Data_Coverage.nb

August 15, 2017

```
In [19]: from IPython.display import HTML
         HTML('''<script>
         code_show=true;
         function code_toggle() {
          if (code_show){
          $('div.input').hide();
          } else {
          $('div.input').show();
          }
          code_show = !code_show
         }
         $( document ).ready(code_toggle);
         </script>''')

Out[19]: <IPython.core.display.HTML object>

In [20]: from IPython.display import HTML
         HTML('''
         <style>
             .yourDiv {position: fixed;top: 100px; right: 0px;
                       background: white;
                       height: 100%;
                       width: 300px;
                       padding: 20px;
                       z-index: 10000}
         </style>
         <script>
         function showthis(url) {
                 window.open(url, "pres",
                         "toolbar=yes,scrollbars=yes,resizable=yes,top=10,left=400,width=500,hei
                 return(false);
         }
         </script>

         <div class=yourDiv>
             <h4>MENU</h4><br>
             <a href=#Data>1. Data</a><br>
```

```
            <a href=#SpatialCoverage>2. Spatial Coverage</a><br>
            <a href=#TemporalCoverage>3. Temporal Coverage</a><br>
            <a href=#ClassOverlaps>4. Farm size class overlaps</a><br>
            <a href=#YieldLookUpTable>5. Yield look-up table</a><br><br>

            <a href="javascript:code_toggle()">Toggle Code On/Off</a><br>
            <a href=#Top>Top</a><br>
            <a href=#LeftOff>Left Off Here</a><br>
        </div>
        ''')
```

Out[20]: <IPython.core.display.HTML object>

#
Data Coverage Overview
##
What portion of the global food supply is produced by smallholders?
###
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Data
1. Harvested area per farm size class 2. Yield per crop per farm size class
To Dos:

- Update this document with new database codes. This is partially updated, but after the spartial coverage section, it relies on the old data.

In [26]:
```
# Import dependencies
import warnings
warnings.filterwarnings('ignore')
import pandas as pd
import geopandas as gpd
import seaborn as sns
from matplotlib import pyplot as plt
import matplotlib.pyplot as plt
from matplotlib.path import Path
import matplotlib.patches as patches
from matplotlib.pyplot import cm
import matplotlib as mpl
import numpy as np
import re
import geopy
import mpld3
import plotly.plotly as py
import cmocean

pd.set_option('display.max_columns', 500)
%matplotlib inline
```

In [3]:
```
# Set all plotting params:
title_sz = 20
x_lab_tick_sz = 18
y_lab_tick_sz = 18
x_lab_label_sz = 18
y_lab_label_sz = 18
lengend_sz = 16
```

In [4]:
```
# Import data
# df = pd.read_csv('/Users/Vinny_Ricciardi/Documents/Data_Library_Big/Survey/Global/Farm
#                  'CropbyFarmsize_2_20170711.csv',
#                  low_memory=False)

# df = pd.read_csv('/Users/Vinny_Ricciardi/Downloads/farmsize_df.csv',
#                  low_memory=False)

PATH = '/Users/Vinny_Ricciardi/Documents/Data_Library_Big/Survey/Global/Farm_Size/Data/F
df = pd.read_csv(PATH, low_memory=False)
```

In [76]:
```
# df = df.query("theme == 'Landuse'")
```

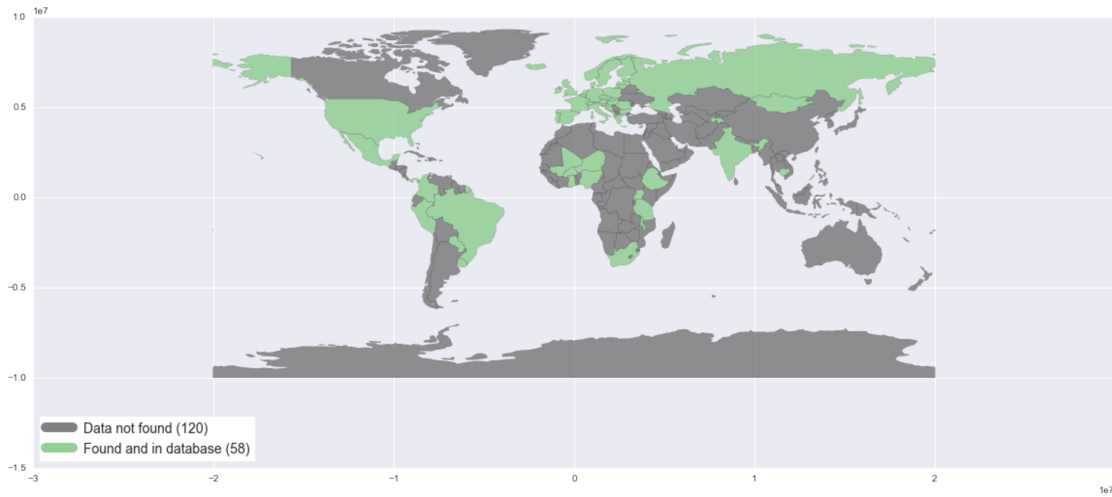
Spatial Coverage

In [5]:
```
df['NAME_0'].replace(['United States of America'], ['United States'], inplace=True)
df['NAME_0'].replace(['Bosnia and Herzegovina'], ['Bosnia and Herz.'], inplace=True)
df['NAME_0'].replace(['United Republic of Tanzania'], ['Tanzania'], inplace=True)
df['NAME_0'].replace(['Russian Federation'], ['Russia'], inplace=True)
df['NAME_0'].replace(['Czech Republic'], ['Czech Rep.'], inplace=True)
df['NAME_0'].replace(['Czech Republic'], ['Czech Rep.'], inplace=True)
df['NAME_0'].replace(['Czech Republic'], ['Czech Rep.'], inplace=True)
```

To do: - What percentage of global production does our sample represent?

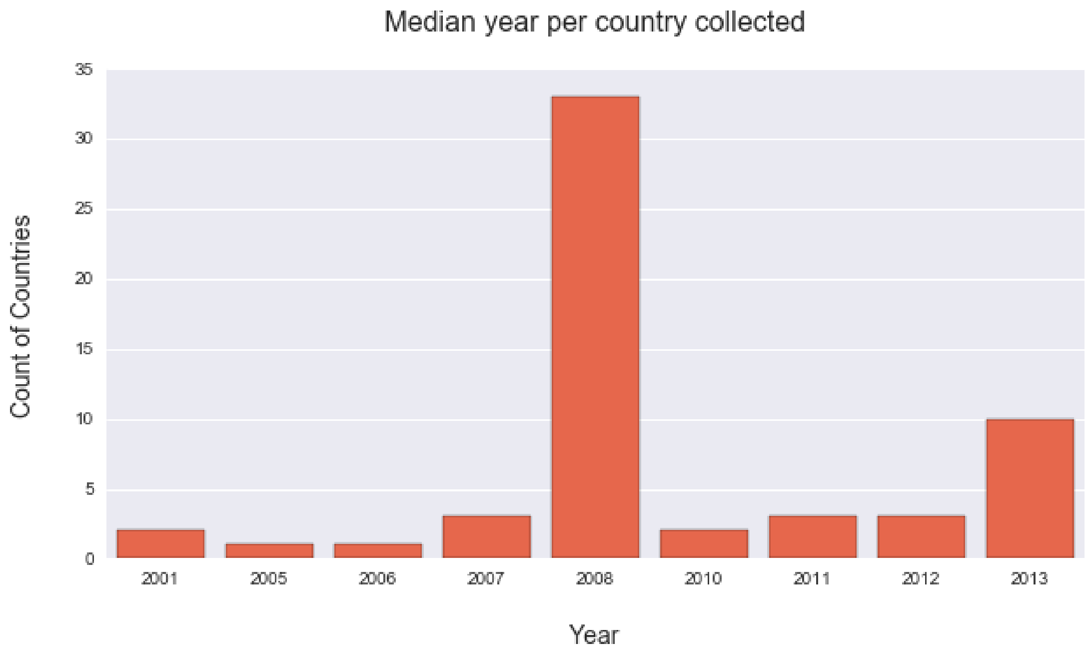
In [25]:
```
pivoted = pd.pivot_table(df,
                         index='NAME_0',
                         values='Crop',
                         aggfunc=lambda x: len(x.unique()))
pivoted = pivoted.reset_index()
pivoted = pivoted.sort_values('Crop', ascending=False)
pivoted['Data_Available'] = pivoted['Crop'].astype(int)

world = gpd.read_file(gpd.datasets.get_path('naturalearth_lowres'))

world = world.to_crs(epsg=3786)

world = pd.merge(world, pivoted,
                 how='outer',
                 left_on='name',
                 right_on='NAME_0')
```

```
world['Orig_crop'] = world['Crop'].fillna(0)
world['coverage'] = np.where(world['Crop'] > 0,
                             'Found and downloaded',
                             np.where(world['Crop'] == -1,
                                      'Found not downloaded',
                                      'No data found'))

warnings.filterwarnings('ignore')

x = len(pivoted.NAME_0.unique())

try:
    fig, ax = plt.subplots(figsize=(20, 10))
    ax.set_aspect('equal')
    world.plot(column='coverage', cmap='Accent', ax=ax, alpha=0.7, linewidth=0.1)  #cmo
except:
    pass

ndf, fad = world.coverage.value_counts()
cmap_ = cmocean.tools.get_dict(cmocean.cm.deep, N=4)

p1 = mpl.lines.Line2D([], [],
                             color=[x / 255. for x in [128, 128, 130]],
                             linewidth=10,
                             label='Data not found ({})'.format(ndf))
p2 = mpl.lines.Line2D([], [],
                             color=[x / 255. for x in [148, 207, 150]],
                             linewidth=10,
                             label='Found and in database ({})'.format(fad))

handles = [p1, p2]
labels = [h.get_label() for h in handles]

legend = ax.legend(handles=handles, labels=labels, frameon=True,
                   fontsize=14, loc='lower left')

legend.get_frame().set_facecolor('#ffffff')

plt.show()
```



Temporal Coverage

```
In [14]: df = df.sort_values('NAME_0')
         grouped = df.groupby('NAME_0').mean()
         grouped['year'] = grouped['year'].astype(int)
         grouped = grouped.sort('year')

         fig = plt.figure(figsize=(10, 5))
         ax = fig.add_subplot(111)
         sns.countplot(x=grouped.year, color='#FF5733', ax=ax)
         ax.set_title('\n Median year per country collected \n', fontsize=title_sz-4)
         ax.set_xlabel('\nYear\n', fontsize=y_lab_tick_sz-4)
         ax.set_ylabel('\nCount of Countries\n', fontsize=y_lab_tick_sz-4)
         mpl.rcParams['xtick.labelsize'] = x_lab_tick_sz-8
         mpl.rcParams['ytick.labelsize'] = y_lab_tick_sz-8
         plt.show()
```



Farm size class overlaps

First, I counted the number of records per farm size stratum, then plotted each farm size stratum by the amount of records per stratum.

Here is the resulted graph of records per farm size stratum. The x-axis is the size of the farm size stratum, where each rectangle's horizontal plane represents the range the farm size stratum covers. The y-axis is the relative amount of records per farm size stratum; to make the overlaps easier to see, each subsequent rectangle starts a little higher than the previous (hence, the y-axis is only relative).

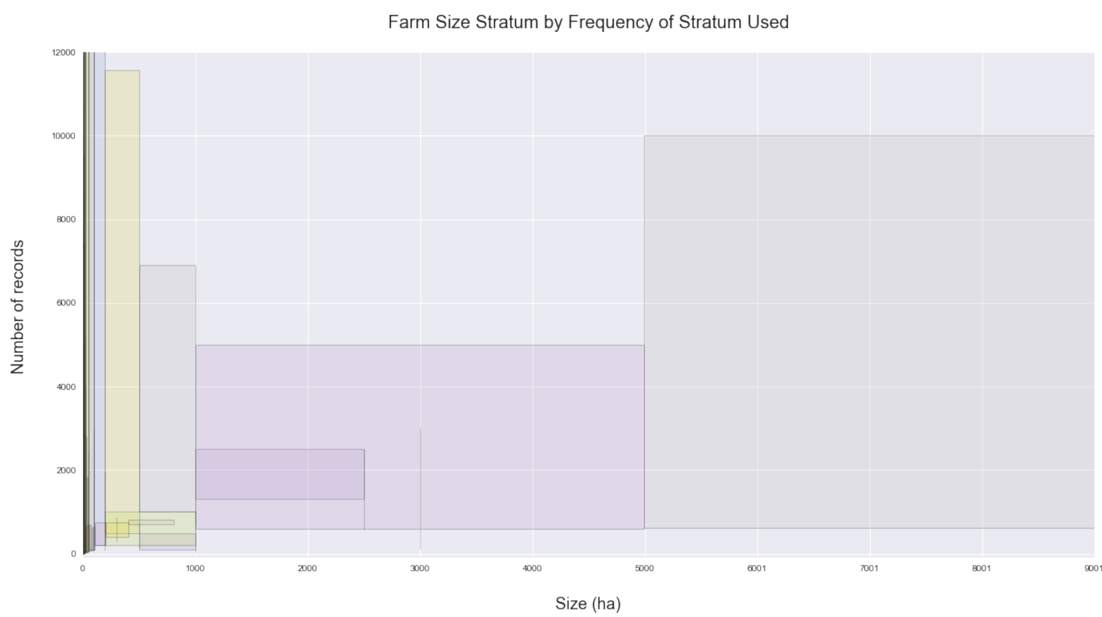
```
In [16]: df = df.query("fs_class_min != ['Total', 'defined', 'landless', 'undefined'] & "
                       "fs_class_max != 'MORE'")

         df['fs_class_min'] = df['fs_class_min'].astype(str).str.replace(u'+', '')
         df['fs_class_min'] = df['fs_class_min'].astype(float)

         # df['fs_class_min'] = (df['fs_class_min'] * 0.404686).where(df['fs_class_unit'] == 'ac

         df['fs_class_max'] = df['fs_class_max'].astype(float)
         # df['fs_class_max'] = (df['fs_class_max'] * 0.404686).where(df['fs_class_unit'] == 'ac

         df['fs_Range'] = df['fs_class_min'].astype('str').map(str) + '_' + df['fs_class_max'].a

         df = df.sort_values(['fs_Range'])

         grouped = df.groupby(['fs_Range', 'fs_class_min', 'fs_class_max']).count()
```

```
grouped = grouped.reset_index()
grouped1 = grouped.loc[:, ['fs_Range', 'NAME_0']]
grouped2 = grouped1.fs_Range.str.split('_', expand=True)
grouped = grouped1.join(grouped2)
grouped.columns = ['fs_Range', 'Count', 'Low', 'High']
grouped['Low'] = grouped['Low'].astype(float)
grouped['High'] = grouped['High'].astype(float)
grouped = grouped.sort_values(['Low', 'High'])
# grouped['Count_sqrt'] = np.sqrt(grouped['Count'])
grouped['Count_sqrt'] = grouped['Count']
grouped['High'].fillna(-999, inplace=True)
grouped['High'] = np.where(grouped['High'] == -999, 100, grouped['High'])
```

In [27]:
```
def plt_farmSize_A(level=None, ax=ax):

    color = cm.get_cmap('Set2')
    # color2 = cm.rainbow(np.linspace(0,1,len(grouped)))

    for i in range(0, len(grouped)):

        try:
            verts = [
                (grouped['Low'][i], grouped['High'][i]), # left, bottom
                (grouped['Low'][i], grouped['Count_sqrt'][i]), # left, top
                (grouped['High'][i], grouped['Count_sqrt'][i]), # right, top
                (grouped['High'][i], grouped['High'][i]), # right, bottom
                (0., 0.), # ignored
                ]

            codes = [Path.MOVETO,
                     Path.LINETO,
                     Path.LINETO,
                     Path.LINETO,
                     Path.CLOSEPOLY,
                     ]

            path = Path(verts, codes)
            patch = patches.PathPatch(path, facecolor=color(4*i), lw=1, alpha=0.2)
            ax.add_patch(patch)

        except:
            pass

    if level:
        ax.set_xlim(0, level[0])
        ax.set_ylim(0, level[1])

        major_ticks = np.arange(0, level[1], 2)
```

```
            minor_ticks = np.arange(0, level[1], 1)

        else:
            ax.set_xlim(0, grouped['Count_sqrt'].max() / 10)
            ax.set_ylim(-100, grouped['High'].max() + (grouped['High'].max() / 5))

            major_ticks = np.arange(0, grouped['High'].max(), round(grouped['High'].max()+1
            minor_ticks = np.arange(0, grouped['High'].max(), round(grouped['High'].max()+1

        ax.set_xticks(major_ticks)
        ax.set_xticks(minor_ticks, minor=True)
        ax.set_title('\n Farm Size Stratum by Frequency of Stratum Used \n', fontsize=title
        ax.set_xlabel('\n Size (ha) \n', fontsize=x_lab_label_sz)
        ax.set_ylabel('\n Number of records \n', fontsize=x_lab_label_sz)
        mpl.rcParams['xtick.labelsize'] = x_lab_tick_sz
        mpl.rcParams['ytick.labelsize'] = y_lab_tick_sz

        return plt.show()
```

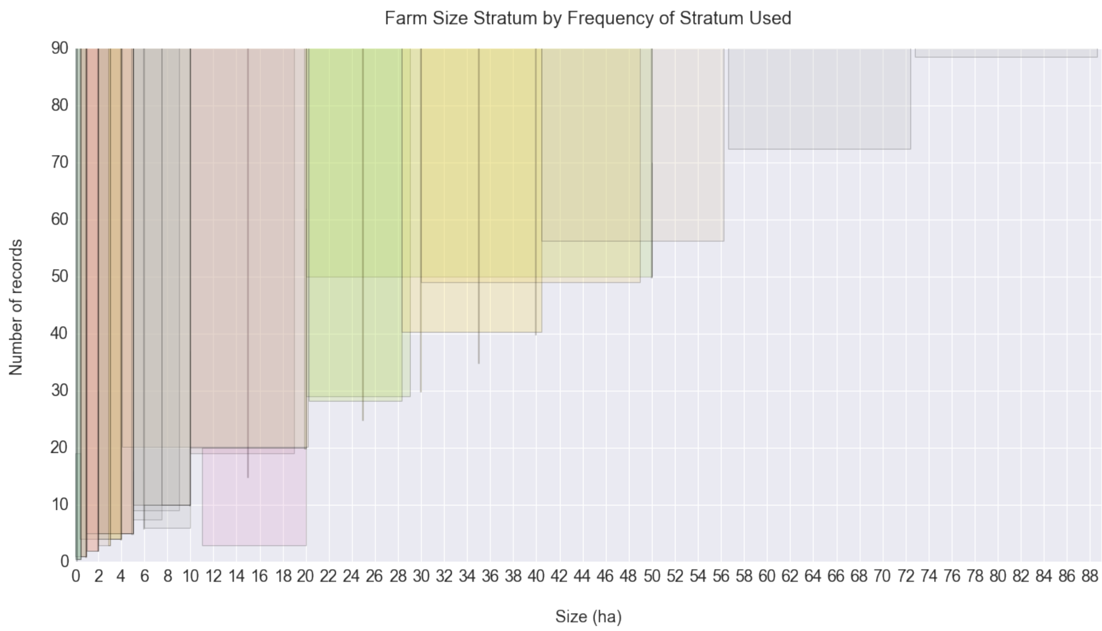
```
In [28]: fig, ax = plt.subplots(figsize=(20, 10))
         plt_farmSize_A(level=None, ax=ax)
         # ax.set_xlim([0, 9])
         plt.show()
```



From the above graph, the larger farm size stratum have less overlap, while the smaller farm size stratum contain a lot of overlap. Here is a zoomed in plot of the smaller farm size stratum.

Note: if the acres are all covnerted to hectares, then there is no overlap, but if not converted there is a large amount of overlap - at this point, they are converted to ha , but I am not certain the data needs to be converted or is already in ha form.

In [29]:
```
fig, ax = plt.subplots(figsize=(20, 10))
plt_farmSize_A(level=[1, 90], ax=ax)
plt.show()
```



Left Off

In [33]:
```
# dd = df
# grouped.fs_Range.unique()

# fig = plt.figure(figsize=(20, 10));
# ax = fig.add_subplot(111);

# sns.barplot(grouped['Count'], grouped['fs_Range'],
#             linewidth=2.5, facecolor=(1, 1, 1, 0),
#             errcolor='0.2', edgecolor='0.2',
#             ax=ax);
# ax.set_xlabel('');
# ax.set_ylabel('');
```

In [33]:
```
df.head()
```

Out[33]:
```
        Unnamed: 0                   Crop  Item_Code         NAME_0  \
277068      277068                  Maize       56.0   South Africa
```

```
517122      517122         Taro (cocoyam)      136.0  South Africa
64575        64575             Beans, dry      176.0  South Africa
356066      356066  Onions, shallots, green      402.0  South Africa
356062      356062  Onions, shallots, green      402.0  South Africa

              NAME_1 NAME_2 NAME_3  es1   shpID data_unit  fs_class_min  \
277068    North West      1      1  ZAF  ZAF006        kg           0.0
517122  KwaZulu-Natal      1      1  ZAF  ZAF003        kg           0.0
64575        Limpopo      1      1  ZAF  ZAF004        kg           0.0
356066  KwaZulu-Natal      1      1  ZAF  ZAF003        kg           0.0
356062    Free State      1      1  ZAF  ZAF008        kg           0.0

        fs_class_max cen_sur  microdata    year  Crop_area  Cultivated_area  \
277068           0.5     sur          1  2013.0        NaN              NaN
517122           0.5     sur          1  2013.0        NaN              NaN
64575            0.5     sur          1  2013.0        NaN              NaN
356066           0.5     sur          1  2013.0        NaN              NaN
356062           0.5     sur          1  2013.0        NaN              NaN

        Harvested_area  Planted_area     Production  Production_fix  \
277068             NaN           NaN    3506.214143     3506.214143
517122             NaN           NaN    2752.762018     2752.762018
64575              NaN           NaN  489505.717731   489505.717731
356066             NaN           NaN     608.991577      608.991577
356062             NaN           NaN   23531.608014    23531.608014

        Production_fix_dummy  Production_constant  perc_Feed  perc_Food  \
277068                     0                  NaN   0.353458   0.577147
517122                     0                  NaN   0.945150   0.088123
64575                      0                  NaN   0.544437   0.880528
356066                     0                  NaN   0.029214   0.872882
356062                     0                  NaN   0.029214   0.872882

        perc_Seed  perc_Waste  perc_Processing  perc_Other  production_Feed  \
277068   0.011652    0.043327     3.134402e-03    0.013312      1239.299599
517122   0.088911    0.032152     6.978855e-01    0.923138      2601.772425
64575    0.095791    0.023681     8.528724e-01    0.742447    266505.189514
356066   0.012694    0.097903     8.622064e-07    0.058187        17.791161
356062   0.012694    0.097903     8.622064e-07    0.058187       687.455531

        production_Feed_k  production_Food  production_Food_k  \
277068                NaN      2023.601409                NaN
517122                NaN       242.580561                NaN
64575                 NaN    431023.518971                NaN
356066                NaN       531.578067                NaN
356062                NaN     20540.327921                NaN

        production_Other  production_Other_k  production_Seed  \
```

```
277068      46.673506                 NaN       40.855561
517122    2541.178647                 NaN      244.750116
64575   363432.150132                 NaN    46890.115329
356066      35.435591                 NaN        7.730775
356062    1369.241324                 NaN      298.719354

        production_Seed_k  production_Waste  production_Waste_k  \
277068                NaN        151.912037                 NaN
517122                NaN         88.505907                 NaN
64575                 NaN      11592.083431                 NaN
356066                NaN         59.622349                 NaN
356062                NaN       2303.824563                 NaN

        production_Processing  production_Processing_k        kcal       fat  \
277068              10.989885                      NaN  963.666667  8.643333
517122            1921.112714                      NaN    6.785714  0.032621
64575           417485.893937                      NaN    8.666667  0.036667
356066               0.000525                      NaN   27.333333  0.263333
356062               0.020289                      NaN   27.333333  0.263333

          protein  production_Feed_kcal  production_Feed_k_kcal  \
277068  24.616667          1.194272e+06                     NaN
517122   0.398929          1.765488e+04                     NaN
64575    0.586667          2.309712e+06                     NaN
356066   1.220000          4.862917e+02                     NaN
356062   1.220000          1.879045e+04                     NaN

        production_Food_kcal  production_Food_k_kcal  production_Other_kcal  \
277068          1.950077e+06                     NaN           4.497770e+04
517122          1.646082e+03                     NaN           1.724371e+04
64575           3.735537e+06                     NaN           3.149745e+06
356066          1.452980e+04                     NaN           9.685728e+02
356062          5.614356e+05                     NaN           3.742593e+04

        production_Other_k_kcal  production_Seed_kcal  production_Seed_k_kcal  \
277068                      NaN          39371.142355                     NaN
517122                      NaN           1660.804360                     NaN
64575                       NaN         406380.999517                     NaN
356066                      NaN            211.307854                     NaN
356062                      NaN           8164.995665                     NaN

        production_Waste_kcal  production_Waste_k_kcal  \
277068          146392.566499                      NaN
517122             600.575799                      NaN
64575           100464.723067                      NaN
356066            1629.677549                      NaN
356062           62971.204710                      NaN
```

```
        production_Processing_kcal  production_Processing_k_kcal  \
277068                1.059059e+04                           NaN   
517122                1.303612e+04                           NaN   
64575                 3.618211e+06                           NaN   
356066                1.435209e-02                           NaN   
356062                5.545688e-01                           NaN   

        production_Feed_fat  production_Feed_k_fat  production_Food_fat  \
277068         10711.679531                    NaN         17490.661513   
517122            84.872067                    NaN             7.913188   
64575           9771.856949                    NaN         15804.195696   
356066             4.685006                    NaN           139.982224   
356062           181.029956                    NaN          5408.953019   

        production_Food_k_fat  production_Other_fat  production_Other_k_fat  \
277068                    NaN            403.414668                     NaN   
517122                    NaN             82.895446                     NaN   
64575                     NaN          13325.845505                     NaN   
356066                    NaN              9.331372                     NaN   
356062                    NaN            360.566882                     NaN   

        production_Seed_fat  production_Seed_k_fat  production_Waste_fat  \
277068           353.128233                    NaN           1313.026375   
517122             7.983961                    NaN              2.887139   
64575           1719.304229                    NaN            425.043059   
356066             2.035771                    NaN             15.700552   
356062            78.662763                    NaN            606.673801   

        production_Waste_k_fat  production_Processing_fat  \
277068                     NaN                  94.989235   
517122                     NaN                  62.668359   
64575                      NaN               15307.816111   
356066                     NaN                   0.000138   
356062                     NaN                   0.005343   

        production_Processing_k_fat  production_Feed_protein  \
277068                          NaN             30507.425119   
517122                          NaN              1037.921357   
64575                           NaN            156349.711182   
356066                          NaN                21.705216   
356062                          NaN               838.695748   

        production_Feed_k_protein  production_Food_protein  \
277068                        NaN             49814.321356   
517122                        NaN                96.772317   
64575                         NaN            252867.131130   
356066                        NaN               648.525241   
356062                        NaN             25059.200063   
```

```
        production_Food_k_protein  production_Other_protein  \
277068                        NaN               1148.946133
517122                        NaN               1013.748767
64575                         NaN             213213.528077
356066                        NaN                 43.231421
356062                        NaN               1670.474416

        production_Other_k_protein  production_Seed_protein  \
277068                         NaN              1005.727728
517122                         NaN                97.637814
64575                          NaN             27508.867660
356066                         NaN                 9.431546
356062                         NaN               364.437611

        production_Seed_k_protein  production_Waste_protein  \
277068                        NaN               3739.567982
517122                        NaN                 35.307535
64575                         NaN               6800.688946
356066                        NaN                 72.739266
356062                        NaN               2810.665966

        production_Waste_k_protein  production_Processing_protein  \
277068                         NaN                     270.534324
517122                         NaN                     766.386751
64575                          NaN                  244925.057776
356066                         NaN                       0.000641
356062                         NaN                       0.024753

        production_Processing_k_protein fs_Range
277068                              NaN  0.0_0.5
517122                              NaN  0.0_0.5
64575                               NaN  0.0_0.5
356066                              NaN  0.0_0.5
356062                              NaN  0.0_0.5
```

To Do: - We will need to see what these overlaps look like once the dataset compilation is complete, then determine the farm size classes we want to use. - Also plot per farm size range on the y-axis, farm size on the x-axis??

```
In [45]: pivot = pd.pivot_table(df, index=['NAME_0', 'fs_class_min', 'fs_class_max'], values='Pr
         pivot = pivot.reset_index()
         pivot
```

```
Out[45]:          NAME_0  fs_class_min  fs_class_max  Production_fix
         0       Albania      0.000000      1.000000             165
         1       Albania      1.000000      2.000000             143
         2       Albania      2.000000      5.000000             136
```

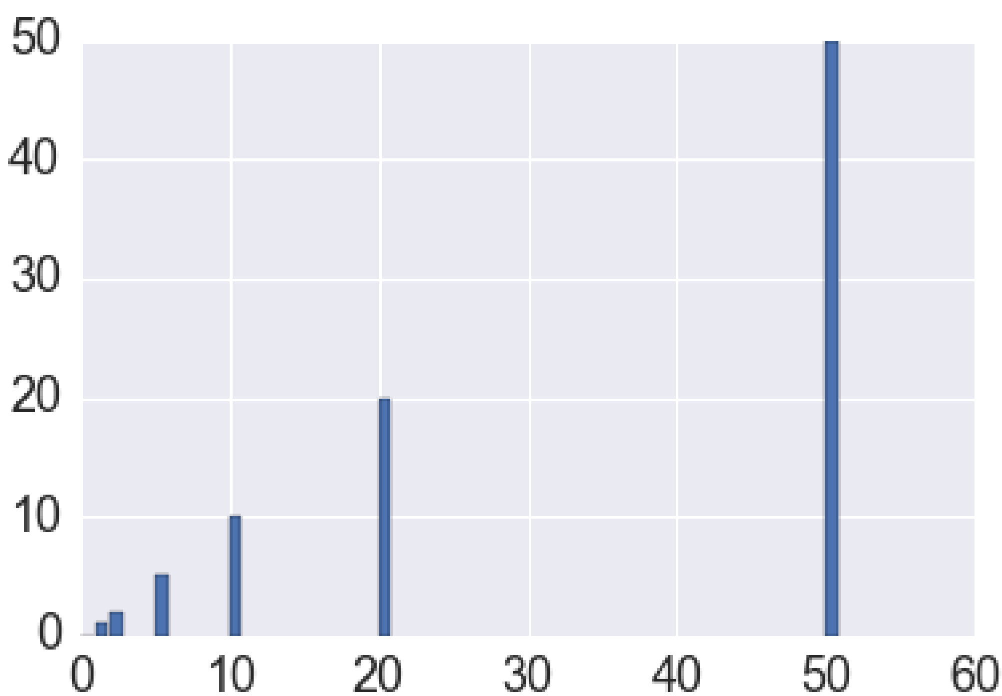
3	Albania	5.000000	10.000000	77
4	Albania	10.000000	20.000000	43
5	Albania	20.000000	50.000000	2
6	Albania	50.000000	100.000000	4
7	Austria	2.000000	4.000000	840
8	Austria	5.000000	9.000000	840
9	Austria	10.000000	19.000000	840
10	Austria	20.000000	29.000000	840
11	Austria	30.000000	49.000000	840
12	Austria	50.000000	99.000000	840
13	Belgium	2.000000	4.000000	1008
14	Belgium	5.000000	9.000000	1008
15	Belgium	10.000000	19.000000	1008
16	Belgium	20.000000	29.000000	1008
17	Belgium	30.000000	49.000000	1008
18	Belgium	50.000000	99.000000	1008
19	Bosnia and Herz.	0.000000	1.000000	84
20	Bosnia and Herz.	1.000000	2.000000	80
21	Bosnia and Herz.	2.000000	5.000000	84
22	Bosnia and Herz.	5.000000	10.000000	77
23	Bosnia and Herz.	10.000000	20.000000	49
24	Bosnia and Herz.	20.000000	50.000000	30
25	Bosnia and Herz.	50.000000	100.000000	18
26	Bosnia and Herz.	100.000000	200.000000	33
27	Bosnia and Herz.	200.000000	1000.000000	20
28	Brazil	0.100000	0.200000	1288
29	Brazil	0.200000	0.500000	1288
..	...	...	...	...
405	Uganda	2.000000	5.000000	67
406	Uganda	5.000000	10.000000	30
407	Uganda	10.000000	20.000000	15
408	Uganda	20.000000	50.000000	10
409	United Kingdom	2.000000	4.000000	3248
410	United Kingdom	5.000000	9.000000	3256
411	United Kingdom	10.000000	19.000000	3252
412	United Kingdom	20.000000	29.000000	3248
413	United Kingdom	30.000000	49.000000	3236
414	United Kingdom	50.000000	99.000000	3248
415	United States	0.404685	4.006381	487
416	United States	4.046850	20.193782	664
417	United States	20.234250	28.287482	584
418	United States	28.327950	40.428032	610
419	United States	40.468500	56.251215	634
420	United States	56.655900	72.438615	623
421	United States	72.843300	88.626015	570
422	United States	89.030700	104.813415	573
423	United States	105.218100	201.937815	687
424	United States	202.342500	404.280315	679

```
425      United States    404.685000    808.965315                 644
426            Uruguay      1.000000      2.000000                 102
427            Uruguay      2.000000      5.000000                 230
428            Uruguay      5.000000     10.000000                 288
429            Uruguay     10.000000     20.000000                 312
430            Uruguay     20.000000     50.000000                 412
431            Uruguay     50.000000    100.000000                 330
432            Uruguay    100.000000    200.000000                 302
433            Uruguay    200.000000    500.000000                 246
434            Uruguay    500.000000   1000.000000                 200

[435 rows x 4 columns]
```

In [56]:
```
tmp = pivot.query("NAME_0 == 'Albania'")
# plt.barh(tmp['fs_class_min'], tmp['fs_class_max'])
```

In [80]:
```
plt.bar(tmp['fs_class_min'], tmp['fs_class_min'])
```

Out[80]:
```
<Container object of 7 artists>
```



In [ ]: