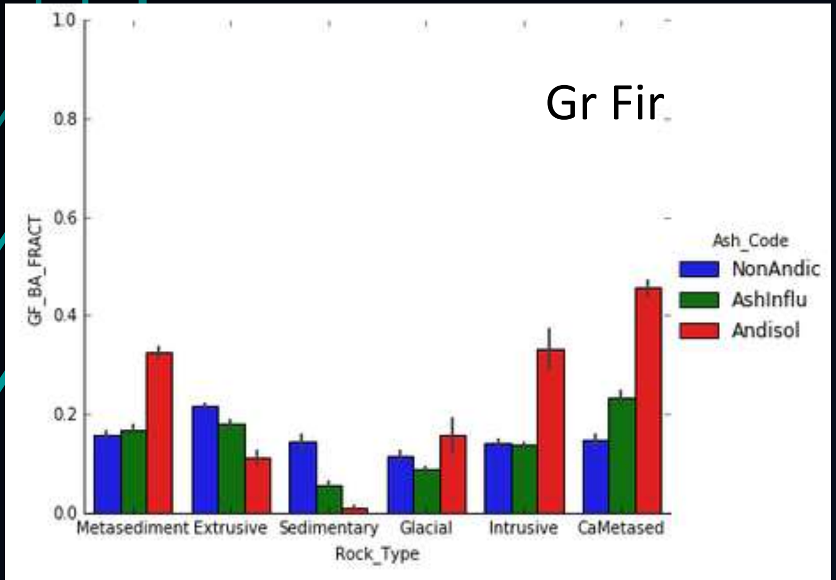


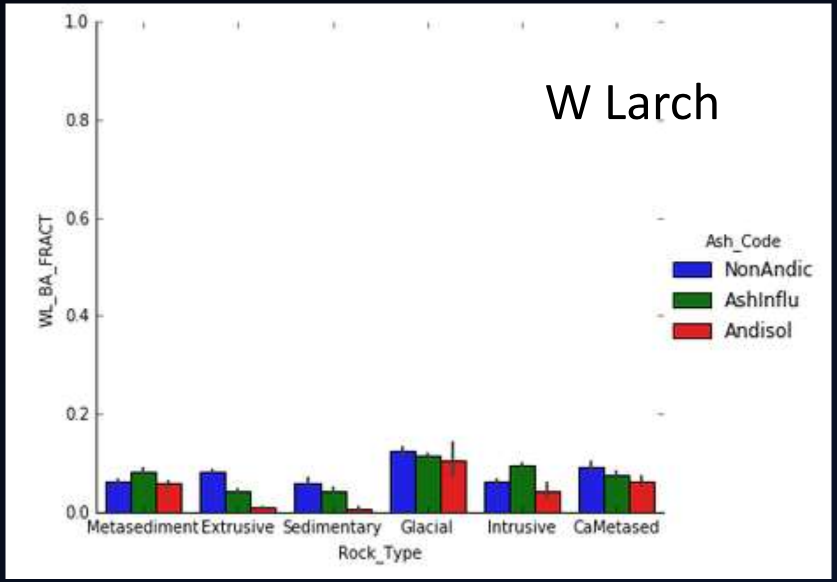


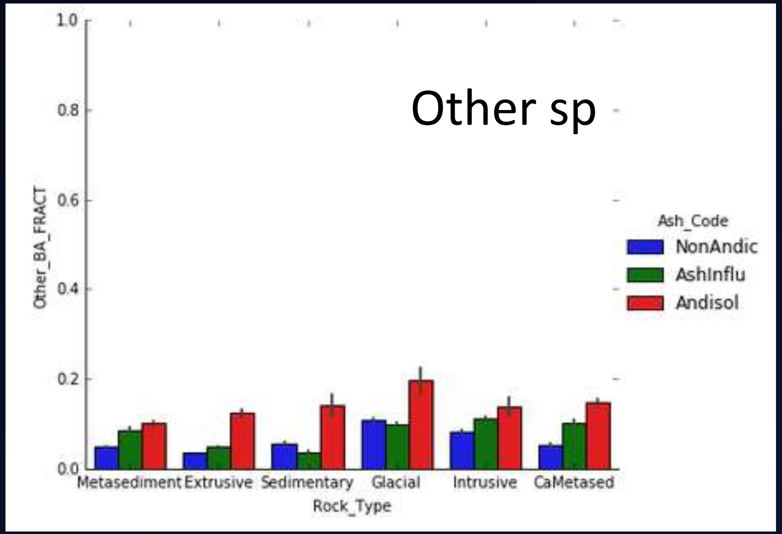
Influence of Soils and Volcanic Ash on Tree Species Diversity



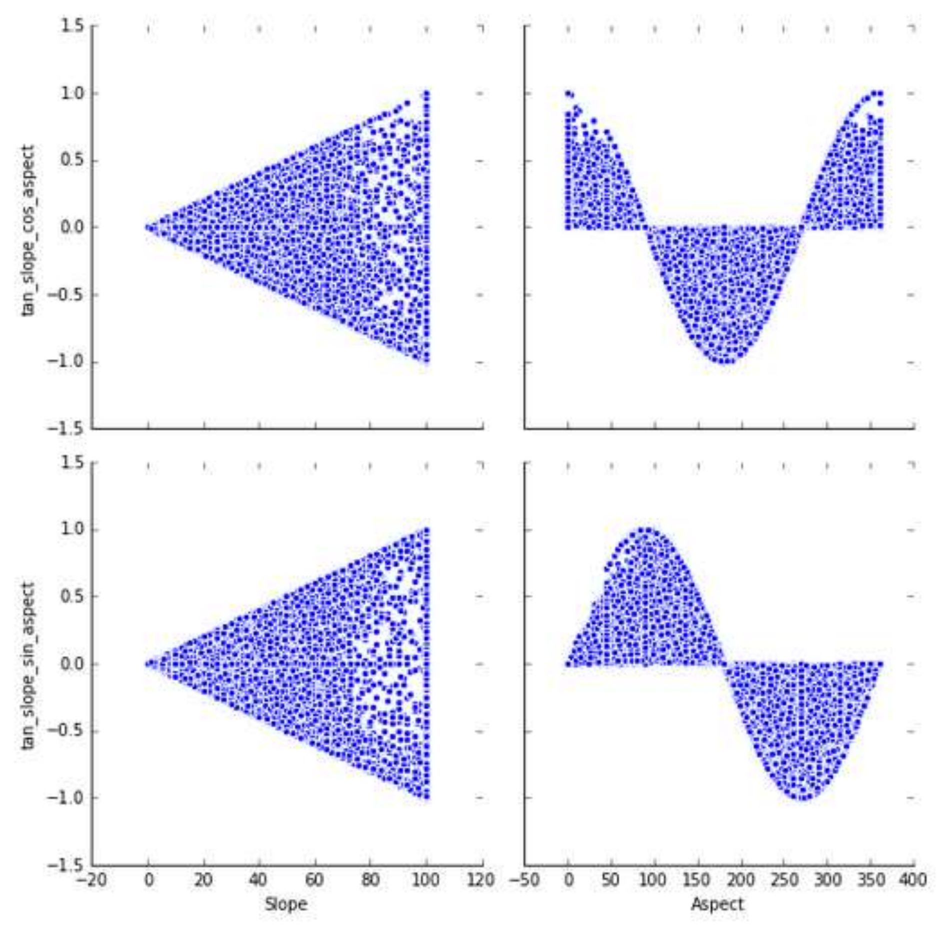


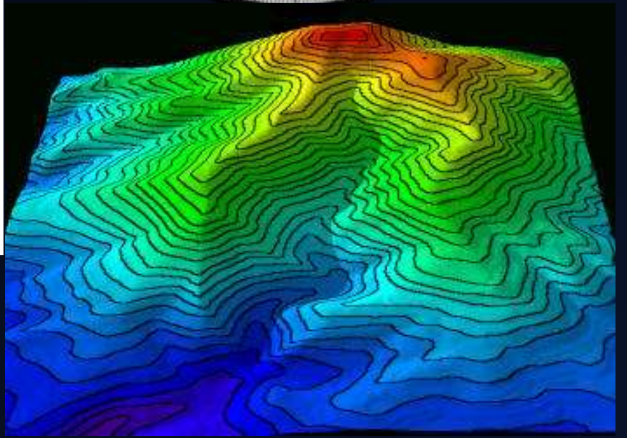


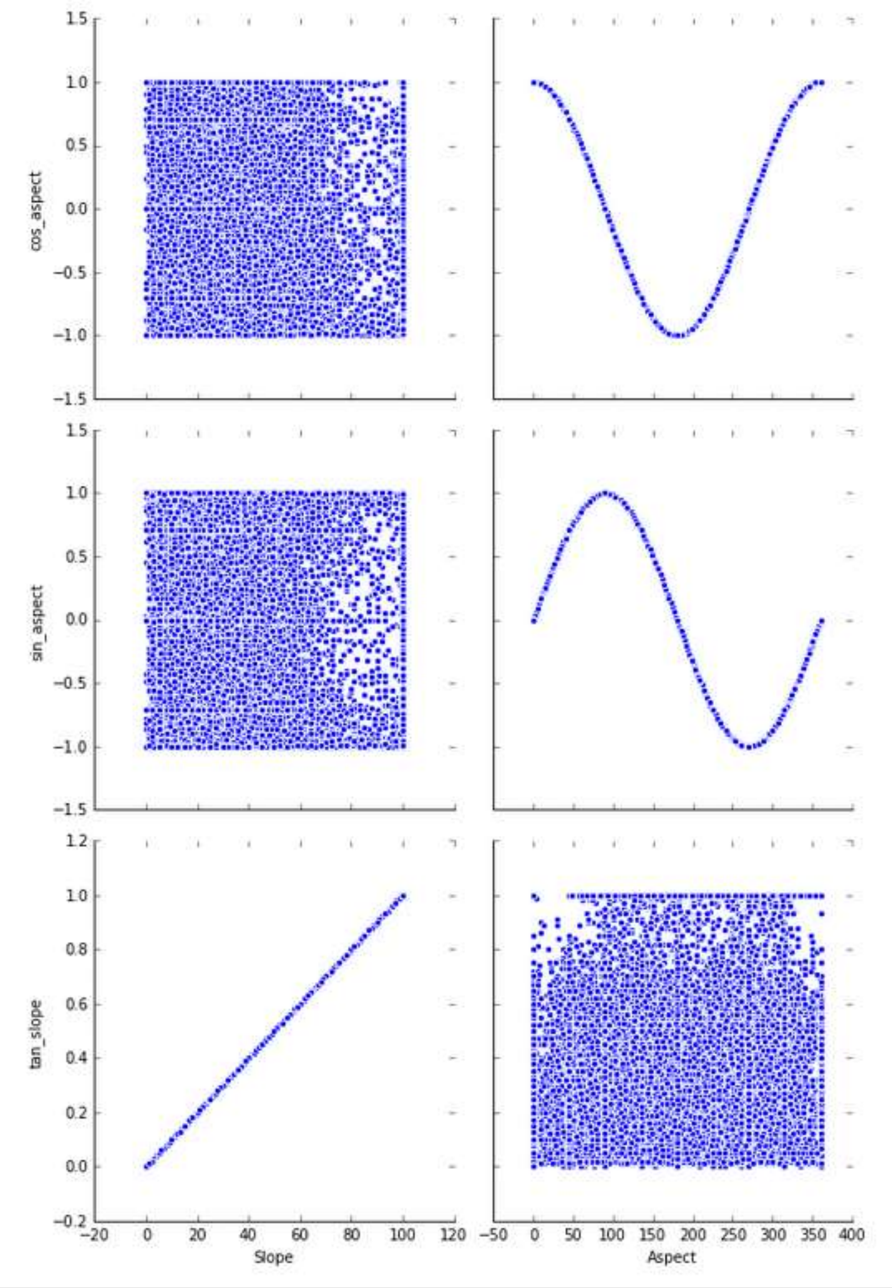




Topography - Transformations

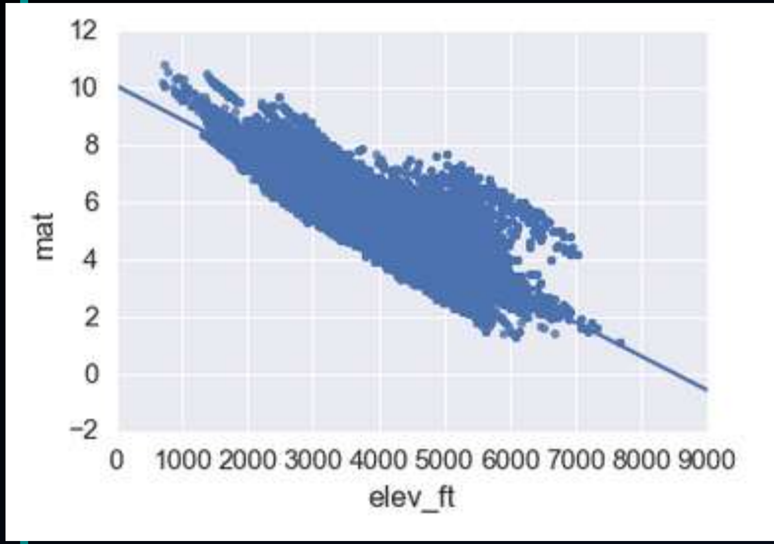


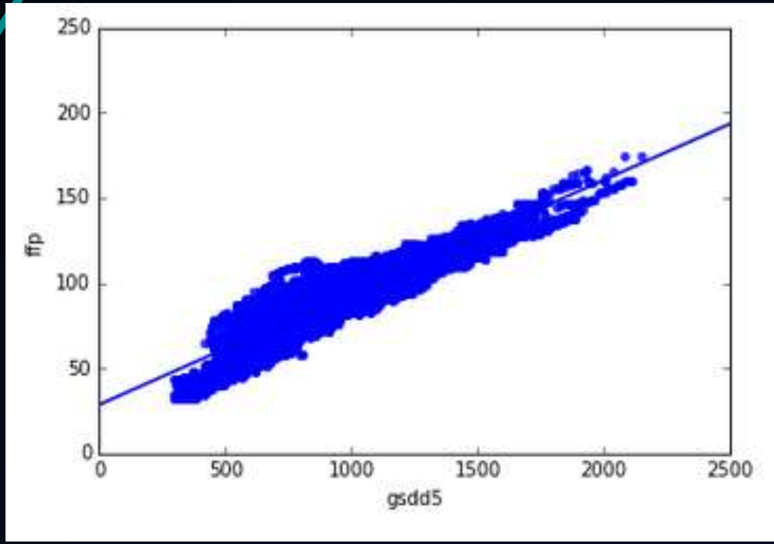


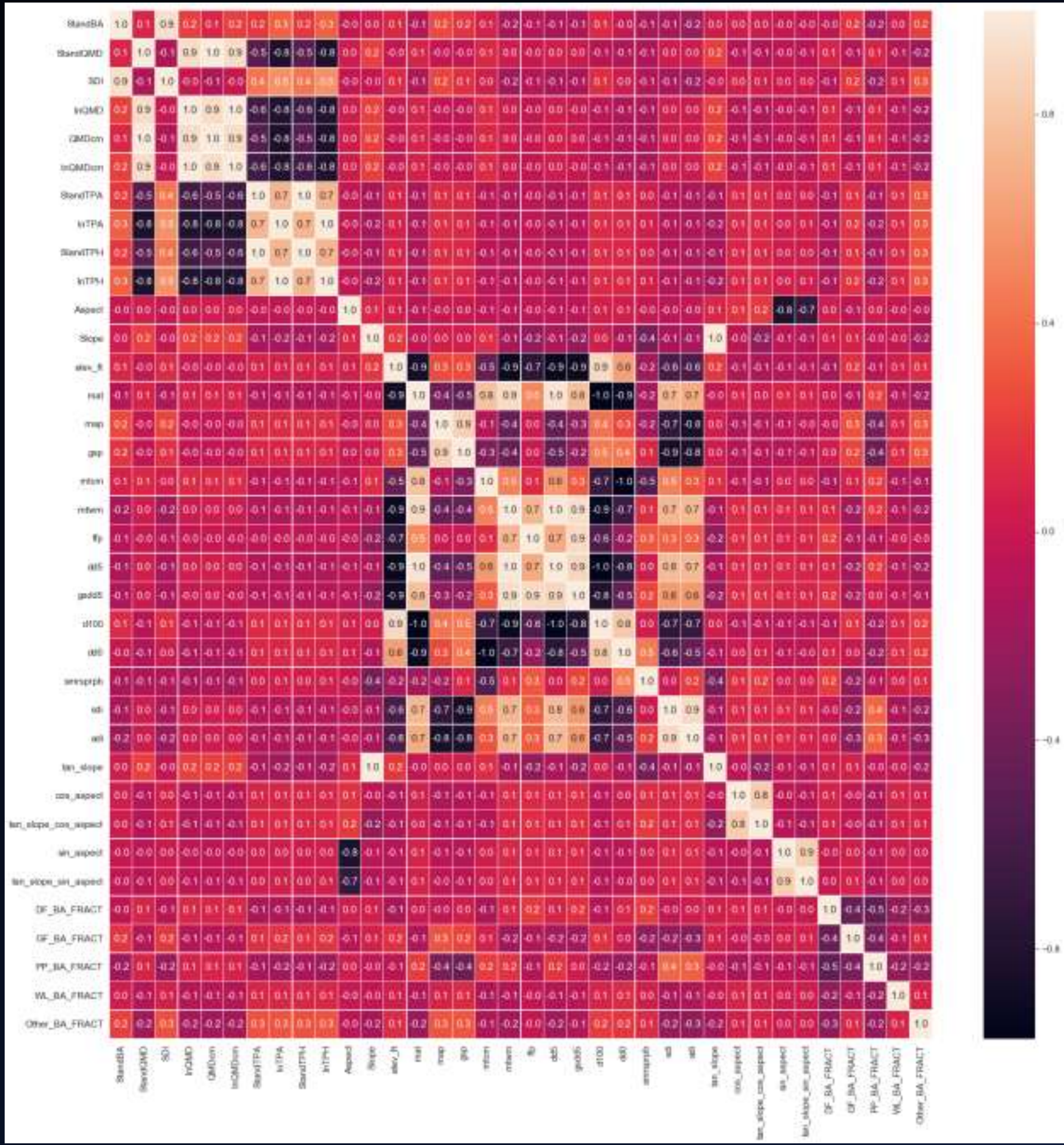


Stage (1976)

Variable Correlation





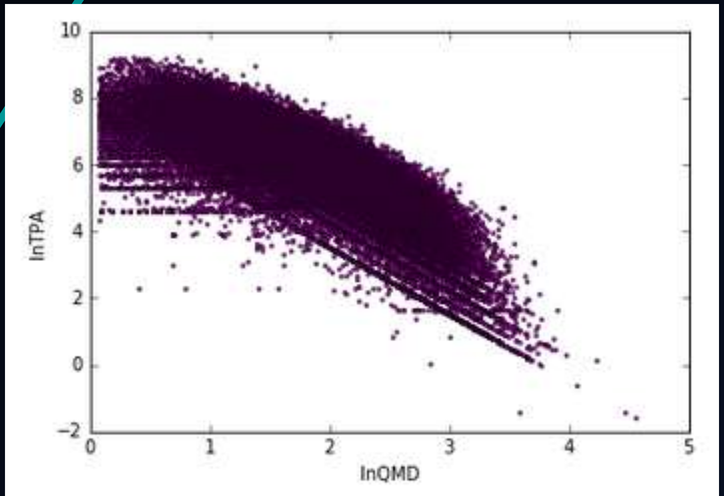


Supervised Learning - Regression

- Log transformation of QMD and TPA
- Dummy code Rock Type and Ash Code
- Drop all directly correlated tree measurements
- Split data into training and testing
- Model Types
  - Linear Regression, Lasso and Ridge
  - CART – Decision Tree Regressor, Random Forest Regressor
    - AdaBoost, Gradient Boosting Regressor, Bagging Regressor

Linear Regression – Predict StandQMD

```
lr.intercept_: -7045.62176661
Training set score: 0.66
Test set score: 0.65
Number of features used: 36
```



Other_BA_FRACT	7047.414139
DF_BA_FRACT	7047.142416
GF_BA_FRACT	7047.116622
WL_BA_FRACT	7047.040406
PP_BA_FRACT	7046.976608
tan_slope	0.156619
smrsprpb	0.145986
mat	0.071586
tan_slope_cos_aspect	0.065483
Rock_Type_Sedimentary	0.027985
Rock_Type_Metasediment	0.022761
adi	0.015666
sin_aspect	0.007457
d100	0.006841
Rock_Type_Intrusive	0.006363
sdi	0.006020
ffp	0.002953
Ash_Code_AshInflu	0.002535
gsp	0.001068
dd5	0.000785
map	0.000125
elev_ft	-0.000015
gsdd5	-0.000071
dd0	-0.000177
Ash_Code_Andisol	-0.001159
Ash_Code_NonAndic	-0.001481
Rock_Type_CaMetased	-0.004457
Rock_Type_Extrusive	-0.004698
mtcm	-0.027546
tan_slope_sin_aspect	-0.032724
cos_aspect	-0.032766
Longitude	-0.044987
Rock_Type_Glacial	-0.047965
Latitude	-0.068330
mtwm	-0.160969
lnTPA	-0.390331

Ridge Regression – Predict StandQMD

```
ridge.intercept_: 1.47492547262
Training set score: 0.66
Test set score: 0.65
Number of features used: 36
```

```
lr.intercept_: -7045.62176661
Training set score: 0.66
Test set score: 0.65
Number of features used: 36
```

Other_BA_FRACT	0.271179
tan_slope	0.156663
smrsprpb	0.141751
mat	0.072584
tan_slope_cos_aspect	0.065286
Rock_Type_Sedimentary	0.028219
Rock_Type_Metasediment	0.022739
adi	0.015117
sin_aspect	0.007527
d100	0.006866
Rock_Type_Intrusive	0.006216
sdi	0.006006
DF_BA_FRACT	0.005198
ffp	0.002925
Ash_Code_AshInflu	0.002686
gsp	0.001056
dd5	0.000785
map	0.000125
elev_ft	-0.000014
gsdd5	-0.000069
dd0	-0.000181
Ash_Code_NonAndic	-0.001101
Ash_Code_Andisol	-0.001584
Rock_Type_Extrusive	-0.004449
Rock_Type_CaMetased	-0.004681
GF_BA_FRACT	-0.020509
mtcm	-0.027799
cos_aspect	-0.032692
tan_slope_sin_aspect	-0.032825
Longitude	-0.045048
Rock_Type_Glacial	-0.048043
Latitude	-0.067596
WL_BA_FRACT	-0.094253
PP_BA_FRACT	-0.160755
mtwm	-0.161415
lnTPA	-0.389893

Lasso Regression – Predict StandQMD

```
lasso.intercept_: 0.447147013876
Training set score: 0.65
Test set score: 0.64
Number of features used: 10
```

ffp	0.000839
map	0.000303
gsp	0.000153
elev_ft	0.000077
dd5	0.000064
Ash_Code_NonAndic	0.000000
tan_slope_cos_aspect	0.000000
mat	0.000000
mtcm	0.000000
mtwm	-0.000000
d100	-0.000000
smrsprpb	-0.000000
sdi	0.000000
adi	0.000000
Ash_Code_AshInflu	-0.000000
cos_aspect	0.000000
tan_slope	0.000000
sin_aspect	-0.000000
tan_slope_sin_aspect	-0.000000
Ash_Code_Andisol	-0.000000
Rock_Type_Sedimentary	0.000000
Rock_Type_Metasediment	-0.000000
Rock_Type_Intrusive	-0.000000
Rock_Type_Glacial	-0.000000
Rock_Type_Extrusive	0.000000
Rock_Type_CaMetased	-0.000000
Other_BA_FRACT	0.000000
WL_BA_FRACT	-0.000000
GF_BA_FRACT	0.000000
DF_BA_FRACT	0.000000
Latitude	-0.000000
gsdd5	-0.000134
dd0	-0.000605
Longitude	-0.028567
PP_BA_FRACT	-0.056050
lnTPA	-0.381808

```
ridge.intercept_: 1.47492547262
Training set score: 0.66
Test set score: 0.65
Number of features used: 36
```

```
lr.intercept_: -7045.62176661
Training set score: 0.66
Test set score: 0.65
Number of features used: 36
```

Decision Tree Regressor– Predict StandQMD

```
Decision Tree regressor score on training set: 1.00
Decision Tree regressor on test set: 0.56
```

lnTPA	0.718698
Latitude	0.028218
DF_BA_FRACT	0.026059
Longitude	0.024624
GF_BA_FRACT	0.014233
PP_BA_FRACT	0.014209
Other_BA_FRACT	0.013516
tan_slope	0.012769
tan_slope_cos_aspect	0.011592
smrsprpb	0.011429
tan_slope_sin_aspect	0.011007
map	0.010530
WL_BA_FRACT	0.010518
gsp	0.008364
ffp	0.008137
elev_ft	0.008101
cos_aspect	0.007680
sdi	0.007642
gsdd5	0.007550
adi	0.007129
sin_aspect	0.006955
dd0	0.006061
mtcm	0.004814
dd5	0.004774
mtwm	0.002961
d100	0.002874
mat	0.002558
Rock_Type_Metasediment	0.001064
Rock_Type_Intrusive	0.001063
Rock_Type_CaMetased	0.000876
Ash_Code_NonAndic	0.000862
Rock_Type_Glacial	0.000829
Ash_Code_AshInflu	0.000816
Ash_Code_Andisol	0.000685
Rock_Type_Sedimentary	0.000538
Rock_Type_Extrusive	0.000266

```python
from sklearn.ensemble import AdaBoostRegressor
adtr=AdaBoostRegressor(DecisionTreeRegressor()).fit(X_train, y_train)
print('AdaDecision Tree regressor score on training set: {:.2f}'
     .format(adtr.score(X_train, y_train)))
print('AdaDecision Tree regressor on test set: {:.2f}'
     .format(adtr.score(X_test, y_test)))
```

```
AdaDecision Tree regressor score on training set: 1.00
AdaDecision Tree regressor on test set: 0.78
```

lnTPA	0.598687
Latitude	0.035090
Longitude	0.032417
DF_BA_FRACT	0.031248
GF_BA_FRACT	0.022556
tan_slope	0.020395
Other_BA_FRACT	0.018274
tan_slope_sin_aspect	0.017667
tan_slope_cos_aspect	0.017637
WL_BA_FRACT	0.016417
PP_BA_FRACT	0.016111
map	0.015663
smrsprpb	0.015038
gsp	0.013798
elev_ft	0.013544
adi	0.011661
sin_aspect	0.011241
cos_aspect	0.011199
ffp	0.011030
sdi	0.010557
gsdd5	0.010529
dd0	0.010135
mtcm	0.007809
dd5	0.006689
mtwm	0.004602
d100	0.004537
mat	0.003868
Rock_Type_Metasediment	0.001836
Rock_Type_Intrusive	0.001636
Ash_Code_NonAndic	0.001563
Ash_Code_AshInflu	0.001386
Rock_Type_Glacial	0.001326
Rock_Type_CaMetased	0.001117
Ash_Code_Andisol	0.001002
Rock_Type_Sedimentary	0.000980
Rock_Type_Extrusive	0.000756

Random Tree Regressor– Predict StandQMD

```
Accuracy of Random Forest regressor on training set: 0.97
Accuracy of Random Forest regressor on test set: 0.79
```

lnTPA	0.716281
Latitude	0.028615
Longitude	0.025533
DF_BA_FRACT	0.025123
GF_BA_FRACT	0.014232
Other_BA_FRACT	0.013403
PP_BA_FRACT	0.013289
tan_slope	0.013201
tan_slope_cos_aspect	0.011995
tan_slope_sin_aspect	0.011471
smrsprpb	0.010716
map	0.010651
WL_BA_FRACT	0.010522
gsp	0.008946
elev_ft	0.008657
ffp	0.007725
adi	0.007654
cos_aspect	0.007500
sin_aspect	0.007351
gsdd5	0.007301
sdi	0.007191
dd0	0.006729
mtcm	0.005147
dd5	0.004690
mtwm	0.003129
d100	0.002974
mat	0.002604
Rock_Type_Metasediment	0.001127
Rock_Type_Intrusive	0.001024
Ash_Code_NonAndic	0.001008
Ash_Code_AshInflu	0.000967
Rock_Type_CaMetased	0.000799
Rock_Type_Glacial	0.000781
Ash_Code_Andisol	0.000626
Rock_Type_Sedimentary	0.000561
Rock_Type_Extrusive	0.000473

```python
from sklearn.ensemble import AdaBoostRegressor
adrfr=AdaBoostRegressor(RandomForestRegressor()).fit(X_train, y_train)
print('AdaDecision Tree regressor score on training set: {:.2f}'
     .format(adrfr.score(X_train, y_train)))
print('AdaDecision Tree regressor on test set: {:.2f}'
     .format(adrfr.score(X_test, y_test)))
```

```
AdaDecision Tree regressor score on training set: 0.99
AdaDecision Tree regressor on test set: 0.79
```

lnTPA	0.552742
Latitude	0.036026
Longitude	0.034869
DF_BA_FRACT	0.033559
GF_BA_FRACT	0.025164
tan_slope	0.022995
tan_slope_cos_aspect	0.020022
tan_slope_sin_aspect	0.019898
Other_BA_FRACT	0.019586
map	0.017925
WL_BA_FRACT	0.017612
PP_BA_FRACT	0.017153
smrsprpb	0.016892
elev_ft	0.015622
gsp	0.015462
adi	0.013306
sin_aspect	0.013170
cos_aspect	0.013077
ffp	0.012819
sdi	0.012442
gsdd5	0.012419
dd0	0.011701
mtcm	0.009220
dd5	0.008050
mtwm	0.005354
d100	0.005078
mat	0.004529
Rock_Type_Metasediment	0.002055
Rock_Type_Intrusive	0.001856
Ash_Code_AshInflu	0.001803
Ash_Code_NonAndic	0.001703
Rock_Type_Glacial	0.001556
Rock_Type_CaMetased	0.001303
Rock_Type_Sedimentary	0.001145
Ash_Code_Andisol	0.001042
Rock_Type_Extrusive	0.000846

Regression Performance Comparison

Model	Training Score (R^2)	Testing Score (R^2)
Linear	0.66	0.65
Lasso	0.66	0.65
Ridge	0.65	0.64
Decision Tree	1.00	0.57
Decision Tree w/ Ada	**1.00**	**0.78**
Random Forest	**0.97**	**0.79**
Random Forest w/ Ada	**0.99**	**0.79**
Bagging Regressor	**0.97**	**0.79**
Gradient Boost	0.76	0.75
K Nearest Neighbor	0.42	0.10

Classification Performance Comparison

Model	Training Accuracy	Test Accuracy	Area Under Curve
Logistic Regression	0.95	0.95	0.80213
Rand Forest Classifier	0.99	0.95	0.79658
Rand Forest Classifier w/ Ada	**1.00**	**0.95**	**0.85680**
KNN Classifier	0.95	0.95	0.69410
GaussianNB	0.82	0.82	0.75723
Decision Tree Classifier	1.00	0.92	0.62728
Decision Tree Classifier w/ Ada	1.00	0.92	0.62705
Neural Network (MLPClassifier)	0.95	0.95	0.43518

Regression on Basal Area with no TPA or QMD

```
from sklearn.ensemble import AdaBoostRegressor
adrfr=AdaBoostRegressor(RandomForestRegressor()).fit(X_train, y_train)
print('AdaDecision Tree regressor score on training set: {:.2f}'
     .format(adrfr.score(X_train, y_train)))
print('AdaDecision Tree regressor on test set: {:.2f}'
     .format(adrfr.score(X_test, y_test)))
```

```
AdaDecision Tree regressor score on training set: 0.95
AdaDecision Tree regressor on test set: 0.44
```

Latitude	0.086128
GF_BA_FRACT	0.078033
map	0.073871
Longitude	0.070420
DF_BA_FRACT	0.061130
Other_BA_FRACT	0.058203
tan_slope_sin_aspect	0.048448
tan_slope_cos_aspect	0.047401
WL_BA_FRACT	0.040783
tan_slope	0.039022
elev_ft	0.034497
gsp	0.034357
adi	0.031354
smrsprpb	0.030109
sin_aspect	0.027685
sdi	0.027187
gsdd5	0.026676
cos_aspect	0.026394
PP_BA_FRACT	0.026155
dd0	0.024480
ffp	0.022505
dd5	0.018546
mtcm	0.015422
mtwm	0.009947
d100	0.009258
mat	0.008066
Ash_Code_NonAndic	0.003466
Ash_Code_AshInflu	0.003354
Rock_Type_Intrusive	0.003271
Rock_Type_Metasediment	0.003256
Rock_Type_CaMetased	0.002928
Rock_Type_Glacial	0.002389
Rock_Type_Extrusive	0.002123
Ash_Code_Andisol	0.001991
Rock_Type_Sedimentary	0.001145

Many small trees or a few big trees?

Tree measurements are necessary

Association

```
treed['NS_Aspect']=pd.cut(treed.cos_aspect,bins=[-1,0,1],labels=["South","North"])
treed=pd.get_dummies(treed,columns=["NS_Aspect"])
```

```
treed['EW_Aspect']=pd.cut(treed.sin_aspect,bins=[-1,0,1],labels=["West","East"])
treed=pd.get_dummies(treed,columns=["EW_Aspect"])
```

- Dummy code categorical variables
- Bin all other variables
  - Species BA Fractions – 0%, 25%, 50%, 75%, 100%
  - Climate – quantile cut of Low, Med and High
  - Aspect – South or North, East or West
  - Slope – Flat, Slight slope, Steep, Very steep
  - Elevation – 1000 ft increments
- Find Frequent Item sets, generate rules, explore

```
treed['temp']=pd.qcut(treed.mat,3,labels=["low","med","high"])
treed=pd.get_dummies(treed,columns=["temp"])
```

```
treed['precip']=pd.qcut(treed.map,3,labels=["low","med","high"])
treed=pd.get_dummies(treed,columns=["precip"])
```

```
treed['gs_precip']=pd.qcut(treed.gsp,3,labels=["low","med","high"])
treed=pd.get_dummies(treed,columns=["gs_precip"])
```

```
treed['temp_cold_month']=pd.qcut(treed.mtcm,3,labels=["low","med","high"])
treed=pd.get_dummies(treed,columns=["temp_cold_month"])
```

```
treed['temp_warm_month']=pd.qcut(treed.mtwm,3,labels=["low","med","high"])
treed=pd.get_dummies(treed,columns=["temp_warm_month"])
```

```
treed['Slope']=pd.cut(treed.Slope,bins=[0,10,30,50,101],labels=["flat","SlightSlope","Steep","VerySteep"])
treed=pd.get_dummies(treed,columns=["Slope"])
```

Association

- Mostly found climate related associations

```
lowADIrules=rules[ rules['consequents'] == {'a_dry_index_low'} ]
lowADIrules.sort_values(['lift'],ascending=False)
```

	antecedents	consequents	antecedent support	consequent support	support	confidence	lift	leverage	conviction
33746	(Slope_Steep, d100_high, precip_high)	(a_dry_index_low)	0.071656	0.333341	0.071656	1.000000	2.999935	0.047770	inf
1693	(elevation_btw_4_5thou, s_dry_index_low, preci...	(a_dry_index_low)	0.098998	0.333341	0.098998	1.000000	2.999935	0.065998	inf
13044	(dd5_low, Ash_Code_NonAndic, precip_high)	(a_dry_index_low)	0.062044	0.333341	0.062044	1.000000	2.999935	0.041362	inf
14624	(dd5_low, d100_high, precip_high)	(a_dry_index_low)	0.154731	0.333341	0.154731	1.000000	2.999935	0.103153	inf

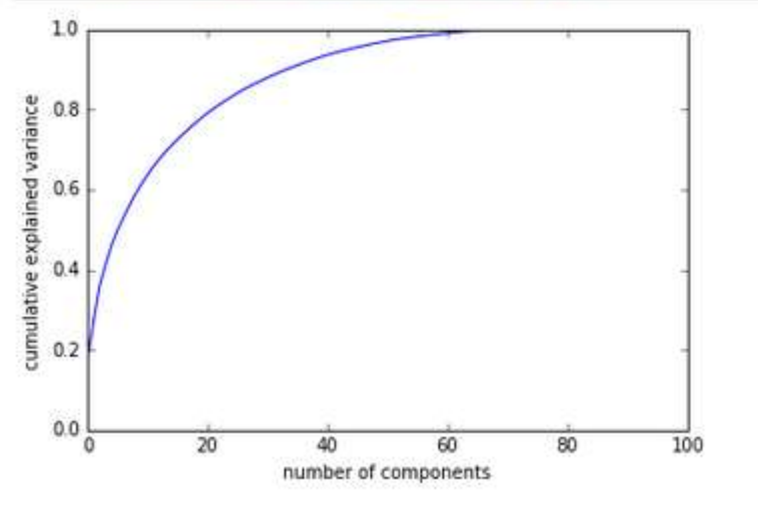
```
highADIrules=rules[ rules['consequents'] == {'a_dry_index_high'} ]
highADIrules.sort_values(['lift'],ascending=False)
```

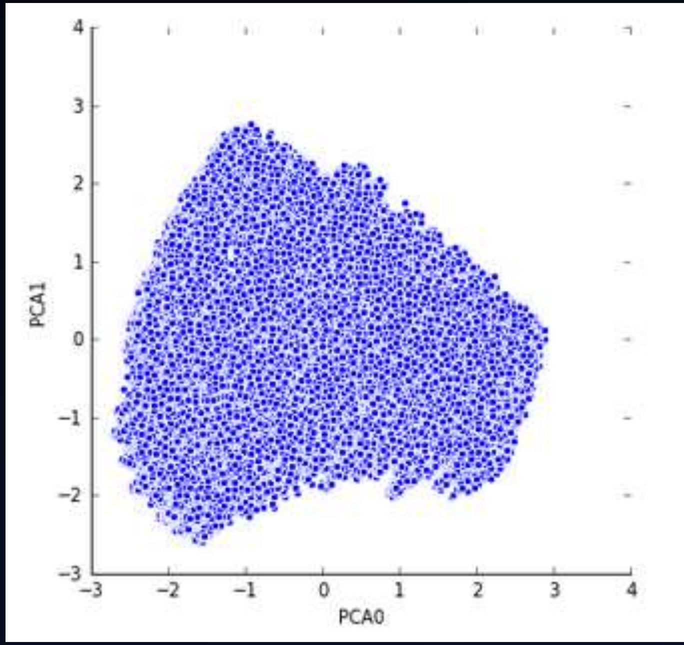
	antecedents	consequents	antecedent support	consequent support	support	confidence	lift	leverage	conviction
17583	(temp_warm_month_high, precip_low, Ash_Code_As...	(a_dry_index_high)	0.080694	0.33333	0.080694	1.000000	3.000032	0.053796	inf
8246	(dd5_high, precip_low, Rock_Type_Glacial)	(a_dry_index_high)	0.050473	0.33333	0.050473	1.000000	3.000032	0.033649	inf
28822	(gsdd5_high, precip_low, Rock_Type_Glacial)	(a_dry_index_high)	0.053071	0.33333	0.053071	1.000000	3.000032	0.035381	inf
29013	(dd5_high, precip_low, Ash_Code_AshInflu)	(a_dry_index_high)	0.078573	0.33333	0.078573	1.000000	3.000032	0.052382	inf
4164	(temp_warm_month_high, precip_low, gs_precip_low)	(a_dry_index_high)	0.159267	0.33333	0.159267	1.000000	3.000032	0.106178	inf
29108	(temp_warm_month_high, temp_cold_month_high, p...	(a_dry_index_high)	0.054705	0.33333	0.054705	1.000000	3.000032	0.036470	inf
29320	(dd5_high, precip_low)	(a_dry_index_high)	0.165610	0.33333	0.165610	1.000000	3.000032	0.110407	inf

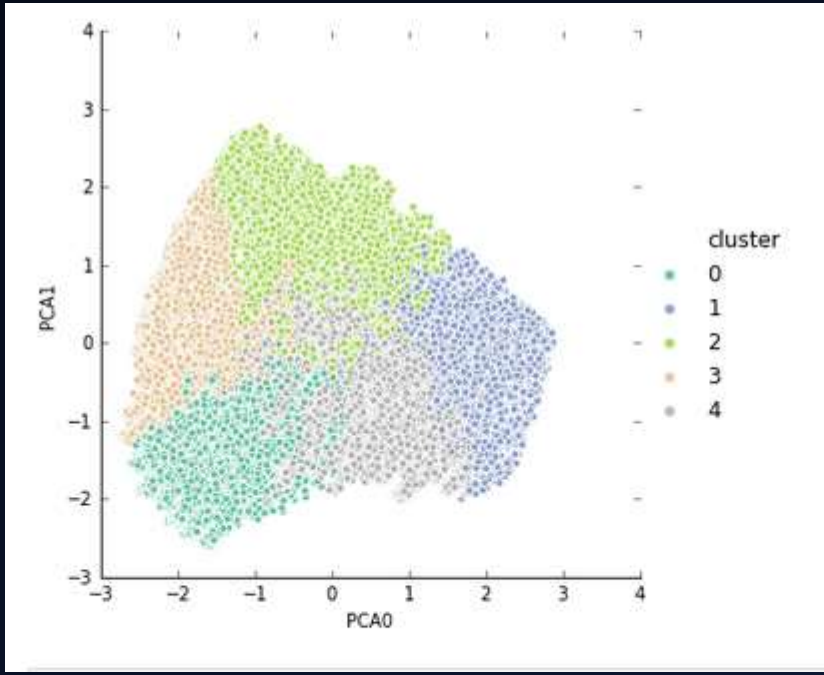
Clustering

- Data did not seem suited for clustering analysis

```
from sklearn.decomposition import PCA
pca = PCA().fit(treed)
plt.plot(np.cumsum(pca.explained_variance_ratio_))
plt.xlabel('number of components')
plt.ylabel('cumulative explained variance');
```

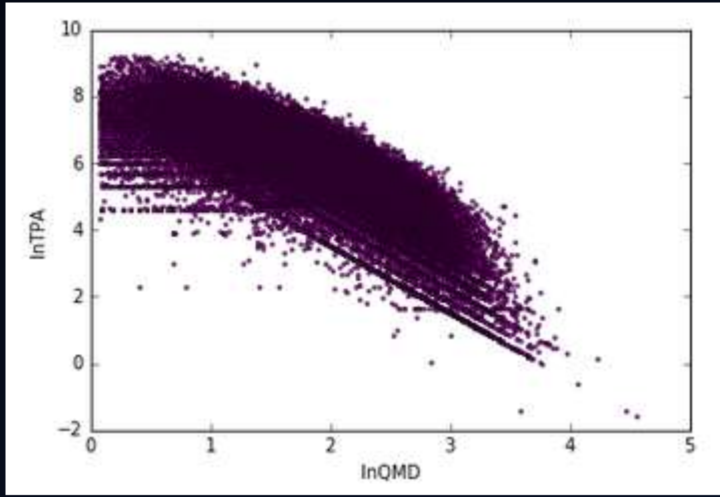






Stand Density Index

- Reineke (1933) – Stand Density Index
  - Outer boundary of lnQMD and lnTPA
  - Found slope was constant, -1.605
  - Intercept changed with species
  - maxSDI = TPA at QMD of 10 in (25.4 cm)



Apr. 1, 1933 Stand-Density Index for Even-Aged Forests 629

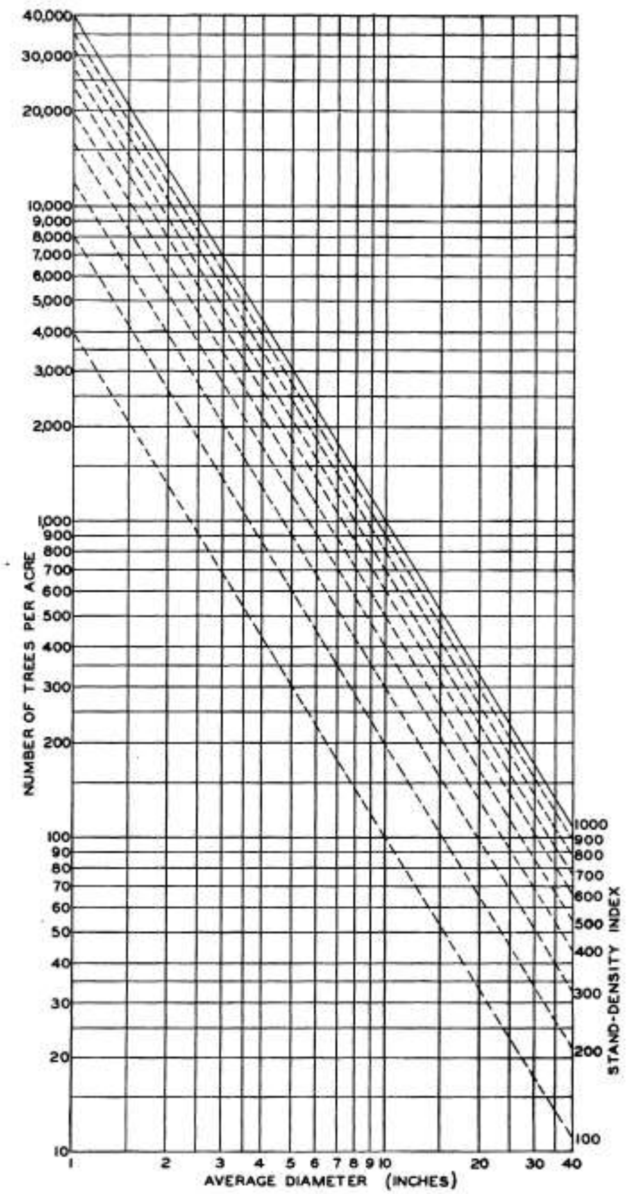


FIGURE 1.—Reference curve (solid line). The stand-density index of each of the broken-line parallel curves is the number of trees indicated by each at 10 inches average diameter

Quantile Regression

- First find median regression line (q=0.5)
- Then find quantile of interest (95%-99%)

```
mod = smf.quantreg('lnTPH ~ lnQMDcm', trees, groups=trees["Ash_Code"])   #lnQMDcm
res = mod.fit(q=.5) #, vcov='robust', kernal='epa', bandwidth='hsheather'
print(res.summary())
```

```
                         QuantReg Regression Results
==============================================================================
Dep. Variable:                  lnTPH   Pseudo R-squared:               0.3829
Model:                       QuantReg   Bandwidth:                     0.09308
Method:                 Least Squares   Sparsity:                        2.154
Date:                Wed, 21 Nov 2018   No. Observations:                92386
Time:                        10:16:46   Df Residuals:                    92384
                                        Df Model:                            1
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept     11.1635      0.015    748.507      0.000      11.134      11.193
lnQMDcm       -1.6210      0.005   -313.338      0.000      -1.631      -1.611
==============================================================================
```

```
quantiles = np.arange(.95, .99, .01)
def fit_model(q):
    res = mod.fit(q=q)
    return [q, res.params['Intercept'], res.params['lnQMDcm']] + \
            res.conf_int().loc['lnQMDcm'].tolist()

models = [fit_model(x) for x in quantiles]
models = pd.DataFrame(models, columns=['q', 'a', 'b','lb','ub'])

ols = smf.ols('lnTPH ~ lnQMDcm', trees).fit()
ols_ci = ols.conf_int().loc['lnQMDcm'].tolist()
ols = dict(a = ols.params['Intercept'],
           b = ols.params['lnQMDcm'],
           lb = ols_ci[0],
           ub = ols_ci[1])

print(models)
print(ols)
```

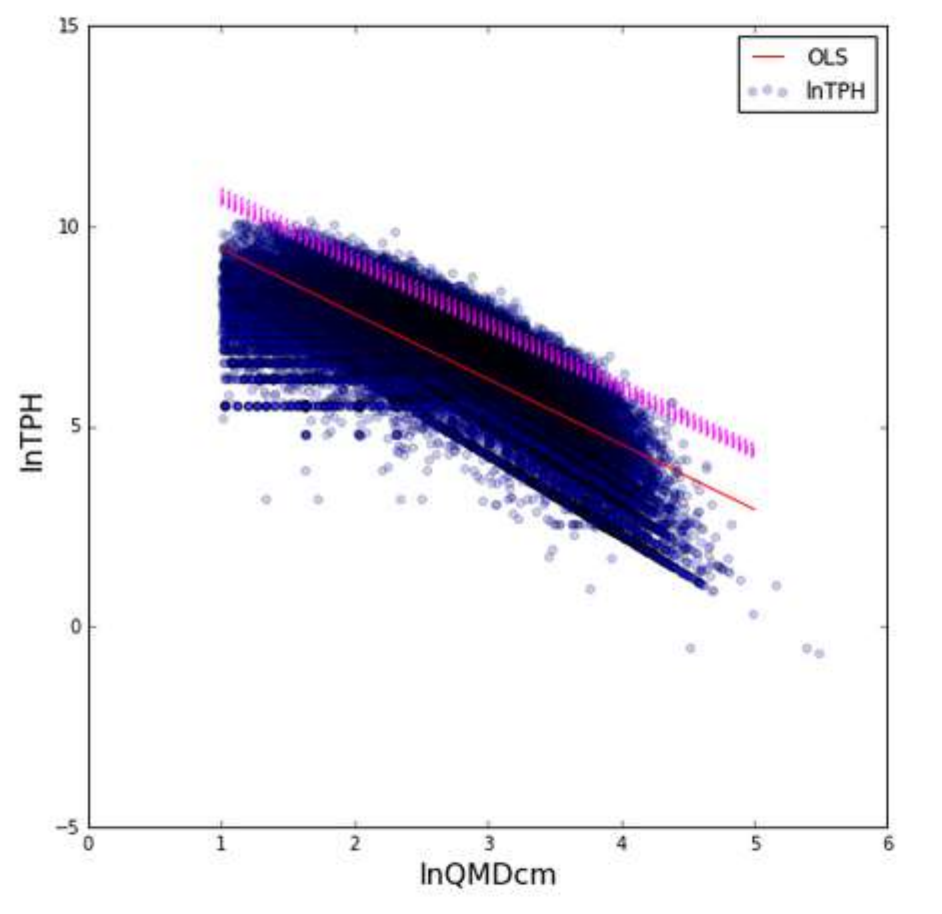
```
      q          a         b        lb        ub
0  0.95  12.149182 -1.580227 -1.587096 -1.573358
1  0.96  12.201068 -1.579904 -1.586958 -1.572850
2  0.97  12.262594 -1.579376 -1.586837 -1.571916
3  0.98  12.367274 -1.587021 -1.595094 -1.578948
4  0.99  12.506766 -1.595745 -1.604812 -1.586678
{'a': 11.062999725583264, 'b': -1.6269061507989382, 'lb': -1.6351082889892656, 'ub': -1.6187040126086107}
```

Quantile Regression

$$lnTPH = \beta_0 + \beta_1 lnQMD$$

Solve for index 25.4 cm

q	a	b	lb	ub
0.99	12.506766	-1.595745	-1.604812	-1.586678



$$lnTPH = 12.506766 - 1.595745ln(25.4)$$

maxSDI = 1,548 TPH (627 TPA)

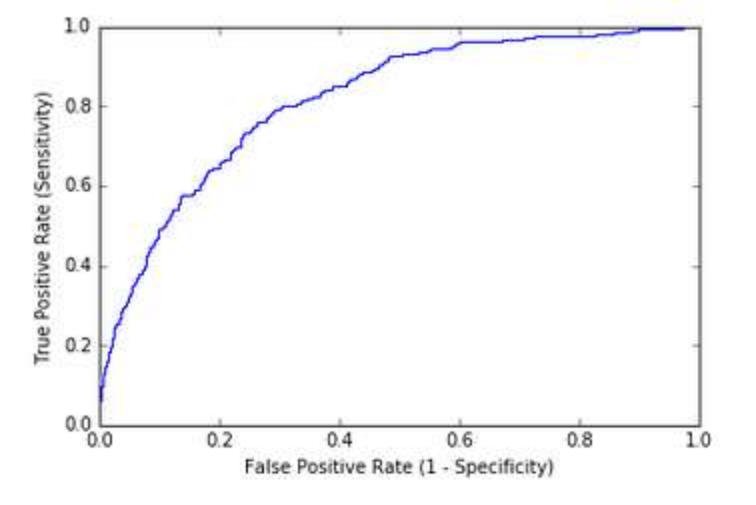
Predict if stand will fall above or below maxSDI

- Add new column based on 99% quantile maxSDI equation
  - If standTPH > then falls above, if standTPH< then falls below
  - Above or Below ==> map as 1 and 0
- Logistic Regression
  - Remove all tree variables, leaving only climate, topography, lat/long, BA_Fract

```
treesdimax['Above_Below'].value_counts()

0    91461
1      925
Name: Above_Below, dtype: int64
```

```
Accuracy Score: 0.99022
AUC: 0.81873
[[22868     4]
 [  222     3]]
```



Conclusion

- Tree density is important to forest management decisions
- This was a regression analysis
- Tree measurements are important
- Climate, topography and species mixing affects stand dynamics
- Quantile regression is just one tool to get at maximumSDI

Future

- What stands line on/near max SDI line? Continue logistic regression
  - Association of each at quantile?
- Figure out variable importance in quantile regression
- Explore variable correlation further
- Spatial analysis using lat/long

https://www.uidaho.edu/cnr

Selected References

- Reineke, L.H. 1933. Perfecting a stand-density index for even-aged forests. Journal of Agricultural Research 46:627-638.
- Kimsey, M.J., Shaw, T., and Coleman, M. 2018. Site Sensitive Maxmimum Stand Density Index Models for Mixed Confier Stands Scross the Inland Northwest, USA. *submitted*
- Stage, A.R., 1976. An Expression for the Effect of Aspect, Slope, and Habitat Type on Tree Growth Note by A. R. Stage. For. Sci. 22, 457–460.
- VanderSchaaf, C.L. and Burkhart, H.E., 2007. Comparison of Methods to Estimate Reineke's Maximum Size-Density Relationship Species Boundary Line Slope. Forest Science 53(3)

A Density Management Diagram for Longleaf Pine Stands with Application to Red-Cockaded Woodpecker Habitat

John D. Shaw and James N. Long

Top Species by Expenditure (Cumulative FY1991-FY2014)		
Rank	**Species**	**Expenditure**
1	Red-Cockaded Woodpecker	$179.7 million
2	Desert Tortoise	$125.2 million
3	San Clemente Loggerhead Shrike	$39.9 million
4	Mexican Spotted Owl	$23.4 million
5	Black-Capped Vireo	$21.9 million
6	California Least Tern	$20.6 million
7	Western Snowy Plover	$19.8 million
8	Bald Eagle	$18.8 million
	Florida Scrub Jay	$18.6 million
	den-Cheeked Warbler	$18.5 million

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