General_Results

August 15, 2017

```
In [2]: 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[2]: <IPython.core.display.HTML object>

In [4]: HTML('''
        <style>
            .yourDiv {position: fixed;top: 100px; right: 0px;
                      background: white;
                      height: 100%;
                      width: 175px;
                      padding: 10px;
                      z-index: 10000}
        </style>
        <script>
        function showthis(url) {
                window.open(url, "pres",
                        "toolbar=yes,scrollbars=yes,resizable=yes,top=10,left=400,width=500,heig
                return(false);
        }
        </script>

        <div class=yourDiv>
            <h4>MENU</h4><br>
            <a href=#Data>1. Data</a><br>
            <a href=#FoodFeedOtherAcross>2. Food, Feed, Other</a><br>
            <a href=#FoodFeedOtherWithin>3. Within Farmsizes</a><br><br>
```

```
            <a href=#Top>Top</a><br>
            <a href="javascript:code_toggle()">Toggle Code On/Off</a><br>
            <a href=#LeftOff>Left Off Here</a><br>
            <a href='https://vinnyricciardi.github.io/farmsize_site/'>Site Index</a><br>
        </div>
        ''')
```

Out[4]: <IPython.core.display.HTML object>

General Results
This page overviews our general results:

- The main findings are that in our sample of 58 countries, farms < 2 ha produce 8% of the total food supply, while farms < 50 ha produce 41% of the total food supply. The largest differences (in terms of effect size) in the amount of food produced were between the very large farm and the smallest farm categories in terms of how much food each produced. 68% of all the food came from 20 to 100 ha and 200 to 1000 ha farm sizes.
- This study also measures what percentage of each farm size class's crop producion goes towards food, feed, processing, seed, waste, or other. The farm size category with the largest percentage of food produced compared to other cateogories within thier farm size group, are from 100 to 1000 ha, where 70% of thier crop production goes towards food.
- 55% of crop production on farms < 2 ha goes towards food, while 16% goes towards feed, and the remainder either goes towards other, waste, processing, or seed (respectively).
- The farm size contributing to the largest amount of food waste (post-harvest loss, not consumer based food waste) are farms between 50-100 ha.

In [50]:
```
import warnings
warnings.filterwarnings('ignore')
import seaborn as sns
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from matplotlib import cm
import copy
import matplotlib.gridspec as gridspec
from collections import OrderedDict
from pivottablejs import pivot_ui  # python setup.py install --user
%matplotlib inline
```

In [51]:
```
def read_data(path):

    data = pd.read_csv(path, low_memory=False)
    data['Farm_Sizes'] = pd.cut(data['fs_class_max'],
                                bins=[0, 1, 2, 5, 10, 20, 50,
                                      100, 200, 500, 1000, 100000])
```

```
    global variables
    variables = OrderedDict([('Farm_Sizes', 'Farm_Sizes'),
                             ('production_Food_kcal', 'Food'),
                             ('production_Feed_kcal', 'Feed'),
                             ('production_Seed_kcal', 'Seed'),
                             ('production_Waste_kcal', 'Waste'),
                             ('production_Processing_kcal', 'Processing'),
                             ('production_Other_kcal', 'Other')])

    data = data.loc[:, variables.keys()]
    data.columns = variables.values()

    return data
```

```
In [52]: def piv(data, func=np.nansum):

             pivot = pd.pivot_table(data,
                                    index=['Farm_Sizes'],
                                    values=variables.values()[1:],
                                    aggfunc=func)

             return pivot
```

```
In [53]: def perc(data, how='within'):

             if how is 'within':

                 pivot = piv(data)
                 pivot = pivot.transpose()

                 for variable in pivot.columns:
                     pivot[variable] = pivot[variable] / pivot[variable].sum()

                 return pivot.transpose()


             elif how is 'cumsum':

                 pivot = piv(data)

                 for variable in pivot.columns:
                     pivot[variable] = pivot[variable] / pivot[variable].sum()

                 pivot = pivot.cumsum(axis=0)

                 return pivot
```

```
            elif how is 'across':

                pivot = piv(data)

                for variable in pivot.columns:
                    pivot[variable] = pivot[variable] / pivot[variable].sum()

                return pivot.transpose()

            else:

                print 'Require how argument'
```

```
In [481]: def plot_stacked_bar(data, how='within', fig_=True, ax=None):

              txt1 = ['Feed', 'Food', 'Other', 'Processing', 'Seed', 'Waste']
              txt2 = ['< 1', '1 to 2', '2 to 5', '5 to 10', '10 to 20',
                      '20 to 50', '50 to 100', '100 to 200', '200 to 500',
                      '500 to 1000', '> 1000']
              txt3 = ['< 1', '2 to 5', '10 to 20', '50 to 100', '200 to 500', '> 1000']

              if how is 'within':

                  legend_txts = copy.copy(txt1)
                  labels_txts = copy.copy(txt2)
                  cmap = cm.get_cmap('Set3')
                  kind = 'bar'

              elif how is 'across':

                  legend_txts = copy.copy(txt2)
                  labels_txts = copy.copy(txt1)
                  cmap = cm.get_cmap('YlGnBu')
                  kind = 'bar'

              elif how is 'cumsum':

                  legend_txts = copy.copy(txt1)
                  labels_txts = copy.copy(txt3)
                  cmap = cm.get_cmap('Set3')
                  kind = 'area'

              else:
                  pass

              if fig_ is True:

                  fig = plt.figure(figsize=[10, 5], facecolor='white')
```

```
    ax = fig.add_subplot(111)

else:
    pass

data.plot(kind=kind,
          stacked=True,
          cmap=cmap,
          alpha=0.9,
          linewidth=0,
          grid=False,
          ax=ax)

# Axis main
ax.set_axis_bgcolor("#d6d7e5")
ax.set_clip_on(False)
box = ax.get_position()
ax.set_position([box.x0, box.y0, box.width * 0.8, box.height])

# Legend
legend_txts_r = copy.deepcopy(legend_txts)
legend_txts_r.reverse()
handles, labels = ax.get_legend_handles_labels()
legend = ax.legend(handles[::-1], labels[::-1],
                   loc='center left',
                   frameon=1,
                   bbox_to_anchor=(1, 0.5))

for i in xrange(len(legend_txts_r)):
    legend.get_texts()[i].set_text(legend_txts_r[i])

frame = legend.get_frame()
frame.set_color('white')

# Axis particulars
ax.set_xticklabels(labels_txts)
ax.set_xticklabels(ax.xaxis.get_majorticklabels(), rotation=45)

if how is 'within':
    ax.set_xlabel('Farm Sizes (ha)')
    ax.set_ylabel('Percentage\n')
    ax.set_ylim([0, 1])
    ax.set_title('Type of production per farm size\n', fontsize=12)

elif how is 'across':
    ax.set_xlabel('Category')
    ax.set_ylabel('Percentage\n')
    ax.set_ylim([0, 1])
```

```
                ax.set_title('Type of production across farm size\n', fontsize=12)

            elif how is 'cumsum':
                ax.set_xlabel('Farm Sizes (ha)')
                ax.set_ylabel('Percentage\n')
                ax.set_title('Type of production per farm size: Cumulative\n', fontsize=12)

            if fig_ is True:
                return plt.show()

            else:
                return ax
```

```
In [55]: PATH = '/Users/Vinny_Ricciardi/Documents/Data_Library_Big/Survey/Global/Farm_Size/Data/
         df = read_data(PATH)
```

```
In [466]: df_within = perc(df, how='within')
          df_across = perc(df, how='across')
          df_cumsum = perc(df, how='cumsum')
          df_raw = piv(df)
```

```
In [467]: tmp1 = df_within.copy()
          tmp1['Type'] = 'Within'

          tmp2 = df_across.copy()
          tmp2 = tmp2.transpose()
          tmp2['Type'] = 'Across'

          tmp3 = df_cumsum.copy()
          tmp3['Type'] = 'Cumsum'

          tmp4 = df_raw.copy()
          tmp4['Type'] = 'Raw'

          tmp = pd.concat([tmp1, tmp2, tmp3, tmp4])
          tmp = tmp.reset_index()
          tmp['Farm_Sizes'] = tmp['Farm_Sizes'].str.replace('(', '')
          tmp['Farm_Sizes'] = tmp['Farm_Sizes'].str.replace(']', '')
```

Data

Here is a link to an interactive pivot table so you can explore the data. Use 'type' to change whether you are looking at the percentage of crop produced for each category 'within' a farm size group, 'across' groups, via a 'cumulative' percentage across groups, or raw kcal produced. Use the dropdown labeled 'Food' to recalculate based on another production category.

The default setting shows a heatmap for which farm size classes have the highest food production (kcal/person) per category. The 500 to 1000 farm size class makes up 52% of all food production in our dataset, which accounts for 73% of this group's total crop production.

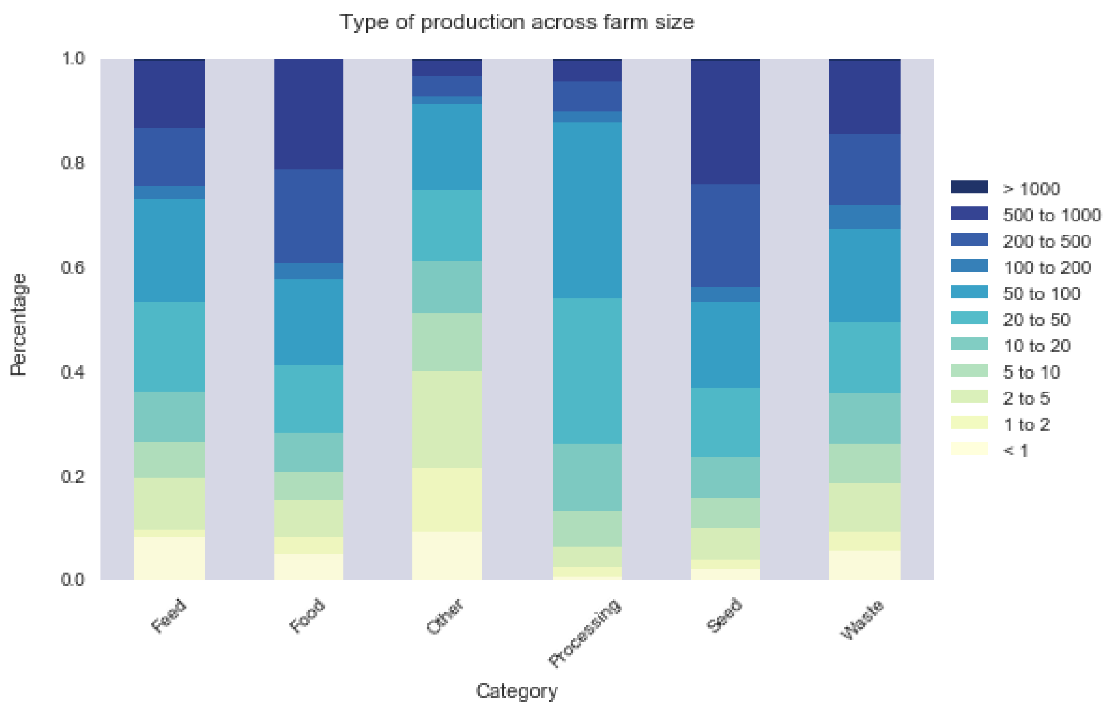
The three charts below were derived from the pivot table.

```
In [58]: # pivot_ui(tmp)  # Enable for pivot table interactivitity within this Jupyter notebook
```

Food Feed Other by Farm Size

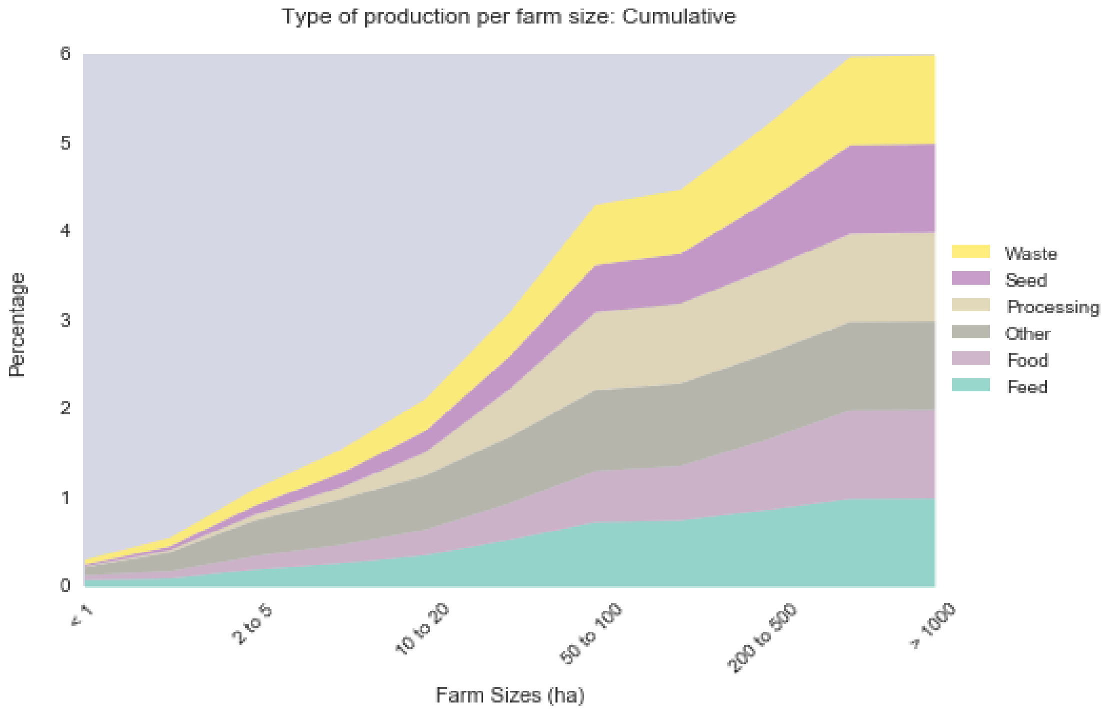
This plot shows the percentage that each farm size contributes to each category (e.g., food, feed, other, etc.) For example, farms under 1 ha produce 5% of the total food supply in our sample.

```
In [482]: plot_stacked_bar(df_across, how='across', fig_=True)
```



This plot also shows the percentage that each farm size contributes to each category but in cumulative percentages. For example, farms under 2 ha produce 8% of the total food supply in our sample and farms 20 ha and under produce 48% of the total food supply in our sample. Again, here is a link to an interactive pivot table so you can explore the data in more detail.

```
In [478]: plot_stacked_bar(df_cumsum, how='cumsum', fig_=True)
```



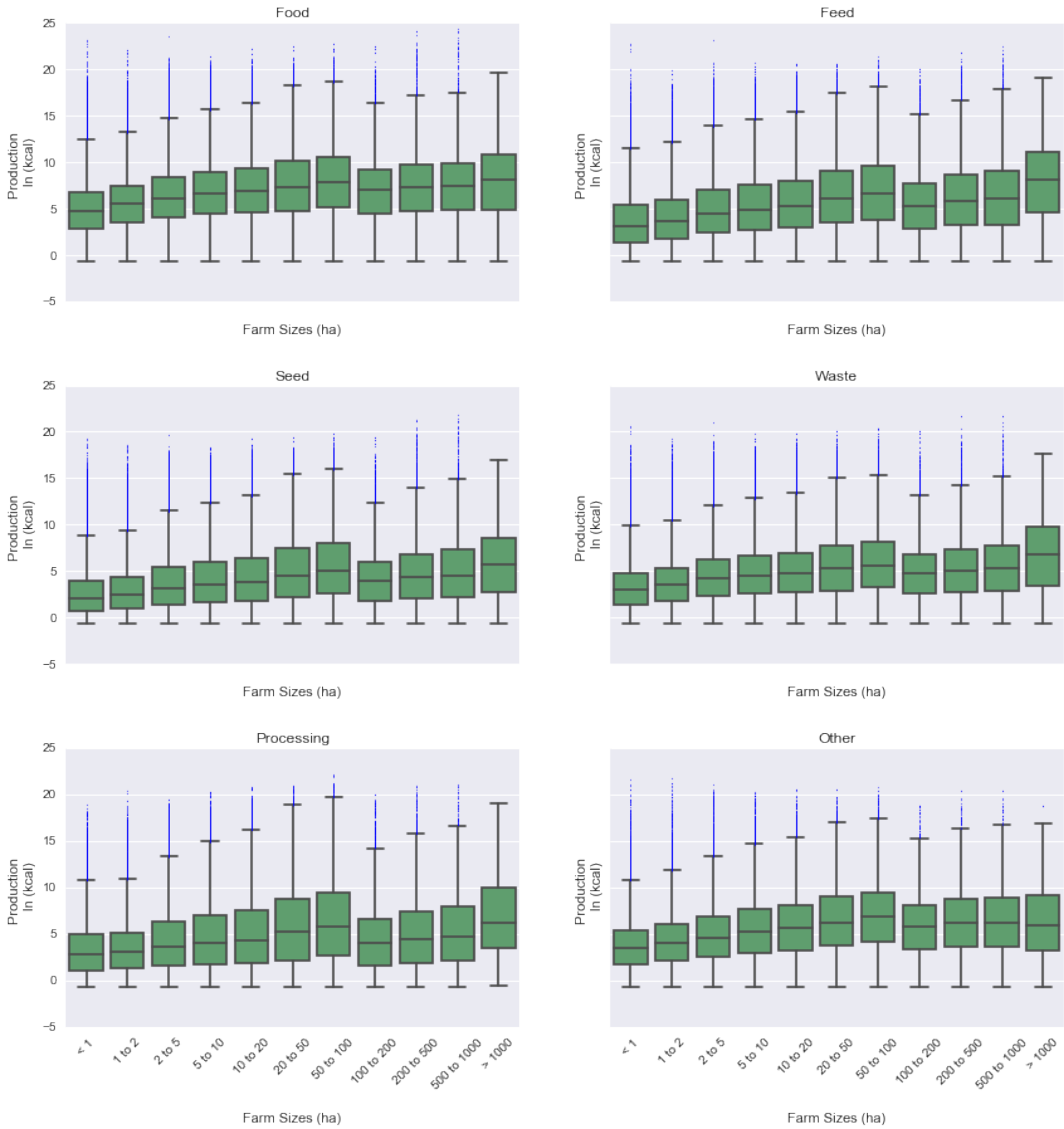

```
In [452]: def factor_plot(data, id_var='Farm_Sizes'):

              data = pd.melt(data, id_vars='Farm_Sizes')
              data = data.loc[data['value'] > 0.5]
              data['log'] = np.log(data['value'])

              fs_order = ['(0, 1]', '(1, 2]', '(2, 5]', '(5, 10]',
                          '(10, 20]', '(20, 50]', '(50, 100]', '(100, 200]', '(200, 500]',
                          '(500, 1000]', '(1000, 100000]']

              if id_var is 'Farm_Sizes':

                  col = 'variable'
                  x = 'Farm_Sizes'
                  y = 'log'
                  order = fs_order

              else:

                  data = data.sort('Farm_Sizes')
                  data['Farm_Sizes'] = pd.Categorical(data['Farm_Sizes'], fs_order)
                  data = data.sort('Farm_Sizes')
                  col = 'Farm_Sizes'
                  x = 'variable'
```

```
        y = 'log'
        order = None

    g = sns.factorplot(x=x, y=y,
                       col=col,
                       data=data,
                       kind='box',
                       col_wrap=2,
                       color='#55a868',
                       fliersize=1,
                       aspect = 1.5,
                       order=order)

    g.fig.subplots_adjust(wspace=0.2, hspace=0.3)

    titles = data.variable.unique()

    fs_txt = ['< 1', '1 to 2', '2 to 5', '5 to 10', '10 to 20',
              '20 to 50', '50 to 100', '100 to 200', '200 to 500',
              '500 to 1000', '> 1000']

    if id_var is 'Farm_Sizes':

        for ax, title in zip(g.axes.flat, titles):

            ax.set_title(title)
            ax.set_ylabel('Production \n ln (kcal)')
            ax.set_xticklabels(fs_txt)
            ax.set_xticklabels(ax.xaxis.get_majorticklabels(), rotation=45)
            ax.set_xlabel('\nFarm Sizes (ha)')

    else:

        for ax, title in zip(g.axes.flat, fs_txt):

            ax.set_title(title)
            ax.set_ylabel('Production \n ln (kcal)')
            ax.set_xticklabels(ax.xaxis.get_majorticklabels(), rotation=45)
            ax.set_xlabel('\nPoduction Category')
```

```
In [92]: number_of_records = len(df)
```

In order to better understand whether there are differences between the farm size groups, these boxplots show the total amount of crops produced (in logged kcal for standardization). Across all production categories (e.g., food, feed, other, etc.) there are no visual differences in the means and confidence intervals. But, there are (a) a lot of outliers in each plot that indicate high variance, and (b) since our sample is very large (58 countries which comprise of 564134 total records due to subnational units and crop types) we cannot use p-values to determine significance.

```
In [424]: factor_plot(df, id_var='Farm_Sizes')
```



To circumvent the large dataset issue, the effect size was used to determine differences between farm sizes rather than statistical significance. Cohen's d was calculated via taking the (mean of farmsize 1 - mean of farmsize 2) / (standard deviation of farmsize 1) then taking the absolute value. The relative significance was calculated by thresholds according to Sullivan and Feinn 2012.

Where the Cohen d's effect size values correspond to percent non-overlapping observations, as in:

Relative Size	Effect Size	Percentile	% of Non- overlap
	0	50	0

Relative Size	Effect Size	Percentile	% of Non- overlap
Small	0.2	58	15
Medium	0.5	69	33
Large	0.8	79	47
	1.0	84	55
	1.5	93	71
	2.0	97	81

```
In [418]: def cohens_d(data1, data2, how='within'):

              cols = data1.columns
              check = []

              for i in xrange(0, len(cols)):

                  for j in xrange(1, len(cols)):

                      col_name = str(cols[i]) + '_' + str(cols[j])
                      col_name_r = str(cols[j]) + '_' + str(cols[i])

                      if col_name in check:

                          pass

                      elif cols[i] is cols[j]:

                          pass

                      else:

                          data1[col_name] = ((data1[cols[i]] - data1[cols[j]]) / data2[cols[i]])
                          check.append(col_name)
                          check.append(col_name_r)

              data = data1.iloc[:, len(cols):]

              data = data.reset_index()

              if how is 'within':

                  data = pd.melt(data, id_vars='Farm_Sizes', value_name='cohens_d')

              else:

                  data = pd.melt(data, id_vars='index', value_name='cohens_d')

              data['cohens_d_level'] = np.where(data['cohens_d'] <= 0.2, 'small',
```

```
                                    np.where(data['cohens_d'] >= 0.8, 'large',
                                             'medium'))

        return data
```

Here are the results:

```
In [436]: data = df.copy()
          data['Farm_Sizes'] = data['Farm_Sizes'].astype(str)
          means = pd.pivot_table(data, columns='Farm_Sizes', aggfunc=np.nanmean)
          sds = pd.pivot_table(data, columns='Farm_Sizes', aggfunc=np.nanstd)
          out = cohens_d(means, sds, how='across')
          out = out.loc[out['cohens_d_level'] == 'large']
          out['Farm_Sizes'] = out['Farm_Sizes'].str.replace(']', ')')
          out['Farm_Sizes'] = out['Farm_Sizes'].str.replace('_', ' and ')
          out.columns = ['Category', 'Farm sizes compared', 'Cohens d', 'Relative effect size']
          out.sort('Cohens d')
```

Out[436]:

	Category	Farm sizes compared	Cohens d	Relative effect size
109	Food	(1, 2) and (500, 1000)	0.848607	large
157	Food	(10, 20) and (500, 1000)	0.879428	large
94	Seed	(1, 2) and (200, 500)	0.911315	large
57	Processing	(0, 1) and (500, 1000)	0.987951	large
239	Waste	(1000, 100000) and (500, 1000)	1.111736	large
292	Seed	(20, 50) and (500, 1000)	1.119664	large
160	Seed	(10, 20) and (500, 1000)	1.220897	large
58	Seed	(0, 1) and (500, 1000)	1.415773	large
108	Feed	(1, 2) and (500, 1000)	1.433436	large
51	Processing	(0, 1) and (50, 100)	1.441876	large
319	Food	(5, 10) and (500, 1000)	1.622606	large
268	Seed	(2, 5) and (500, 1000)	1.692324	large
220	Seed	(1000, 100000) and (200, 500)	1.750565	large
112	Seed	(1, 2) and (500, 1000)	2.004887	large
322	Seed	(5, 10) and (500, 1000)	2.092567	large
217	Food	(1000, 100000) and (200, 500)	2.107617	large
238	Seed	(1000, 100000) and (500, 1000)	3.869504	large
235	Food	(1000, 100000) and (500, 1000)	4.411742	large

```
In [450]: tmp = pd.DataFrame(pd.pivot_table(out, index='Farm sizes compared', aggfunc='count').m
          tmp = tmp.reset_index()
          tmp.columns = ['Farm sizes compared', 'Count of large effect size']
          tmp
```

Out[450]:

	Farm sizes compared	Count of large effect size
0	(0, 1) and (50, 100)	1
1	(1, 2) and (200, 500)	1
2	(2, 5) and (500, 1000)	1
3	(20, 50) and (500, 1000)	1
4	(0, 1) and (500, 1000)	2

```
5         (10, 20) and (500, 1000)                                 2
6   (1000, 100000) and (200, 500)                                  2
7          (5, 10) and (500, 1000)                                 2
8           (1, 2) and (500, 1000)                                 3
9  (1000, 100000) and (500, 1000)                                  3
```

In [451]:
```python
tmp = pd.DataFrame(pd.pivot_table(out, index='Category', aggfunc='count').max(axis=1))
tmp = tmp.reset_index()
tmp.columns = ['Category', 'Count of large effect size']
tmp
```

Out[451]:

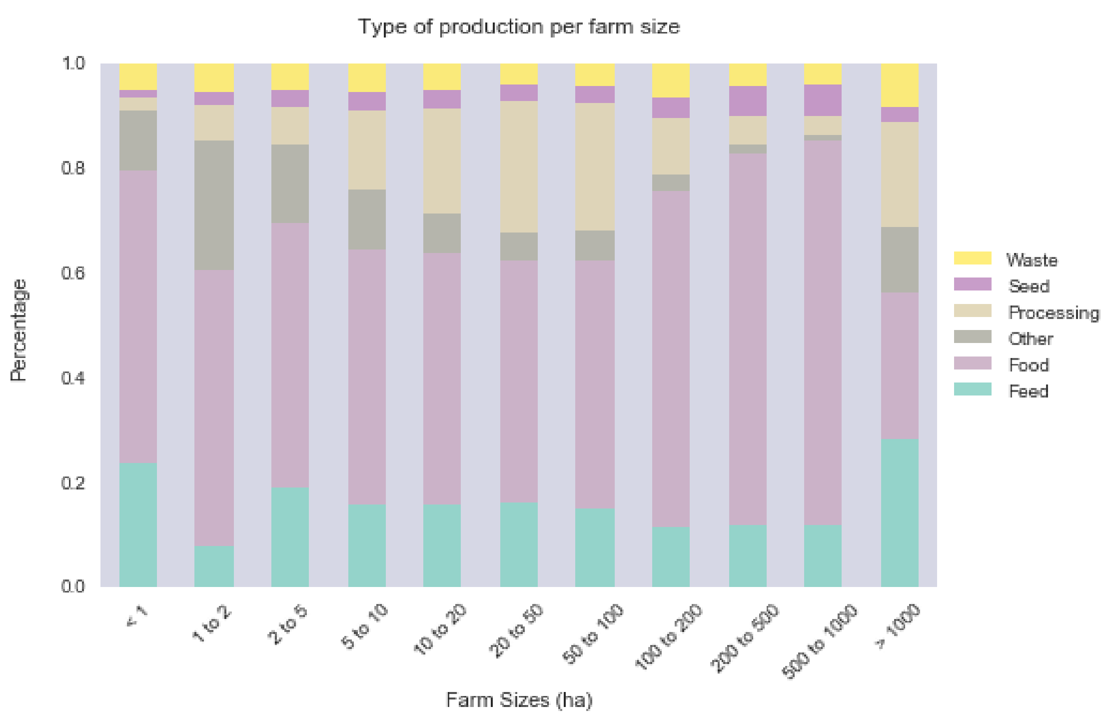
	Category	Count of large effect size
0	Feed	1
1	Waste	1
2	Processing	2
3	Food	5
4	Seed	9

From this we can see that there was the most differences between the (1, 2) and (500, 1000) farm size classes and (1000, 100000) and (500, 1000) farm size classes. For all farm size classes, the majority of differences were in the amount of seed and food production.

Food Feed Other within Farm Size Groups

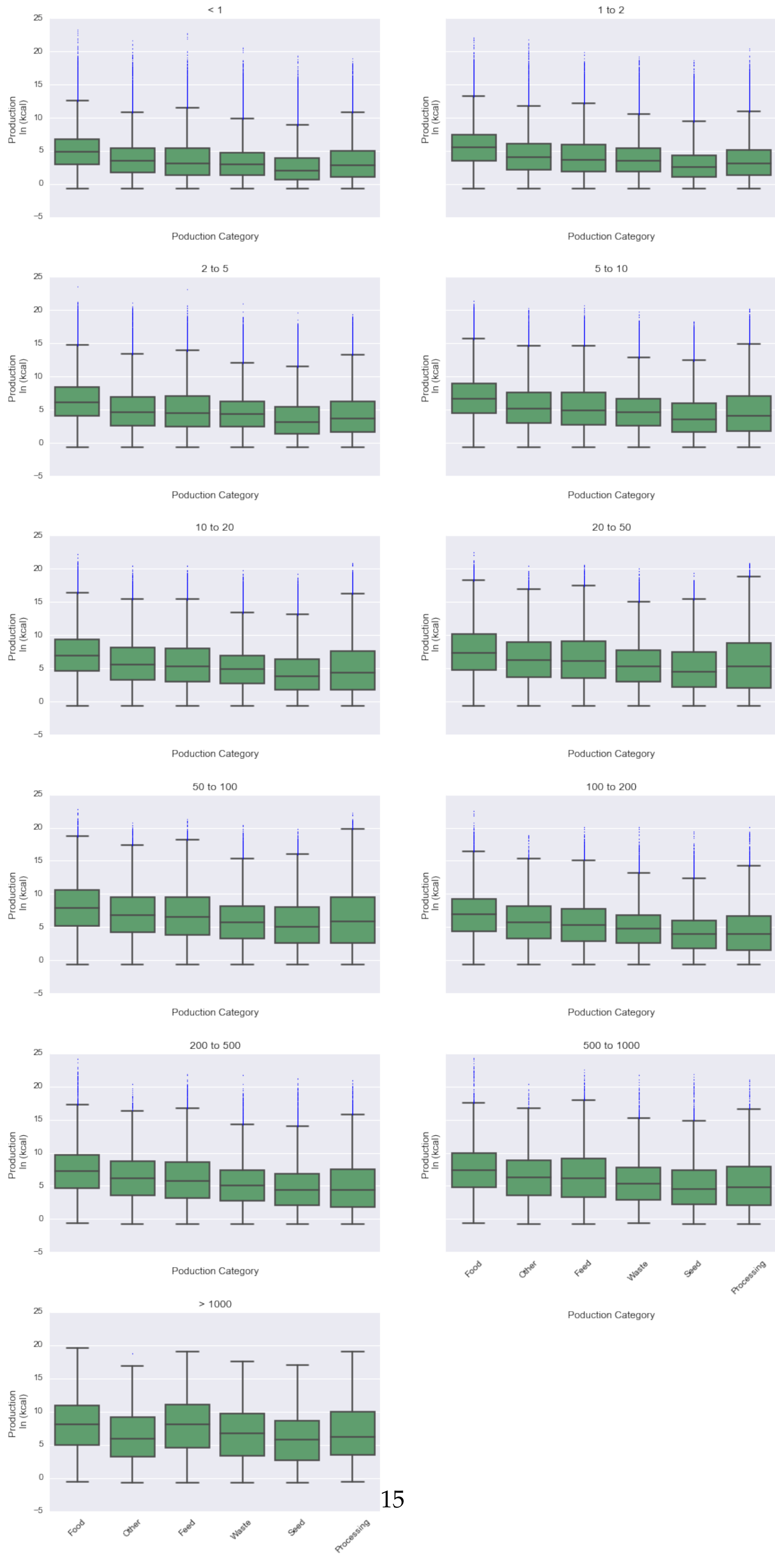
This plot shows the percentage of Food, Feed, Seed, Waste, Processing, and Other for each farm size category. For example, 56% of crop production for farms under 1 ha is food, while 6% of their crop production is waste.

In [479]:
```python
plot_stacked_bar(df_within, how='within', fig_=True)
```



These plots compare crop production within each farm size class:

```
In [453]: factor_plot(df, id_var='variable')
```


< 1
1 to 2
2 to 5
5 to 10
10 to 20
20 to 50
50 to 100
100 to 200
200 to 500
500 to 1000
> 1000
Production
ln (kcal)
Poduction Category
25
20
15
10
5
0
−5
Food
Other
Feed
Waste
Seed
Processing

We calculate the effect size for the differences within each farm size group, but across production cateogries (e.g., food, feed, other). There were only medium differences in effect size when looking at how each farm size group allocated their production.

```
In [457]: means = pd.pivot_table(df, index='Farm_Sizes', aggfunc=np.nanmean)
          sds =  pd.pivot_table(df, index='Farm_Sizes', aggfunc=np.nanstd)
          out = cohens_d(means, sds, how='within')
          out = out.loc[out['cohens_d_level'] != 'small']

          out['Farm_Sizes'] = out['Farm_Sizes'].str.replace(']', ')')
          out['variable'] = out['variable'].str.replace('_', ' and ')
          out.columns = ['Farm sizes', 'Categories commpared', 'Cohens d', 'Relative effect size
          out.sort('Cohens d')
```

```
Out[457]:      Farm sizes Categories commpared  Cohens d Relative effect size
          1        (1, 2)        Feed and Food  0.200763               medium
          7    (100, 200)        Feed and Food  0.236428               medium
          8    (200, 500)        Feed and Food  0.263749               medium
          9   (500, 1000)        Feed and Food  0.266787               medium
```

Global Estimates

```
In [486]: data = df.copy()
```

```
In [487]: data.head()
```

```
Out[487]:    Farm_Sizes  Food  Feed  Seed  Waste  Processing  Other
          0      (1, 2]   NaN   NaN   NaN    NaN         NaN    NaN
          1    (20, 50]   NaN   NaN   NaN    NaN         NaN    NaN
          2    (20, 50]   0.0   0.0   0.0    0.0         0.0    0.0
          3   (50, 100]   0.0   0.0   0.0    0.0         0.0    0.0
          4    (20, 50]   0.0   0.0   0.0    0.0         0.0    0.0
```

Left Off

To Do: - Need to calculate bootstraps and jackknife estimates

```
In [ ]:
```