Assignment 2 - Exploratory Data Analysis

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1 The Question

How do estimates of forest growth and yield produced by the Forest Vegetation Simulator (FVS) compare to historical and contemporary data and accounts? Are additional adjustments needed to the model to make it more accurate or informative for decision-making?

2 The Data Sources

In this project, I considered four general data sources: 1. Data I produced using the the Forest Vegetation Simulator 2. Several published Yield Tables for Douglas-fir 3. Remeasurements from permanent forest research plots published in the literature 4. Plot measurements collected from Oregon and Washington by the USDA Forest Service's Forest Inventory & Analysis (FIA) program.

1. Forest Vegetation Simulator The Forest Vegetation Simulator (FVS) is an open-source project of the USDA Forest Service, which they succinctly describe as: `>The Forest Vegetation Simulator (FVS) is a forest growth simulation model. It simulates forest vegetation change in response to natural succession, disturbances, and management. It recognizes all major tree species and can simulate nearly any type of management or disturbance at any time during the simulation. Outputs include tree volumes, biomass, density, canopy cover, harvest yields, fire effects, and much, much more.`

I performed 230 stochastic simulations of the development of Douglas-fir plantations from establishment up to 200 years of age using the ORGANON Pacific Coast Variant of FVS. These simulations were executed using a parallel processing workflow developed in Python using Jupyter Notebooks.

Site Index is a measure of the productive potential of a site, and describes the average height of dominant trees reached in a forest stand at some benchmark age (usually 50 or 100 years). More productive sites yield taller and larger trees more quickly, and thus have higher Site Indices than less productive sites. Simulations were run for Site Indices ranging from 50 to 160 using a step of 5. This produced 23 different Site Index values, each of which was simulated stochastically 10 times.

2. Long-term Plot Data I transcribed data from a couple of the studies that have conducted long-term measurements of forest plots to investigate the changes in forest conditions over time have been published. These data provide a deep (in terms of time), but relatively narrow (in terms of number of independent plots) glimpse at forest growth and yield: `>Curtis, R.O., Marshall, D.D. (2002). "Levels-of-growing-stock cooperative study in Douglas-fir: report no. 14Stampede Creek, 30-year results" (Research Paper No. PNW-RP-543). U.S. Department of Agriculture, Forest Service, Pacific Northwest Research Station, Portland, OR.` link to PDF

> `Williamson, R.L. (1963). "Growth and yield records from well-stocked stands of Douglas-fir" (Research Paper No. PNW-RP-4). U.S. Department of Agriculture, Forest Service, Pacific Northwest Forest and Range Experiment Station, Portland, OR.` link to PDF

3. FIA Data Thousands of forest inventory plots are measured every year by the USDA Forest Service across the country. These data provide a broad (in terms of number of independent plots), but relatively shallow (in terms of measurements over time) overview of forest growth and yield. FIA data was downloaded for Oregon and Washington, and results for Douglas-fir forests were queried from these databases.

These data were queried from the Access databases, and cleaned/formatted in Microsoft Excel.

```
In [1]: import pandas as pd
        import numpy as np
        import psycopg2
        from matplotlib import pyplot as plt
        import seaborn as sns
        %matplotlib inline
```

```
In [2]: sns.set_style('darkgrid')
```

Read the FVS simulation data from the PostgreSQL database

```
In [3]: conn = psycopg2.connect("dbname='Rotations' user='postgres' host='localhost'") # passw
        SQL = '''
        SELECT summary.*, cases.mgmtid, CAST (cases.standid AS INT) AS siteindex
        FROM summary, cases
        WHERE summary.caseid = cases.caseid AND cases.mgmtid = 'GROW';
        '''
        # read the query into a pandas dataframe
        grow = pd.read_sql(SQL, conn)
        conn.close()
```

```
In [4]: # add a new variable, siteclass, to the dataframe by binning site index into categorie
        grow['siteclass'] = pd.cut(grow.siteindex, bins=[0,75,95,115,135,160], labels=[5, 4, 3
        # calculate thousands of board feet and hundreds of cubic feet
        grow['MBF'] = grow.bdft / 1000
        grow['tcuft_CCF'] = grow.tcuft / 100
        grow['mcuft_CCF'] = grow.mcuft / 100
```

```
In [5]: print(grow.columns)
        cols = ['age', 'tpa', 'ba', 'sdi', 'topht', 'qmd', 'MBF', 'tcuft_CCF']
        grow[cols].describe()
```

```
Index(['caseid', 'standid', 'year', 'age', 'tpa', 'ba', 'sdi', 'ccf', 'topht',
       'qmd', 'tcuft', 'mcuft', 'bdft', 'rtpa', 'rtcuft', 'rmcuft', 'rbdft',
       'atba', 'atsdi', 'atccf', 'attopht', 'atqmd', 'prdlen', 'acc', 'mort',
       'mai', 'fortyp', 'sizecls', 'stkcls', 'mgmtid', 'siteindex',
       'siteclass', 'MBF', 'tcuft_CCF', 'mcuft_CCF'],
      dtype='object')
```

Out[5]:

	age	tpa	ba	sdi	topht
count	9430.000000	9430.000000	9430.000000	9430.000000	9430.000000
mean	100.000000	195.019194	294.984093	416.696076	124.894804
std	59.163935	81.499988	136.281415	163.924993	62.888186
min	0.000000	1.000000	0.000000	0.000000	5.000000
25%	50.000000	134.000000	216.000000	363.000000	80.000000
50%	100.000000	186.000000	346.000000	500.000000	122.000000
75%	150.000000	264.000000	402.000000	529.000000	172.000000
max	200.000000	451.000000	485.000000	536.000000	269.000000

	qmd	MBF	tcuft_CCF
count	9430.000000	9430.000000	9430.000000
mean	17.119294	96.990059	160.083199
std	7.761623	72.436612	104.766063
min	0.100000	0.000000	0.000000
25%	12.287275	35.364000	73.247500
50%	18.195800	87.786500	156.770000
75%	23.091575	151.991750	243.522500
max	36.546600	325.808000	442.680000

Our data includes 10 different simulations I ran for each of 23 different levels of site index. For each level of site index, a stochastic simulation approach was used to allow variability in model outputs. We need to summarize data across these 10 runs to produce classical Yield Tables.

```
In [6]: # to make Yield Tables, let's use the mean of the simulations
        grow_group = grow.groupby(by=['siteindex', 'year']).mean().reset_index()

        # replace NaN's with zeros
        grow_group['MBF'] = grow_group['MBF'].replace(to_replace=np.nan, value=0)
```

```
In [7]: # choose a value we want to generate a table for
        metric = 'MBF'
        tables = grow_group.loc[grow_group.year % 10 == 0] # trim the data to show every 10 ye
        tables = tables.loc[tables.siteindex % 10 == 0] # trim the data to show site indices i

        # use a pivot table to show value by year (row) and site index (column)
        tables.loc[tables.year >=20].pivot(index='year', # exclude ages <20
```

```
                                       columns='siteindex',
                                       values=metric).style.format("{:,.1f}")
```

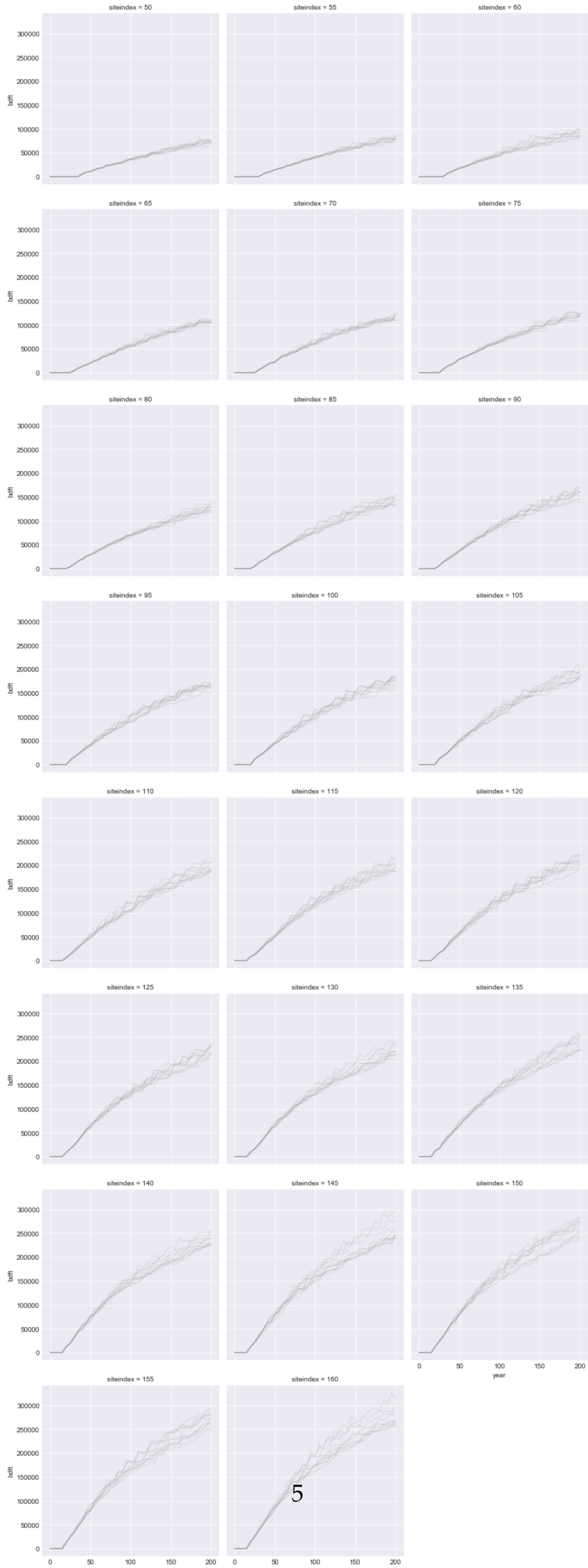
Out[7]: <pandas.io.formats.style.Styler at 0x1d5436746a0>

2.1 Visualize the data from all of our our simulations

```
In [8]: grow = grow.sort_values(by=['siteclass', 'caseid', 'year'])
```

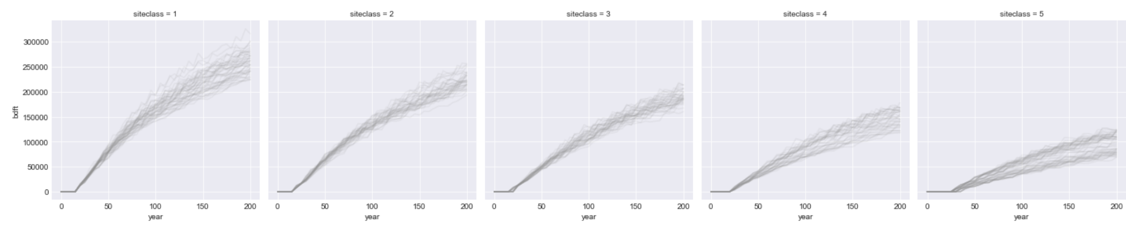
Show all the FVS data grouped by Site Index

```
In [9]: g = sns.FacetGrid(data=grow, col='siteindex', hue='caseid',
                          col_wrap=3, size=4, sharey=True, sharex=True,
                         palette=sns.color_palette('Greys',1))
        g = g.map(plt.plot, 'year', 'bdft', alpha=0.15)
```


siteindex = 50
siteindex = 55
siteindex = 60
siteindex = 65
siteindex = 70
siteindex = 75
siteindex = 80
siteindex = 85
siteindex = 90
siteindex = 95
siteindex = 100
siteindex = 105
siteindex = 110
siteindex = 115
siteindex = 120
siteindex = 125
siteindex = 130
siteindex = 135
siteindex = 140
siteindex = 145
siteindex = 150
siteindex = 155
siteindex = 160
bdft
year

Show all the FVS data grouped into the five Site Classes

```
In [10]: g = sns.FacetGrid(data=grow, col='siteclass', hue='caseid',
                           palette=sns.color_palette('Greys',1),
                           size=4, sharey=True, sharex=True)
         g = g.map(plt.plot, 'year', 'bdft', alpha=0.10)
```



2.2 Visualize the data from the FIA Databases

```
In [11]: fia = pd.read_csv('FIA_conds.csv')
         print(fia.columns)
         fia.describe()
```

```
Index(['condid', 'state', 'site_baseage', 'siteclass', 'site_species',
       'forest_type', 'siteindex_orig', 'stand_age', 'BA', 'QMD', 'TPA',
       'total_cubic_net', 'total_cubic_gross', 'sawlog_cubic_net',
       'sawlog_cubic_gross', 'boardfoot_net', 'boardfoot_gross'],
      dtype='object')
```

Out[11]:

	condid	site_baseage	siteclass	site_species	forest_type	\
count	5.397000e+03	5397.000000	5397.000000	5397.0	5397.0	
mean	1.784318e+14	96.868631	4.104317	202.0	201.0	
std	1.576986e+14	12.115700	0.732375	0.0	0.0	
min	4.475710e+11	50.000000	1.000000	202.0	201.0	
25%	2.296206e+13	100.000000	4.000000	202.0	201.0	
50%	1.774492e+14	100.000000	4.000000	202.0	201.0	
75%	3.022475e+14	100.000000	5.000000	202.0	201.0	
max	4.511326e+14	100.000000	5.000000	202.0	201.0	

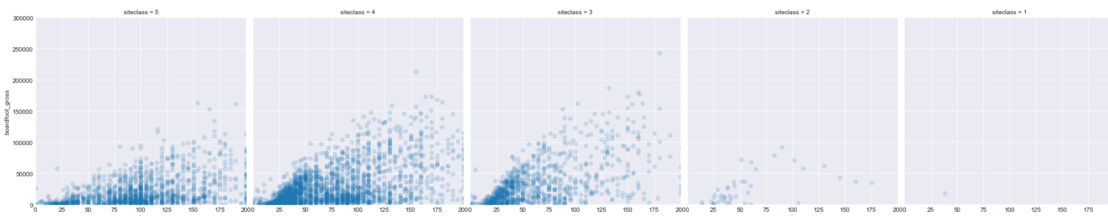
	siteindex_orig	stand_age	BA	QMD	TPA	\
count	5397.000000	5397.000000	5397.000000	5397.000000	5397.000000	
mean	103.480452	100.480637	198.292084	6.074904	177.704202	
std	21.984129	86.503964	440.866865	2.507652	344.137650	
min	15.000000	0.000000	3.480000	2.547244	0.990000	

25%	88.000000	40.000000	104.040000	4.346457	96.280000
50%	104.000000	80.000000	170.400000	5.460630	156.460000
75%	120.000000	125.000000	251.370000	7.086614	228.680000
max	187.000000	750.000000	30965.540000	26.771654	24072.180000

	total_cubic_net	total_cubic_gross	sawlog_cubic_net \
count	5397.000000	5397.000000	5397.000000
mean	5364.311443	5920.556565	4555.557063
std	4929.583171	5542.517794	4556.799675
min	32.260000	36.290000	13.570000
25%	1687.760000	1843.610000	1169.940000
50%	3785.850000	4135.480000	2979.340000
75%	7574.870000	8247.940000	6519.910000
max	34599.400000	40804.040000	33157.590000

	sawlog_cubic_gross	boardfoot_net	boardfoot_gross
count	5397.000000	5397.000000	5397.000000
mean	4662.850378	29628.721203	30341.000873
std	4670.304339	31701.778115	32513.212526
min	19.870000	58.170000	78.020000
25%	1192.410000	6770.590000	6908.440000
50%	3022.980000	17958.990000	18387.240000
75%	6657.940000	41682.900000	42651.840000
max	34031.940000	236865.110000	242902.720000

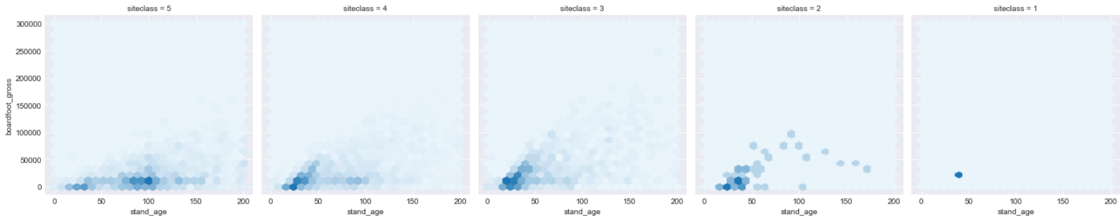
In [12]:
```
g = sns.lmplot(data=fia, x='stand_age', y='boardfoot_gross', col='siteclass', col_orde
               fit_reg=False, ci=None, x_ci=None, scatter_kws={'alpha':0.15})
g.set(xlim=(0,200))
g.set(ylim=(0,300000));
```



Try with hexbins instead of a scatter plot

In [13]:
```
def hexbin(x, y, color, **kwargs):
    cmap = sns.light_palette(color, as_cmap=True)
    plt.hexbin(x, y, gridsize=25, cmap=cmap, **kwargs)

g = sns.FacetGrid(fia, col="siteclass", col_order=[5,4,3,2,1], size=4)
g.map(hexbin, "stand_age", "boardfoot_gross", extent=[0, 200, 0, 300000]);
```



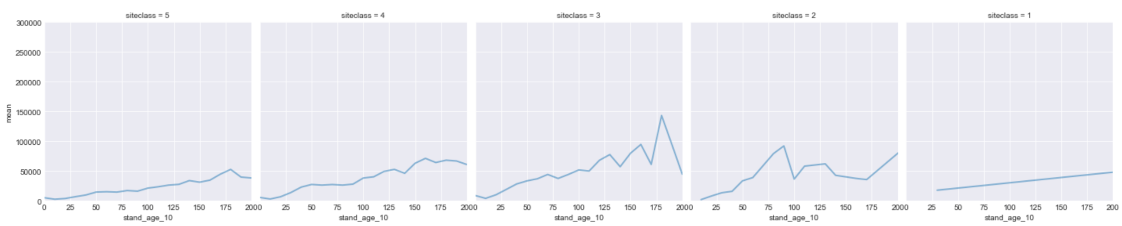
This way of viewing the data shows density where more plots were observed, but this isn't quite what I'm intending to capture. I'd prefer to know what a reasonable range of timber volume (boardfoot gross) might be at each age. Instead, the hexbin washes out the older ages because there are fewer samples.

Let's bin the ages into 10-year intervals and then graph the mean timber volume over time for each site class.

```
In [14]: fia['stand_age_10'] = fia.stand_age // 10 * 10
         fia_group = fia.groupby(by=['siteclass', 'stand_age_10']).agg(['mean', 'std', 'count']
```

Seaborn makes it look like the data are continuous across min/max observed ages

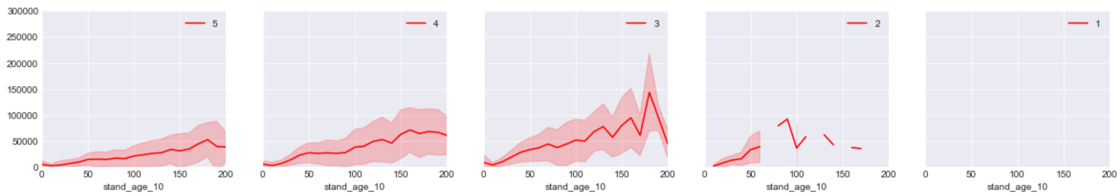
```
In [15]: g = sns.FacetGrid(data=fia_group.reset_index(), col='siteclass', col_order=[5,4,3,2,1]
                           palette=sns.color_palette('Blues',1),
                           size=4, sharey=True, sharex=True)
         g = g.map(plt.plot, 'stand_age_10', 'mean', alpha=0.50, lw=2.0)
         g.set(xlim=(0,200))
         g.set(ylim=(0,300000));
```



But plotting directly from grouped and pivoted dataframe shows gaps in observed ages

```
In [16]: fig, axs = plt.subplots(1,5, figsize=(20,3), sharey=True, sharex=True)
         fia_pivot = pd.pivot_table(fia_group.reset_index(),
                        index='stand_age_10', columns='siteclass', values=['mean', 'std'])
         fia_pivot = fia_pivot.sort_index(axis=1, ascending=False)
         fia_pivot['mean'].plot(subplots=True, legend=True, ax=axs, style=['r','r','r','r', 'r
         for i in range(2,6):
             axs[5-i].fill_between(x=fia_pivot.index,
                                   y1=fia_pivot['mean'][i]-fia_pivot['std'][i],
```

```
                                            y2=fia_pivot['mean'][i]+fia_pivot['std'][i],
                                            alpha=0.2, color='r')
    plt.xlim(0,200)
    plt.ylim(0,300000);
```



2.3 Visualize the data from the permanent plots

```
In [17]: perm = pd.read_csv('PermanentPlots.csv')
         print(perm.columns)
         perm.describe()
```

```
Index(['Source', 'ID', 'Location', 'Plot', 'si100', 'siteclass', 'age',
       'boardfeet_scribner', 'total_cubic', 'si50'],
      dtype='object')
```

```
Out[17]:              Plot       si100   siteclass         age  boardfeet_scribner  \
         count  240.000000  219.000000  240.000000  240.000000          238.000000
         mean    14.004167  160.735160    2.416667   70.675000        50611.273109
         std     29.363755   24.226061    0.813930   19.885041        27372.543262
         min      1.000000  116.000000    1.000000   33.000000          980.000000
         25%      2.000000  141.000000    2.000000   55.000000        29315.500000
         50%      4.000000  170.000000    2.000000   67.000000        49175.000000
         75%      7.000000  175.000000    3.000000   83.000000        69212.000000
         max    122.000000  205.000000    4.000000  119.000000       143848.000000

                  total_cubic   si50
         count     238.000000   21.0
         mean    11095.726891  111.0
         std      3787.857376    0.0
         min      2211.000000  111.0
         25%      8460.000000  111.0
         50%     11120.000000  111.0
         75%     13367.000000  111.0
         max     25716.000000  111.0
```

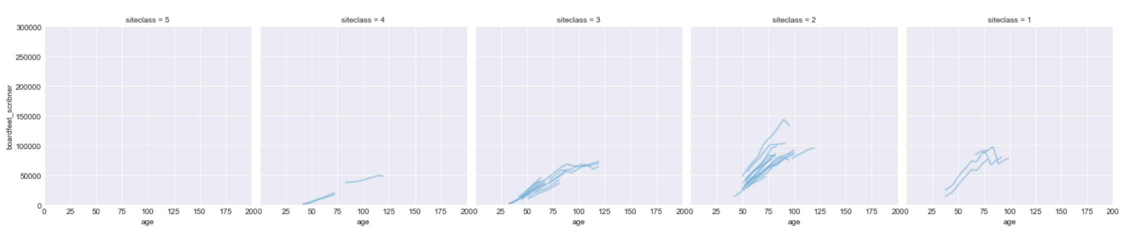
```
In [18]: perm.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 240 entries, 0 to 239
```

```
Data columns (total 10 columns):
Source                 240 non-null object
ID                     240 non-null object
Location               240 non-null object
Plot                   240 non-null int64
si100                  219 non-null float64
siteclass              240 non-null int64
age                    240 non-null float64
boardfeet_scribner     238 non-null float64
total_cubic            238 non-null float64
si50                   21 non-null float64
dtypes: float64(5), int64(2), object(3)
memory usage: 18.8+ KB
```

```
In [19]: perm = perm.dropna(subset=['boardfeet_scribner'])
         perm = perm.sort_values(by=['siteclass', 'ID', 'age'])
```

```
In [20]: g = sns.FacetGrid(data=perm, col='siteclass', col_order=[5,4,3,2,1], hue='ID',
                           palette=sns.color_palette('Blues',1),
                           size=4, sharey=True, sharex=True)
         g = g.map(plt.plot, 'age', 'boardfeet_scribner', alpha=0.50, lw=2.0)
         g.set(xlim=(0,200))
         g.set(ylim=(0,300000));
```



2.4 Prepare a final graphic that integrates FVS Simulations and field-observed data

```
In [21]: perm_pivot = pd.pivot_table(perm, index=['ID', 'age'], columns='siteclass', values='bo
         perm_pivot = perm_pivot.sort_index(axis=1, ascending=False)
         grow_pivot = pd.pivot_table(grow, index=['caseid', 'age'], columns='siteclass', value
         grow_pivot = grow_pivot.sort_index(axis=1, ascending=False)
```

```
In [22]: fig, axs = plt.subplots(1,5, figsize=(20,5), sharey=True, sharex=True)
         fia_pivot['mean'].plot(subplots=True, legend=False, ax=axs, style=['r']*5)
         for i in range(2,6):
             axs[5-i].fill_between(x=fia_pivot.index,
                                   y1=fia_pivot['mean'][i]-fia_pivot['std'][i],
                                   y2=fia_pivot['mean'][i]+fia_pivot['std'][i],
                                   alpha=0.2, color='r')
```

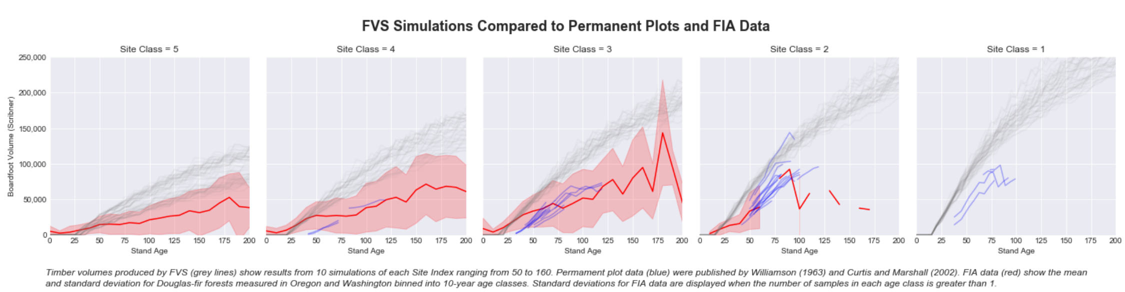
```
perm_pivot.reset_index(level=1).groupby('ID').plot(x='age',
                                                    subplots=True, legend=False,
                                                    ax=axs[1:], style=['b']*4, alpha=0

grow_pivot.reset_index(level=1).groupby('caseid').plot(x='age',
                                                    subplots=True, legend=False,
                                                    ax=axs, style=['gray']*5, alpha=0.

# create titles and axis labels for each subplot
for i in range(5):
    axs[i].set_title('Site Class = '+str(5-i))
    axs[i].set(xlabel='Stand Age')
axs[0].set(ylabel='Boardfoot Volume (Scribner)')

# set limits of axes
plt.xlim(0,200)
plt.ylim(0,250000)
# reformat ticks to have thousand separators
axs[0].set_yticklabels(['{:,}'.format(int(x)) for x in axs[0].get_yticks().tolist()])

fig.suptitle('FVS Simulations Compared to Permanent Plots and FIA Data',
             fontsize=18, fontweight='bold')
plt.tight_layout()
fig.subplots_adjust(top=0.85, bottom=0.22)
caption = '''
Timber volumes produced by FVS (grey lines) show results from 10 simulations \
of each Site Index ranging from 50 to 160. Permament plot data (blue) were published
Williamson (1963) and Curtis and Marshall (2002). FIA data (red) show the mean
and standard deviation for Douglas-fir forests measured in Oregon and Washington binne
into 10-year age classes. Standard deviations for FIA data are displayed when the \
number of samples in each age class is greater than 1.
'''
plt.figtext(0.04, 0, caption, wrap=True,
            style='italic', fontsize=12,
           linespacing=1.5)
plt.savefig('FVS_vs_Data.png');
```



This figure demonstrates that FVS tends to produce estimates of timber volume that are usually higher than the volumes observed on FIA and permanent plots. This justifies further investigation into other stand-level metrics (such as total cubic volume, average diameter, basal area, and trees per acre) to determine whether this bias also appears in those values, or whether it is limited to the calculations of boardfoot volume. If the bias is limited to boardfoot volume estimates, a direct adjustment to solely the volume calculation may be appropriate. If the bias is pervasive across all stand attributes, adjustments to underlying growth and/or mortality rates of FVS may be required.