Biomass_Regression_All_Data_three_vars

May 24, 2017

This script builds a regression model to predict biomass based on lidar metrics. Data points at all scan angles are used.

In [1]:
```
%matplotlib inline
import pandas, statsmodels, numpy, math, scipy.stats
from matplotlib import pyplot as plt
#from __future__ import division
from numpy import log as ln
import warnings
warnings.filterwarnings('ignore')
```

Data Prep Notes: The clipped las files were imported into ArcMap and converted to point shapefiles. The point shapefiles were each joined to the plot discs to add columns for plot ID and biomass. The joined points were then exported to .csvs in the directory `CSVs_ClippedAndJoined`. The order of fields should run: x, y, z(height), angle, plotID, biomass. Points from discs with no associated biomass were dropped.

In [2]:
```
firstfile = r"D:\Users\jkelly\CSVs_ClippedAndJoined\first_all_clipped_and_j
first = pandas.read_csv(firstfile, header=0)
lastfile = r"D:\Users\jkelly\CSVs_ClippedAndJoined\last_all_clipped_and_joi
last = pandas.read_csv(lastfile, header=0)
groundfile = r"D:\Users\jkelly\\CSVs_ClippedAndJoined\Grounds_clipped_and_j
ground = pandas.read_csv(groundfile, header=0)
```

In [3]:
```
first.columns=['X1','Y1','X','Y','height','angle','PlotID','biomass']
del first['X1']
del first['Y1']
last.columns=['X1','Y1','X','Y','height','angle','PlotID','biomass']
del last['X1']
del last['Y1']
ground.columns=['X1','Y1','X','Y','height','angle','PlotID','biomass']
del ground['X1']
del ground['Y1']
```

In [4]:
```
first=first.sort('PlotID')
last=last.sort('PlotID')
ground=ground.sort('PlotID')
```

The following function produces a series of metrics summarizing the lidar height measurements on each inventory plot for first, last and ground returns: mean, coefficient of variation, 10th, 50th and 90th deciles for height and density fraction, following Gobakken et al, 2012.

```
In [5]: def heightstats(SERIES, I):
            # function to compute "cloud metrics" on a height or elevation series
            totalechoes = len(SERIES)
            MEAN = numpy.mean(SERIES)
            CV = scipy.stats.variation(SERIES)
            #coeff of var (ratio of biased standard dev to mean)
            H10 = numpy.percentile(SERIES, 10)
            H10series = SERIES[SERIES > H10]
            H10count = len(H10series)
            D10 = H10count/totalechoes
            # "canopy density" = the proportion of laser
            # hits above fraction to total # of echoes
            # described in Gobakken et al. 2012, p. 447
            H50 = numpy.percentile(SERIES, 50)
            H50series = SERIES[SERIES > H50]
            H50count = len(H50series)
            D50 = H50count/totalechoes
            H90 = numpy.percentile(SERIES, 90)
            H90series = SERIES[SERIES > H90]
            H90count = len(H90series)
            D90 = H90count/totalechoes

            outlist = [I, MEAN, CV, H10, H50, H90, D10, D50, D90]

            return(outlist)
```

The next section builds a dataframe associating each plot with its biomass, elevation, and computed summary statistics. The plot-level biomass numbers given in the data are in units of Mg/ha, which are here converted to the actual mass on a the 0.04 ha plots.

```
In [6]: heightlist = []
        for i in first.PlotID.unique():
            # subset corresponding to ith plot id
            L = last[last.PlotID == i]
            F = first[first.PlotID == i]
            G = ground[ground.PlotID == float(i)]

            # just height column from subset
            Last_heightseries = L.height
            First_heightseries = F.height
            elevseries = G.height

            # just biomass column from subset
            biomass = L.biomass*0.04
            # the 0.04 is to convert Mg/ha to Mg/400m^2 plot
```

```python
            if len(Last_heightseries)>=1 and len(First_heightseries)>=1:
                # ^^^  gets rid of empty height series

                # fetch "cloud metrics"
                Last_stats = heightstats(Last_heightseries, i)
                First_stats = heightstats(First_heightseries, i)

                if len(elevseries) > 0:
                    Gmean = numpy.mean(elevseries)
                else: Gmean = -1

                # build a list for next row in dataframe
                stats = Last_stats
                for item in First_stats:
                    stats.append(item)
                b = numpy.mean(biomass)
                stats.append(b)
                stats.append(Gmean)
                if b>0: heightlist.append(stats) #gets rid of NaN


        heightarray = numpy.array(heightlist)     # build the dataframe
        df = pandas.DataFrame(heightarray)
        columnlist = ['PlotID', 'L_mean', 'L_cv', 'L_h10', 'L_h50',
                      'L_h90', 'L_d10', 'L_d50', 'L_d90', 'PlotID_again',
                      'F_mean', 'F_cv', 'F_h10', 'F_h50', 'F_h90', 'F_d10',
                      'F_d50', 'F_d90', 'Biomass', 'elev']

        df.columns = columnlist
        # delete duplicate columns
        del df['PlotID_again']
```

In [19]:
```python
df.describe()
```

Out[19]:

	PlotID	L_mean	L_cv	L_h10	L_h50	L_
count	154.000000	154.000000	154.000000	154.000000	154.000000	154.000
mean	93.116883	2.882272	1.508728	0.002792	0.931591	8.772
std	50.724934	1.713424	0.433447	0.012153	1.381876	4.358
min	2.000000	0.206482	0.666363	0.000000	0.040000	0.240
25%	55.250000	1.588867	1.202409	0.000000	0.140000	5.492
50%	96.000000	2.550631	1.426635	0.000000	0.270000	8.385
75%	135.750000	4.170365	1.715680	0.000000	0.993750	11.716
max	178.000000	7.915523	2.857065	0.120000	6.380000	19.804

	L_d10	L_d50	L_d90	F_mean	...	F_
count	154.000000	154.000000	154.000000	154.000000	...	154.000
mean	0.842814	0.496161	0.100046	11.446377	...	3.730

```
std       0.039673    0.005197    0.000534    3.564578     ...         4.210
min       0.729089    0.468468    0.098137    1.220464     ...         0.000
25%       0.820128    0.494567    0.099872    9.087133     ...         0.101
50%       0.847703    0.498274    0.100080   10.943383     ...         1.979
75%       0.873282    0.499613    0.100323   13.433398     ...         6.494
max       0.899889    0.500000    0.102804   21.774059     ...        16.210

              F_h50       F_h90       F_d10       F_d50       F_d90       Biom
count  154.000000  154.000000  154.000000  154.000000  154.000000  154.000
mean    12.367338   17.210695    0.896085    0.499204    0.099676    5.752
std      4.041083    3.812580    0.013928    0.002669    0.000431    2.823
min      0.070000    4.961000    0.789216    0.468215    0.097949    0.912
25%      9.820000   14.464000    0.898350    0.499200    0.099473    3.642
50%     12.105000   16.930000    0.899754    0.499585    0.099782    5.196
75%     15.020000   19.537500    0.899880    0.499881    0.100000    6.925
max     23.000000   26.640000    0.900173    0.500000    0.100654   17.463

               elev        Yhat       resid
count  154.000000  154.000000  154.000000
mean     3.118651    5.673073    0.079899
std      1.874205    2.902675    1.235315
min      0.194529    2.434643   -3.777283
25%      1.573210    3.766871   -0.531332
50%      2.635528    4.686643    0.058783
75%      4.435760    6.479547    0.715873
max      8.226820   19.683735    4.903069

[8 rows x 21 columns]
```

Then a regression model is developed and its statistics are displayed. Though Gobakken et al developed different models for different forest classes, in each case both the response and explanatory variables were log-transformed. However, an exhaustive trial of all one-, two- and three-variable combinations revealed the "best" model –in terms of R^2, as well as AIC compared on identical variables – to be one which log-transforms the 50th percentile cutoff for height of first returns and the mean of last returns, but also includes the untransformed value for 50th percentile. To rule out (multi) collinearity, models with a condition number greater than 50 were excluded from consideration.

```
In [60]: def formula_tester(VAR1, VAR2, VAR3):
             try:
                 #three variables three logs (not a contender)
                 #Formula = "ln(Y) ~ 1 + ln(" + VAR1 + ") + ln(" + VAR2 + ") + ln("

                 # three variables two logs - best model so far
                 Formula = "ln(Y) ~ 1 + ln(" + VAR1 + ") + ln(" + VAR2 + ") + " + V

                 # three variables one log -- good
                 #Formula = "ln(Y) ~ 1 + ln(" + VAR1 + ") + " + VAR2 + " + " + VAR3
```

```
                # three variables no log
                #Formula = "ln(Y) ~ 1 + " + VAR1 + " + " + VAR2 + " + " + VAR3

                # one variable log (not a contender)
                #Formula = "ln(Y) ~ 1 + ln( " + VAR1 + ")"

                # two variables two logs (not a contender)
                #Formula = "ln(Y) ~ 1 + ln( " + VAR1 + ") + " + "ln( " + VAR2 + ")

                #two variables one log -- not bad
                #Formula = "ln(Y) ~ 1 + ln(" + VAR1 + ") +" + VAR2

                result = sm.ols(formula=Formula, data=df).fit()
                if result.condition_number < 50 and result.rsquared>0.77:
                    return(result.rsquared, result.aic, VAR1, VAR2, VAR3)
                    #return(result.rsquared, result.aic, VAR1, VAR2) #two variable
                else:
                    return()
            except:
                return()
```

In [61]:
```
import statsmodels.formula.api as sm

Y = df['Biomass']
variable_list = ["df['F_mean']","df['L_mean']","df['F_cv']","df['L_cv']",
                 "df['F_h10']","df['L_h10']","df['F_h50']","df['L_h50']",
                 "df['F_h90']","df['L_h90']","df['F_d10']","df['L_d10']",
                 "df['F_d50']","df['L_d50']","df['F_d90']","df['L_d90']",
                 "df['elev']"]

regression_parameters_list = []
for variable1 in variable_list:
    for variable2 in variable_list:
        for variable3 in variable_list:
            regression_parameters_list.append(formula_tester(variable1, va
        parameters = formula_tester(variable1, variable2, variable3)

        #remove empty tuples and report best r-squareds
        if len(parameters) > 1 and parameters[0]>0.7:
            regression_parameters_list.append(parameters)
sorted(filter(lambda a: a != (), regression_parameters_list))
#regression_parameters_list
```

Out[61]:
```
[(0.7765797723388364 6,
  -12.290081906506089,
  "df['F_h50']",
  "df['F_h50']",
  "df['F_h50']"),
```

```
 (0.78999759828180161,
  -19.828142703340745,
  "df['F_h50']",
  "df['elev']",
  "df['F_h50']"),
 (0.78999759828180161,
  -19.828142703340745,
  "df['elev']",
  "df['F_h50']",
  "df['F_h50']"),
 (0.79410704800067033,
  -22.871580665461238,
  "df['F_h50']",
  "df['L_mean']",
  "df['F_h50']"),
 (0.79410704800067033,
  -22.871580665461181,
  "df['L_mean']",
  "df['F_h50']",
  "df['F_h50']")]
```

This was the best regression model with 3 independent variables, condition number < 50.

```
In [24]: var1 = df['L_mean']
         var2 = df['F_h50']
         var3 = df['F_h50']

         var1str = "ln(df['L_mean'])"
         var2str = "ln(df['F_h50'])"
         var3str = "df['F_h50']"

         Formula = "ln(Y) ~ 1 + " + var1str + " + " + var2str + " + " + var3str
         result = sm.ols(formula=Formula, data=df).fit()
         print(result.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                  ln(Y)   R-squared:                       0.794
Model:                            OLS   Adj. R-squared:                  0.790
Method:                 Least Squares   F-statistic:                     192.8
Date:                Tue, 16 May 2017   Prob (F-statistic):           2.92e-51
Time:                        11:38:07   Log-Likelihood:                 15.436
No. Observations:                 154   AIC:                            -22.87
Df Residuals:                     150   BIC:                            -10.72
Df Model:                           3
Covariance Type:            nonrobust
================================================================================
                     coef    std err          t      P>|t|      [95.0% Conf. Int.
--------------------------------------------------------------------------------
```

```
Intercept              0.6916      0.064     10.811      0.000          0.565      0.81
ln(df['L_mean'])       0.1349      0.038      3.573      0.000          0.060      0.21
ln(df['F_h50'])       -0.3184      0.037     -8.532      0.000         -0.392     -0.24
df['F_h50']            0.1284      0.009     14.769      0.000          0.111      0.14
==============================================================================
Omnibus:                       54.093   Durbin-Watson:                   1.804
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              271.744
Skew:                          -1.155   Prob(JB):                     9.81e-60
Kurtosis:                       9.084   Cond. No.                         49.3
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly sp
```

```
In [34]: result.bse
```

```
Out[34]: Intercept            0.063969
         ln(df['L_mean'])     0.037759
         ln(df['F_h50'])      0.037320
         df['F_h50']          0.008696
         dtype: float64
```

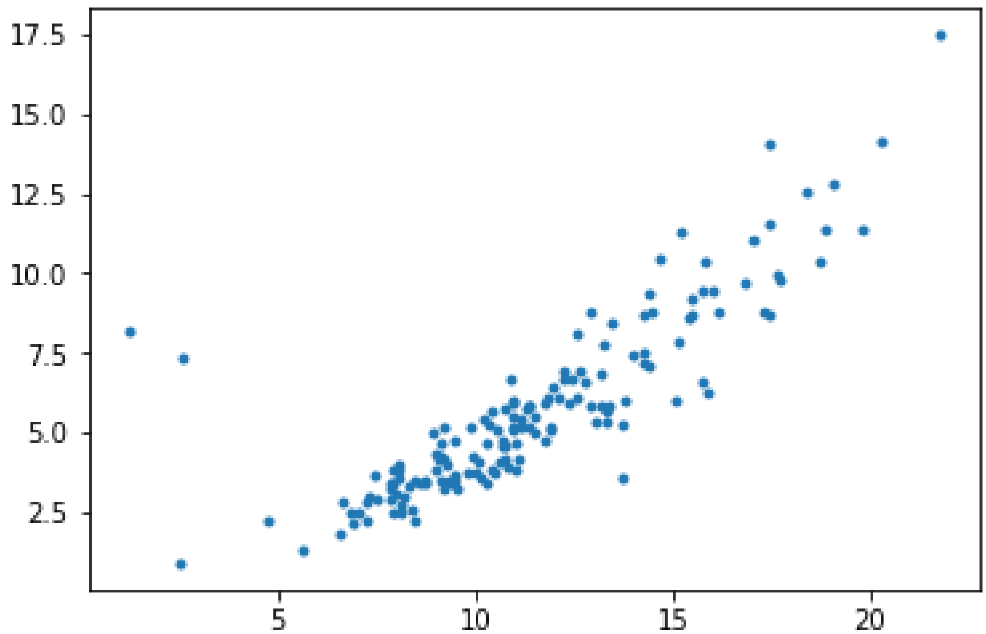
```
In [25]: intercept = result.params[0]
         b1 = result.params[1]
         b2 = result.params[2]
         b3 = result.params[3]
         intercept, b1, b2, b3
```

```
Out[25]: (0.69157584075617873,
          0.1349292756691241,
          -0.31840448145553918,
          0.12843720787213342)
```

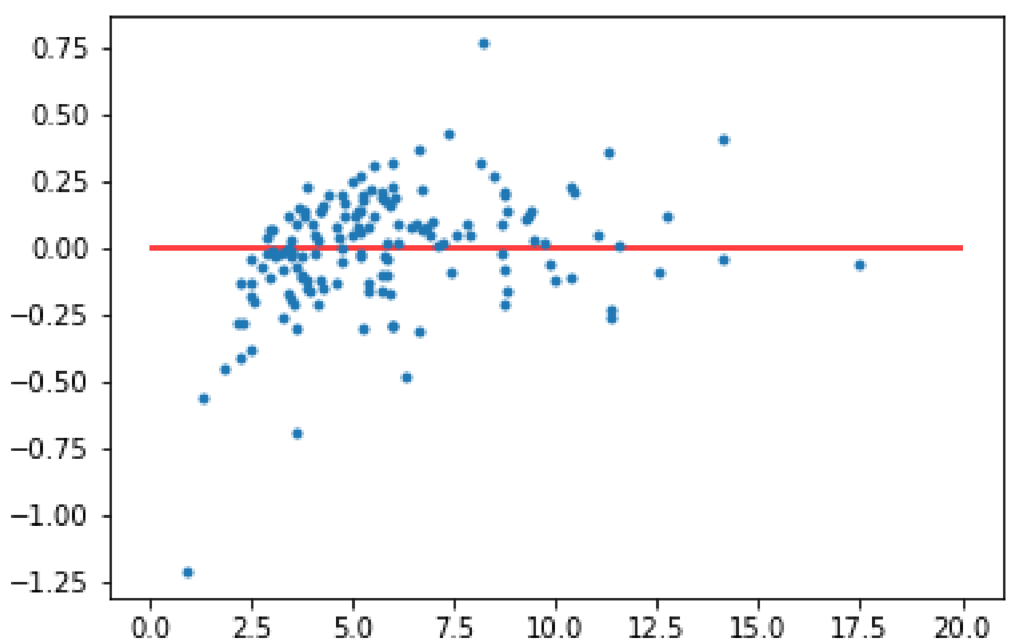
```
In [64]: f = open('parameters_all.csv', 'w')
         with f:
             f.write(str(intercept)+' \n ')
             f.write(str(b1)+ ' \n ' )
             f.write(str(b2)+ '\n' )
             f.write(str(b3)+ '\n')
         f.close()
```

Inspecting the data and residuals:

```
In [27]: #X = ln(df.F_h50)
         X = df.F_mean
         Y = df.Biomass
         plt.plot(X, Y, '.')
         plt.show()
```



In [28]:
```
R = result.resid
plt.plot(Y, R, '.')
plt.hlines(0,0, 20,colors=u'r')
plt.show()
```



In [30]:
```
df.mean()
```

Out[30]:
```
PlotID     93.116883
L_mean      2.882272
L_cv        1.508728
L_h10       0.002792
L_h50       0.931591
L_h90       8.772786
L_d10       0.842814
L_d50       0.496161
L_d90       0.100046
F_mean     11.446377
F_cv        0.504331
F_h10       3.730494
F_h50      12.367338
F_h90      17.210695
F_d10       0.896085
F_d50       0.499204
F_d90       0.099676
Biomass     5.752972
elev        3.118651
Yhat        0.112888
resid       5.640083
dtype: float64
```

In [18]:
```
#df.to_csv("ALL_plots_yhat")
```