In [1]:
```
# Dataframe manipulation libraries
import pandas as pd
import numpy as np
from scipy import stats # to detect outliers

# Graph Libraries
from matplotlib import pyplot as plt
import seaborn as sns

import numpy as np
import pandas as pd
import seaborn as sns # for visualiation
import matplotlib.pyplot as plt
import data_prep as dp

from numpy.random import seed
from numpy.random import randn
from numpy import mean
from numpy import std

from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score
from sklearn.metrics import mean_absolute_error
from sklearn.metrics import median_absolute_error
from sklearn.metrics import explained_variance_score
from sklearn.pipeline import make_pipeline
from sklearn.model_selection import GridSearchCV
from sklearn.model_selection import KFold
from sklearn.model_selection import cross_val_score
from sklearn.ensemble import ExtraTreesRegressor
from sklearn.neighbors import KNeighborsRegressor
from xgboost import XGBRegressor
from xgboost import plot_importance
from sklearn.ensemble import RandomForestRegressor
from sklearn.tree import DecisionTreeRegressor
from sklearn.pipeline import Pipeline
from sklearn.feature_selection import SelectFromModel
from sklearn.svm import LinearSVC


# Load data
features_train = pd.read_csv('./data/dengue_features_train.csv')
labels_train = pd.read_csv('./data/dengue_labels_train.csv')
features_test = pd.read_csv('./data/dengue_features_test.csv')
```

Predicting Dengue

Zoshua Colah, Arsalan Ahmed

Hi, welcome to our Modelling Dengue Notebook. We are two rookie undergraduate students at the University of Washington in an introductory ML class applying Machine Learning models to predict Dengue in San Juan & Iquitos as part of the Driven Data Challenge.

Our notebook is extremely long due to the amount of EDA we did and the number of datasets we created and tested with various Machine Learning models.

To help you navigate this document better, we recommend taking a look at our Table of Contents:*

Setup & Importing Data & Understanding Column Names

We have created a separate data_prep.py file to help us easily generate our datasets without any clutter. We have introduced the following new columns as part of the feature generation process:

1. Rolling Averages for all climate and vegetation features (read discussion below)
2. Month: the month number

Rolling Averages

There can be a lot of fluctuation in our variables which can cause bias in our model. To help reduce the bias we have introduced Rolling Averages to help provide a better understanding of the overall current scenario.

We have added rolling average columns for all the climate variables and vegetation indexes

A simple rolling average (also called a moving average, if you wanted to know) is the unweighted mean of the last n values. In simple words: An average of the last n values in a data set, applied row-by-row, so that you get a series of average

One year has 52 weeks on average. Initially we decided to take n as 52 because of this.

However after running a for loop to find the week with the least MOE and best fit, we found that n as 50 would be better. Hence n is 50.

Please refer to our supplement files to see this.

Missingness of our Data

We have followed the following steps

1. Take a sample of our data
2. Check for total number of missing values in each column
3. Percentage of data missing from our dataframe

Below we can see the count of missing values for each city and visualize where exactly do we have missing values for each column.

Source of Inspiration for the Visualization (https://github.com/AlexJF12/predicting-dengue/blob/master/1%20-%20Dengue%20cases%20data%20cleaning.ipynb)

San Juan

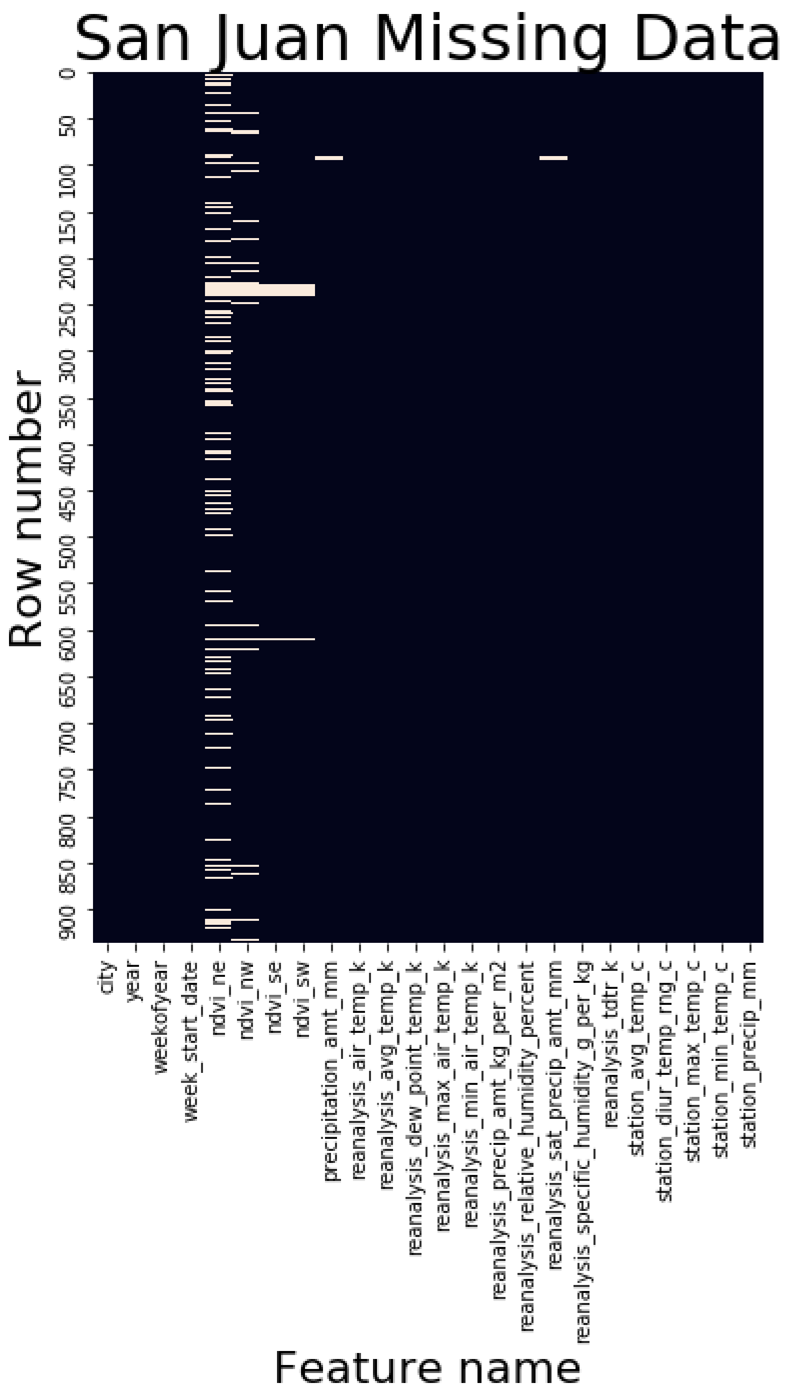
```
In [2]: df_sj = features_train[features_train['city'] == 'sj']
        missing_values_count = df_sj.isnull().sum()
        missing_values_count
```

```
Out[2]: city                                       0
        year                                       0
        weekofyear                                 0
        week_start_date                            0
        ndvi_ne                                  191
        ndvi_nw                                   49
        ndvi_se                                   19
        ndvi_sw                                   19
        precipitation_amt_mm                       9
        reanalysis_air_temp_k                      6
        reanalysis_avg_temp_k                      6
        reanalysis_dew_point_temp_k                6
        reanalysis_max_air_temp_k                  6
        reanalysis_min_air_temp_k                  6
        reanalysis_precip_amt_kg_per_m2            6
        reanalysis_relative_humidity_percent       6
        reanalysis_sat_precip_amt_mm               9
        reanalysis_specific_humidity_g_per_kg      6
        reanalysis_tdtr_k                          6
        station_avg_temp_c                         6
        station_diur_temp_rng_c                    6
        station_max_temp_c                         6
        station_min_temp_c                         6
        station_precip_mm                          6
        dtype: int64
```

From the visualization below we notice that the vegetation index column for the north east has a lot of missing values

```
In [3]: fig, ax = plt.subplots(figsize=(6,8))
        sns.heatmap(df_sj.isnull().reset_index(drop=True),ax=ax, cbar = False, yti
        cklabels = 50)

        plt.ylabel("Row number", size = 22)
        plt.xlabel("Feature name", size = 22)
        plt.title("San Juan Missing Data", size = 32)
```

```
Out[3]: Text(0.5,1,'San Juan Missing Data')
```



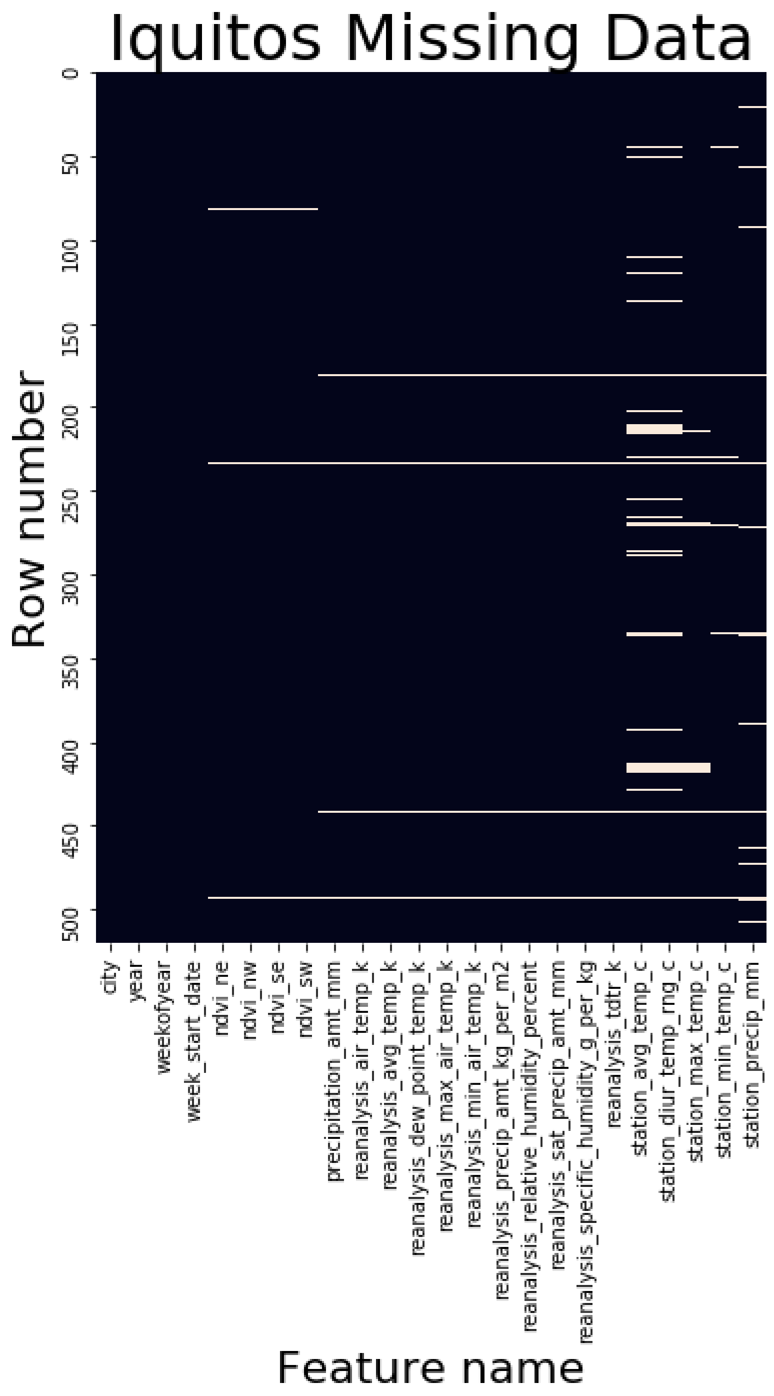
Iquitos

```
In [4]: df_iq = features_train[features_train['city'] == 'iq']
        missing_values_count = df_iq.isnull().sum()
        missing_values_count
```

```
Out[4]: city                                      0
        year                                      0
        weekofyear                                0
        week_start_date                           0
        ndvi_ne                                   3
        ndvi_nw                                   3
        ndvi_se                                   3
        ndvi_sw                                   3
        precipitation_amt_mm                      4
        reanalysis_air_temp_k                     4
        reanalysis_avg_temp_k                     4
        reanalysis_dew_point_temp_k               4
        reanalysis_max_air_temp_k                 4
        reanalysis_min_air_temp_k                 4
        reanalysis_precip_amt_kg_per_m2           4
        reanalysis_relative_humidity_percent      4
        reanalysis_sat_precip_amt_mm              4
        reanalysis_specific_humidity_g_per_kg     4
        reanalysis_tdtr_k                         4
        station_avg_temp_c                       37
        station_diur_temp_rng_c                  37
        station_max_temp_c                       14
        station_min_temp_c                        8
        station_precip_mm                        16
        dtype: int64
```

We can notice that there are missing values for particular short intervals of time for Iquitos

```
In [5]: fig, ax = plt.subplots(figsize=(6,8))
        sns.heatmap(df_iq.isnull().reset_index(drop=True),ax=ax, cbar = False, yti
        cklabels = 50)

        plt.ylabel("Row number", size = 22)
        plt.xlabel("Feature name", size = 22)
        plt.title("Iquitos Missing Data", size = 32)

Out[5]: Text(0.5,1,'Iquitos Missing Data')
```



How did we handle missing values?

We handled missing values by using Forward Fill.

Take a peak at the Training Data

We do not look at testing data before model validation ever as it influences our decision making when making models.

In [6]:
```
print("Training Features")
features_train.sample(3)
```

```
Training Features
```

Out[6]:

	city	year	weekofyear	week_start_date	ndvi_ne	ndvi_nw	ndvi_se	ndvi_sw	precipi
1420	iq	2009	43	2009-10-22	0.2968	0.308486	0.362300	0.361657	82.59
441	sj	1998	43	1998-10-22	0.0213	0.085000	0.196967	0.196200	32.09
415	sj	1998	17	1998-04-23	0.0671	0.091367	0.144486	0.147957	22.22

3 rows × 24 columns

In [7]:
```
print("Training Labels")
labels_train.sample(3)
```

```
Training Labels
```

Out[7]:

	city	year	weekofyear	total_cases
510	sj	2000	7	7
867	sj	2007	1	10
361	sj	1997	15	11

General Column Names & Data Types

City and Date Indicators

- **city** – City abbreviations: sj for San Juan and iq for Iquitos
- **year** - Year
- **weekofyear** - Week Number
- **dayofyear** - Day of Year Number
- **month** - Month Number of the Year
- **week_start_date** – Date given in yyyy-mm-dd format
- **total_cases** - Total Cases for that week
- **previous_week_cases** - Total Cases in the previous week
- **odd_year** - Whether year is odd or not

Satellite vegetation - Normalized difference vegetation index (NDVI) - NOAA's CDR Normalized Difference Vegetation Index (0.5x0.5 degree scale) measurements

- **ndvi_ne** – Pixel northeast of city centroid
- **ndvi_nw** – Pixel northwest of city centroid
- **ndvi_se** – Pixel southeast of city centroid
- **ndvi_sw** – Pixel southwest of city centroid

PERSIANN satellite precipitation measurements (0.25x0.25 degree scale)

- **precipitation_amt_mm – Total precipitation**

NOAA's NCEP Climate Forecast System Reanalysis measurements (0.5x0.5 degree scale)

- **reanalysis_sat_precip_amt_mm** – Total precipitation
- **reanalysis_dew_point_temp_k** – Mean dew point temperature
- **reanalysis_air_temp_k** – Mean air temperature
- **reanalysis_relative_humidity_percent** – Mean relative humidity
- **reanalysis_specific_humidity_g_per_kg** – Mean specific humidity
- **reanalysis_precip_amt_kg_per_m2** – Total precipitation
- **reanalysis_max_air_temp_k** – Maximum air temperature
- **reanalysis_min_air_temp_k** – Minimum air temperature
- **reanalysis_avg_temp_k** – Average air temperature
- **reanalysis_tdtr_k** – Diurnal temperature range

NOAA's GHCN daily climate data weather station measurements

- **station_max_temp_c** – Maximum temperature
- **station_min_temp_c** – Minimum temperature
- **station_avg_temp_c** – Average temperature
- **station_precip_mm** – Total precipitation
- **station_diur_temp_rng_c** – Diurnal temperature range

Note: to avoid clutter we have not put the column names for our rolling average columns

San Juan

```
In [8]: data_sj = dp.features_train(features_train, labels_train, 'sj')
        data_sj_n = dp.normalize(data_sj)
        data_test_sj = dp.features_test(features_test, features_train, 'sj')
        data_test_sj_n = dp.normalize(data_test_sj)
```

```
In [9]: data_sj.columns
```

```
Out[9]: Index(['city', 'year', 'weekofyear', 'week_start_date', 'ndvi_ne', 'ndvi_n
        w',
               'ndvi_se', 'ndvi_sw', 'precipitation_amt_mm', 'reanalysis_air_temp_
        k',
               'reanalysis_avg_temp_k', 'reanalysis_dew_point_temp_k',
               'reanalysis_max_air_temp_k', 'reanalysis_min_air_temp_k',
               'reanalysis_precip_amt_kg_per_m2',
               'reanalysis_relative_humidity_percent', 'reanalysis_tdtr_k',
               'station_avg_temp_c', 'station_diur_temp_rng_c', 'station_max_temp_
        c',
               'station_min_temp_c', 'station_precip_mm', 'total_cases', 'month',
               'odd_year', 'ndvi_mean', 'ndvi_mean_rolling_avg', 'ndvi_ne_rolling_a
        vg',
               'ndvi_nw_rolling_avg', 'ndvi_se_rolling_avg', 'ndvi_sw_rolling_avg',
               'precipitation_amt_mm_rolling_avg', 'reanalysis_air_temp_k_rolling_a
        vg',
               'reanalysis_avg_temp_k_rolling_avg',
               'reanalysis_dew_point_temp_k_rolling_avg',
               'reanalysis_max_air_temp_k_rolling_avg',
               'reanalysis_min_air_temp_k_rolling_avg',
               'reanalysis_precip_amt_kg_per_m2_rolling_avg',
               'reanalysis_relative_humidity_percent_rolling_avg',
               'reanalysis_tdtr_k_rolling_avg', 'station_avg_temp_c_rolling_avg',
               'station_diur_temp_rng_c_rolling_avg', 'station_max_temp_c_rolling_a
        vg',
               'station_min_temp_c_rolling_avg', 'station_precip_mm_rolling_avg'],
              dtype='object')
```

Understanding our Data

Peek at San Juan Data

Displaying the first 5 rows

Note: We have added Day of the Year and Odd Year and Month as as additional columns

```
In [10]: data_sj.head(5)
```

Out[10]:

	city	year	weekofyear	week_start_date	ndvi_ne	ndvi_nw	ndvi_se	ndvi_sw	precipita
50	sj	1991	16	1991-04-16	0.077400	0.102400	0.163550	0.206167	44.57
51	sj	1991	17	1991-04-23	0.077400	0.188450	0.188314	0.224943	32.72
52	sj	1991	18	1991-04-30	0.209167	0.160575	0.176171	0.176171	0.00
53	sj	1991	19	1991-05-07	0.115950	0.180175	0.106386	0.111186	35.38
54	sj	1991	20	1991-05-14	0.115950	0.104550	0.151150	0.096400	4.16

5 rows × 45 columns

Summary for San Juan Data

Key Insights:

1. Total Cases: Mean: 34.212834 Standard Dev: 51.399375

2. Average Temperature: Mean: 299.273178 Standard Dev: 1.219425

3. Precipitation in mm: Mean: 35.340973 Standard Dev: 44.672851

4. Humidity per kg: Mean: 16.550246 Standard Dev: 1.559292

```
In [11]: data_sj.describe().T
```

Out[11]:

	count	mean	std	min
year	886.0	1999.308126	4.934472	1991.000000
weekofyear	886.0	26.480813	15.013259	1.000000
ndvi_ne	886.0	0.051028	0.102386	-0.406250
ndvi_nw	886.0	0.059181	0.086382	-0.456100
ndvi_se	886.0	0.174379	0.057095	-0.015533
ndvi_sw	886.0	0.163999	0.055124	-0.063457
precipitation_amt_mm	886.0	35.505632	44.926028	0.000000
reanalysis_air_temp_k	886.0	299.174070	1.239851	295.938571
reanalysis_avg_temp_k	886.0	299.286448	1.223895	296.114286
reanalysis_dew_point_temp_k	886.0	295.113696	1.565015	289.642857
reanalysis_max_air_temp_k	886.0	301.406433	1.262127	297.800000
reanalysis_min_air_temp_k	886.0	297.312867	1.288898	292.600000
reanalysis_precip_amt_kg_per_m2	886.0	30.139537	35.075494	0.000000
reanalysis_relative_humidity_percent	886.0	78.537296	3.358534	66.735714
reanalysis_tdtr_k	886.0	2.523396	0.501501	1.357143
station_avg_temp_c	886.0	27.004708	1.415040	22.842857
station_diur_temp_rng_c	886.0	6.721961	0.822567	4.528571
station_max_temp_c	886.0	31.582167	1.717921	26.700000
station_min_temp_c	886.0	22.623928	1.490222	17.800000
station_precip_mm	886.0	27.037359	29.686567	0.000000
total_cases	886.0	34.770880	52.603328	0.000000
month	886.0	6.413093	3.450834	1.000000
ndvi_mean	886.0	0.112147	0.053678	-0.092565
ndvi_mean_rolling_avg	886.0	0.115907	0.026916	0.071922
ndvi_ne_rolling_avg	886.0	0.057172	0.049868	-0.042738
ndvi_nw_rolling_avg	886.0	0.065999	0.050388	-0.014226
ndvi_se_rolling_avg	886.0	0.175246	0.015392	0.144019
ndvi_sw_rolling_avg	886.0	0.165212	0.013830	0.136402
precipitation_amt_mm_rolling_avg	886.0	35.524514	7.353901	17.331600
reanalysis_air_temp_k_rolling_avg	886.0	299.163491	0.392223	298.517657
reanalysis_avg_temp_k_rolling_avg	886.0	299.277186	0.393867	298.636143
reanalysis_dew_point_temp_k_rolling_avg	886.0	295.120660	0.304288	294.366914
reanalysis_max_air_temp_k_rolling_avg	886.0	301.401984	0.413498	300.686000

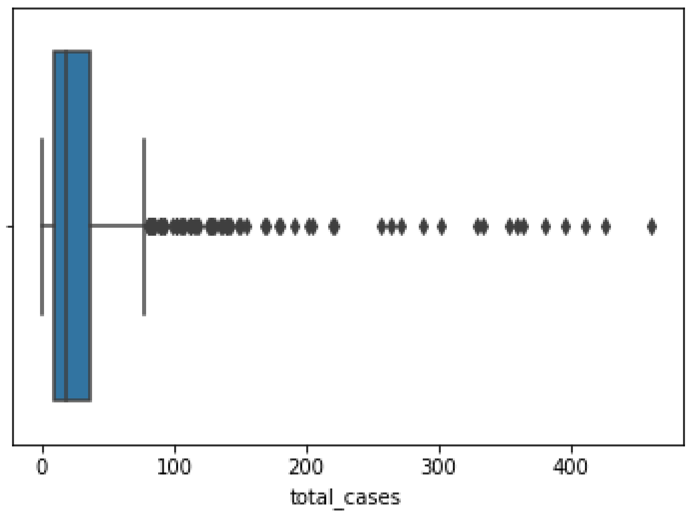
	count	mean	std	min
reanalysis_min_air_temp_k_rolling_avg	886.0	297.306108	0.317801	296.760000
reanalysis_precip_amt_kg_per_m2_rolling_avg	886.0	30.421307	7.558366	16.958400
reanalysis_relative_humidity_percent_rolling_avg	886.0	78.620778	1.103141	75.686343
reanalysis_tdtr_k_rolling_avg	886.0	2.516519	0.207171	2.189714
station_avg_temp_c_rolling_avg	886.0	27.011856	0.267859	26.292000
station_diur_temp_rng_c_rolling_avg	886.0	6.758192	0.326031	6.083429
station_max_temp_c_rolling_avg	886.0	31.613230	0.465189	30.390000
station_min_temp_c_rolling_avg	886.0	22.602619	0.209389	22.022000
station_precip_mm_rolling_avg	886.0	26.883235	5.290813	15.932000

Looking for outliers in our Data

From the plot below we notice that there are outliers in total cases for the past so many years between 90 and 500 cases

```
In [12]: sns.boxplot(x=data_sj['total_cases'])
```

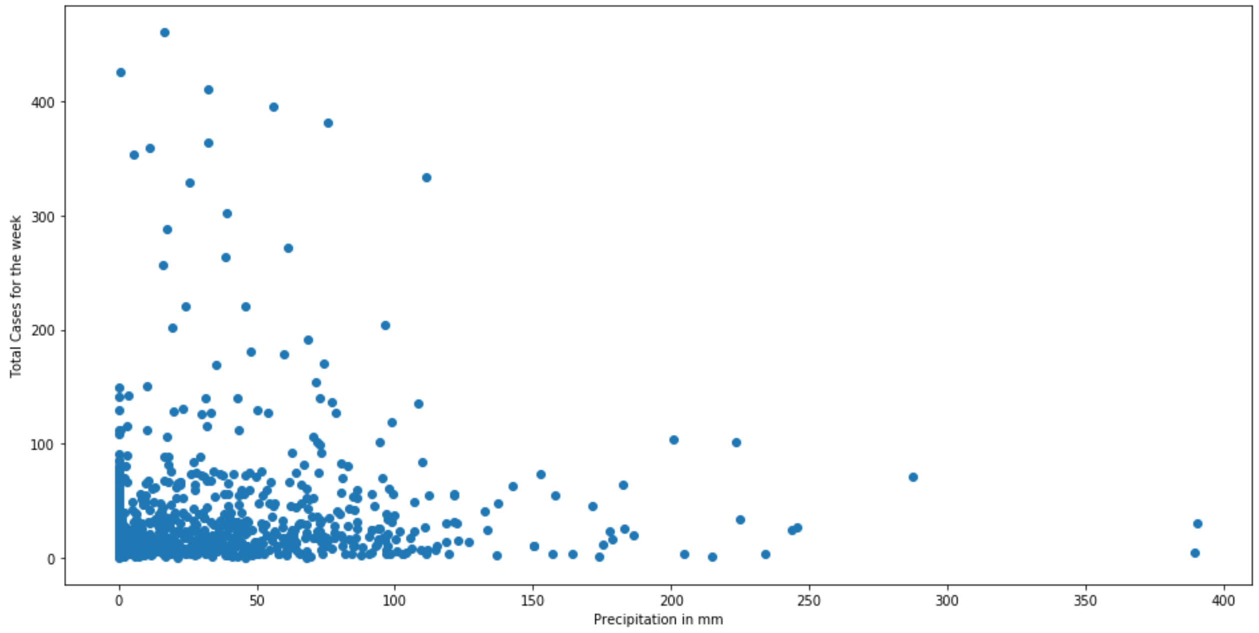
```
Out[12]: <matplotlib.axes._subplots.AxesSubplot at 0x1a150f3080>
```



Looking at the plot below, we can most of data points are lying bottom left side but there are points which are far from the population like top left & bottom right corner.

This also indicates that higher rainfall does not necessarrily lead to higher total number of cases for the week

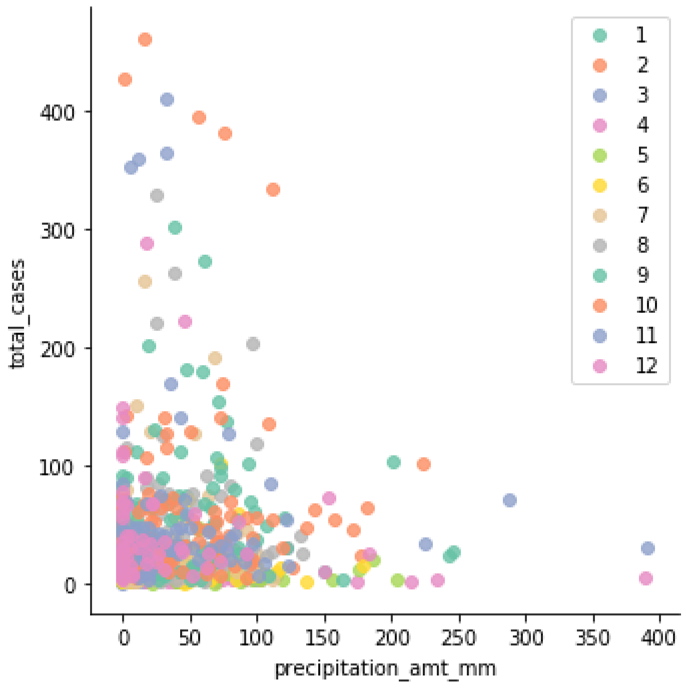
In [13]:
```
fig, ax = plt.subplots(figsize=(16,8))
ax.scatter(data_sj['precipitation_amt_mm'],data_sj['total_cases'])
ax.set_xlabel('Precipitation in mm')
ax.set_ylabel('Total Cases for the week')
plt.show()
```



We will handle our outliers after exploring our data further. This is so that we get a better understanding of the domain before we remove or reset outliers.

Below is the same scatter plot with each dot colored by month

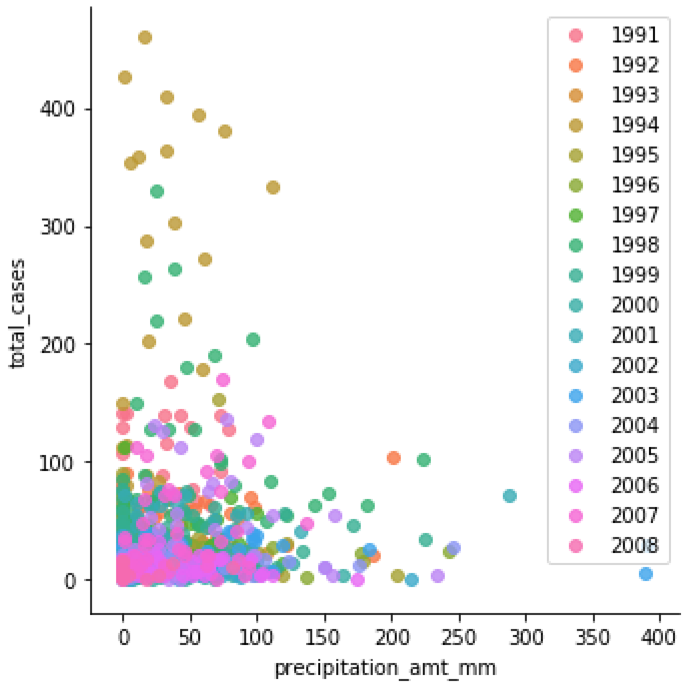
```
In [14]: # Use the 'hue' argument to provide a factor variable
         sns.lmplot( x="precipitation_amt_mm", y="total_cases", data=data_sj, fit_r
         eg=False,
                    hue='month', legend=False, palette="Set2")

         # Move the legend to an empty part of the plot
         plt.legend(loc='upper right')

Out[14]: <matplotlib.legend.Legend at 0x1a1525fb00>
```



Below is a scatter plot with each dot colored by month

```
In [15]: # Use the 'hue' argument to provide a factor variable
         sns.lmplot( x="precipitation_amt_mm", y="total_cases", data=data_sj, fit_r
         eg=False,
                    hue='year', legend=False)

         # Move the legend to an empty part of the plot
         plt.legend(loc='upper right')
```

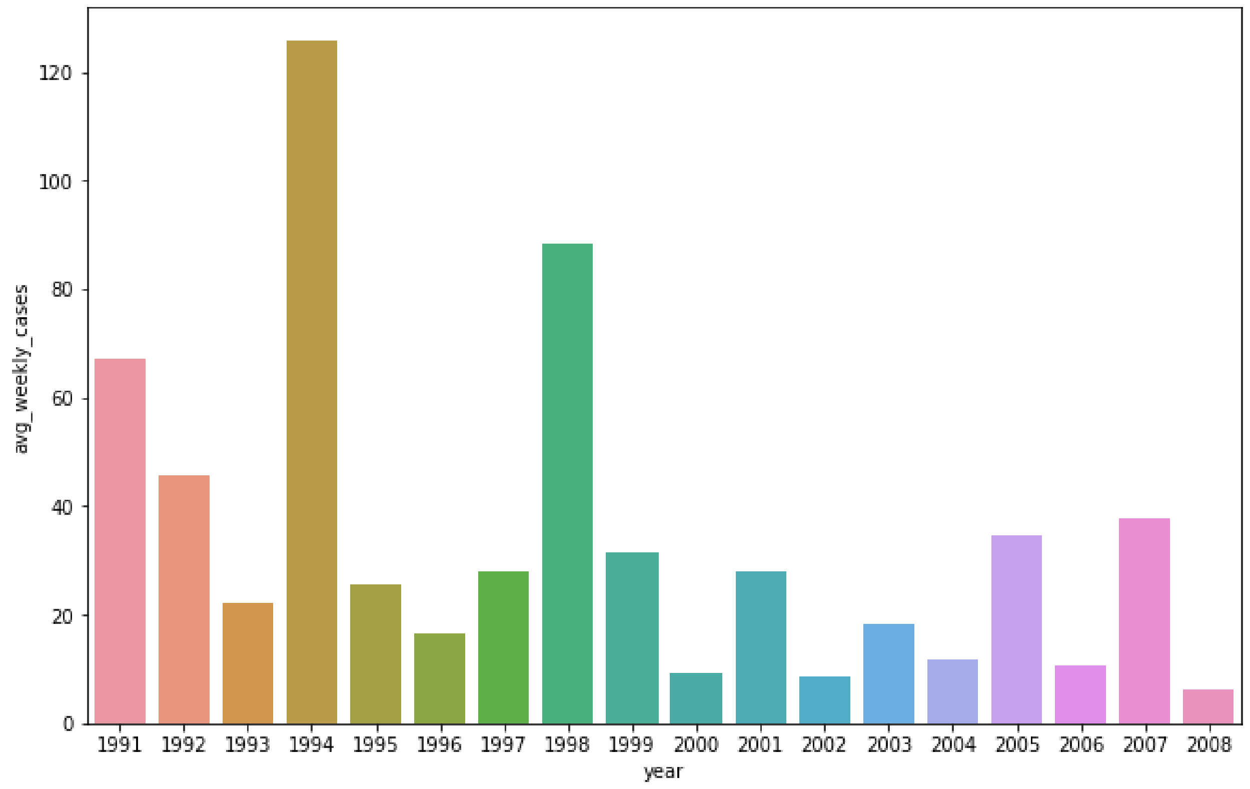
```
Out[15]: <matplotlib.legend.Legend at 0x1a1522d828>
```



Below is a bar chart showing the average number of cases in each week for each year. We notice that the average for the years 94 and 98 are extremely high this may be due to outliers for these years. We will get to see this in the EDA.

```
In [16]: weekly_avg_sj = pd.DataFrame(data_sj.groupby(['year'])['total_cases'].mean
         ().reset_index(name='avg_weekly_cases'))
         plt.subplots(figsize=(11,7))
         sns.barplot(x='year', y='avg_weekly_cases', data=weekly_avg_sj)
```

```
Out[16]: <matplotlib.axes._subplots.AxesSubplot at 0x1a152c1b00>
```



Exploring our Data

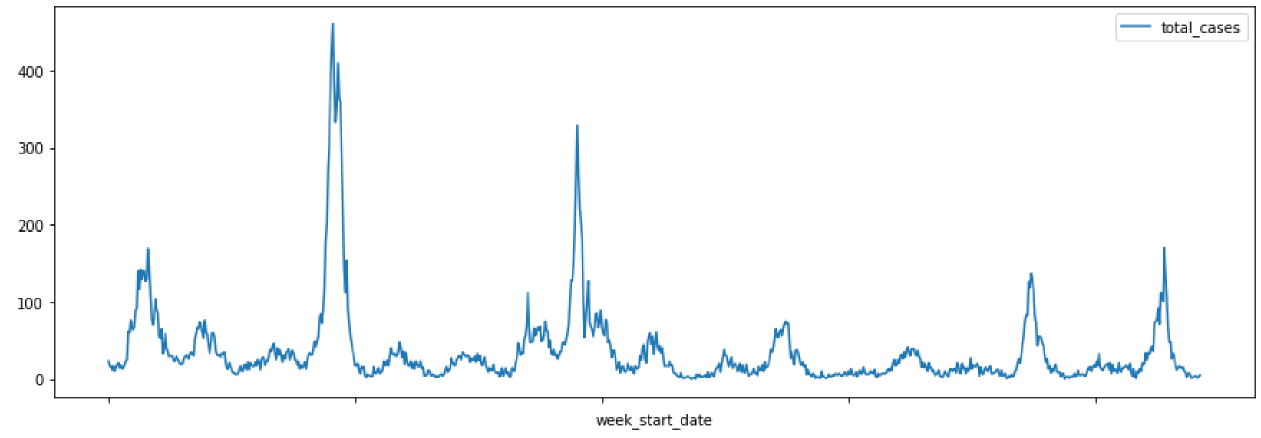
Our first step in exploring the data was to see Dengue changed with time. The reason we decided on this was to see how Dengue changed with time and if there was any seasonality.

As Alex Freemain points out in his EDA on Github, the spikes in the time-series are obvious outbreaks. It will be important to predict these outbreaks for health reasons and hence predicting just the general cyclic trend of Dengue will not be enough.

Below we will notice that the number of visualizations for each week are not consitent and vary with depending on the time of year. This can be a seasonlity trend as we will also notice that the rainfall received changes with time, during which the mosquitoes come out, bite and spread dengue.

```
In [17]: data_sj.plot(x='week_start_date', y='total_cases', figsize = (15,5))
```

```
Out[17]: <matplotlib.axes._subplots.AxesSubplot at 0x1a09710c88>
```



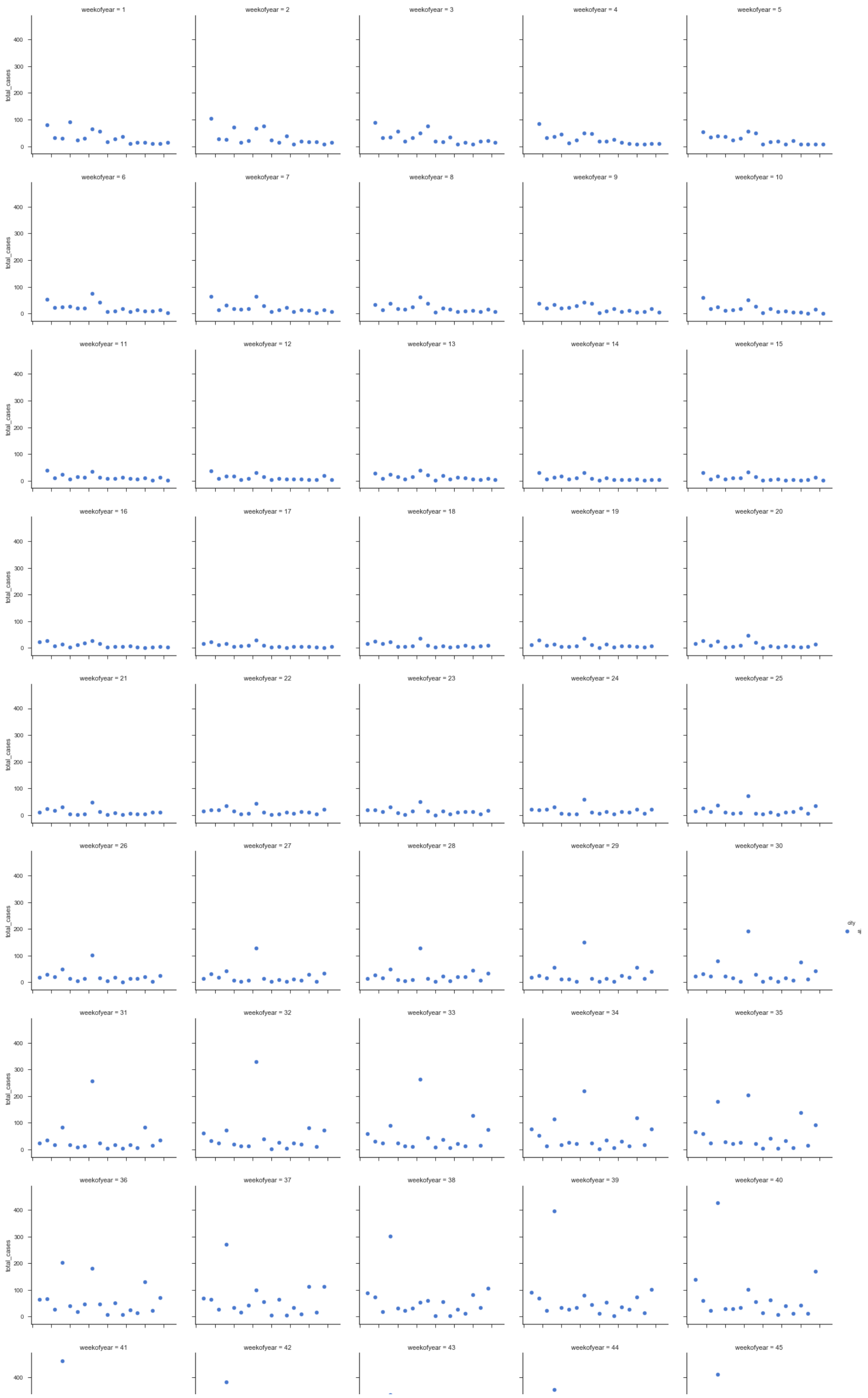
Facet Scatter Plot of Total Cases each week in San Juan

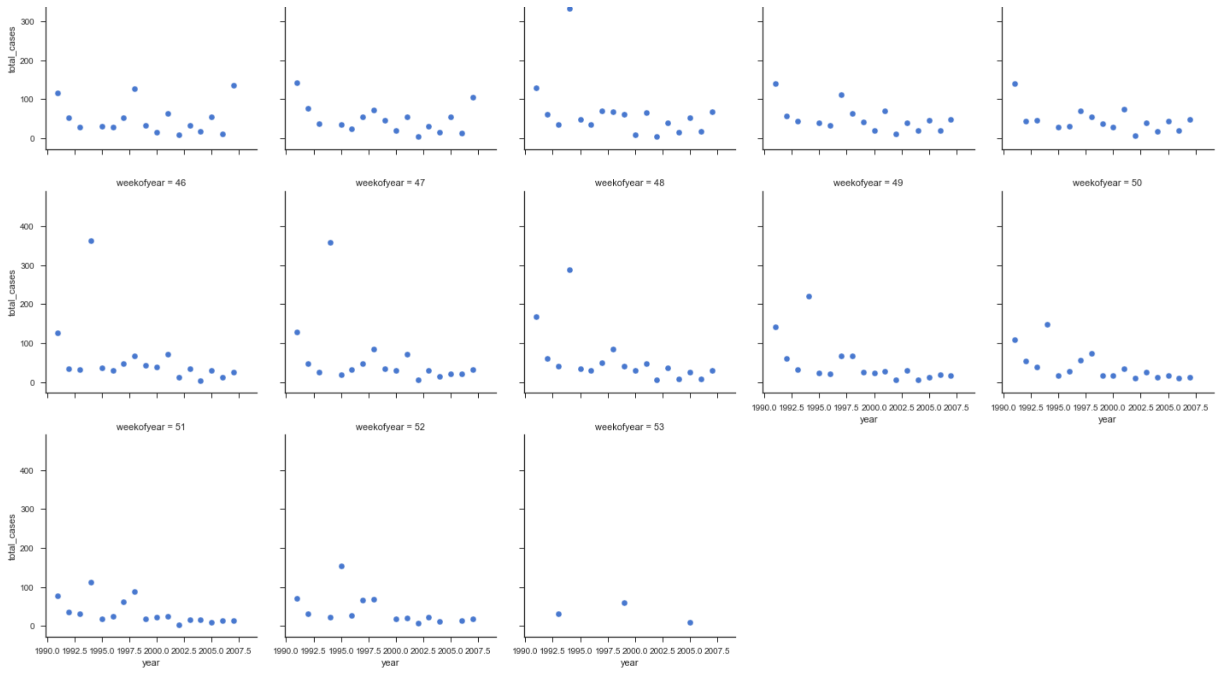
Exploring the total number of cases (y) in each week for each year(x)

- There appears to be a significant change in the total number of cases during the latter half of the weeks of the year.

While the facet scatter plot has helped us identify the change, it will help to map this out through a simple wide scatter plot for San Juan

In [18]:
```
sns.set(style="ticks", palette="muted")
g = sns.FacetGrid(data_sj, col="weekofyear",  hue="city", col_wrap=5, size
=4)
g = (g.map(plt.scatter, "year", "total_cases", edgecolor="w").add_legend
())
```


weekofyear = 1
weekofyear = 2
weekofyear = 3
weekofyear = 4
weekofyear = 5
weekofyear = 6
weekofyear = 7
weekofyear = 8
weekofyear = 9
weekofyear = 10
weekofyear = 11
weekofyear = 12
weekofyear = 13
weekofyear = 14
weekofyear = 15
weekofyear = 16
weekofyear = 17
weekofyear = 18
weekofyear = 19
weekofyear = 20
weekofyear = 21
weekofyear = 22
weekofyear = 23
weekofyear = 24
weekofyear = 25
weekofyear = 26
weekofyear = 27
weekofyear = 28
weekofyear = 29
weekofyear = 30
weekofyear = 31
weekofyear = 32
weekofyear = 33
weekofyear = 34
weekofyear = 35
weekofyear = 36
weekofyear = 37
weekofyear = 38
weekofyear = 39
weekofyear = 40
weekofyear = 41
weekofyear = 42
weekofyear = 43
weekofyear = 44
weekofyear = 45
total_cases
0
100
200
300
400
city
sj

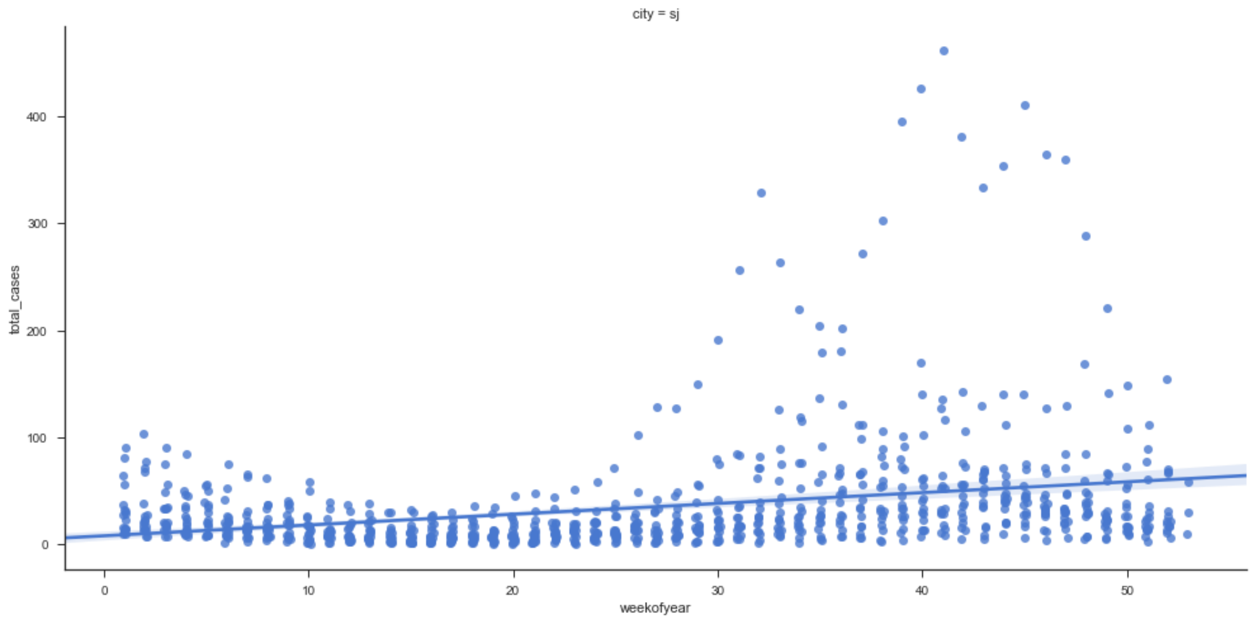


Simplified Scatter Chart of Total Cases by each week in San Juan

Key Insights:

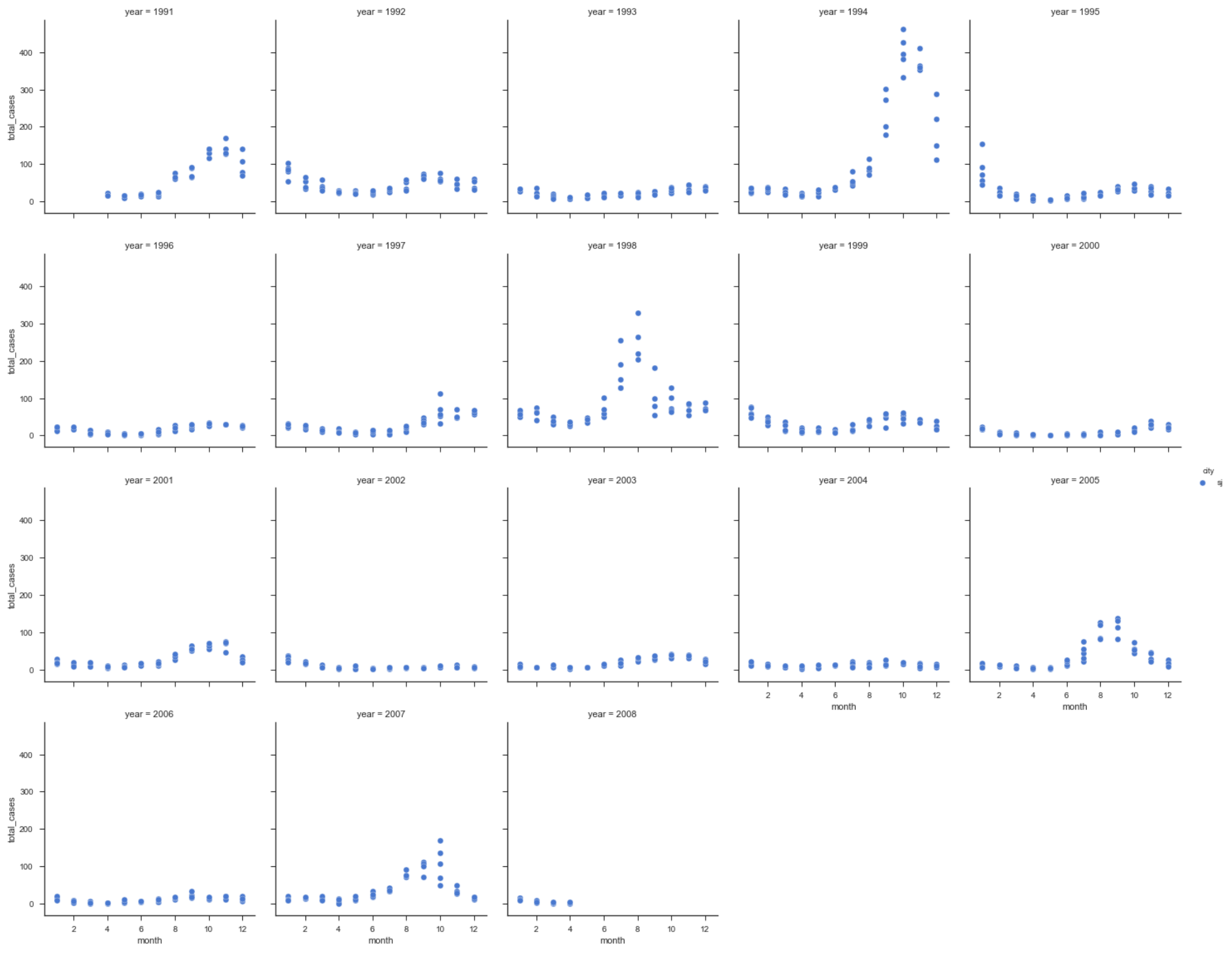
- In San Juan, for weeks 25 - 50, we can see there are outliers where the numbers of cases is larger than the normal amount of cases. This can be due to an outbreak in the city on different occassions.

```
In [19]: g = sns.lmplot(x="weekofyear", y="total_cases", hue="city", col="city", da
         ta=data_sj, aspect= 2, size = 7, x_jitter=.1)
```



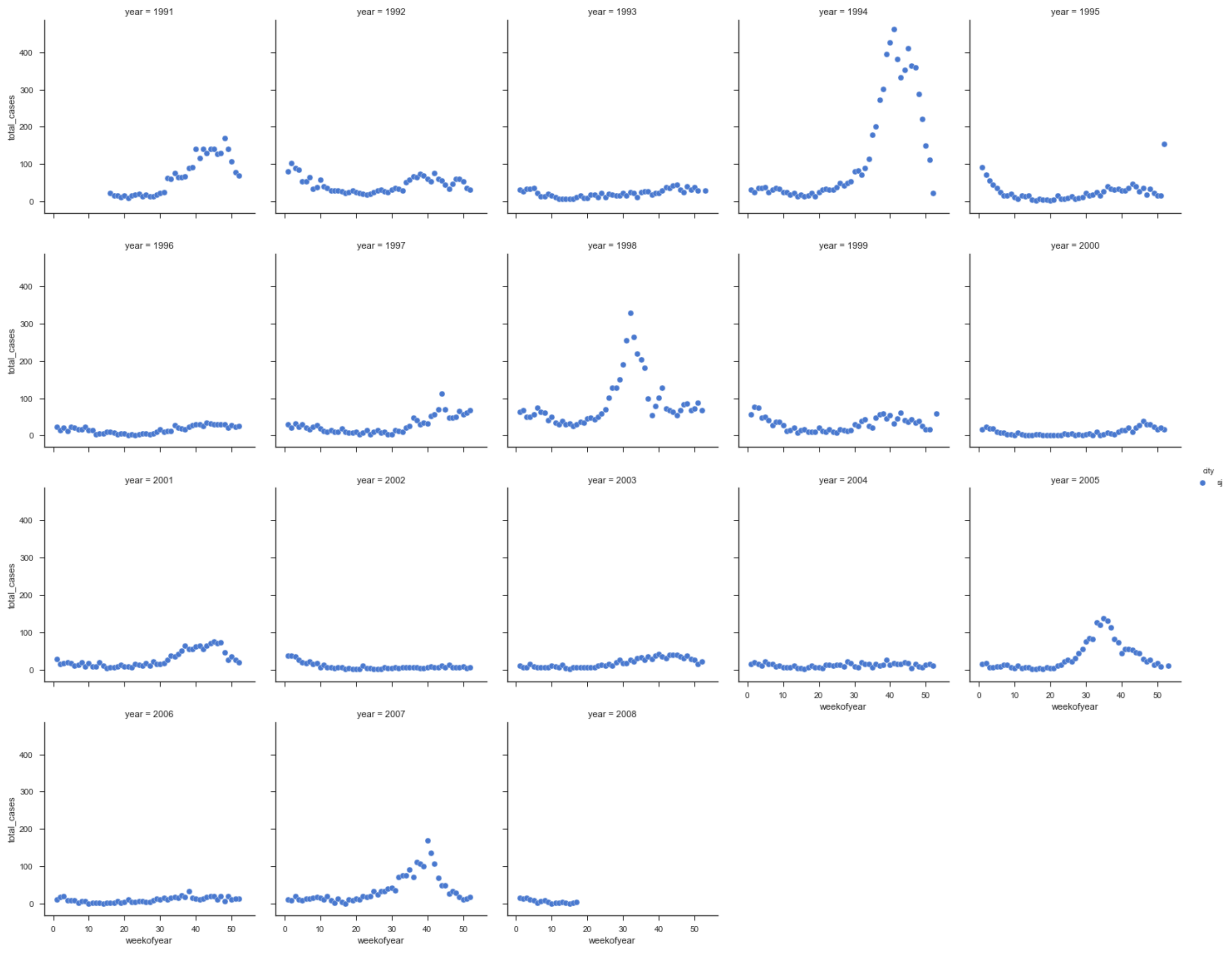
Facet Chart of Total Number of Cases (y) for each month(x) by Year

```
In [20]: sns.set(style="ticks", palette="muted")
         g = sns.FacetGrid(data_sj, col="year",  hue="city", col_wrap=5, size=4)
         g = (g.map(plt.scatter, "month", "total_cases", edgecolor="w").add_legend
         ())
```



Facet Chart of Total Cases for each year

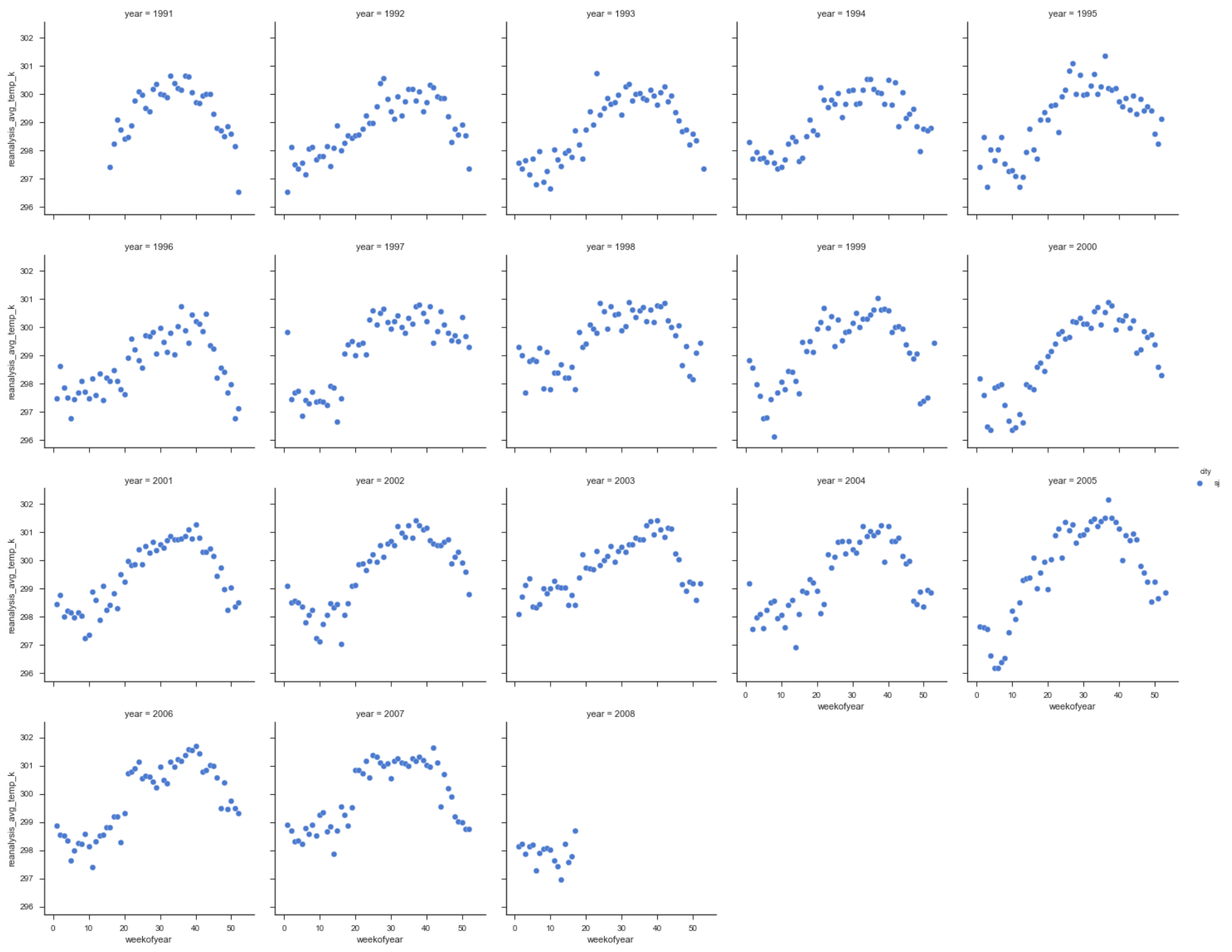
```
In [21]: sns.set(style="ticks", palette="muted")
         g = sns.FacetGrid(data_sj, col="year",  hue="city", col_wrap=5, size=4)
         g = (g.map(plt.scatter, "weekofyear", "total_cases", edgecolor="w").add_le
         gend())
```



Facet Chart of Temperature (y) for each week (x) by Year

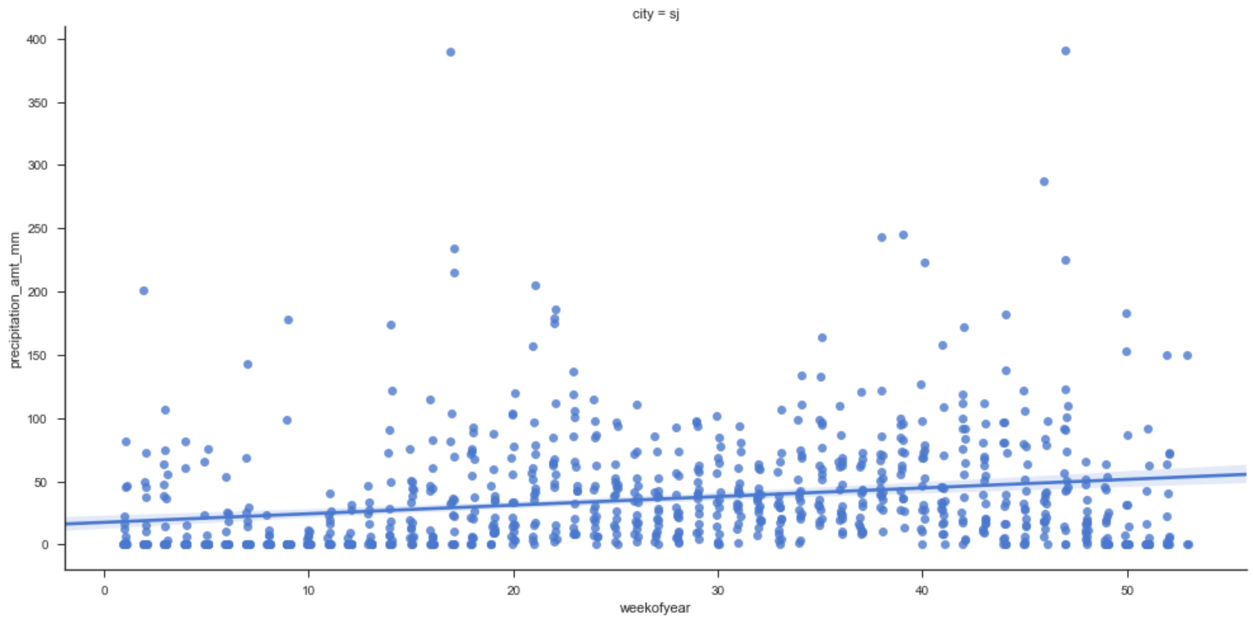
Key Insight: We notice that the temperature range for all years lies between 296 K and 302 K

```
In [22]: sns.set(style="ticks", palette="muted")
         g = sns.FacetGrid(data_sj, col="year",  hue="city", col_wrap=5, size=4)
         g = (g.map(plt.scatter, "weekofyear", "reanalysis_avg_temp_k", edgecolor=
         "w").add_legend())
```



Precipitation (y) for each week(x) by Year

```
In [23]: g = sns.lmplot(x="weekofyear", y="precipitation_amt_mm", hue="city", col=
         "city", data=data_sj, aspect= 2, size = 7, x_jitter=.1)
```



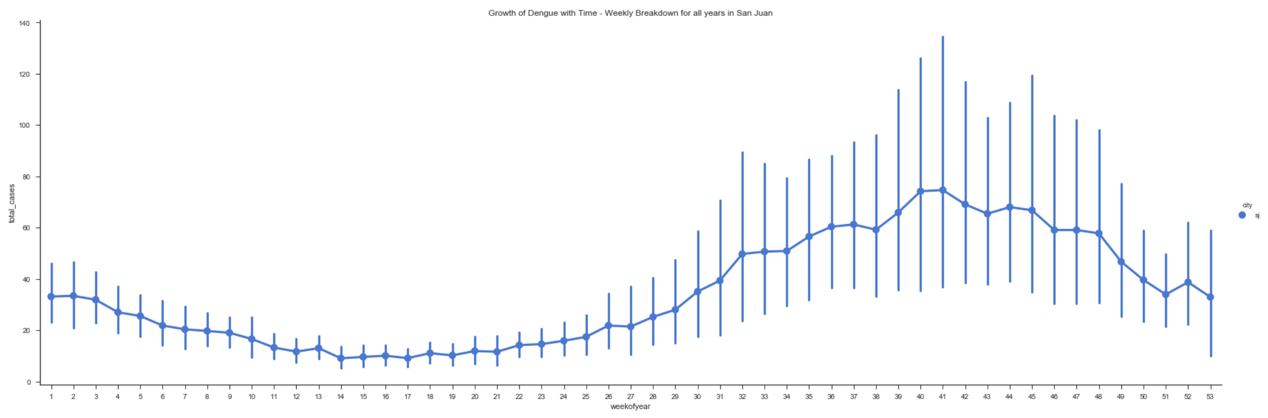
Plotting Change in Total Dengue Cases & Precipitation by Week

Dengue Cases

Key Insights:

- In San Juan, year over year we can see an increase in the total cases starting Week 24, which rollsover to Week 11 in the next year

```
In [24]: sns.factorplot(x="weekofyear", y="total_cases", hue="city", size=8, aspect
         =3,data=data_sj)
         plt.title("Growth of Dengue with Time - Weekly Breakdown for all years in
          San Juan")

Out[24]: Text(0.5,1,'Growth of Dengue with Time - Weekly Breakdown for all years in
         San Juan')
```



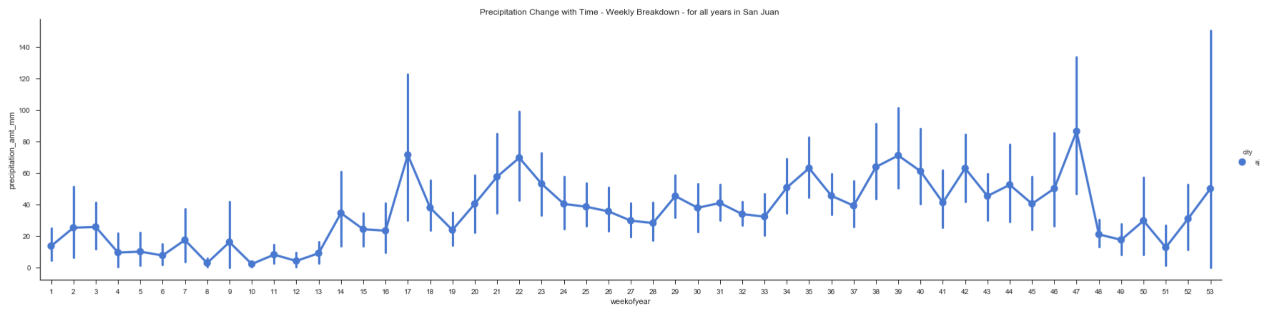
Precipitation

Key Insights from both charts below:

- On average San Juan receives heavy rainfall from week 14 to week 47

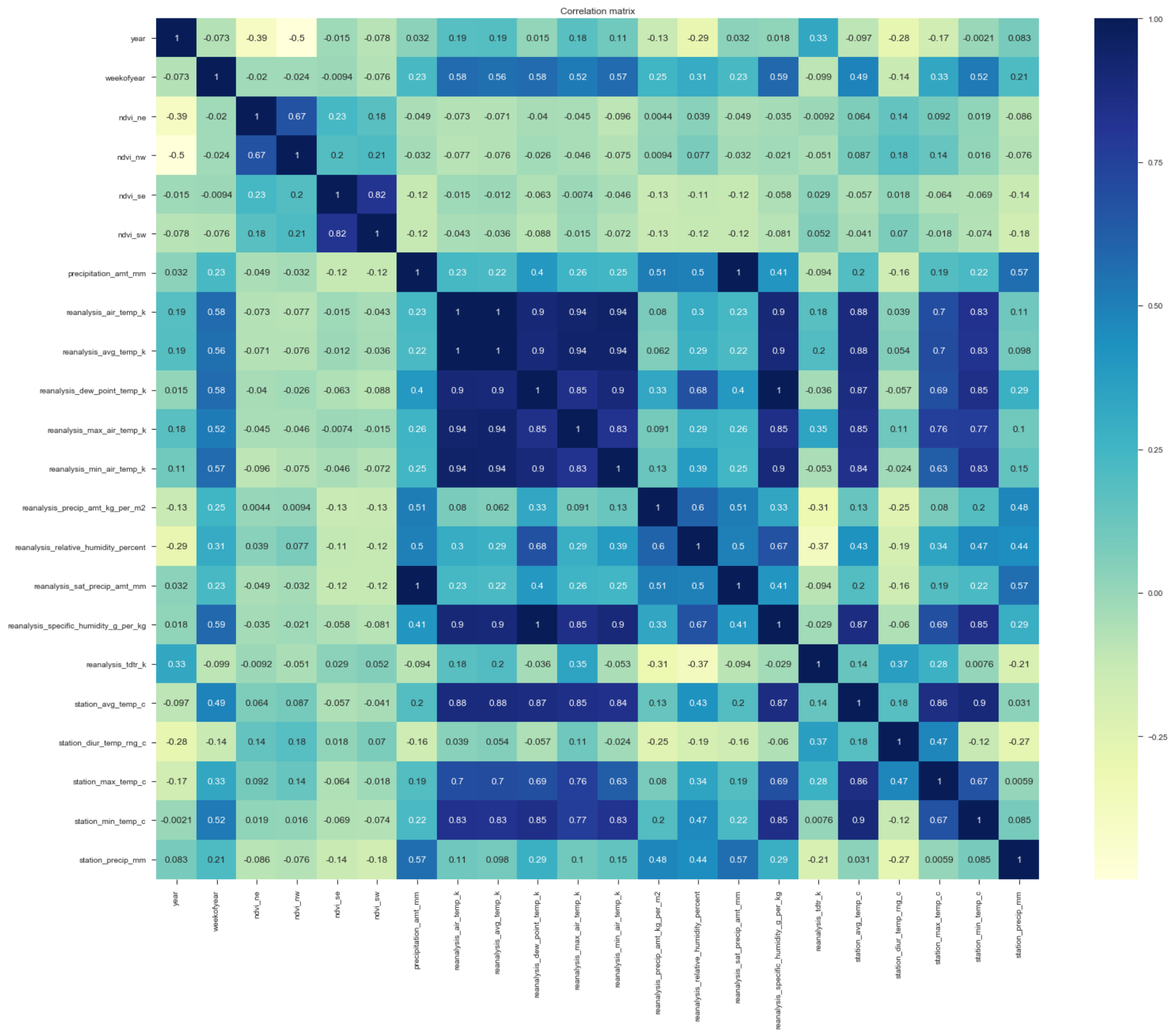
```
In [25]: sns.factorplot(x="weekofyear", y="precipitation_amt_mm", hue="city", size=
         6, aspect=4,data=data_sj)
         plt.title("Precipitation Change with Time - Weekly Breakdown - for all yea
         rs in San Juan ")
```

```
Out[25]: Text(0.5,1,'Precipitation Change with Time - Weekly Breakdown - for all yea
         rs in San Juan ')
```



Correlation Heat Map

```
In [26]: plt.figure(figsize=(25,20))
         plt.title('Correlation matrix')
         sns.heatmap(df_sj.corr(), cmap="YlGnBu", annot = True)

Out[26]: <matplotlib.axes._subplots.AxesSubplot at 0x1a18fc9c88>
```



As mentioned in the Benchmark file by Driven Data:

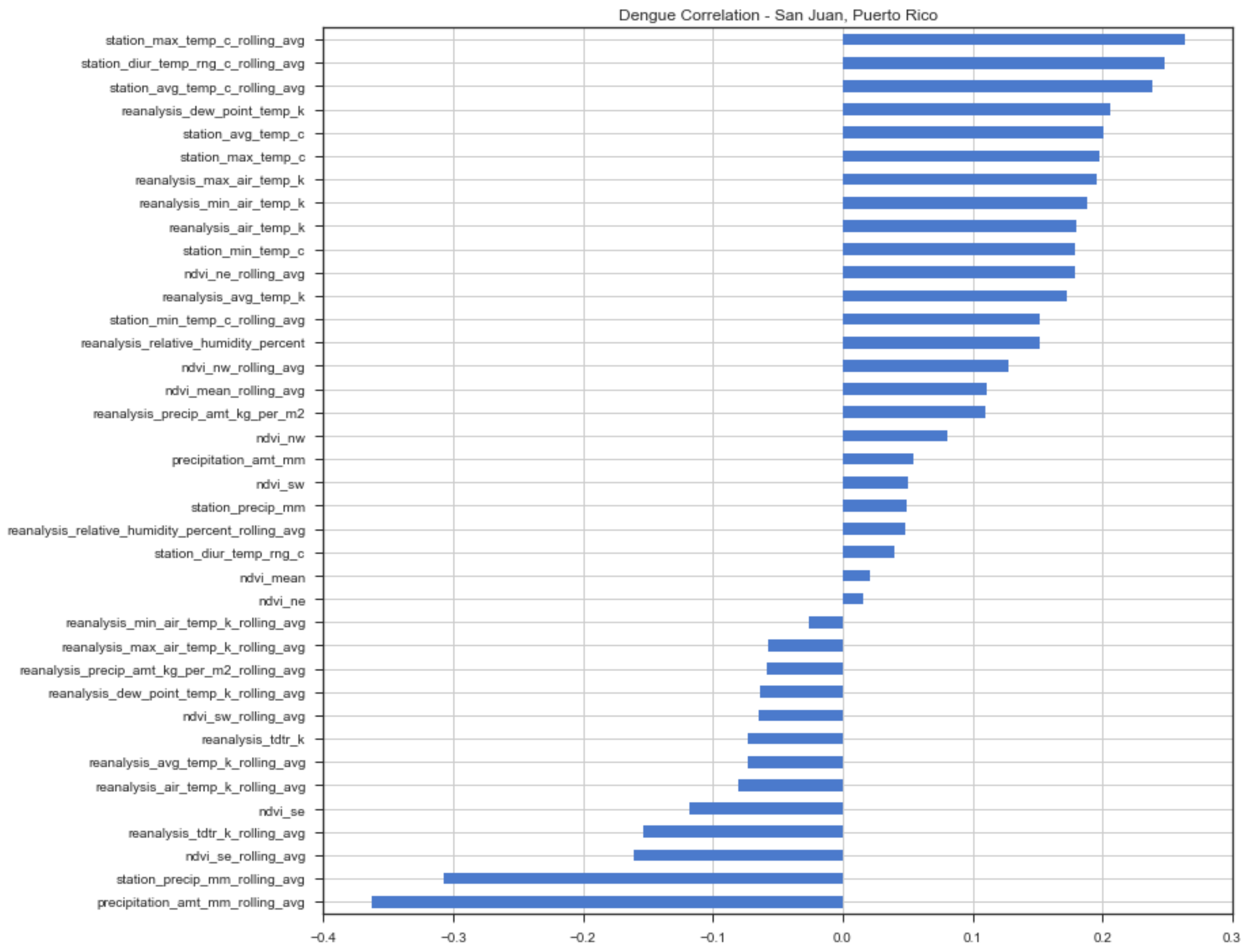
Many of the temperature data are strongly correlated, which is expected. But the total_cases variable doesn't have many obvious strong correlations. Interestingly, total_cases seems to only have weak correlations with other variables. Many of the climate variables are much more strongly correlated. Interestingly, the vegetation index also only has weak correlation with other variables. These correlations may give us some hints as to how to improve our model.

Correlation for Dengue Cases

The graphs below represent correlation of the dependent variable 'Dengue Cases' with the environmental and climate variables in San Juan. We checked the correlation between the given variables with the percent dengue cases each week with respect to year. Using weekly dengue cases percentage values we standardized the data resulting in better correlation with the variables. Since the region and climate of two cities is different, we can see there is a significant difference in the correlation behavior of our variables among two cities.

```
In [27]: #Code to generate correlation graphs below for the two cities
         corr_sj = data_sj.corr(method='pearson')
         corr_sj = corr_sj['total_cases'].to_frame(name = 'corr_with_cases_sj')
         corr_sj = corr_sj.sort_values(by=['corr_with_cases_sj'])
         corr_sj = (corr_sj.drop('total_cases')
              .drop('year')
              .drop('month')
              .drop('weekofyear')
              .drop('odd_year'))
         corr_sj.plot(kind='barh', title='Dengue Correlation - San Juan, Puerto Ric
         o', xlim=(-.40,.30), grid = True, legend = False, color = '#4B7ACC', figsi
         ze=(12,12))
```

```
Out[27]: <matplotlib.axes._subplots.AxesSubplot at 0x1a15c672e8>
```



A few observations as mentioned in the benchmark file

The wetter the better

The correlation strengths differ for each city, but it looks like reanalysis_specific_humidity_g_per_kg and reanalysis_dew_point_temp_k are the most strongly correlated with total_cases. This makes sense: we know mosquitos thrive wet climates, the wetter the better!

Hot and heavy

As we all know, "cold and humid" is not a thing. So it's not surprising that as minimum temperatures, maximum temperatures, and average temperatures rise, the total_cases of dengue fever tend to rise as well.

Sometimes it rains, so what

Interestingly, the precipitation measurements bear little to no correlation to total_cases, despite strong correlations to the humidity measurements, as evident by the heatmaps above.

A few good variables as recommended by the Benchmark File

- reanalysis_specific_humidity_g_per_kg
- reanalysis_dew_point_temp_k
- station_avg_temp_c
- station_min_temp_c

Outlier Engineering for San Juan

As we noticed earlier there are outliers in our dataset. Let us see how many outliers we have. However after testing our model we have seen that it will as we will not be able to predict the outbreaks. This is why we will not remove them.

In [28]:
```
data = data_sj['total_cases']
# calculate summary statistics
data_mean, data_std = mean(data), std(data)
# identify outliers
cut_off = data_std * 3
lower, upper = data_mean - cut_off, data_mean + cut_off
# identify outliers
outliers = [x for x in data if x < lower or x > upper]
print('Identified outliers: %d' % len(outliers))
# remove outliers
outliers_removed = [x for x in data if x >= lower and x <= upper]
print('Non-outlier observations: %d' % len(outliers_removed))
```

```
Identified outliers: 19
Non-outlier observations: 867
```

From above we notice that we have 20 outliers (outside of 3 S.D. for total cases in San Juan) and we have 916 non-outlier observations for total cases

In [29]:
```
dp.remove_outliers(data_sj).head(4)
```

Out[29]:

	city	year	weekofyear	week_start_date	ndvi_ne	ndvi_nw	ndvi_se	ndvi_sw	precipita
50	sj	1991	16	1991-04-16	0.077400	0.102400	0.163550	0.206167	44.57
51	sj	1991	17	1991-04-23	0.077400	0.188450	0.188314	0.224943	32.72
52	sj	1991	18	1991-04-30	0.209167	0.160575	0.176171	0.176171	0.00
53	sj	1991	19	1991-05-07	0.115950	0.180175	0.106386	0.111186	35.38

4 rows × 45 columns

Iquitos

In [30]:
```
# Iquitos
data_iq = dp.features_train(features_train, labels_train, 'iq')
data_iq_n = dp.normalize(data_iq)
data_test_iq = dp.features_test(features_test, features_train, 'iq')
data_test_iq_n = dp.normalize(data_test_iq)
```

Understanding our Data

Peek at Iquitos Data

Displaying the first 5 rows

Note: We have added Day of the Year and Odd Year and Month as as additional columns

In [31]:
```
data_iq.head(5)
```

Out[31]:

	city	year	weekofyear	week_start_date	ndvi_ne	ndvi_nw	ndvi_se	ndvi_sw	precipita
50	iq	2001	25	2001-06-18	0.104100	0.108243	0.059657	0.113757	53.93
51	iq	2001	26	2001-06-25	0.192300	0.275286	0.316457	0.325414	1.22
52	iq	2001	27	2001-07-02	0.229083	0.193267	0.270457	0.242186	52.10
53	iq	2001	28	2001-07-09	0.359717	0.311057	0.264986	0.438843	39.09
54	iq	2001	29	2001-07-16	0.319500	0.205086	0.194743	0.361633	52.05

5 rows × 45 columns

Summary for Iquitos Data

In [32]:
```
data_iq.describe().T
```

Out[32]:

	count	mean	std	min
year	470.0	2005.480851	2.643465	2001.000000
weekofyear	470.0	26.555319	15.045918	1.000000
ndvi_ne	470.0	0.263711	0.082528	0.061729
ndvi_nw	470.0	0.239630	0.076005	0.058950
ndvi_se	470.0	0.247751	0.077269	0.029880
ndvi_sw	470.0	0.267684	0.087281	0.064743
precipitation_amt_mm	470.0	64.678915	35.520757	0.000000
reanalysis_air_temp_k	470.0	297.874556	1.115203	294.635714
reanalysis_avg_temp_k	470.0	299.134316	1.280958	294.892857
reanalysis_dew_point_temp_k	470.0	295.599456	1.382201	290.088571
reanalysis_max_air_temp_k	470.0	307.004681	2.303825	300.000000
reanalysis_min_air_temp_k	470.0	292.939149	1.676426	286.900000
reanalysis_precip_amt_kg_per_m2	470.0	58.680085	49.587288	0.000000
reanalysis_relative_humidity_percent	470.0	89.087781	7.085957	64.658571
reanalysis_tdtr_k	470.0	9.084985	2.361020	3.714286
station_avg_temp_c	470.0	27.548163	0.920630	21.400000
station_diur_temp_rng_c	470.0	10.399840	1.580170	5.200000
station_max_temp_c	470.0	33.968511	1.376295	30.100000
station_min_temp_c	470.0	21.294255	1.237315	16.400000
station_precip_mm	470.0	63.175957	64.888176	0.000000
total_cases	470.0	8.355319	11.033353	0.000000
month	470.0	6.417021	3.447524	1.000000
ndvi_mean	470.0	0.254694	0.073466	0.084155
ndvi_mean_rolling_avg	470.0	0.254757	0.007212	0.236173
ndvi_ne_rolling_avg	470.0	0.264432	0.012296	0.236632
ndvi_nw_rolling_avg	470.0	0.239183	0.008237	0.219585
ndvi_se_rolling_avg	470.0	0.248357	0.010846	0.224243
ndvi_sw_rolling_avg	470.0	0.267057	0.010683	0.247221
precipitation_amt_mm_rolling_avg	470.0	65.075334	4.825460	55.332600
reanalysis_air_temp_k_rolling_avg	470.0	297.828192	0.233296	297.431000
reanalysis_avg_temp_k_rolling_avg	470.0	299.084070	0.254839	298.609286
reanalysis_dew_point_temp_k_rolling_avg	470.0	295.513967	0.369938	294.367971
reanalysis_max_air_temp_k_rolling_avg	470.0	306.972136	0.441428	306.020000

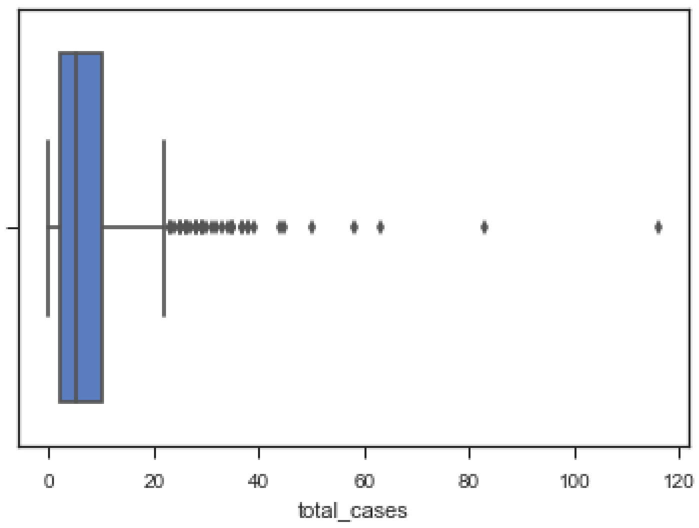
	count	mean	std	min
reanalysis_min_air_temp_k_rolling_avg	470.0	292.872174	0.336433	292.192000
reanalysis_precip_amt_kg_per_m2_rolling_avg	470.0	57.189437	8.397619	44.586000
reanalysis_relative_humidity_percent_rolling_avg	470.0	88.905583	1.769299	83.941857
reanalysis_tdtr_k_rolling_avg	470.0	9.119981	0.490505	8.050286
station_avg_temp_c_rolling_avg	470.0	27.516075	0.205202	27.097110
station_diur_temp_rng_c_rolling_avg	470.0	10.423599	0.556245	9.238300
station_max_temp_c_rolling_avg	470.0	33.939579	0.402596	32.830000
station_min_temp_c_rolling_avg	470.0	21.245689	0.375061	20.330000
station_precip_mm_rolling_avg	470.0	64.128596	16.988350	31.106000

Looking for outliers in our Data

From the plot below we notice that there are outliers in total cases for the past so many years between 90 and 500 cases

```
In [33]: sns.boxplot(x=data_iq['total_cases'])
```

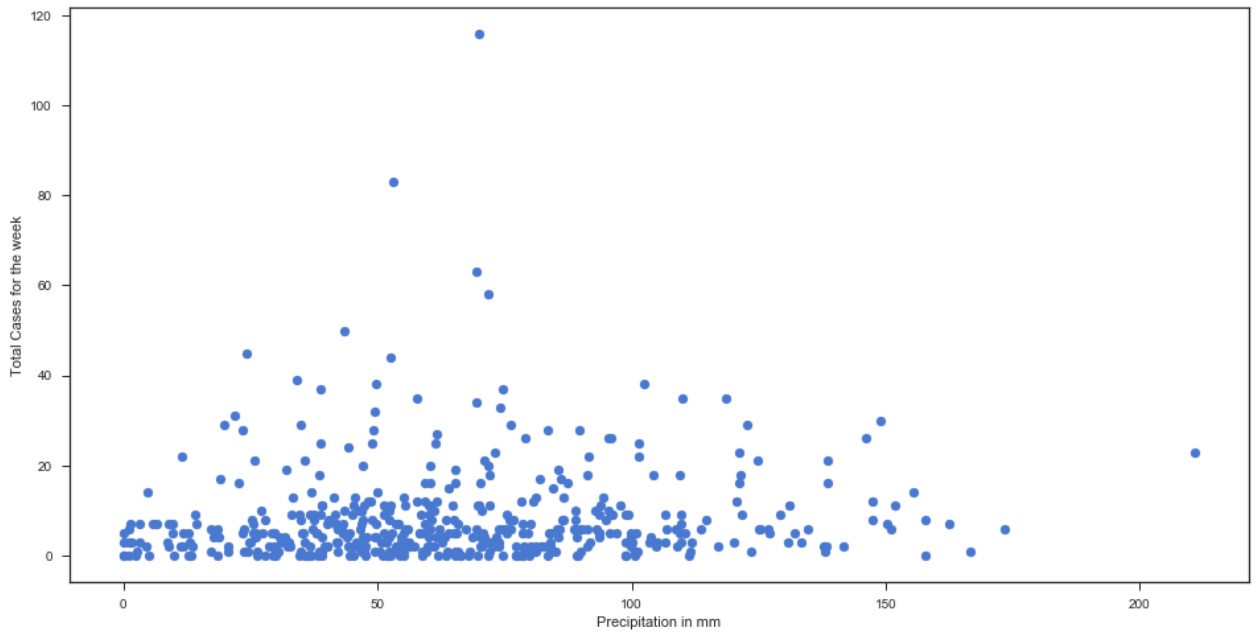
```
Out[33]: <matplotlib.axes._subplots.AxesSubplot at 0x1a15de7160>
```



Looking at the plot below, we can most of data points are lying bottom left side but there are points which are far from the population like top left & bottom right corner.

This also indicates that higher rainfall does not necessarrily lead to higher total number of cases for the week

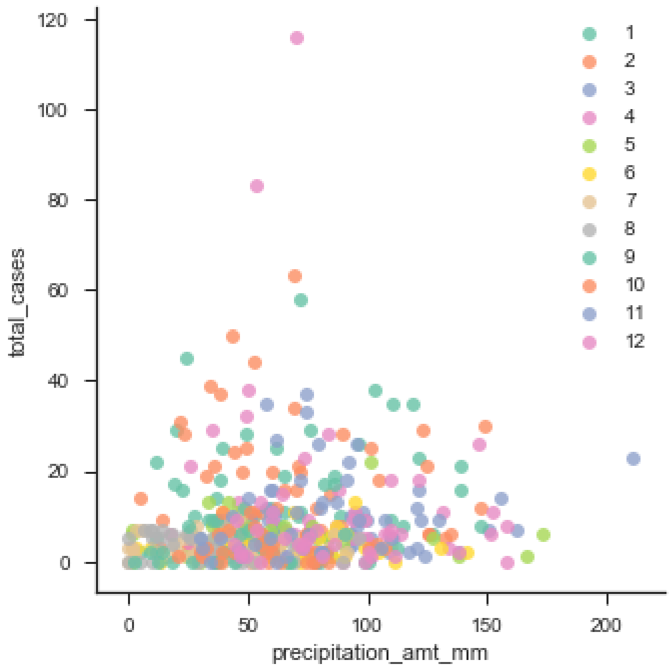
In [34]:
```
fig, ax = plt.subplots(figsize=(16,8))
ax.scatter(data_iq['precipitation_amt_mm'],data_iq['total_cases'])
ax.set_xlabel('Precipitation in mm')
ax.set_ylabel('Total Cases for the week')
plt.show()
```



We will handle our outliers after exploring our data further. This is so that we get a better understanding of the domain before we remove or reset outliers.

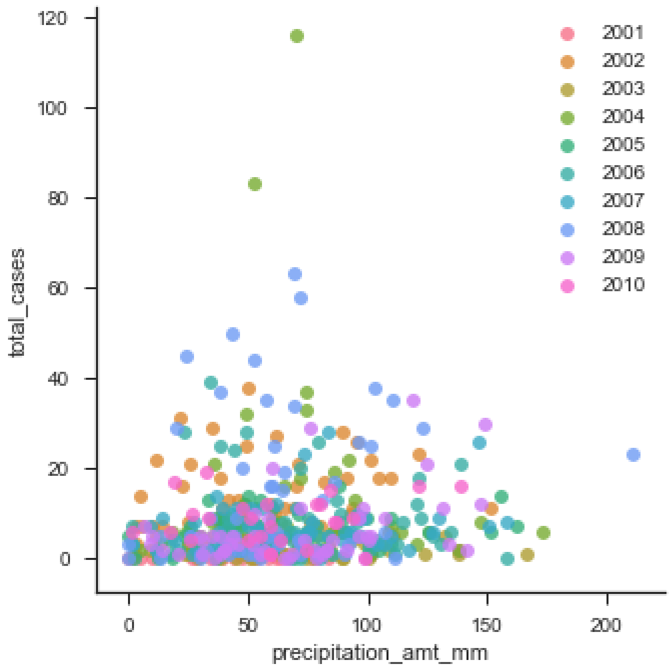
Below is the same scatter plot with each dot colored by month

```
In [35]: # Use the 'hue' argument to provide a factor variable
         sns.lmplot( x="precipitation_amt_mm", y="total_cases", data=data_iq, fit_r
         eg=False,
                     hue='month', legend=False, palette="Set2")

         # Move the legend to an empty part of the plot
         plt.legend(loc='upper right')

Out[35]: <matplotlib.legend.Legend at 0x1a163eccc0>
```



```
In [36]: # Use the 'hue' argument to provide a factor variable
         sns.lmplot( x="precipitation_amt_mm", y="total_cases", data=data_iq, fit_r
         eg=False,
                    hue='year', legend=False)

         # Move the legend to an empty part of the plot
         plt.legend(loc='upper right')
```

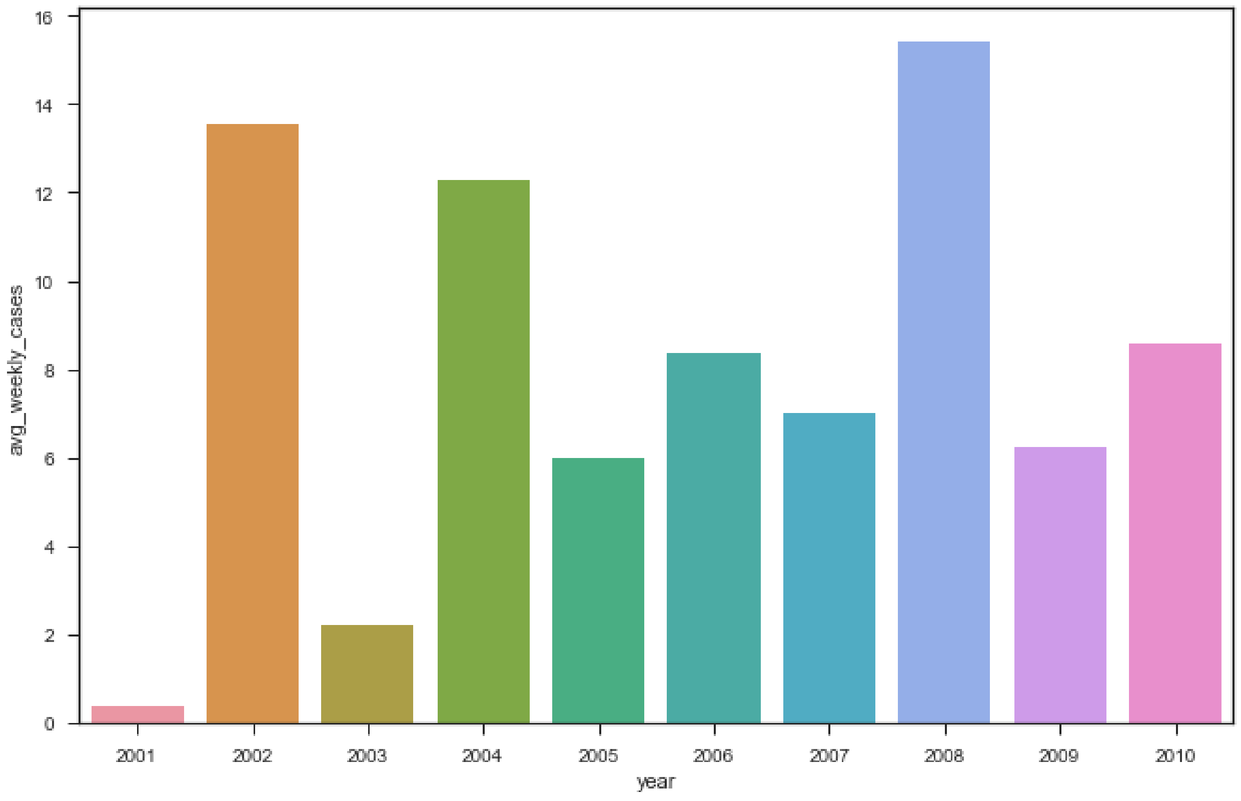
```
Out[36]: <matplotlib.legend.Legend at 0x1a1a263be0>
```



Below is a bar chart showing the average number of cases in each week for each year. We notice that the average for the year 2003 is really low.

```
In [37]: weekly_avg_sj = pd.DataFrame(data_iq.groupby(['year'])['total_cases'].mean
         ().reset_index(name='avg_weekly_cases'))
         plt.subplots(figsize=(11,7))
         sns.barplot(x='year', y='avg_weekly_cases', data=weekly_avg_sj)
```

```
Out[37]: <matplotlib.axes._subplots.AxesSubplot at 0x1a18fe3b38>
```



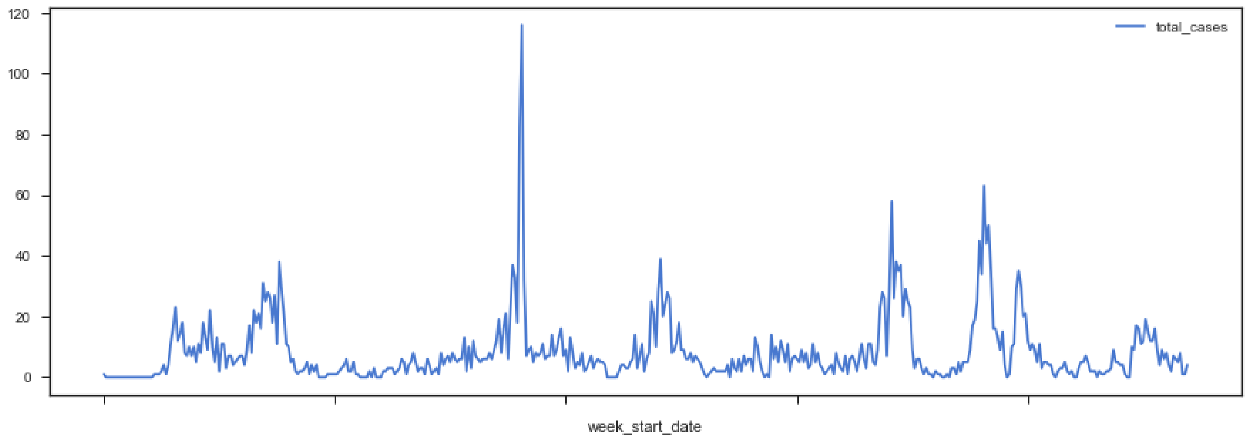
Exploring our Data

Total Number of Cases with time

We notice that there has been an outbreak on some occassions with a sudden drop in weekly cases for some years.

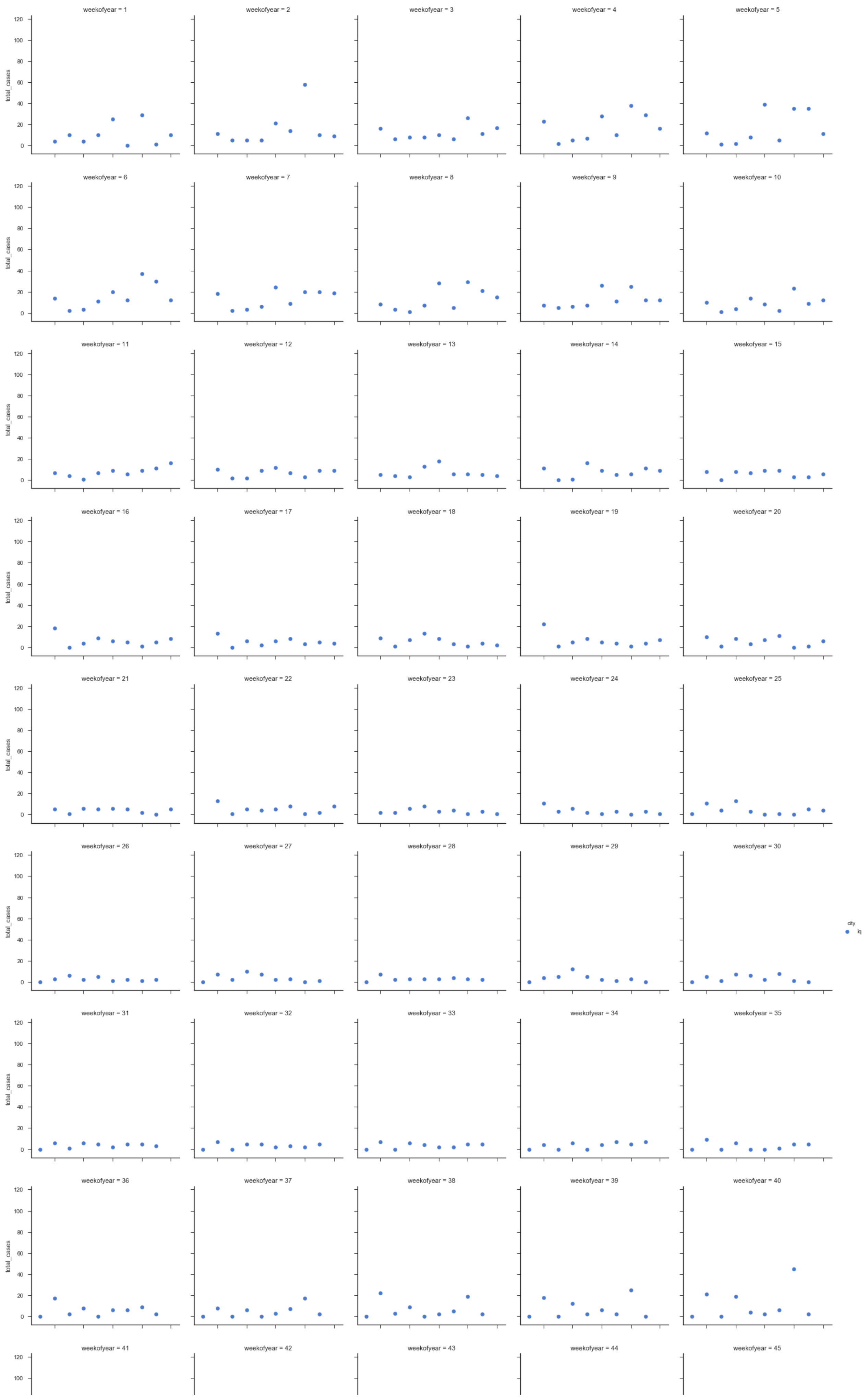
```
In [38]: data_iq.plot(x='week_start_date', y='total_cases', figsize = (15,5))
```

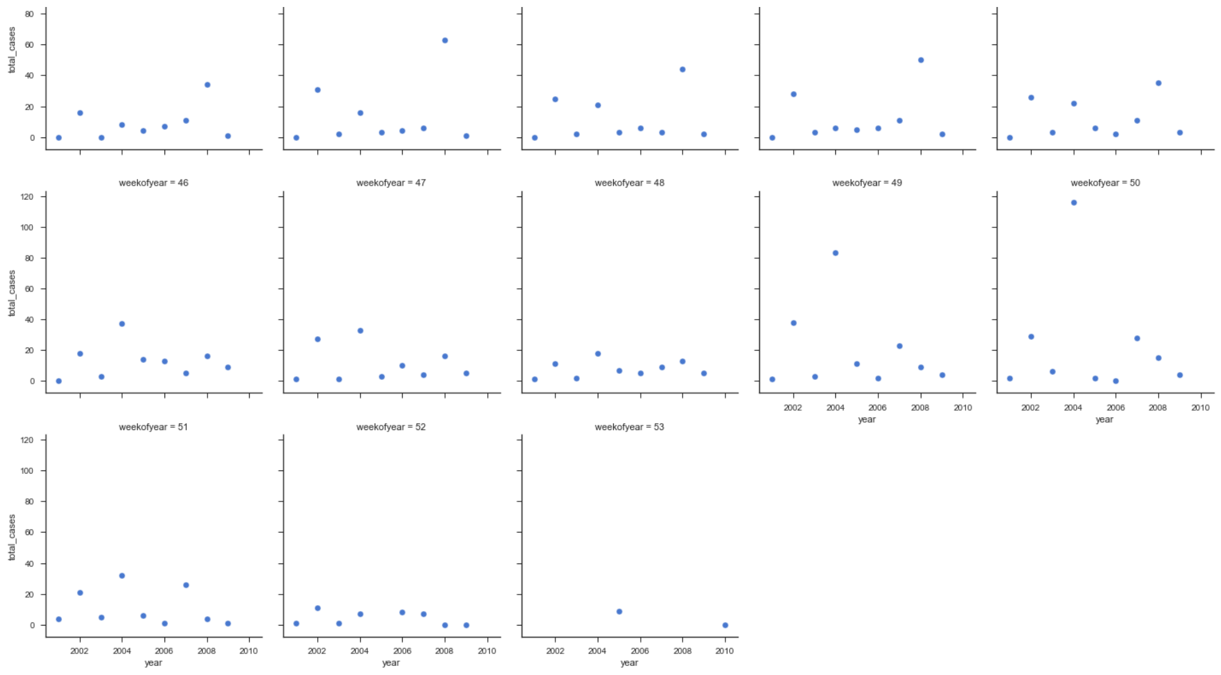
```
Out[38]: <matplotlib.axes._subplots.AxesSubplot at 0x1a178cec88>
```



Facet Scatter Plot of Total Cases in Each Week for each Year

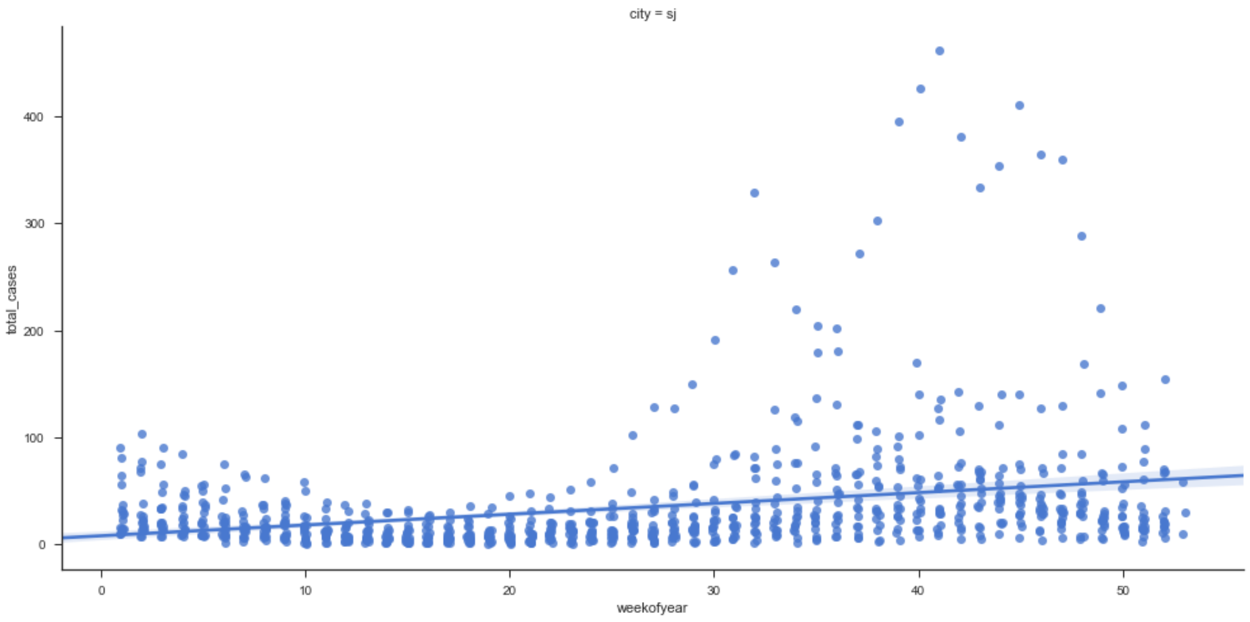
In [39]:
```
sns.set(style="ticks", palette="muted")
g = sns.FacetGrid(data_iq, col="weekofyear",  hue="city", col_wrap=5, size
=4)
g = (g.map(plt.scatter, "year", "total_cases", edgecolor="w").add_legend
())
```


weekofyear = 1
weekofyear = 2
weekofyear = 3
weekofyear = 4
weekofyear = 5
weekofyear = 6
weekofyear = 7
weekofyear = 8
weekofyear = 9
weekofyear = 10
weekofyear = 11
weekofyear = 12
weekofyear = 13
weekofyear = 14
weekofyear = 15
weekofyear = 16
weekofyear = 17
weekofyear = 18
weekofyear = 19
weekofyear = 20
weekofyear = 21
weekofyear = 22
weekofyear = 23
weekofyear = 24
weekofyear = 25
weekofyear = 26
weekofyear = 27
weekofyear = 28
weekofyear = 29
weekofyear = 30
weekofyear = 31
weekofyear = 32
weekofyear = 33
weekofyear = 34
weekofyear = 35
weekofyear = 36
weekofyear = 37
weekofyear = 38
weekofyear = 39
weekofyear = 40
weekofyear = 41
weekofyear = 42
weekofyear = 43
weekofyear = 44
weekofyear = 45
total_cases
0
20
40
60
80
100
120
city
iq



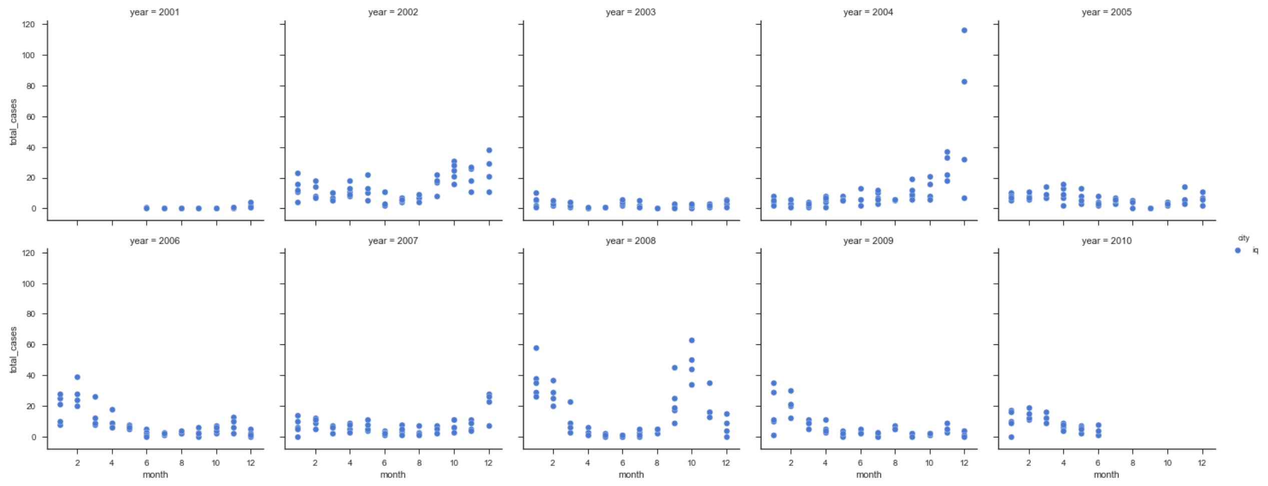
Total Cases by Week in Iquitos

```
In [40]: g = sns.lmplot(x="weekofyear", y="total_cases", hue="city", col="city", da
         ta=data_sj, aspect= 2, size = 7, x_jitter=.1)
```



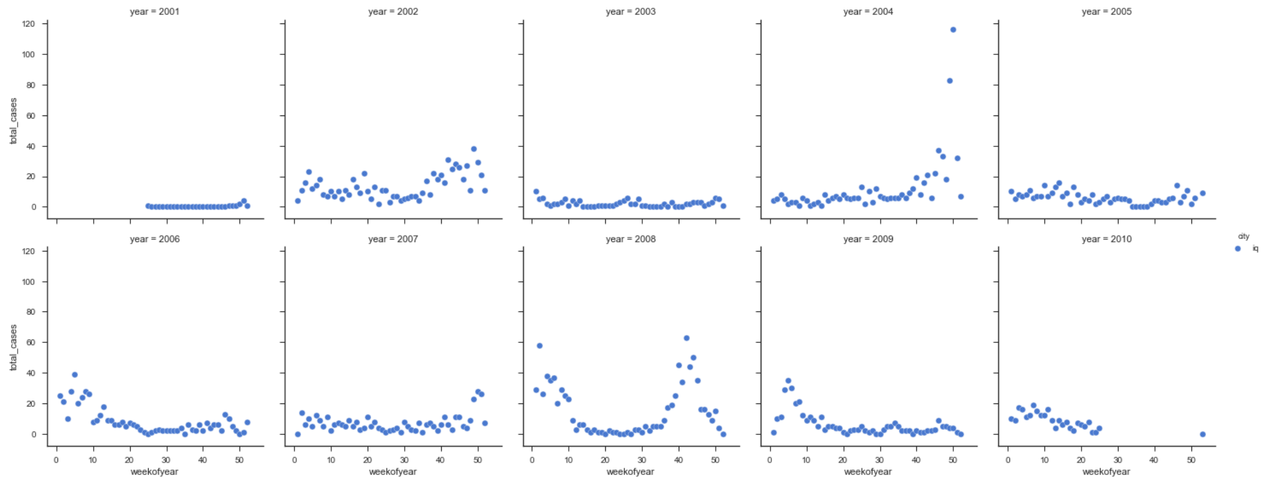
Facet Grid of total cases in each month for each year

In [41]:
```
sns.set(style="ticks", palette="muted")
g = sns.FacetGrid(data_iq, col="year",  hue="city", col_wrap=5, size=4)
g = (g.map(plt.scatter, "month", "total_cases", edgecolor="w").add_legend
())
```



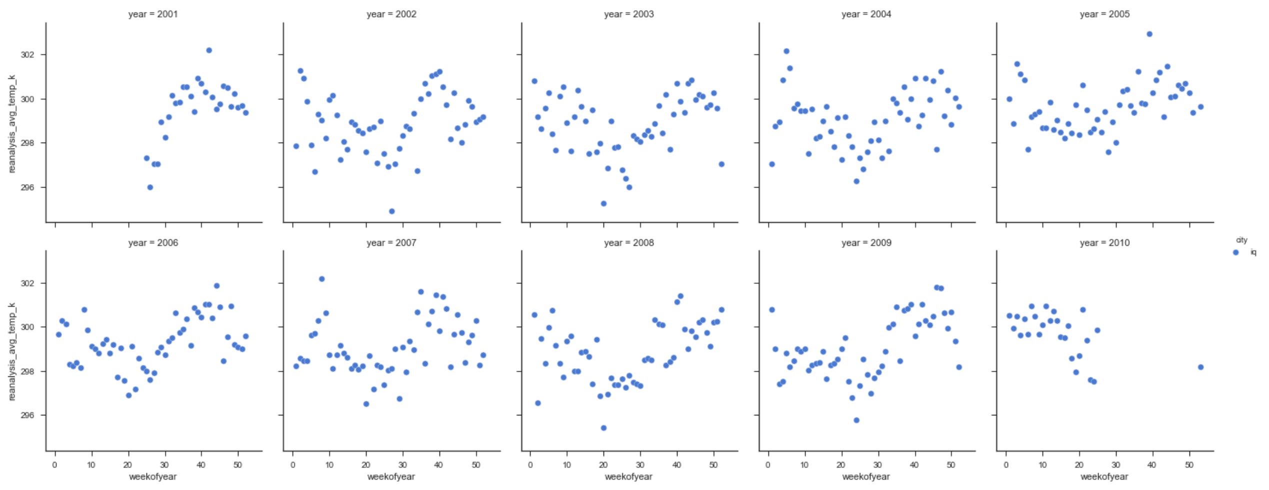
Facet Grid of total cases in each week for each year

In [42]:
```
sns.set(style="ticks", palette="muted")
g = sns.FacetGrid(data_iq, col="year",  hue="city", col_wrap=5, size=4)
g = (g.map(plt.scatter, "weekofyear", "total_cases", edgecolor="w").add_le
gend())
```



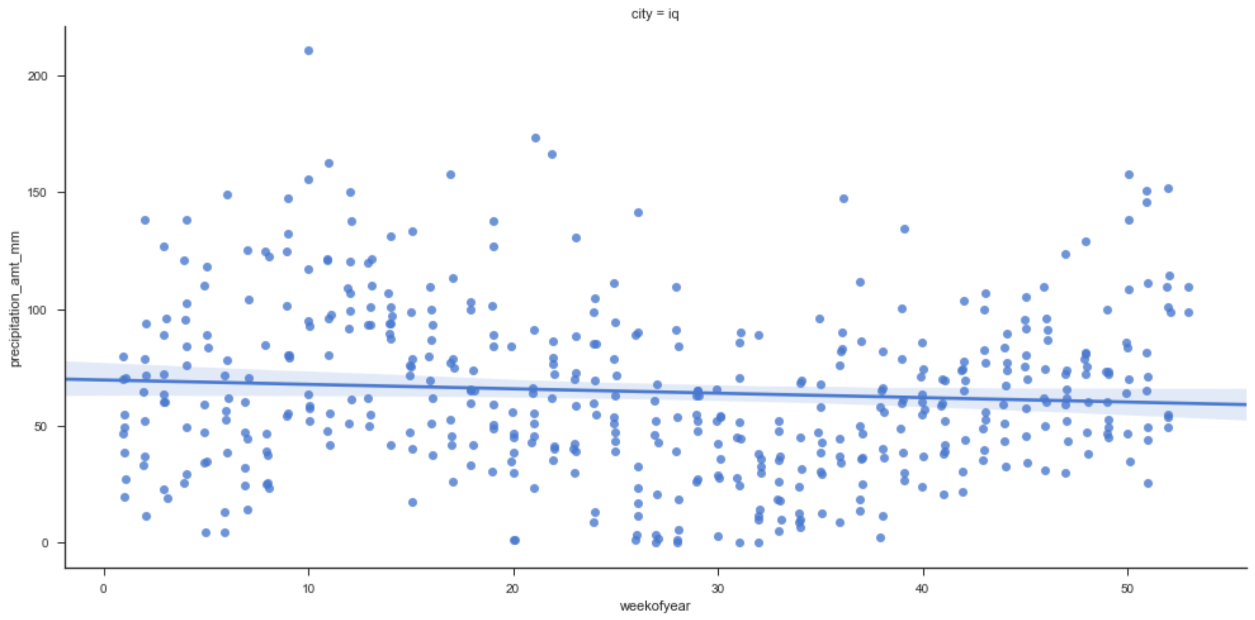
Facet Grid of Temperature in each year

In [43]:
```
sns.set(style="ticks", palette="muted")
g = sns.FacetGrid(data_iq, col="year",  hue="city", col_wrap=5, size=4)
g = (g.map(plt.scatter, "weekofyear", "reanalysis_avg_temp_k", edgecolor=
"w").add_legend())
```



Precipitation in each week of year

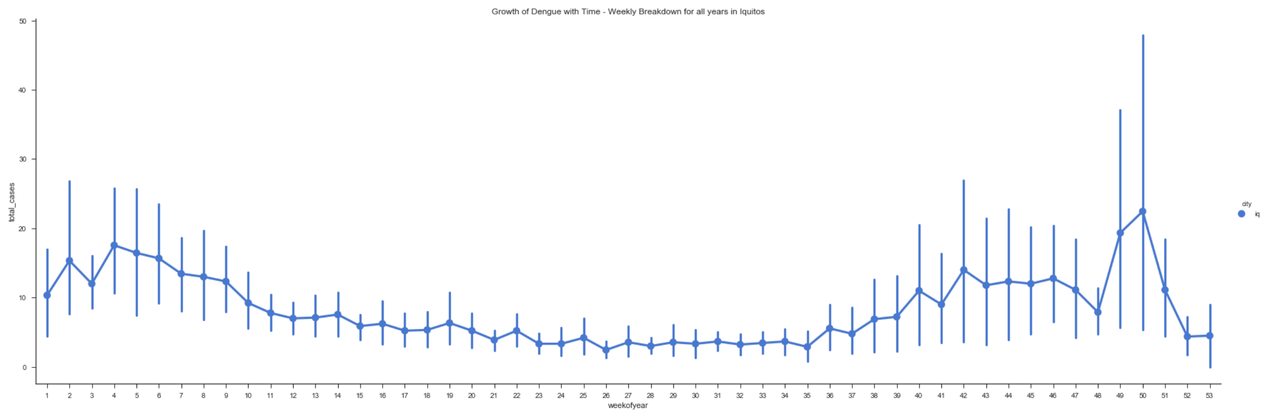
In [44]:
```
g = sns.lmplot(x="weekofyear", y="precipitation_amt_mm", hue="city", col=
"city", data=data_iq, aspect= 2, size = 7, x_jitter=.1)
```



Average Growth of Dengue by Week Number

```
In [45]: sns.factorplot(x="weekofyear", y="total_cases", hue="city", size=8, aspect
         =3,data=data_iq)
         plt.title("Growth of Dengue with Time - Weekly Breakdown for all years in
          Iquitos")
```

```
Out[45]: Text(0.5,1,'Growth of Dengue with Time - Weekly Breakdown for all years in
         Iquitos')
```

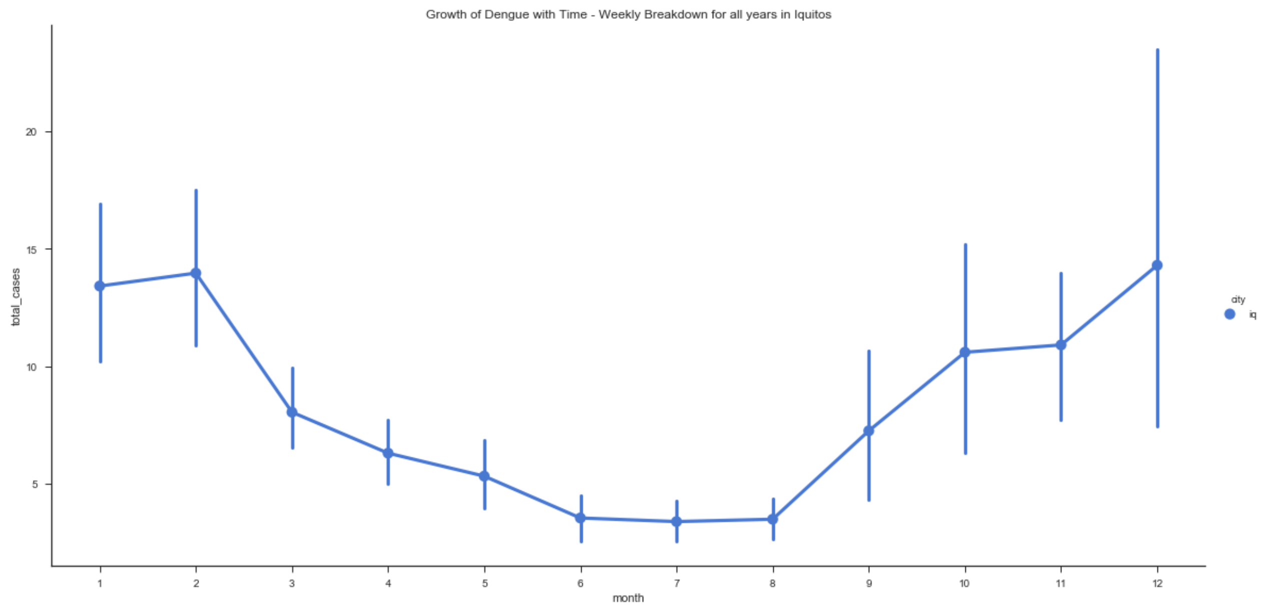


Average Growth of Dengue by Month Number

From the graphs below we notice that total number of dengue cases decreases as the total amount of precipitation decreases.

```
In [46]: sns.factorplot(x="month", y="total_cases", hue="city", size=8, aspect=2,da
         ta=data_iq)
         plt.title("Growth of Dengue with Time - Weekly Breakdown for all years in
          Iquitos")
```

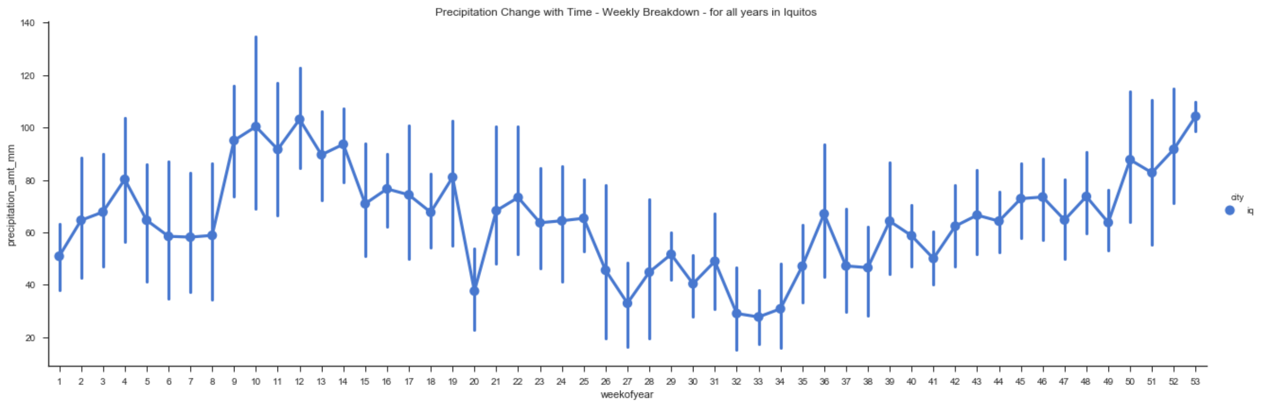
```
Out[46]: Text(0.5,1,'Growth of Dengue with Time - Weekly Breakdown for all years in
         Iquitos')
```



Average Precipitation by Week Number

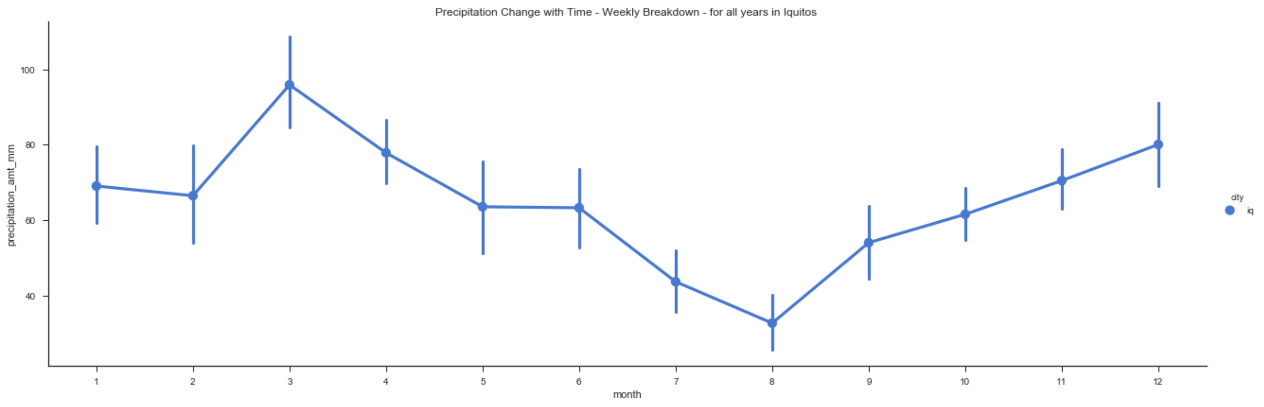
In [47]:
```
sns.factorplot(x="weekofyear", y="precipitation_amt_mm", hue="city", size=
6, aspect=3,data=data_iq)
plt.title("Precipitation Change with Time - Weekly Breakdown - for all yea
rs in Iquitos ")
```

Out[47]:
```
Text(0.5,1,'Precipitation Change with Time - Weekly Breakdown - for all yea
rs in Iquitos ')
```



In [48]:
```
sns.factorplot(x="month", y="precipitation_amt_mm", hue="city", size=6, as
pect=3,data=data_iq)
plt.title("Precipitation Change with Time - Weekly Breakdown - for all yea
rs in Iquitos ")
```

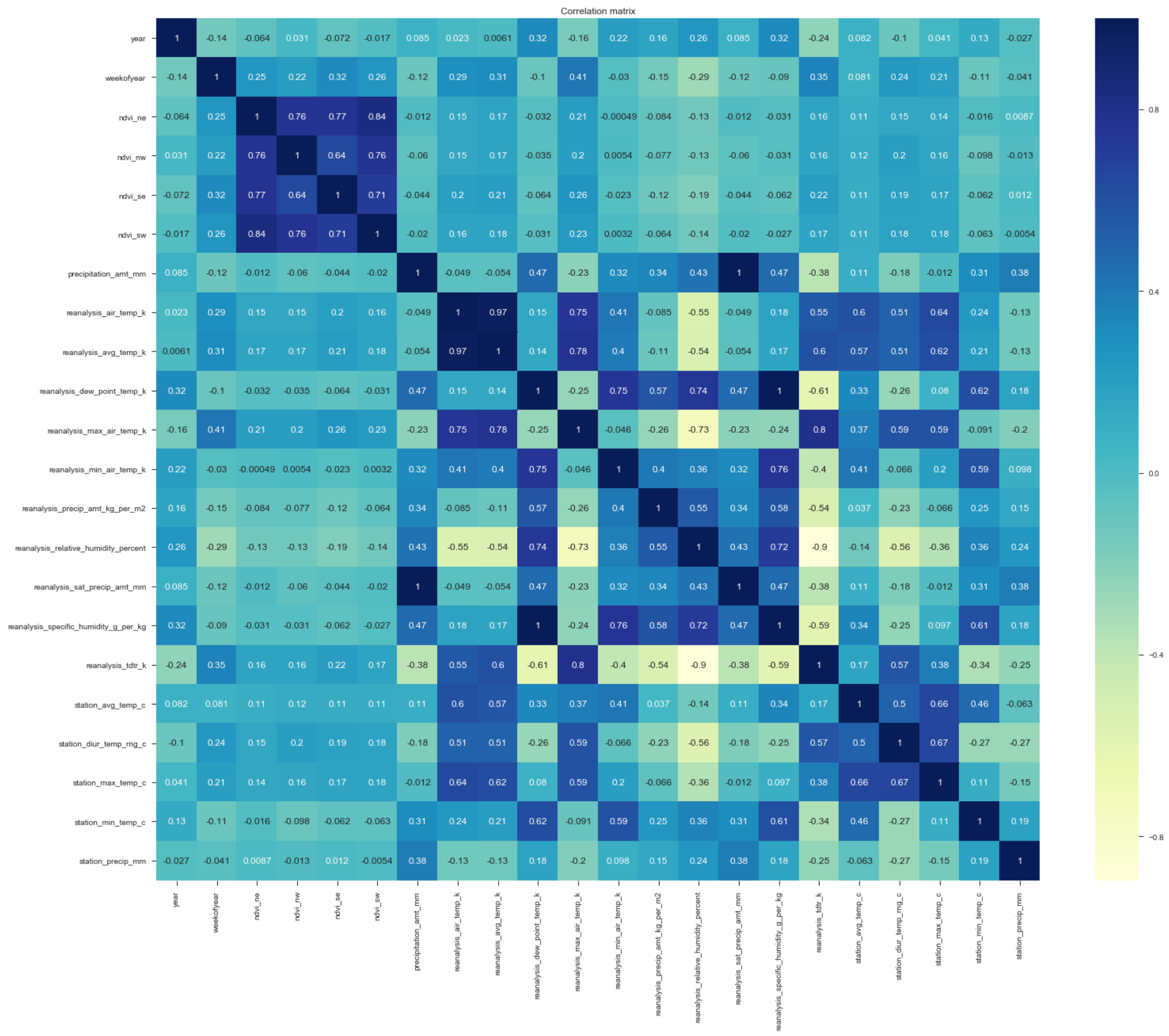
Out[48]:
```
Text(0.5,1,'Precipitation Change with Time - Weekly Breakdown - for all yea
rs in Iquitos ')
```



Correlation Heat Map

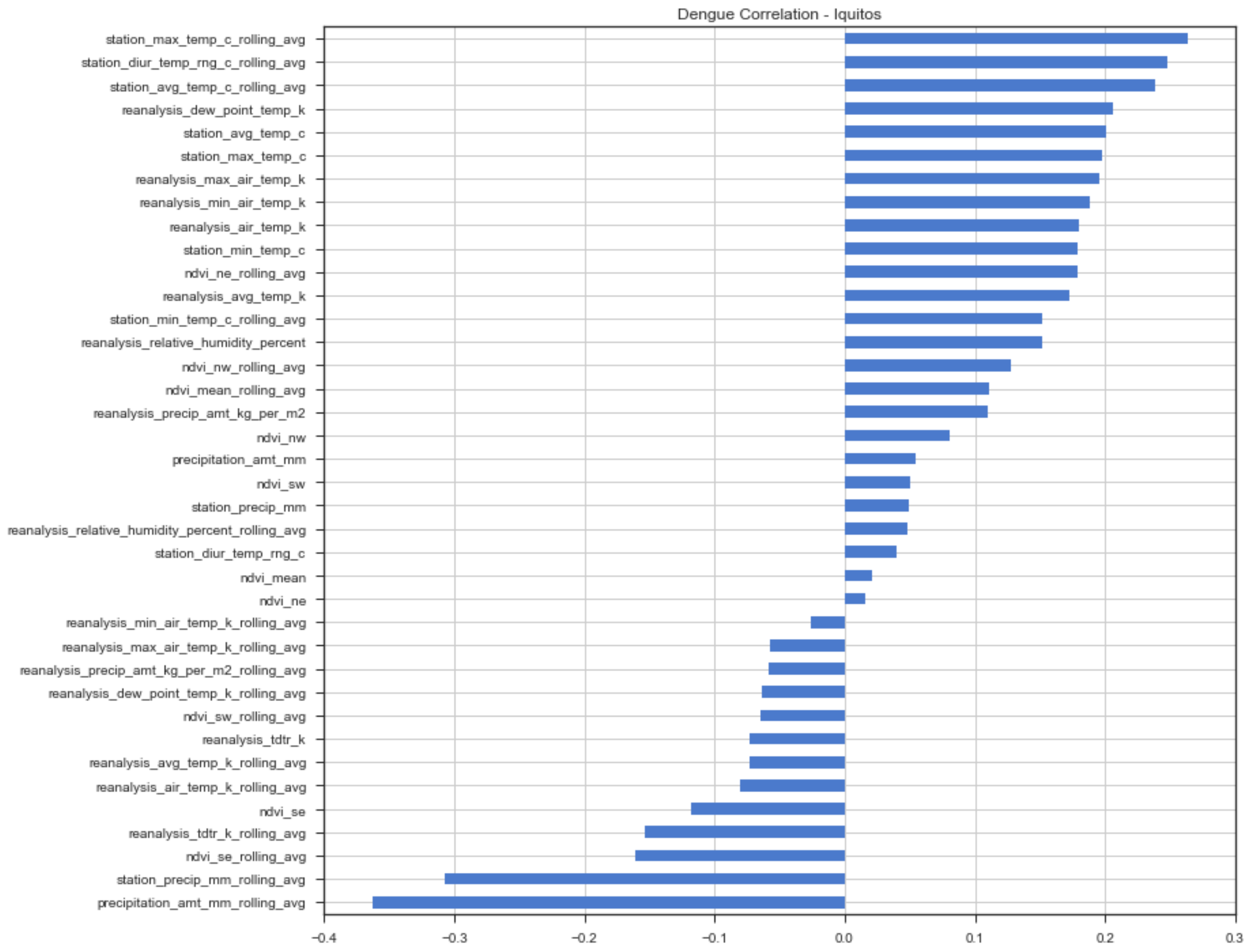
```
In [49]: plt.figure(figsize=(25,20))
         plt.title('Correlation matrix')
         sns.heatmap(df_iq.corr(), cmap="YlGnBu", annot = True)
```

```
Out[49]: <matplotlib.axes._subplots.AxesSubplot at 0x1a1787e2b0>
```



Correlation for Dengue Cases

```
In [50]: #Code to generate correlation graphs below for the two cities
         corr_iq = data_iq.corr(method='pearson')
         corr_iq = corr_iq['total_cases'].to_frame(name = 'corr_with_cases_sj')
         corr_iq = corr_iq.sort_values(by=['corr_with_cases_sj'])
         corr_iq = (corr_iq.drop('total_cases')
              .drop('year')
              .drop('month')
              .drop('weekofyear')
              .drop('odd_year'))
         corr_sj.plot(kind='barh', title='Dengue Correlation - Iquitos', xlim=(-.40
         ,.30), grid = True, legend = False, color = '#4B7ACC', figsize=(12,12))

Out[50]: <matplotlib.axes._subplots.AxesSubplot at 0x1a17c3cc88>
```



```
In [51]: data = data_iq['total_cases']
         # calculate summary statistics
         data_mean, data_std = mean(data), std(data)
         # identify outliers
         cut_off = data_std * 3
         lower, upper = data_mean - cut_off, data_mean + cut_off
         # identify outliers
         outliers = [x for x in data if x < lower or x > upper]
         print('Identified outliers: %d' % len(outliers))
         # remove outliers
         outliers_removed = [x for x in data if x >= lower and x <= upper]
         print('Non-outlier observations: %d' % len(outliers_removed))

         Identified outliers: 7
         Non-outlier observations: 463
```

Machine Learning Models

We will be testing our models with to see which give us the least margin of error and fit perfectly.

Since we are predicting a continuous valued attribute associated with an object we will need to use Regression Machine Learning models from scikit learn.

As part of our modelling process, we did:

1. Feature Importance Weighting
2. Dimensionality Reduction
3. Updated our Features
4. Using Grid Search & Cross Validation we:
   A. Predicted Outcomes and
   B. Printed Mean Absolute Error
5. Graphed out the Predicted vs Actual

For each machine learning model, we will mention:

1. How it works?
2. Why we used it?

At the end of this discussion we will shift to selecting the best model via a comparision visualization collection & then add our concluding thoughts.

K Nearest Neighbor

In K Nearest Neighbor, the target is predicted by local interpolation of the targets associated of the nearest neighbors in the training set.

We decided to use KNN, because it is an extremely recommended algorithm for large sets of time series data.

KNN San Juan

Splitting Training and Test Data

```
In [52]: train_features_sj, test_features_sj, train_outcomes_sj, test_outcomes_sj =
          train_test_split(
             data_sj_n,
             data_sj['total_cases'],
             test_size = 0.3
         )
```

Features Selection

Recursive Feature Elimination

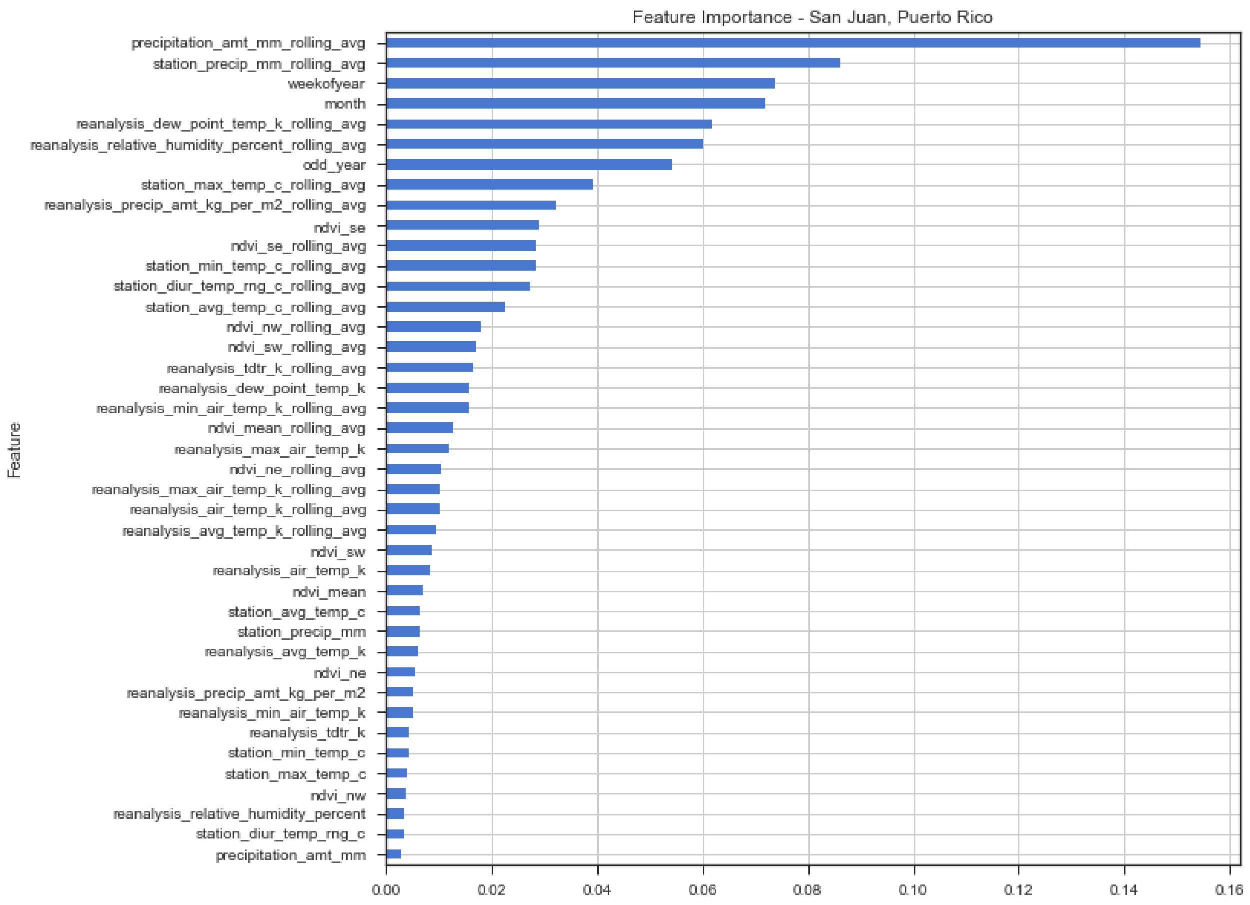
```
In [53]: from sklearn.feature_selection import RFE

         for n in range(1,20,1):

             train_features_sj, test_features_sj, train_outcomes_sj, test_outcomes_
         sj = train_test_split(
                 data_sj_n,
                 data_sj['total_cases'],
                 test_size = 0.3
             )

             rfe = RFE(ExtraTreesRegressor(), n)
             fit = rfe.fit(test_features_sj, test_outcomes_sj)

             train_features_sj, test_features_sj, train_outcomes_sj, test_outcomes_
         sj = train_test_split(
                 data_sj[data_sj_n.columns[fit.ranking_ == 1]],
                 data_sj['total_cases'],
                 test_size = 0.3
             )

             knr_reg = KNeighborsRegressor(n_neighbors = 5, weights = 'distance')
             knr_preds_sj = knr_reg.fit(train_features_sj, train_outcomes_sj).predi
         ct(test_features_sj)
             print('Features:', n, ', MAE:', mean_absolute_error(test_outcomes_sj,
         knr_preds_sj))
```

```
Features: 1 , MAE: 28.133492726958103
Features: 2 , MAE: 22.84540706961099
Features: 3 , MAE: 14.30017510839078
Features: 4 , MAE: 11.772795633589688
Features: 5 , MAE: 12.647825755173752
Features: 6 , MAE: 10.76387359938594
Features: 7 , MAE: 10.176684182946284
Features: 8 , MAE: 25.13937824772532
Features: 9 , MAE: 10.526887460232915
Features: 10 , MAE: 12.151059814442695
Features: 11 , MAE: 18.819214361059434
Features: 12 , MAE: 8.771012704420215
Features: 13 , MAE: 8.768842420700706
Features: 14 , MAE: 13.32234142553923
Features: 15 , MAE: 17.91224213123566
Features: 16 , MAE: 10.084586249925463
Features: 17 , MAE: 16.060444440961188
Features: 18 , MAE: 18.06244747050495
Features: 19 , MAE: 11.930888712527462
```

Extra Tree Regressor

In [54]:
```
model = ExtraTreesRegressor()
feature_imp = pd.DataFrame({'Feature' : [], 'Importance' : []})
for i in range(1,10):
    train_features_sj, test_features_sj, train_outcomes_sj, test_outcomes_
sj = train_test_split(
        data_sj_n,
        data_sj['total_cases'],
        test_size = 0.3
    )
    for i in range(1,10):
        model.fit(train_features_sj, train_outcomes_sj)
        imp = pd.DataFrame({'Feature': data_sj_n.columns, 'Importance':mod
el.feature_importances_})
        frames = [feature_imp, imp]
        feature_imp = pd.concat(frames).reset_index(drop = True)
feature_imp = feature_imp.groupby(['Feature'])['Importance'].mean().to_fra
me(name = 'Importance').reset_index()
feature_imp = feature_imp.set_index('Feature')
feature_imp.sort_values(by='Importance').plot(kind='barh', title='Feature
 Importance - San Juan, Puerto Rico', grid = True, legend = False, figsize
=(10,10))
```

Out[54]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x1a1f63a630>
```



Update Train/Test Data

```
In [55]: # San Juan
         # ['month','reanalysis_relative_humidity_percent', 'reanalysis_dew_point_t
         emp_k', 'station_avg_temp_c', 'reanalysis_tdtr_k']
         train_features_sj, test_features_sj, train_outcomes_sj, test_outcomes_sj =
          train_test_split(
             data_sj_n[['month',
                        'odd_year',
                        'ndvi_sw_rolling_avg',
                        'precipitation_amt_mm_rolling_avg',
                        'reanalysis_dew_point_temp_k_rolling_avg',
                        'reanalysis_precip_amt_kg_per_m2_rolling_avg',
                        'reanalysis_relative_humidity_percent_rolling_avg',
                        'station_diur_temp_rng_c_rolling_avg',
                        'station_max_temp_c_rolling_avg']],
             data_sj['total_cases'],
             test_size = 0.3
         )
```

Grid Search & Cross Validation

Margin of Error

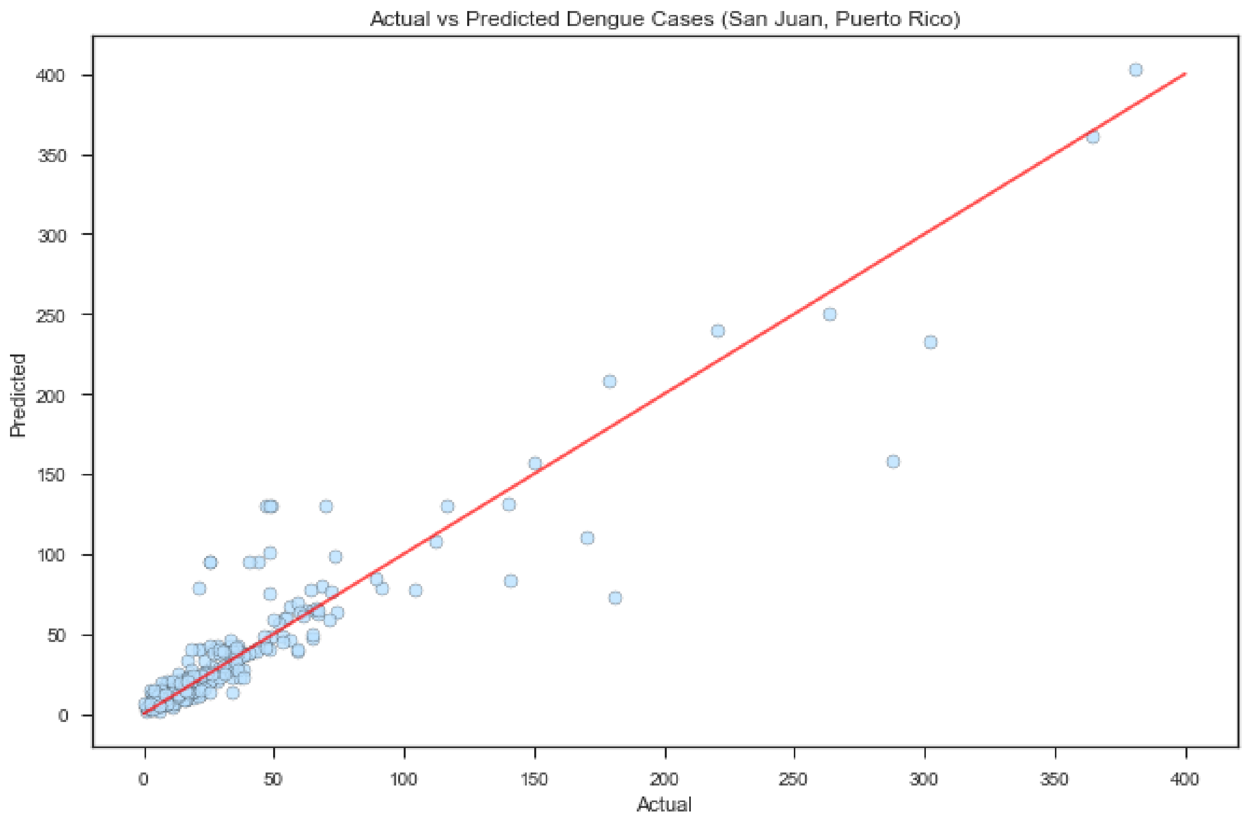
```
In [56]: params = {'n_neighbors':range(2, 30), 'weights':['uniform', 'distance']}
         folds = KFold(n_splits = 10, shuffle=True)
         grid_search = GridSearchCV(KNeighborsRegressor(), param_grid=params, cv=fo
         lds, scoring='neg_mean_absolute_error')
         knr_preds_sj = grid_search.fit(train_features_sj, train_outcomes_sj).predi
         ct(test_features_sj)
         knr_mae_sj = mean_absolute_error(test_outcomes_sj, knr_preds_sj)
         knr_mdae_sj = median_absolute_error(test_outcomes_sj, knr_preds_sj)
         knr_evs_sj = explained_variance_score(test_outcomes_sj, knr_preds_sj)
         print(knr_mae_sj)

         9.547511340188656
```

Optimal Number of Neighbors

```
In [57]: grid_search.cv_results_['params'][grid_search.best_index_]

Out[57]: {'n_neighbors': 5, 'weights': 'distance'}
```

Actual Versus Predicted Scatter Plot

```
In [58]: plt.subplots(figsize=(11,7))
         plt.title('Actual vs Predicted Dengue Cases (San Juan, Puerto Rico)')
         plt.xlabel('Actual')
         plt.ylabel('Predicted')
         plt.scatter(test_outcomes_sj, knr_preds_sj, edgecolors = '#1e1e1e', color=
         '#bae1ff', alpha=0.8)
         plt.plot([0, 400], [0, 400], 'red', alpha=0.7)

Out[58]: [<matplotlib.lines.Line2D at 0x1a162f2a58>]
```



Final KNN Model

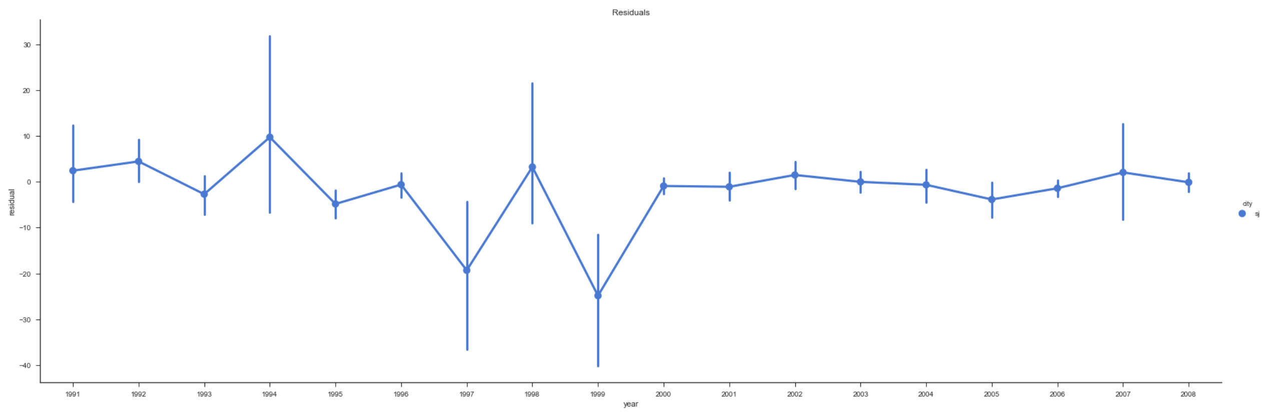
```
In [59]: knr_preds_final_sj = knr_reg.fit(train_features_sj, train_outcomes_sj).pre
         dict(
             data_test_sj_n[['month',
                             'odd_year',
                             'ndvi_sw_rolling_avg',
                             'precipitation_amt_mm_rolling_avg',
                             'reanalysis_dew_point_temp_k_rolling_avg',
                             'reanalysis_precip_amt_kg_per_m2_rolling_avg',
                             'reanalysis_relative_humidity_percent_rolling_avg',
                             'station_diur_temp_rng_c_rolling_avg',
                             'station_max_temp_c_rolling_avg']]
         )
```

```
In [60]: submission_sj = data_test_sj[['city', 'year', 'weekofyear']].copy()
         submission_sj['total_cases'] = np.round(knr_preds_final_sj).astype(int)
```

Residuals

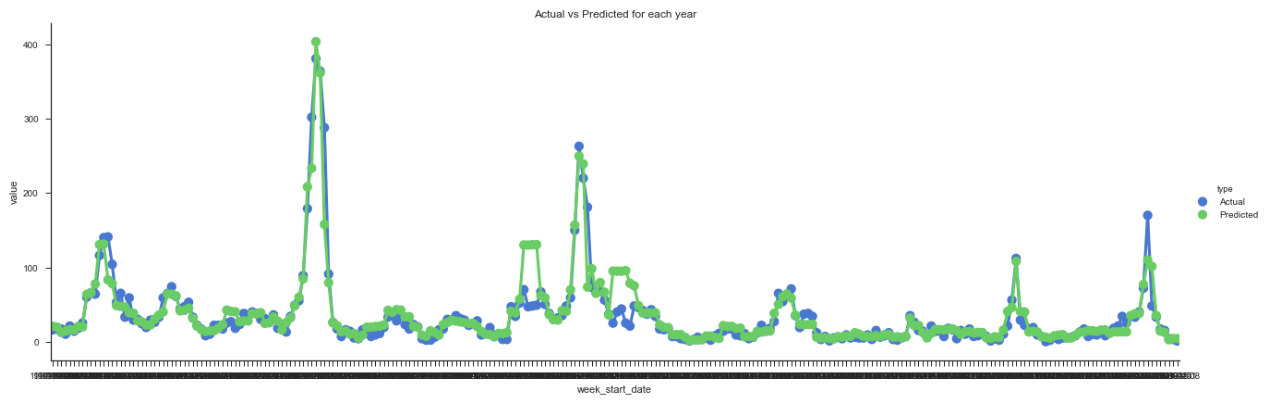
```
In [61]: knn_preds_week_sj = pd.DataFrame(test_features_sj)
         knn_preds_week_sj['Actual'] = test_outcomes_sj.values
         knn_preds_week_sj['Predicted'] = knr_preds_sj
         knn_preds_week_sj = pd.merge(data_sj, knn_preds_week_sj, left_index = True
         , right_index = True)
         knn_preds_week_sj = knn_preds_week_sj.assign(residual=knn_preds_week_sj.Ac
         tual - knn_preds_week_sj.Predicted)
         sns.factorplot(x="year", y="residual", hue="city", size=8, aspect=3,data=k
         nn_preds_week_sj)
         plt.title("Residuals")
```

```
Out[61]: Text(0.5,1,'Residuals')
```



Actual Vs Predicted Time Series Line Graph

```
In [62]: knn_preds_week_sj = knn_preds_week_sj.melt(id_vars=['city', 'year', 'weeko
         fyear', 'week_start_date', 'ndvi_ne', 'ndvi_nw',
                 'ndvi_se', 'ndvi_sw', 'precipitation_amt_mm', 'reanalysis_air_temp_
         k',
                 'reanalysis_avg_temp_k', 'reanalysis_dew_point_temp_k',
                 'reanalysis_max_air_temp_k', 'reanalysis_min_air_temp_k',
                 'reanalysis_precip_amt_kg_per_m2',
                 'reanalysis_relative_humidity_percent', 'reanalysis_tdtr_k',
                 'station_avg_temp_c', 'station_diur_temp_rng_c', 'station_max_temp_
         c',
                 'station_min_temp_c', 'station_precip_mm', 'total_cases', 'month_x'
         ,
                 'odd_year_x', 'ndvi_mean', 'ndvi_mean_rolling_avg',
                 'ndvi_ne_rolling_avg', 'ndvi_nw_rolling_avg', 'ndvi_se_rolling_avg'
         ,
                 'ndvi_sw_rolling_avg_x', 'precipitation_amt_mm_rolling_avg_x',
                 'reanalysis_air_temp_k_rolling_avg',
                 'reanalysis_avg_temp_k_rolling_avg',
                 'reanalysis_dew_point_temp_k_rolling_avg_x',
                 'reanalysis_max_air_temp_k_rolling_avg',
                 'reanalysis_min_air_temp_k_rolling_avg',
                 'reanalysis_precip_amt_kg_per_m2_rolling_avg_x',
                 'reanalysis_relative_humidity_percent_rolling_avg_x',
                 'reanalysis_tdtr_k_rolling_avg', 'station_avg_temp_c_rolling_avg',
                 'station_diur_temp_rng_c_rolling_avg_x',
                 'station_max_temp_c_rolling_avg_x', 'station_min_temp_c_rolling_av
         g',
                 'station_precip_mm_rolling_avg', 'month_y', 'odd_year_y',
                 'ndvi_sw_rolling_avg_y', 'precipitation_amt_mm_rolling_avg_y',
                 'reanalysis_dew_point_temp_k_rolling_avg_y',
                 'reanalysis_precip_amt_kg_per_m2_rolling_avg_y',
                 'reanalysis_relative_humidity_percent_rolling_avg_y',
                 'station_diur_temp_rng_c_rolling_avg_y',
                 'station_max_temp_c_rolling_avg_y', 'residual'], var_name='type')

         sns.factorplot(x='week_start_date', y="value", hue="type", data=knn_preds_
         week_sj, size = 6, aspect =3)
         plt.title("Actual vs Predicted for each year")

Out[62]: Text(0.5,1,'Actual vs Predicted for each year')
```



KNN Iquitos

Train/Test Split

In [63]:
```
train_features_iq, test_features_iq, train_outcomes_iq, test_outcomes_iq =
 train_test_split(
    data_iq_n,
    data_iq['total_cases'],
    test_size = 0.3
)
```

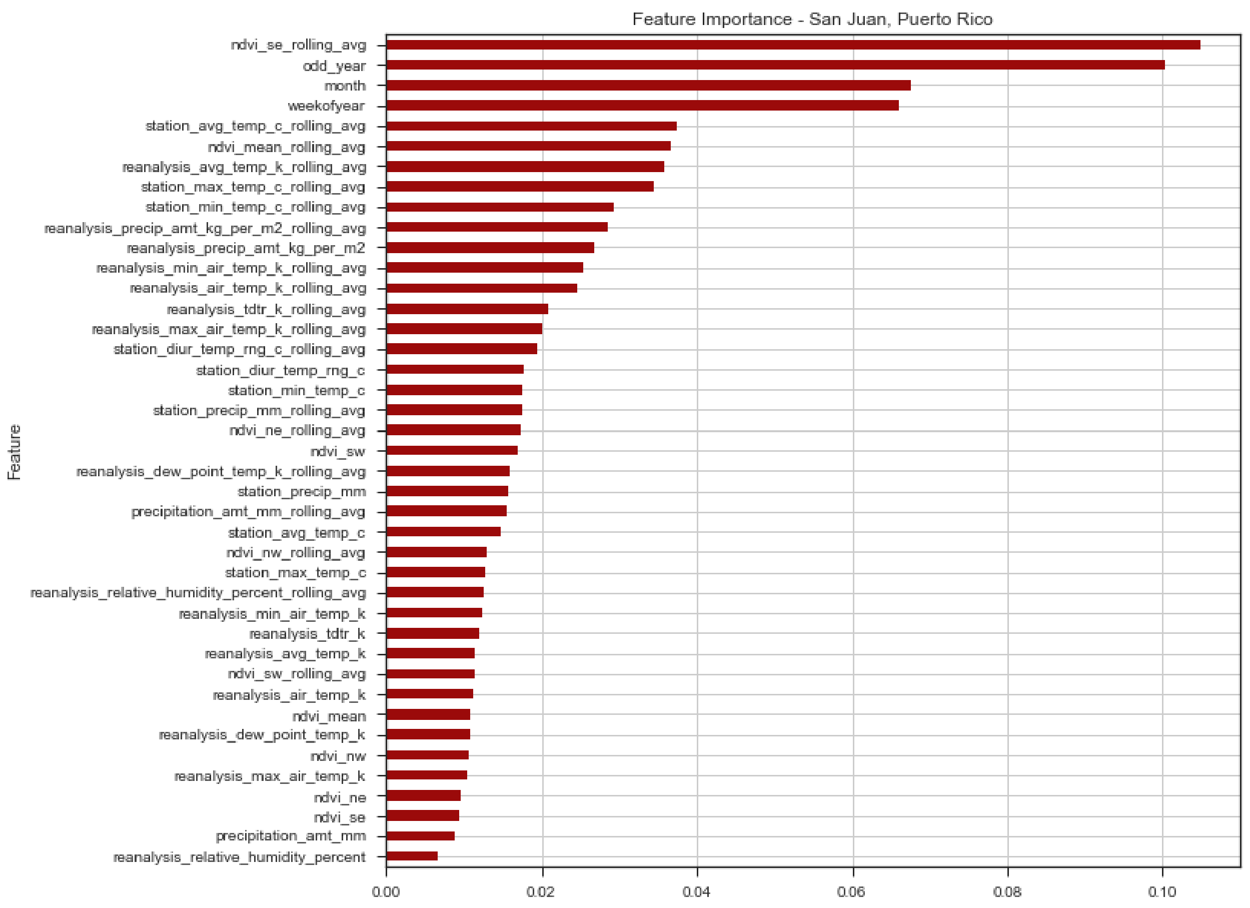
Features Selection

In [64]:
```
from sklearn.feature_selection import RFE

for n in range(1,20,1):

    train_features_iq, test_features_iq, train_outcomes_iq, test_outcomes_
iq = train_test_split(
        data_iq_n,
        data_iq['total_cases'],
        test_size = 0.3
    )

    rfe = RFE(ExtraTreesRegressor(), n)
    fit = rfe.fit(test_features_iq, test_outcomes_iq)

    train_features_iq, test_features_iq, train_outcomes_iq, test_outcomes_
iq = train_test_split(
        data_iq[data_iq_n.columns[fit.ranking_ == 1]],
        data_iq['total_cases'],
        test_size = 0.3
    )

    knr_reg = KNeighborsRegressor(n_neighbors = 5, weights = 'distance')
    knr_preds_iq = knr_reg.fit(train_features_iq, train_outcomes_iq).predi
ct(test_features_iq)
    print('Features:', n, ', MAE:', mean_absolute_error(test_outcomes_iq,
knr_preds_iq))
```

```
Features: 1 , MAE: 7.964772438692862
Features: 2 , MAE: 7.526215023243125
Features: 3 , MAE: 7.422715296960007
Features: 4 , MAE: 6.064308336813999
Features: 5 , MAE: 4.811517233273174
Features: 6 , MAE: 5.325051274918283
Features: 7 , MAE: 5.29844015182675
Features: 8 , MAE: 7.715616600943205
Features: 9 , MAE: 6.176772876340359
Features: 10 , MAE: 5.937164597906182
Features: 11 , MAE: 4.802713410286034
Features: 12 , MAE: 5.425498143588204
Features: 13 , MAE: 6.139650879307358
Features: 14 , MAE: 6.381115757576928
Features: 15 , MAE: 5.071503159448216
Features: 16 , MAE: 5.304012695361466
Features: 17 , MAE: 5.4596383656008
Features: 18 , MAE: 6.031018838052589
Features: 19 , MAE: 5.492852883086299
```

```
In [65]: model = ExtraTreesRegressor()
         feature_imp = pd.DataFrame({'Feature' : [], 'Importance' : []})
         for i in range(1,10):
             train_features_iq, test_features_iq, train_outcomes_iq, test_outcomes_
         iq = train_test_split(
                 data_iq_n,
                 data_iq['total_cases'],
                 test_size = 0.3
             )
             for i in range(1,10):
                 model.fit(train_features_iq, train_outcomes_iq)
                 imp = pd.DataFrame({'Feature': data_iq_n.columns, 'Importance':mod
         el.feature_importances_})
                 frames = [feature_imp, imp]
                 feature_imp = pd.concat(frames).reset_index(drop = True)
         feature_imp = feature_imp.groupby(['Feature'])['Importance'].mean().to_fra
         me(name = 'Importance').reset_index()
         feature_imp = feature_imp.set_index('Feature')
         feature_imp.sort_values(by='Importance').plot(kind='barh', title='Feature
          Importance - San Juan, Puerto Rico', grid = True, legend = False, color =
          '#9b0a0a', figsize=(10,10))
```

```
Out[65]: <matplotlib.axes._subplots.AxesSubplot at 0x1a20881b00>
```



Update Train/Test Data

```
In [66]: train_features_iq, test_features_iq, train_outcomes_iq, test_outcomes_iq =
          train_test_split(
             data_iq_n[['reanalysis_avg_temp_k',
                        'month',
                        'odd_year',
                        'ndvi_nw_rolling_avg',
                        'ndvi_sw_rolling_avg',
                        'reanalysis_max_air_temp_k_rolling_avg',
                        'reanalysis_tdtr_k_rolling_avg',
                        'station_diur_temp_rng_c_rolling_avg',
                        'station_max_temp_c_rolling_avg']],
             data_iq['total_cases'],
             test_size = 0.3
         )
```

Grid Search & Cross Validation

Mean Absolute Error

```
In [67]: params = {'n_neighbors':range(2, 10), 'weights':['uniform', 'distance']}
         folds = KFold(n_splits = 10, shuffle=True)
         grid_search = GridSearchCV(KNeighborsRegressor(), param_grid=params, cv=fo
         lds, scoring='neg_mean_absolute_error')
         knr_preds_iq = grid_search.fit(train_features_iq, train_outcomes_iq).predi
         ct(test_features_iq)
         knr_mae_iq = mean_absolute_error(test_outcomes_iq, knr_preds_iq)
         knr_mdae_iq = median_absolute_error(test_outcomes_iq, knr_preds_iq)
         knr_evs_iq = explained_variance_score(test_outcomes_iq, knr_preds_iq)
         print(knr_mae_iq)

         3.776722996149727
```

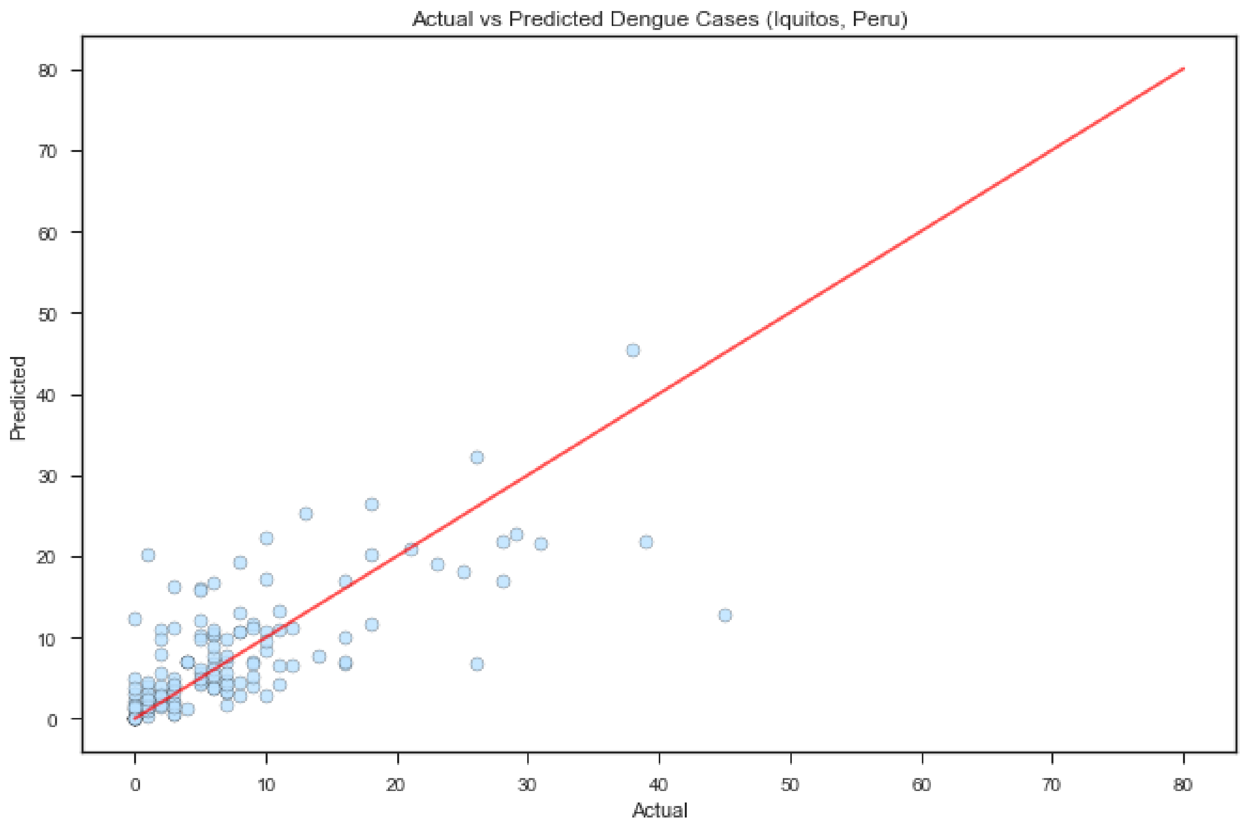
Optimal Number of Neighbors

```
In [68]: grid_search.cv_results_['params'][grid_search.best_index_]

Out[68]: {'n_neighbors': 2, 'weights': 'distance'}
```

Actual vs Predicted Iquitos Scatter Plot

In [69]:
```
plt.subplots(figsize=(11,7))
plt.title('Actual vs Predicted Dengue Cases (Iquitos, Peru)')
plt.xlabel('Actual')
plt.ylabel('Predicted')
plt.scatter(test_outcomes_iq, knr_preds_iq, edgecolors = '#1e1e1e', color=
'#bae1ff', alpha=0.8)
plt.plot([0, 80], [0, 80], 'red', alpha=0.7)
```

Out[69]:
```
[<matplotlib.lines.Line2D at 0x1a15eba940>]
```

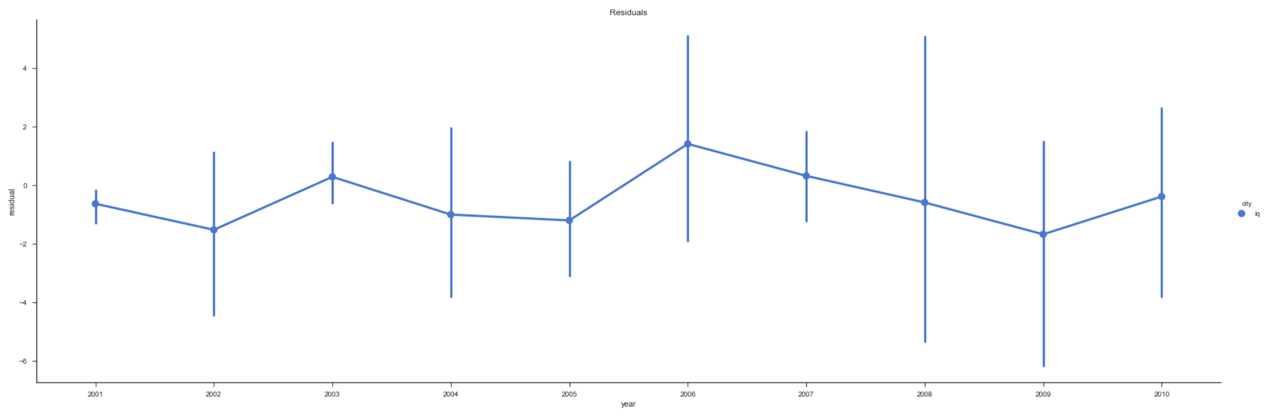


Final KNN Model for IQ

In [70]:
```
knr_preds_final_iq = knr_reg.fit(train_features_iq, train_outcomes_iq).pre
dict(
    data_test_iq_n[['reanalysis_avg_temp_k',
                    'month',
                    'odd_year',
                    'ndvi_nw_rolling_avg',
                    'ndvi_sw_rolling_avg',
                    'reanalysis_max_air_temp_k_rolling_avg',
                    'reanalysis_tdtr_k_rolling_avg',
                    'station_diur_temp_rng_c_rolling_avg',
                    'station_max_temp_c_rolling_avg']]
)

submission_iq = data_test_iq[['city', 'year', 'weekofyear']].copy()
```

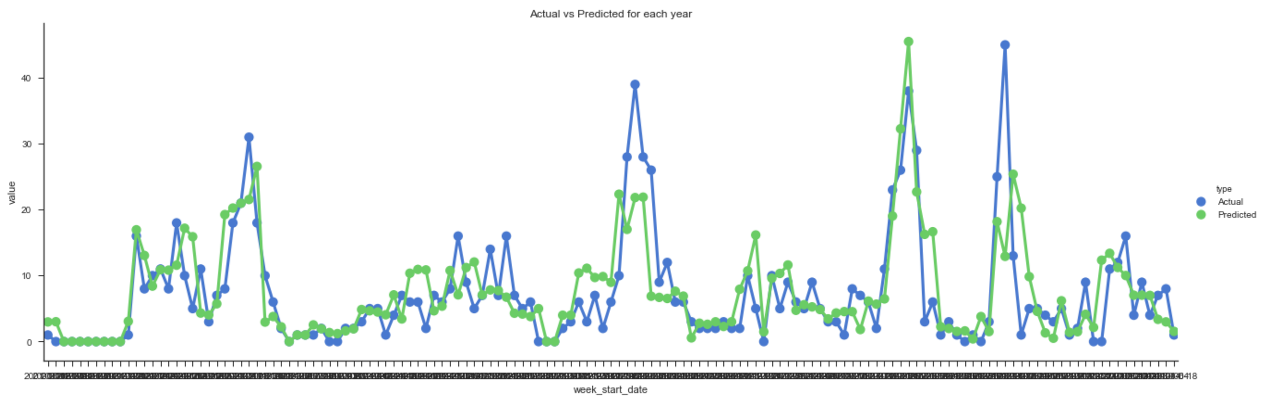
Residuals

```
In [71]: knn_preds_week_iq = pd.DataFrame(test_features_iq)
         knn_preds_week_iq['Actual'] = test_outcomes_iq.values
         knn_preds_week_iq['Predicted'] = knr_preds_iq
         knn_preds_week_iq = pd.merge(data_iq, knn_preds_week_iq, left_index = True
         , right_index = True)
         knn_preds_week_iq = knn_preds_week_iq.assign(residual=knn_preds_week_iq.Ac
         tual - knn_preds_week_iq.Predicted)
         sns.factorplot(x="year", y="residual", hue="city", size=8, aspect=3,data=k
         nn_preds_week_iq)
         plt.title("Residuals")

Out[71]: Text(0.5,1,'Residuals')
```



Actual Vs Predicted Time Series Line Graph

```
In [72]: knn_preds_week_iq = knn_preds_week_iq.melt(id_vars=['city', 'year', 'weeko
         fyear', 'week_start_date', 'ndvi_ne', 'ndvi_nw',
                'ndvi_se', 'ndvi_sw', 'precipitation_amt_mm', 'reanalysis_air_temp_
         k',
                'reanalysis_avg_temp_k_x', 'reanalysis_dew_point_temp_k',
                'reanalysis_max_air_temp_k', 'reanalysis_min_air_temp_k',
                'reanalysis_precip_amt_kg_per_m2',
                'reanalysis_relative_humidity_percent', 'reanalysis_tdtr_k',
                'station_avg_temp_c', 'station_diur_temp_rng_c', 'station_max_temp_
         c',
                'station_min_temp_c', 'station_precip_mm', 'total_cases', 'month_x'
         ,
                'odd_year_x', 'ndvi_mean', 'ndvi_mean_rolling_avg',
                'ndvi_ne_rolling_avg', 'ndvi_nw_rolling_avg_x', 'ndvi_se_rolling_av
         g',
                'ndvi_sw_rolling_avg_x', 'precipitation_amt_mm_rolling_avg',
                'reanalysis_air_temp_k_rolling_avg',
                'reanalysis_avg_temp_k_rolling_avg',
                'reanalysis_dew_point_temp_k_rolling_avg',
                'reanalysis_max_air_temp_k_rolling_avg_x',
                'reanalysis_min_air_temp_k_rolling_avg',
                'reanalysis_precip_amt_kg_per_m2_rolling_avg',
                'reanalysis_relative_humidity_percent_rolling_avg',
                'reanalysis_tdtr_k_rolling_avg_x', 'station_avg_temp_c_rolling_avg'
         ,
                'station_diur_temp_rng_c_rolling_avg_x',
                'station_max_temp_c_rolling_avg_x', 'station_min_temp_c_rolling_av
         g',
                'station_precip_mm_rolling_avg', 'reanalysis_avg_temp_k_y', 'month_
         y',
                'odd_year_y', 'ndvi_nw_rolling_avg_y', 'ndvi_sw_rolling_avg_y',
                'reanalysis_max_air_temp_k_rolling_avg_y',
                'reanalysis_tdtr_k_rolling_avg_y',
                'station_diur_temp_rng_c_rolling_avg_y',
                'station_max_temp_c_rolling_avg_y','residual'], var_name='type')

         sns.factorplot(x='week_start_date', y="value", hue="type", data=knn_preds_
         week_iq, size = 6, aspect =3)
         plt.title("Actual vs Predicted for each year")

Out[72]: Text(0.5,1,'Actual vs Predicted for each year')
```



KNN Submission to Driven Data - Best Score (19.4543)

```
In [73]: frames = [submission_sj, submission_iq]
         submission = pd.concat(frames)
         submission.to_csv('knn_best.csv', index = False)
```

```
/anaconda3/lib/python3.6/site-packages/ipykernel_launcher.py:2: FutureWarni
ng: Sorting because non-concatenation axis is not aligned. A future version
of pandas will change to not sort by default.

To accept the future behavior, pass 'sort=True'.

To retain the current behavior and silence the warning, pass sort=False
```

Xtreme Gradient Boosting

XGBoost is an implementation of gradient boosted decision trees designed for speed and performance that is dominative competitive machine learning.

We used it as it minimises the error of Normal Decision Trees as the implementation of XGBoost offers several advanced features for model tuning, computing environments and algorithm enhancement.

Xtreme Gradient Boosting for San Juan

Training and Test Data

```
In [74]: # Testing & Training Data
         train_features_sj, test_features_sj, train_outcomes_sj, test_outcomes_sj =
          train_test_split(
             data_sj_n,
             data_sj['total_cases'],
             test_size = 0.3
         )
```

Feature Selection

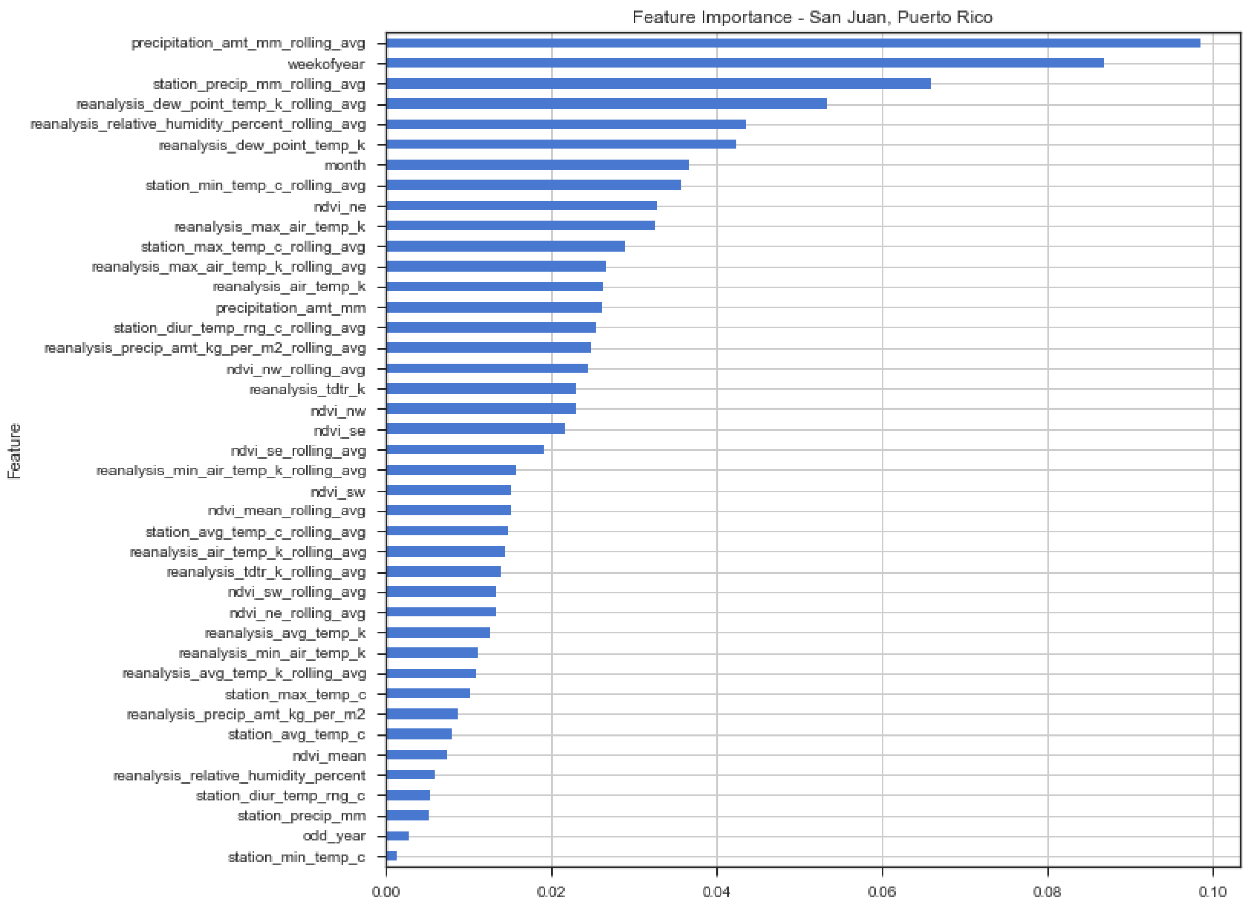
Recursive Feature Elimination

```
In [75]: from sklearn.feature_selection import RFE

         for n in range(1,20,1):

             train_features_sj, test_features_sj, train_outcomes_sj, test_outcomes_
         sj = train_test_split(
                 data_sj_n,
                 data_sj['total_cases'],
                 test_size = 0.3
             )

             rfe = RFE(XGBRegressor(), n)
             fit = rfe.fit(test_features_sj, test_outcomes_sj)

             train_features_sj, test_features_sj, train_outcomes_sj, test_outcomes_
         sj = train_test_split(
                 data_sj[data_sj_n.columns[fit.ranking_ == 1]],
                 data_sj['total_cases'],
                 test_size = 0.3
             )

             xgb_reg = XGBRegressor(n_estimators = 1000, learning_rate = 0.03, max_
         depth = 10, subsample = 0.8, colsample_bytree = 0.701)
             xgb_preds_sj = xgb_reg.fit(train_features_sj, train_outcomes_sj).predi
         ct(test_features_sj)
             print('Features:', n, ', MAE:', mean_absolute_error(test_outcomes_sj,
         xgb_preds_sj))
```

```
Features: 1 , MAE: 33.83979257291421
Features: 2 , MAE: 24.348538034168403
Features: 3 , MAE: 22.326293131462613
Features: 4 , MAE: 16.813920373307134
Features: 5 , MAE: 8.373529181444555
Features: 6 , MAE: 11.650297846112933
Features: 7 , MAE: 10.419811341099273
Features: 8 , MAE: 10.488946499905191
Features: 9 , MAE: 9.157661781275182
Features: 10 , MAE: 10.850977557046074
Features: 11 , MAE: 9.745062968784705
Features: 12 , MAE: 11.008426702560339
Features: 13 , MAE: 9.928849299599353
Features: 14 , MAE: 8.76913256842391
Features: 15 , MAE: 7.686975049793272
Features: 16 , MAE: 8.015233431543622
Features: 17 , MAE: 11.015054046211386
Features: 18 , MAE: 9.846770652702876
Features: 19 , MAE: 9.838708419548837
```

XG Regressor Feature Importance

```
In [76]: model = XGBRegressor()
         feature_imp = pd.DataFrame()
         for i in range(1,10):
             train_features_sj, test_features_sj, train_outcomes_sj, test_outcomes_
         sj = train_test_split(
             data_sj_n,
             data_sj['total_cases'],
             test_size = 0.3
             )
             for i in range(1,10):
                 model.fit(train_features_sj, train_outcomes_sj)
                 imp = pd.DataFrame({'Feature': data_sj_n.columns, 'Importance':mod
         el.feature_importances_})
                 frames = [feature_imp, imp]
                 feature_imp = pd.concat(frames).reset_index(drop = True)
         feature_imp = feature_imp.groupby(['Feature'])['Importance'].mean().to_fra
         me(name = 'Importance').reset_index()
         feature_imp = feature_imp.set_index('Feature')
         feature_imp.sort_values(by='Importance').plot(kind='barh', title='Feature
          Importance - San Juan, Puerto Rico', grid = True, legend = False, figsize
         =(10,10))

Out[76]: <matplotlib.axes._subplots.AxesSubplot at 0x1a1f510ac8>
```



Update Features

```
In [77]: # San Juan
         train_features_sj, test_features_sj, train_outcomes_sj, test_outcomes_sj =
          train_test_split(
             data_sj_n[['precipitation_amt_mm_rolling_avg',
                        'weekofyear',
                        'station_precip_mm_rolling_avg',
                        'reanalysis_dew_point_temp_k_rolling_avg',
                        'reanalysis_relative_humidity_percent_rolling_avg',
                        'station_max_temp_c_rolling_avg',
                        'reanalysis_air_temp_k_rolling_avg',
                        'ndvi_mean_rolling_avg']],
             data_sj['total_cases'],
             test_size = 0.3
         )
```

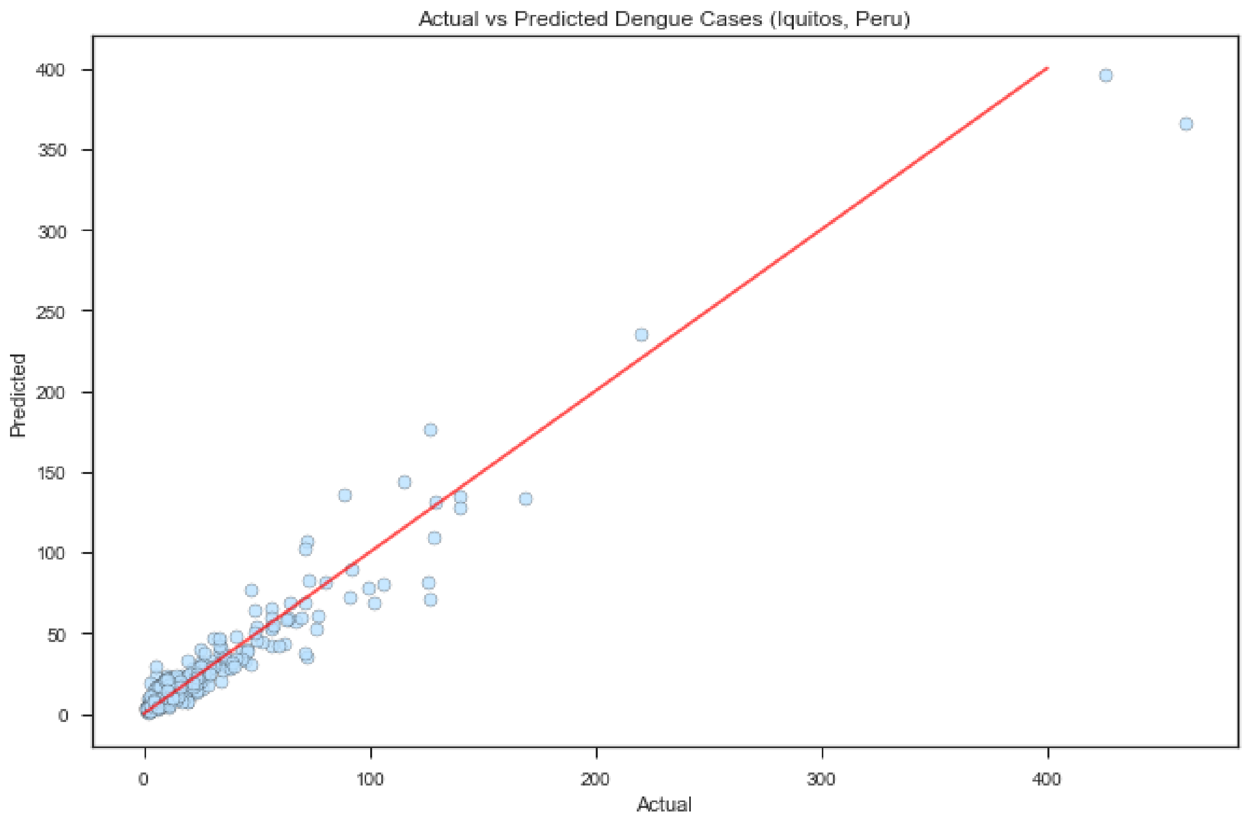
Grid Search & Cross Validation & Mean Absolute Error

```
In [78]: params = {'n_estimators':[1000], 'learning_rate':[0.03], 'max_depth':[10],
          'subsample':[0.8], 'colsample_bytree':[0.701]}
         folds = KFold(n_splits = 10, shuffle=True)
         grid_search = GridSearchCV(XGBRegressor(), param_grid=params, cv=folds, sc
         oring='neg_mean_absolute_error')
         xgb_preds_sj = grid_search.fit(train_features_sj, train_outcomes_sj).predi
         ct(test_features_sj)
         xgb_mae_sj = mean_absolute_error(test_outcomes_sj, xgb_preds_sj)
         xgb_mdae_sj = median_absolute_error(test_outcomes_sj, xgb_preds_sj)
         xgb_evs_sj = explained_variance_score(test_outcomes_sj, xgb_preds_sj)
         print(xgb_mae_sj)

         7.587810327235918
```

Actual vs Predicted San Juan XG Boost Scatter Plot

```
In [79]: plt.subplots(figsize=(11,7))
         plt.title('Actual vs Predicted Dengue Cases (Iquitos, Peru)')
         plt.xlabel('Actual')
         plt.ylabel('Predicted')
         plt.scatter(test_outcomes_sj, xgb_preds_sj, edgecolors = '#1e1e1e', color=
         '#bae1ff', alpha=0.8)
         plt.plot([0, 400], [0, 400], 'red', alpha=0.7)
```

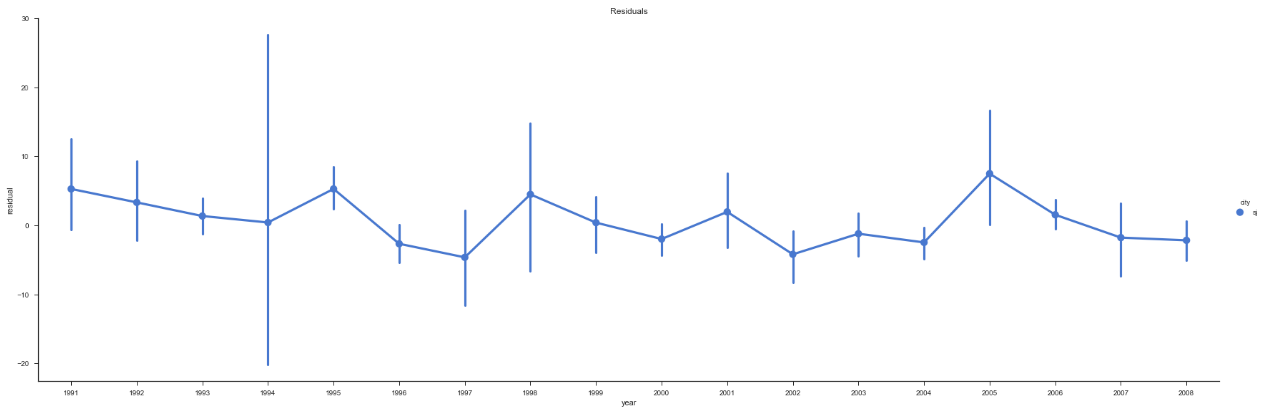
```
Out[79]: [<matplotlib.lines.Line2D at 0x1a1f39de48>]
```



Residuals

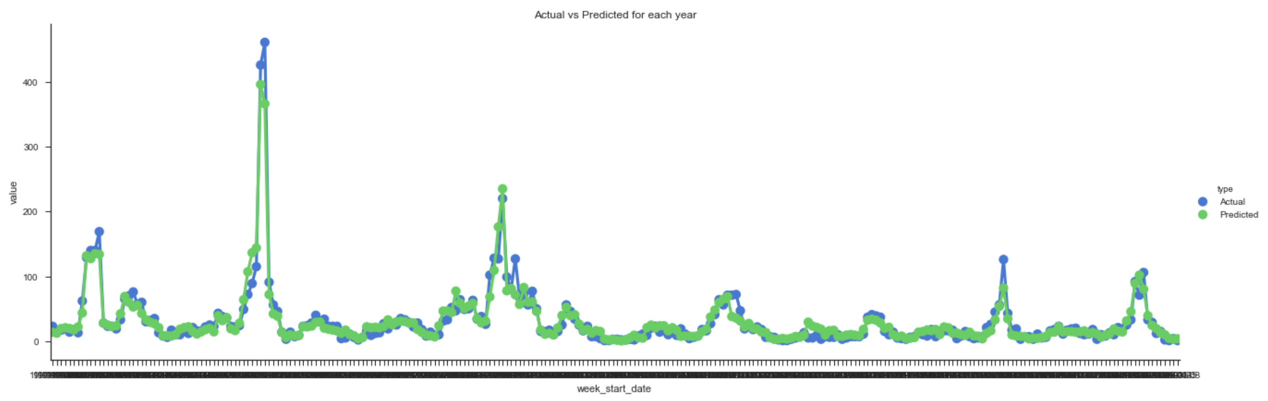
```
In [80]: xgb_preds_week_sj = pd.DataFrame(test_features_sj)
         xgb_preds_week_sj['Actual'] = test_outcomes_sj.values
         xgb_preds_week_sj['Predicted'] = xgb_preds_sj
         xgb_preds_week_sj = pd.merge(data_sj, xgb_preds_week_sj, left_index = True
         , right_index = True)
         plot_d = xgb_preds_week_sj.assign(residual=xgb_preds_week_sj.Actual - xgb_
         preds_week_sj .Predicted)
         sns.factorplot(x="year", y="residual", hue="city", size=8, aspect=3,data=p
         lot_d)
         plt.title("Residuals")
```

```
Out[80]: Text(0.5,1,'Residuals')
```



Actual Vs Predicted Time Series Line Graph

```
In [81]: plot_d = plot_d.melt(id_vars=['city', 'year', 'weekofyear_x', 'week_start_
         date', 'ndvi_ne', 'ndvi_nw',
                'ndvi_se', 'ndvi_sw', 'precipitation_amt_mm', 'reanalysis_air_temp_
         k',
                'reanalysis_avg_temp_k', 'reanalysis_dew_point_temp_k',
                'reanalysis_max_air_temp_k', 'reanalysis_min_air_temp_k',
                'reanalysis_precip_amt_kg_per_m2',
                'reanalysis_relative_humidity_percent', 'reanalysis_tdtr_k',
                'station_avg_temp_c', 'station_diur_temp_rng_c', 'station_max_temp_
         c',
                'station_min_temp_c', 'station_precip_mm', 'total_cases', 'month',
                'odd_year', 'ndvi_mean', 'ndvi_mean_rolling_avg_x',
                'ndvi_ne_rolling_avg', 'ndvi_nw_rolling_avg', 'ndvi_se_rolling_avg'
         ,
                'ndvi_sw_rolling_avg', 'precipitation_amt_mm_rolling_avg_x',
                'reanalysis_air_temp_k_rolling_avg_x',
                'reanalysis_avg_temp_k_rolling_avg',
                'reanalysis_dew_point_temp_k_rolling_avg_x',
                'reanalysis_max_air_temp_k_rolling_avg',
                'reanalysis_min_air_temp_k_rolling_avg',
                'reanalysis_precip_amt_kg_per_m2_rolling_avg',
                'reanalysis_relative_humidity_percent_rolling_avg_x',
                'reanalysis_tdtr_k_rolling_avg', 'station_avg_temp_c_rolling_avg',
                'station_diur_temp_rng_c_rolling_avg',
                'station_max_temp_c_rolling_avg_x', 'station_min_temp_c_rolling_av
         g',
                'station_precip_mm_rolling_avg_x', 'precipitation_amt_mm_rolling_av
         g_y',
                'weekofyear_y', 'station_precip_mm_rolling_avg_y',
                'reanalysis_dew_point_temp_k_rolling_avg_y',
                'reanalysis_relative_humidity_percent_rolling_avg_y',
                'station_max_temp_c_rolling_avg_y',
                'reanalysis_air_temp_k_rolling_avg_y', 'ndvi_mean_rolling_avg_y',
         'residual'], var_name='type')

         sns.factorplot(x='week_start_date', y="value", hue="type", data=plot_d, si
         ze = 6, aspect =3)
         plt.title("Actual vs Predicted for each year")

Out[81]: Text(0.5,1,'Actual vs Predicted for each year')
```



In [82]:
```
xgb_preds_final_sj = xgb_reg.fit(train_features_sj, train_outcomes_sj).pre
dict(
    data_test_sj_n[['precipitation_amt_mm_rolling_avg',
                 'weekofyear',
                 'station_precip_mm_rolling_avg',
                 'reanalysis_dew_point_temp_k_rolling_avg',
                 'reanalysis_relative_humidity_percent_rolling_avg',
                 'station_max_temp_c_rolling_avg',
                 'reanalysis_air_temp_k_rolling_avg',
                 'ndvi_mean_rolling_avg']]
)
```

In [83]:
```
submission_sj = data_test_sj[['city', 'year', 'weekofyear']].copy()
submission_sj['total_cases'] = np.round(xgb_preds_final_sj).astype(int)
```

Iquitos XG Boost

Training & Test Data

In [84]:
```
train_features_iq, test_features_iq, train_outcomes_iq, test_outcomes_iq =
 train_test_split(
    data_iq_n,
    data_iq['total_cases'],
    test_size = 0.3
)
```

Feature Selection

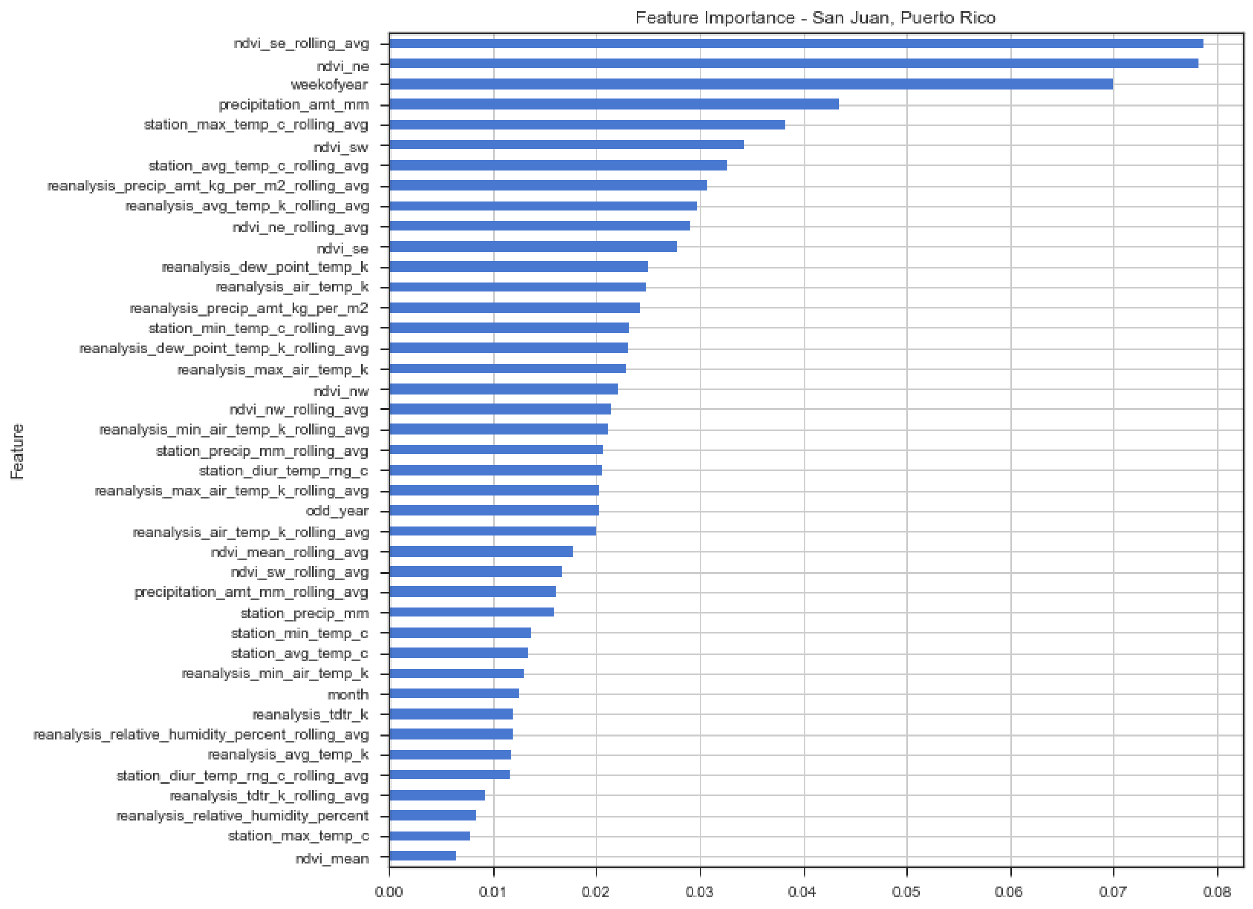
Recursive Feature Elimination

```
In [85]: from sklearn.feature_selection import RFE

         for n in range(1,20,1):

             train_features_iq, test_features_iq, train_outcomes_iq, test_outcomes_
         iq = train_test_split(
                 data_iq_n,
                 data_iq['total_cases'],
                 test_size = 0.3
             )

             rfe = RFE(XGBRegressor(), n)
             fit = rfe.fit(test_features_iq, test_outcomes_iq)

             train_features_iq, test_features_iq, train_outcomes_iq, test_outcomes_
         iq = train_test_split(
                 data_iq[data_iq_n.columns[fit.ranking_ == 1]],
                 data_iq['total_cases'],
                 test_size = 0.3
             )

             xgb_reg = XGBRegressor(n_estimators = 1000, learning_rate = 0.03, max_
         depth = 10, subsample = 0.8, colsample_bytree = 0.701)
             xgb_preds_iq = xgb_reg.fit(train_features_iq, train_outcomes_iq).predi
         ct(test_features_iq)
             print('Features:', n, ', MAE:', mean_absolute_error(test_outcomes_iq,
         xgb_preds_iq))
```

```
Features: 1 , MAE: 7.890125819554566
Features: 2 , MAE: 8.34331096465706
Features: 3 , MAE: 6.853985346800892
Features: 4 , MAE: 6.214191829693233
Features: 5 , MAE: 4.1573253379645925
Features: 6 , MAE: 4.001100015132986
Features: 7 , MAE: 4.153278014761336
Features: 8 , MAE: 4.923468457680222
Features: 9 , MAE: 5.069420959932584
Features: 10 , MAE: 3.7384204093023397
Features: 11 , MAE: 5.08000807157645
Features: 12 , MAE: 4.098495045029525
Features: 13 , MAE: 4.398846993420986
Features: 14 , MAE: 3.1934838455619543
Features: 15 , MAE: 4.212454951189934
Features: 16 , MAE: 4.798559705839089
Features: 17 , MAE: 3.9568794137197183
Features: 18 , MAE: 4.087353930828419
Features: 19 , MAE: 4.943526355721426
```

XG Boost Regressor Feature Importance Graph

```
In [86]: model = XGBRegressor()
         feature_imp = pd.DataFrame()
         for i in range(1,10):
             train_features_iq, test_features_iq, train_outcomes_iq, test_outcomes_
         iq = train_test_split(
             data_iq_n,
             data_iq['total_cases'],
             test_size = 0.3
             )
             for i in range(1,10):
                 model.fit(train_features_iq, train_outcomes_iq)
                 imp = pd.DataFrame({'Feature': data_iq_n.columns, 'Importance':mod
         el.feature_importances_})
                 frames = [feature_imp, imp]
                 feature_imp = pd.concat(frames).reset_index(drop = True)
         feature_imp = feature_imp.groupby(['Feature'])['Importance'].mean().to_fra
         me(name = 'Importance').reset_index()
         feature_imp = feature_imp.set_index('Feature')
         feature_imp.sort_values(by='Importance').plot(kind='barh', title='Feature
          Importance - San Juan, Puerto Rico', grid = True, legend = False, figsize
         =(10,10))

Out[86]: <matplotlib.axes._subplots.AxesSubplot at 0x1a20b3e2b0>
```



Updating Features

In [87]:
```
# ['month','odd_year','reanalysis_relative_humidity_percent', 'reanalysis_
dew_point_temp_k', 'station_avg_temp_c', 'reanalysis_tdtr_k']
#Iquitos
train_features_iq, test_features_iq, train_outcomes_iq, test_outcomes_iq =
 train_test_split(
    data_iq_n[['ndvi_se_rolling_avg',
                'ndvi_ne_rolling_avg',
                'ndvi_nw_rolling_avg',
                'weekofyear',
                'station_max_temp_c_rolling_avg',
                'reanalysis_precip_amt_kg_per_m2_rolling_avg',
                'station_min_temp_c_rolling_avg']],
    data_iq['total_cases'],
    test_size = 0.3
)
```

Grid Search & Cross Validation & Margin of Error

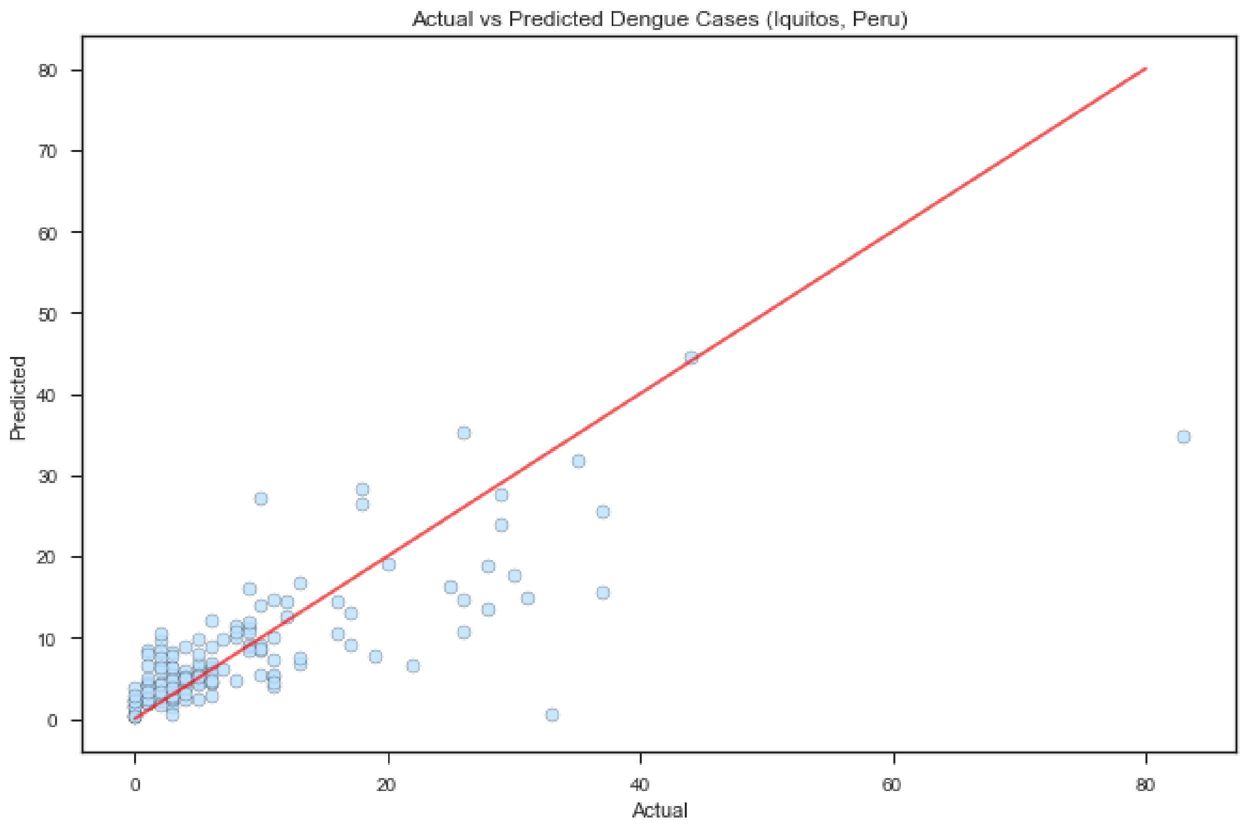
In [88]:
```
params = {'n_estimators':[1000], 'learning_rate':[0.03], 'max_depth':[10],
 'subsample':[0.8], 'colsample_bytree':[0.701]}
folds = KFold(n_splits = 10, shuffle=True)
grid_search = GridSearchCV(XGBRegressor(), param_grid=params, cv=folds, sc
oring='neg_mean_absolute_error')
xgb_preds_iq = grid_search.fit(train_features_iq, train_outcomes_iq).predi
ct(test_features_iq)
xgb_mae_iq = mean_absolute_error(test_outcomes_iq, xgb_preds_iq)
xgb_mdae_iq = median_absolute_error(test_outcomes_iq, xgb_preds_iq)
xgb_evs_iq = explained_variance_score(test_outcomes_iq, xgb_preds_iq)
print(xgb_mae_iq)
```

```
4.195427194554755
```

Predicted vs Actual

```
In [89]: plt.subplots(figsize=(11,7))
         plt.title('Actual vs Predicted Dengue Cases (Iquitos, Peru)')
         plt.xlabel('Actual')
         plt.ylabel('Predicted')
         plt.scatter(test_outcomes_iq, xgb_preds_iq, edgecolors = '#1e1e1e', color=
         '#bae1ff', alpha=0.8)
         plt.plot([0, 80], [0, 80], 'red', alpha=0.7)
```

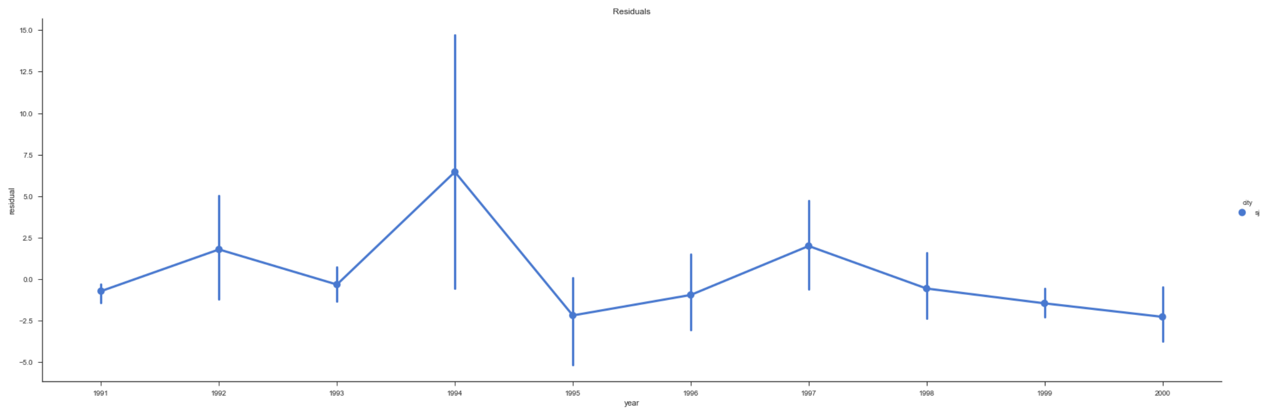
```
Out[89]: [<matplotlib.lines.Line2D at 0x1a20c8b470>]
```



Residuals

In [90]:
```
xgb_preds_week_iq = pd.DataFrame(test_features_iq)
xgb_preds_week_iq['Actual'] = test_outcomes_iq.values
xgb_preds_week_iq['Predicted'] = xgb_preds_iq
xgb_preds_week_iq = pd.merge(data_sj, xgb_preds_week_iq, left_index = True
, right_index = True)
plot_d = xgb_preds_week_iq.assign(residual=xgb_preds_week_iq.Actual - xgb_
preds_week_iq .Predicted)
sns.factorplot(x="year", y="residual", hue="city", size=8, aspect=3,data=p
lot_d)
plt.title("Residuals")
```

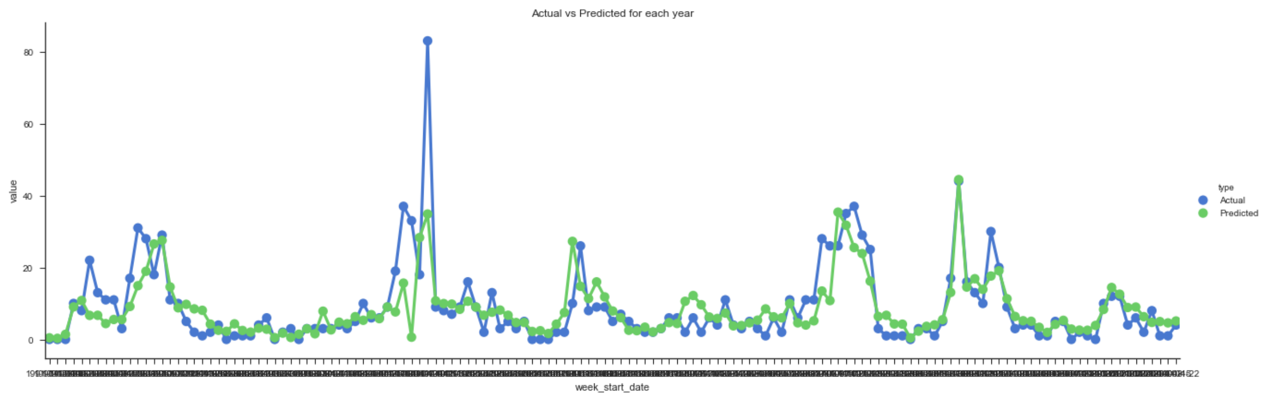
Out[90]:
```
Text(0.5,1,'Residuals')
```



Actual Vs Predicted Time Series Line Graph

```
In [91]: plot_d = plot_d.melt(id_vars=['city', 'year', 'weekofyear_x', 'week_start_
         date', 'ndvi_ne', 'ndvi_nw',
                'ndvi_se', 'ndvi_sw', 'precipitation_amt_mm', 'reanalysis_air_temp_
         k',
                'reanalysis_avg_temp_k', 'reanalysis_dew_point_temp_k',
                'reanalysis_max_air_temp_k', 'reanalysis_min_air_temp_k',
                'reanalysis_precip_amt_kg_per_m2',
                'reanalysis_relative_humidity_percent', 'reanalysis_tdtr_k',
                'station_avg_temp_c', 'station_diur_temp_rng_c', 'station_max_temp_
         c',
                'station_min_temp_c', 'station_precip_mm', 'total_cases', 'month',
                'odd_year', 'ndvi_mean', 'ndvi_mean_rolling_avg',
                'ndvi_ne_rolling_avg_x', 'ndvi_nw_rolling_avg_x',
                'ndvi_se_rolling_avg_x', 'ndvi_sw_rolling_avg',
                'precipitation_amt_mm_rolling_avg', 'reanalysis_air_temp_k_rolling_
         avg',
                'reanalysis_avg_temp_k_rolling_avg',
                'reanalysis_dew_point_temp_k_rolling_avg',
                'reanalysis_max_air_temp_k_rolling_avg',
                'reanalysis_min_air_temp_k_rolling_avg',
                'reanalysis_precip_amt_kg_per_m2_rolling_avg_x',
                'reanalysis_relative_humidity_percent_rolling_avg',
                'reanalysis_tdtr_k_rolling_avg', 'station_avg_temp_c_rolling_avg',
                'station_diur_temp_rng_c_rolling_avg',
                'station_max_temp_c_rolling_avg_x', 'station_min_temp_c_rolling_avg
         _x',
                'station_precip_mm_rolling_avg', 'ndvi_se_rolling_avg_y',
                'ndvi_ne_rolling_avg_y', 'ndvi_nw_rolling_avg_y', 'weekofyear_y',
                'station_max_temp_c_rolling_avg_y',
                'reanalysis_precip_amt_kg_per_m2_rolling_avg_y',
                'station_min_temp_c_rolling_avg_y','residual'], var_name='type')

         sns.factorplot(x='week_start_date', y="value", hue="type", data=plot_d, si
         ze = 6, aspect =3)
         plt.title("Actual vs Predicted for each year")
```

```
Out[91]: Text(0.5,1,'Actual vs Predicted for each year')
```



Final Model

In [92]:
```
xgb_preds_final_iq = xgb_reg.fit(train_features_iq, train_outcomes_iq).pre
dict(
    data_test_iq_n[['ndvi_se_rolling_avg',
                   'ndvi_ne_rolling_avg',
                   'ndvi_nw_rolling_avg',
                   'weekofyear',
                   'station_max_temp_c_rolling_avg',
                   'reanalysis_precip_amt_kg_per_m2_rolling_avg',
                   'station_min_temp_c_rolling_avg']]
)
```

Submission

In [93]:
```
submission_iq = data_test_iq[['city', 'year', 'weekofyear']].copy()
submission_iq['total_cases'] = np.round(xgb_preds_final_iq).astype(int)
```

In [94]:
```
frames = [submission_sj, submission_iq]
submission = pd.concat(frames)
submission.to_csv('xgb.csv', index = False)
```

Decision Tree Regressor

After reading this article (https://petolau.github.io/Regression-trees-for-forecasting-time-series-in-R/) we were inspired to try using decision trees.

We wanted to see if using a simple version of decision trees gave us a lesser mean absolute error and validate the idea of using XG Boost. Hence we used it.

San Juan Decision Tree Regressor

Training and Test Dataset

In [95]:
```
train_features_sj, test_features_sj, train_outcomes_sj, test_outcomes_sj =
 train_test_split(
    data_sj_n,
    data_sj['total_cases'],
    test_size = 0.3
)
```

Feature Selection

Recursive Feature Elimination

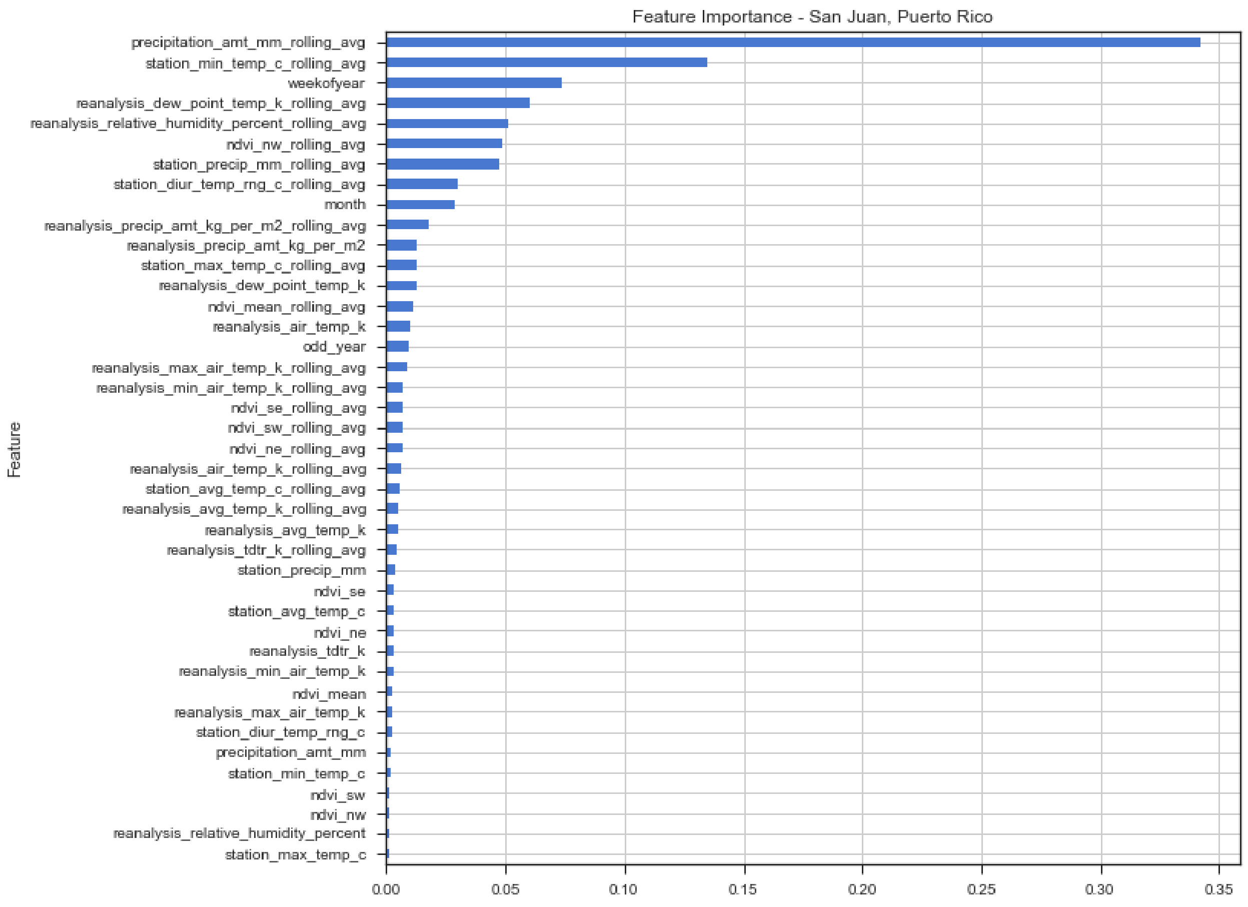
```
In [96]: for n in range(1,20,1):

             train_features_sj, test_features_sj, train_outcomes_sj, test_outcomes_
         sj = train_test_split(
                 data_sj_n,
                 data_sj['total_cases'],
                 test_size = 0.3
             )

             rfe = RFE(DecisionTreeRegressor(), n)
             fit = rfe.fit(test_features_sj, test_outcomes_sj)

             train_features_sj, test_features_sj, train_outcomes_sj, test_outcomes_
         sj = train_test_split(
                 data_sj[data_sj_n.columns[fit.ranking_ == 1]],
                 data_sj['total_cases'],
                 test_size = 0.3
             )

             dt_reg = DecisionTreeRegressor()
             dt_preds_sj = dt_reg.fit(train_features_sj, train_outcomes_sj).predict
         (test_features_sj)
             print('Features:', n, ', MAE:', mean_absolute_error(test_outcomes_sj,
         dt_preds_sj))
```

```
Features: 1 , MAE: 34.425689223057645
Features: 2 , MAE: 19.909774436090224
Features: 3 , MAE: 18.60902255639098
Features: 4 , MAE: 15.736842105263158
Features: 5 , MAE: 17.898496240601503
Features: 6 , MAE: 12.015037593984962
Features: 7 , MAE: 12.428571428571429
Features: 8 , MAE: 14.424812030075188
Features: 9 , MAE: 11.680451127819548
Features: 10 , MAE: 13.575187969924812
Features: 11 , MAE: 13.063909774436091
Features: 12 , MAE: 12.849624060150376
Features: 13 , MAE: 11.345864661654135
Features: 14 , MAE: 12.06766917293233
Features: 15 , MAE: 11.81578947368421
Features: 16 , MAE: 10.545112781954888
Features: 17 , MAE: 14.342105263157896
Features: 18 , MAE: 13.827067669172932
Features: 19 , MAE: 12.274436090225564
```

Feature Importance

```
In [97]: model = DecisionTreeRegressor()
         feature_imp = pd.DataFrame({'Feature' : [], 'Importance' : []})
         for i in range(1,20):
             train_features_sj, test_features_sj, train_outcomes_sj, test_outcomes_
         sj = train_test_split(
                 data_sj_n,
                 data_sj['total_cases'],
                 test_size = 0.3
             )
             for i in range(1,20):
                 model.fit(train_features_sj, train_outcomes_sj)
                 imp = pd.DataFrame({'Feature': data_sj_n.columns, 'Importance':mod
         el.feature_importances_})
                 frames = [feature_imp, imp]
                 feature_imp = pd.concat(frames).reset_index(drop = True)
         feature_imp = feature_imp.groupby(['Feature'])['Importance'].mean().to_fra
         me(name = 'Importance').reset_index()
         feature_imp = feature_imp.set_index('Feature')
         feature_imp.sort_values(by='Importance').plot(kind='barh', title='Feature
          Importance - San Juan, Puerto Rico', grid = True, legend = False, figsize
         =(10,10))
```

```
Out[97]: <matplotlib.axes._subplots.AxesSubplot at 0x1a22ed8940>
```



Updating Features

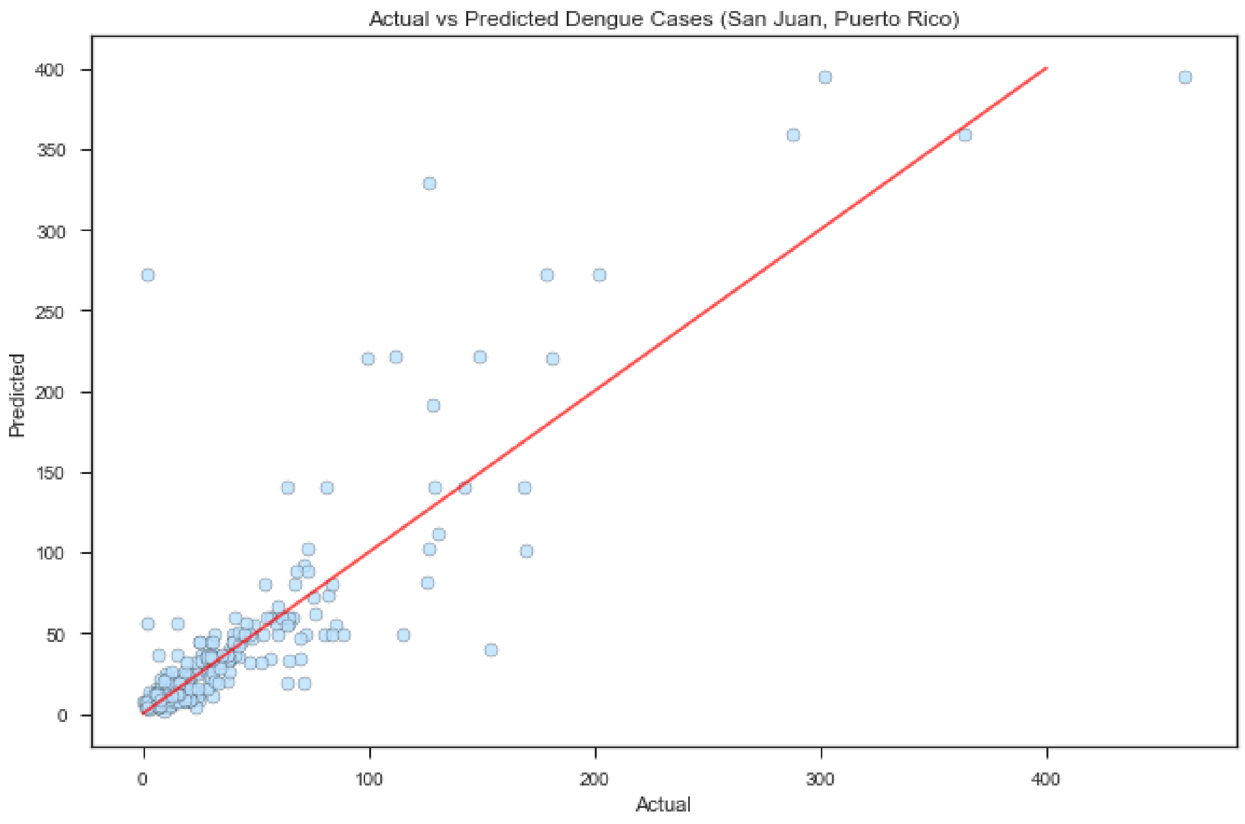
```
In [98]: train_features_sj, test_features_sj, train_outcomes_sj, test_outcomes_sj =
          train_test_split(
             data_sj_n[['precipitation_amt_mm_rolling_avg',
                         'weekofyear',
                         'station_min_temp_c_rolling_avg',
                         'reanalysis_dew_point_temp_k_rolling_avg',
                         'station_precip_mm_rolling_avg',
                         'reanalysis_relative_humidity_percent_rolling_avg',
                         'ndvi_nw_rolling_avg']],
             data_sj['total_cases'],
             test_size = 0.3
         )
```

Grid Search & Cross Validation & Mean Absolute Error

```
In [99]: params = {'max_depth':range(5, 30)}
         folds = KFold(n_splits = 10, shuffle=True)
         grid_search = GridSearchCV(DecisionTreeRegressor(), param_grid=params, cv=
         folds, scoring='neg_mean_absolute_error')
         dt_preds_sj = grid_search.fit(train_features_sj, train_outcomes_sj).predic
         t(test_features_sj)
         dt_mae_sj = mean_absolute_error(test_outcomes_sj, dt_preds_sj)
         dt_mdae_sj = median_absolute_error(test_outcomes_sj, dt_preds_sj)
         dt_evs_sj = explained_variance_score(test_outcomes_sj, dt_preds_sj)
         print(dt_mae_sj)

         13.921697117417736
```

Actual vs Predicted San Juan Decision Tree Scatter Plot

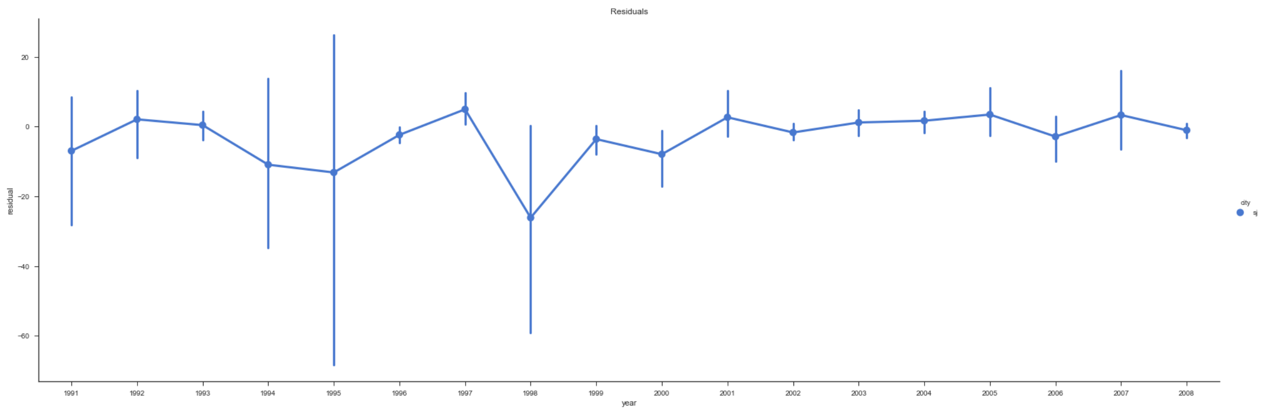
```
In [100]: plt.subplots(figsize=(11,7))
          plt.title('Actual vs Predicted Dengue Cases (San Juan, Puerto Rico)')
          plt.xlabel('Actual')
          plt.ylabel('Predicted')
          plt.scatter(test_outcomes_sj, dt_preds_sj, edgecolors = '#1e1e1e', color=
          '#bae1ff', alpha=0.8)
          plt.plot([0, 400], [0, 400], 'red', alpha=0.7)

Out[100]: [<matplotlib.lines.Line2D at 0x1a2349d4e0>]
```



Residuals

```
In [101]: dt_preds_week_sj = pd.DataFrame(test_features_sj)
          dt_preds_week_sj['Actual'] = test_outcomes_sj.values
          dt_preds_week_sj['Predicted'] = dt_preds_sj
          dt_preds_week_sj = pd.merge(data_sj, dt_preds_week_sj, left_index = True,
          right_index = True)
          plot_d = dt_preds_week_sj.assign(residual=dt_preds_week_sj.Actual - dt_pre
          ds_week_sj .Predicted)
          sns.factorplot(x="year", y="residual", hue="city", size=8, aspect=3,data=p
          lot_d)
          plt.title("Residuals")
```

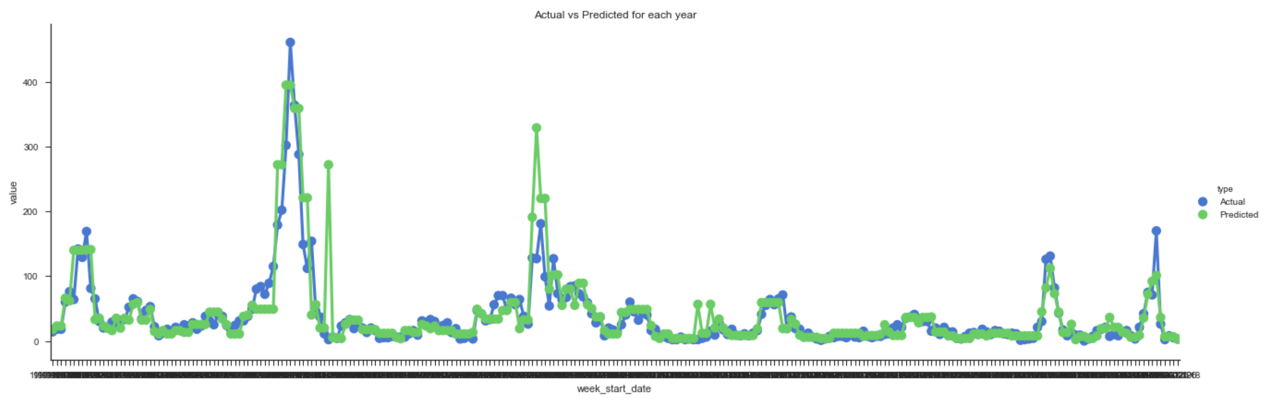
```
Out[101]: Text(0.5,1,'Residuals')
```



Actual Vs Predicted Time Series Line Graph

```
In [102]: plot_d = plot_d.melt(id_vars=['city', 'year', 'weekofyear_x', 'week_start_
date', 'ndvi_ne', 'ndvi_nw',
       'ndvi_se', 'ndvi_sw', 'precipitation_amt_mm', 'reanalysis_air_temp_
k',
       'reanalysis_avg_temp_k', 'reanalysis_dew_point_temp_k',
       'reanalysis_max_air_temp_k', 'reanalysis_min_air_temp_k',
       'reanalysis_precip_amt_kg_per_m2',
       'reanalysis_relative_humidity_percent', 'reanalysis_tdtr_k',
       'station_avg_temp_c', 'station_diur_temp_rng_c', 'station_max_temp_
c',
       'station_min_temp_c', 'station_precip_mm', 'total_cases', 'month',
       'odd_year', 'ndvi_mean', 'ndvi_mean_rolling_avg', 'ndvi_ne_rolling_
avg',
       'ndvi_nw_rolling_avg_x', 'ndvi_se_rolling_avg', 'ndvi_sw_rolling_av
g',
       'precipitation_amt_mm_rolling_avg_x',
       'reanalysis_air_temp_k_rolling_avg',
       'reanalysis_avg_temp_k_rolling_avg',
       'reanalysis_dew_point_temp_k_rolling_avg_x',
       'reanalysis_max_air_temp_k_rolling_avg',
       'reanalysis_min_air_temp_k_rolling_avg',
       'reanalysis_precip_amt_kg_per_m2_rolling_avg',
       'reanalysis_relative_humidity_percent_rolling_avg_x',
       'reanalysis_tdtr_k_rolling_avg', 'station_avg_temp_c_rolling_avg',
       'station_diur_temp_rng_c_rolling_avg', 'station_max_temp_c_rolling_
avg',
       'station_min_temp_c_rolling_avg_x', 'station_precip_mm_rolling_avg_
x',
       'precipitation_amt_mm_rolling_avg_y', 'weekofyear_y',
       'station_min_temp_c_rolling_avg_y',
       'reanalysis_dew_point_temp_k_rolling_avg_y',
       'station_precip_mm_rolling_avg_y',
       'reanalysis_relative_humidity_percent_rolling_avg_y',
       'ndvi_nw_rolling_avg_y','residual'], var_name='type')

sns.factorplot(x='week_start_date', y="value", hue="type", data=plot_d, si
ze = 6, aspect =3)
plt.title("Actual vs Predicted for each year")
```

```
Out[102]: Text(0.5,1,'Actual vs Predicted for each year')
```



Final Model

```
In [103]: dt_preds_final_sj = dt_reg.fit(train_features_sj, train_outcomes_sj).predi
          ct(
              data_test_sj_n[['precipitation_amt_mm_rolling_avg',
                              'weekofyear',
                              'station_min_temp_c_rolling_avg',
                              'reanalysis_dew_point_temp_k_rolling_avg',
                              'station_precip_mm_rolling_avg',
                              'reanalysis_relative_humidity_percent_rolling_avg',
                              'ndvi_nw_rolling_avg']]
          )
```

Submission

```
In [104]: submission_sj = data_test_sj[['city', 'year', 'weekofyear']].copy()
          submission_sj['total_cases'] = np.round(dt_preds_final_sj).astype(int)
```

Decision Tree Iquitos

```
In [105]: train_features_iq, test_features_iq, train_outcomes_iq, test_outcomes_iq =
           train_test_split(
              data_iq_n,
              data_iq['total_cases'],
              test_size = 0.3
          )
```

Feature Selection

Recursive Feature Elimination

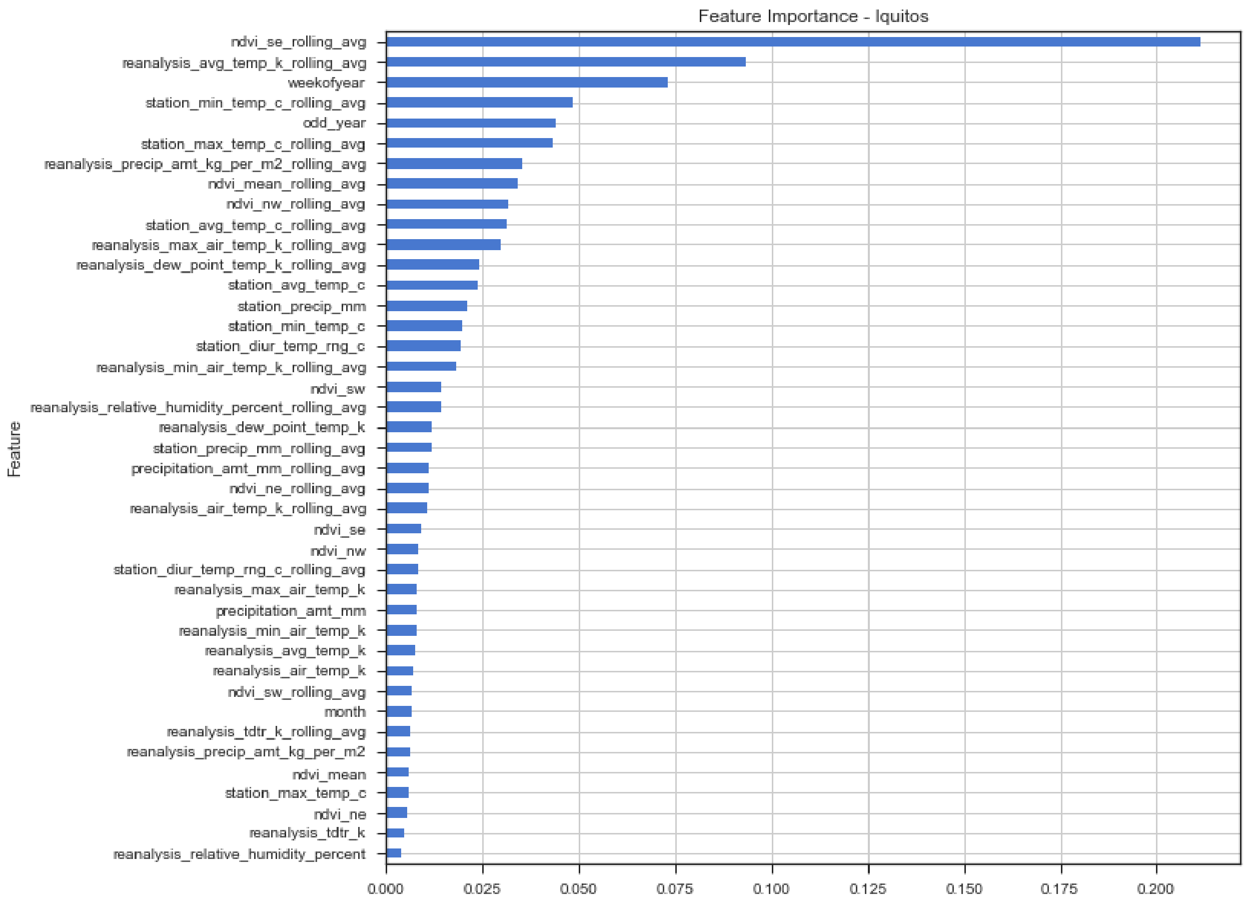
In [106]:
```
for n in range(1,20,1):

    train_features_iq, test_features_iq, train_outcomes_iq, test_outcomes_
iq = train_test_split(
        data_iq_n,
        data_iq['total_cases'],
        test_size = 0.3
    )

    rfe = RFE(DecisionTreeRegressor(), n)
    fit = rfe.fit(test_features_iq, test_outcomes_iq)

    train_features_iq, test_features_iq, train_outcomes_iq, test_outcomes_
iq = train_test_split(
        data_iq[data_iq_n.columns[fit.ranking_ == 1]],
        data_iq['total_cases'],
        test_size = 0.3
    )

    dt_reg = DecisionTreeRegressor()
    dt_preds_iq = dt_reg.fit(train_features_iq, train_outcomes_iq).predict
(test_features_iq)
    print('Features:', n, ', MAE:', mean_absolute_error(test_outcomes_iq,
dt_preds_iq))
```

```
Features: 1 , MAE: 9.624113475177305
Features: 2 , MAE: 7.00709219858156
Features: 3 , MAE: 7.98581560283688
Features: 4 , MAE: 5.368794326241135
Features: 5 , MAE: 4.98581560283688
Features: 6 , MAE: 5.51063829787234
Features: 7 , MAE: 5.453900709219858
Features: 8 , MAE: 5.319148936170213
Features: 9 , MAE: 4.574468085106383
Features: 10 , MAE: 5.3546099290780145
Features: 11 , MAE: 7.056737588652482
Features: 12 , MAE: 4.581560283687943
Features: 13 , MAE: 6.872340425531915
Features: 14 , MAE: 5.24113475177305
Features: 15 , MAE: 4.581560283687943
Features: 16 , MAE: 4.595744680851064
Features: 17 , MAE: 5.3546099290780145
Features: 18 , MAE: 5.070921985815603
Features: 19 , MAE: 6.425531914893617
```

Feature Importance

```
In [107]: model = DecisionTreeRegressor()
          feature_imp = pd.DataFrame({'Feature' : [], 'Importance' : []})
          for i in range(1,20):
              train_features_iq, test_features_iq, train_outcomes_iq, test_outcomes_
          iq = train_test_split(
                  data_iq_n,
                  data_iq['total_cases'],
                  test_size = 0.3
              )
              for i in range(1,20):
                  model.fit(train_features_iq, train_outcomes_iq)
                  imp = pd.DataFrame({'Feature': data_iq_n.columns, 'Importance':mod
          el.feature_importances_})
                  frames = [feature_imp, imp]
                  feature_imp = pd.concat(frames).reset_index(drop = True)
          feature_imp = feature_imp.groupby(['Feature'])['Importance'].mean().to_fra
          me(name = 'Importance').reset_index()
          feature_imp = feature_imp.set_index('Feature')
          feature_imp.sort_values(by='Importance').plot(kind='barh', title='Feature
           Importance - Iquitos', grid = True, legend = False, figsize=(10,10))
```

```
Out[107]: <matplotlib.axes._subplots.AxesSubplot at 0x1a245b70b8>
```



Updating Features

In [108]:
```
train_features_iq, test_features_iq, train_outcomes_iq, test_outcomes_iq =
 train_test_split(
    data_iq_n[['ndvi_se_rolling_avg',
                'reanalysis_avg_temp_k_rolling_avg',
                'weekofyear',
                'station_avg_temp_c_rolling_avg',
                'reanalysis_max_air_temp_k_rolling_avg',
                'odd_year',
                'station_max_temp_c_rolling_avg',
                'reanalysis_min_air_temp_k_rolling_avg']],
    data_iq['total_cases'],
    test_size = 0.3
)
```

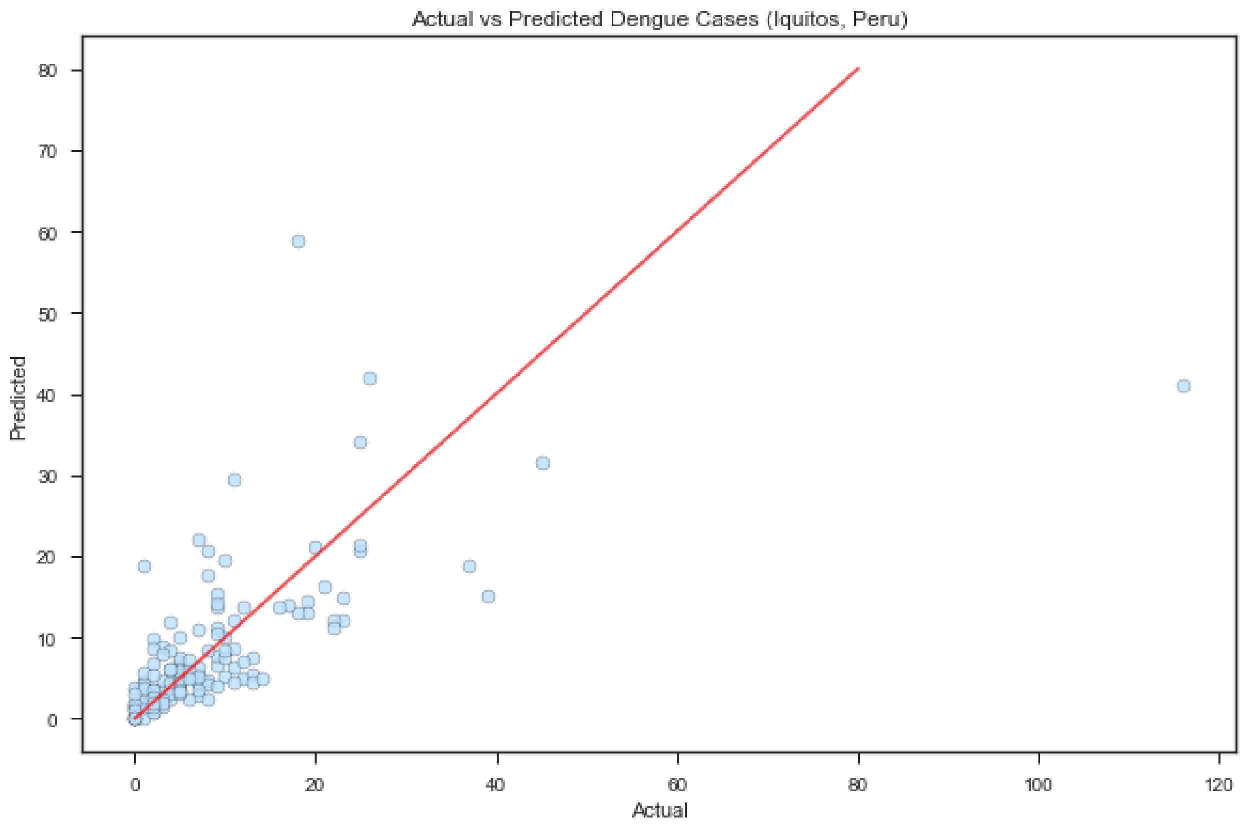
Grid Search & Cross Validation & Margin of Error

In [109]:
```
params = {'n_estimators':range(5, 30)}
folds = KFold(n_splits = 10, shuffle=True)
grid_search = GridSearchCV(RandomForestRegressor(), param_grid=params, cv=
folds, scoring='neg_mean_absolute_error')
dt_preds_iq = grid_search.fit(train_features_iq, train_outcomes_iq).predic
t(test_features_iq)
dt_mae_iq = mean_absolute_error(test_outcomes_iq, dt_preds_iq)
dt_mdae_iq = median_absolute_error(test_outcomes_iq, dt_preds_iq)
dt_evs_iq = explained_variance_score(test_outcomes_iq, dt_preds_iq)
print(dt_mae_iq)
```

```
4.415130023640661
```

Actual vs Predicted Cases for Iquitos Decision Tree

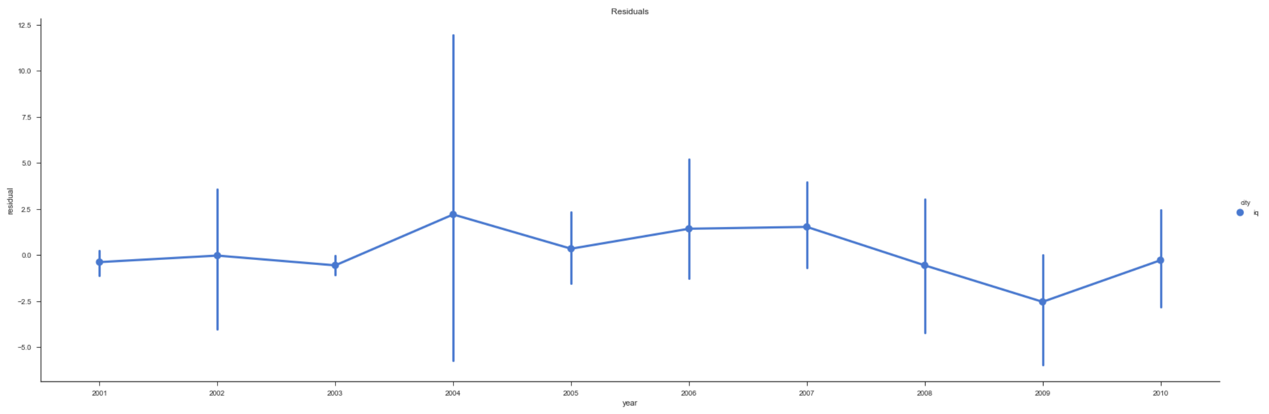
```
In [111]: plt.subplots(figsize=(11,7))
          plt.title('Actual vs Predicted Dengue Cases (Iquitos, Peru)')
          plt.xlabel('Actual')
          plt.ylabel('Predicted')
          plt.scatter(test_outcomes_iq, dt_preds_iq, edgecolors = '#1e1e1e', color=
          '#bae1ff', alpha=0.8)
          plt.plot([0, 80], [0, 80], 'red', alpha=0.7)

Out[111]: [<matplotlib.lines.Line2D at 0x1a25525860>]
```



Residuals

```
In [112]: dt_preds_week_iq = pd.DataFrame(test_features_iq)
          dt_preds_week_iq['Actual'] = test_outcomes_iq.values
          dt_preds_week_iq['Predicted'] = dt_preds_iq
          dt_preds_week_iq = pd.merge(data_iq, dt_preds_week_iq, left_index = True,
          right_index = True)
          plot_d = dt_preds_week_iq.assign(residual=dt_preds_week_iq.Actual - dt_pre
          ds_week_iq .Predicted)
          sns.factorplot(x="year", y="residual", hue="city", size=8, aspect=3,data=p
          lot_d)
          plt.title("Residuals")
```

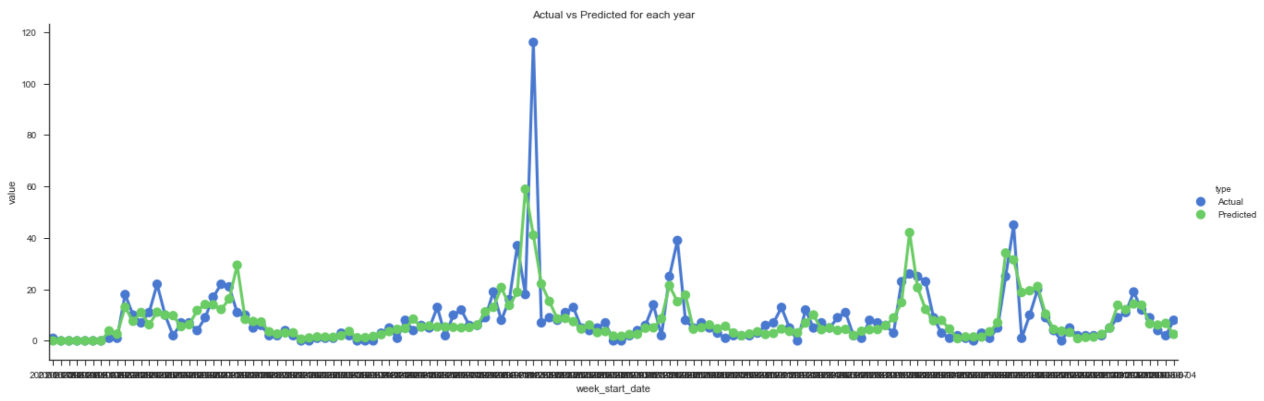
```
Out[112]: Text(0.5,1,'Residuals')
```



Actual Vs Predicted Time Series Line Graph

```
In [113]: plot_d = plot_d.melt(id_vars=['city', 'year', 'weekofyear_x', 'week_start_
          date', 'ndvi_ne', 'ndvi_nw',
                 'ndvi_se', 'ndvi_sw', 'precipitation_amt_mm', 'reanalysis_air_temp_
          k',
                 'reanalysis_avg_temp_k', 'reanalysis_dew_point_temp_k',
                 'reanalysis_max_air_temp_k', 'reanalysis_min_air_temp_k',
                 'reanalysis_precip_amt_kg_per_m2',
                 'reanalysis_relative_humidity_percent', 'reanalysis_tdtr_k',
                 'station_avg_temp_c', 'station_diur_temp_rng_c', 'station_max_temp_
          c',
                 'station_min_temp_c', 'station_precip_mm', 'total_cases', 'month',
                 'odd_year_x', 'ndvi_mean', 'ndvi_mean_rolling_avg',
                 'ndvi_ne_rolling_avg', 'ndvi_nw_rolling_avg', 'ndvi_se_rolling_avg_
          x',
                 'ndvi_sw_rolling_avg', 'precipitation_amt_mm_rolling_avg',
                 'reanalysis_air_temp_k_rolling_avg',
                 'reanalysis_avg_temp_k_rolling_avg_x',
                 'reanalysis_dew_point_temp_k_rolling_avg',
                 'reanalysis_max_air_temp_k_rolling_avg_x',
                 'reanalysis_min_air_temp_k_rolling_avg_x',
                 'reanalysis_precip_amt_kg_per_m2_rolling_avg',
                 'reanalysis_relative_humidity_percent_rolling_avg',
                 'reanalysis_tdtr_k_rolling_avg', 'station_avg_temp_c_rolling_avg_x'
          ,
                 'station_diur_temp_rng_c_rolling_avg',
                 'station_max_temp_c_rolling_avg_x', 'station_min_temp_c_rolling_av
          g',
                 'station_precip_mm_rolling_avg', 'ndvi_se_rolling_avg_y',
                 'reanalysis_avg_temp_k_rolling_avg_y', 'weekofyear_y',
                 'station_avg_temp_c_rolling_avg_y',
                 'reanalysis_max_air_temp_k_rolling_avg_y', 'odd_year_y',
                 'station_max_temp_c_rolling_avg_y',
                 'reanalysis_min_air_temp_k_rolling_avg_y','residual'], var_name='ty
          pe')

          sns.factorplot(x='week_start_date', y="value", hue="type", data=plot_d, si
          ze = 6, aspect =3)
          plt.title("Actual vs Predicted for each year")
```

```
Out[113]: Text(0.5,1,'Actual vs Predicted for each year')
```



Final Model

```
In [114]: dt_preds_final_iq = dt_reg.fit(train_features_iq, train_outcomes_iq).predi
          ct(
              data_test_iq_n[['ndvi_se_rolling_avg',
                              'reanalysis_avg_temp_k_rolling_avg',
                              'weekofyear',
                              'station_avg_temp_c_rolling_avg',
                              'reanalysis_max_air_temp_k_rolling_avg',
                              'odd_year',
                              'station_max_temp_c_rolling_avg',
                              'reanalysis_min_air_temp_k_rolling_avg']]
          )
```

Submissions

```
In [115]: submission_iq = data_test_iq[['city', 'year', 'weekofyear']].copy()
          submission_iq['total_cases'] = np.round(dt_preds_final_iq).astype(int)
```

```
In [116]: frames = [submission_sj, submission_iq]
          submission = pd.concat(frames)
          submission.to_csv('randomforest.csv', index = False)
```

Random Forest Regression

This article (http://astrohackweek.org/blog/time-series-rf.html) helped introduce us to how random forest regression is used for time series forecasting. Since our task is forecasting the total cases we decided to trying using random forest due to it's advantages over a simple decision tree.

San Juan Random Forest Regression

Training and Test Data Split

```
In [117]: train_features_sj, test_features_sj, train_outcomes_sj, test_outcomes_sj =
           train_test_split(
              data_sj_n,
              data_sj['total_cases'],
              test_size = 0.3
          )
```

Feature Selection

Recursive Feature Elimination

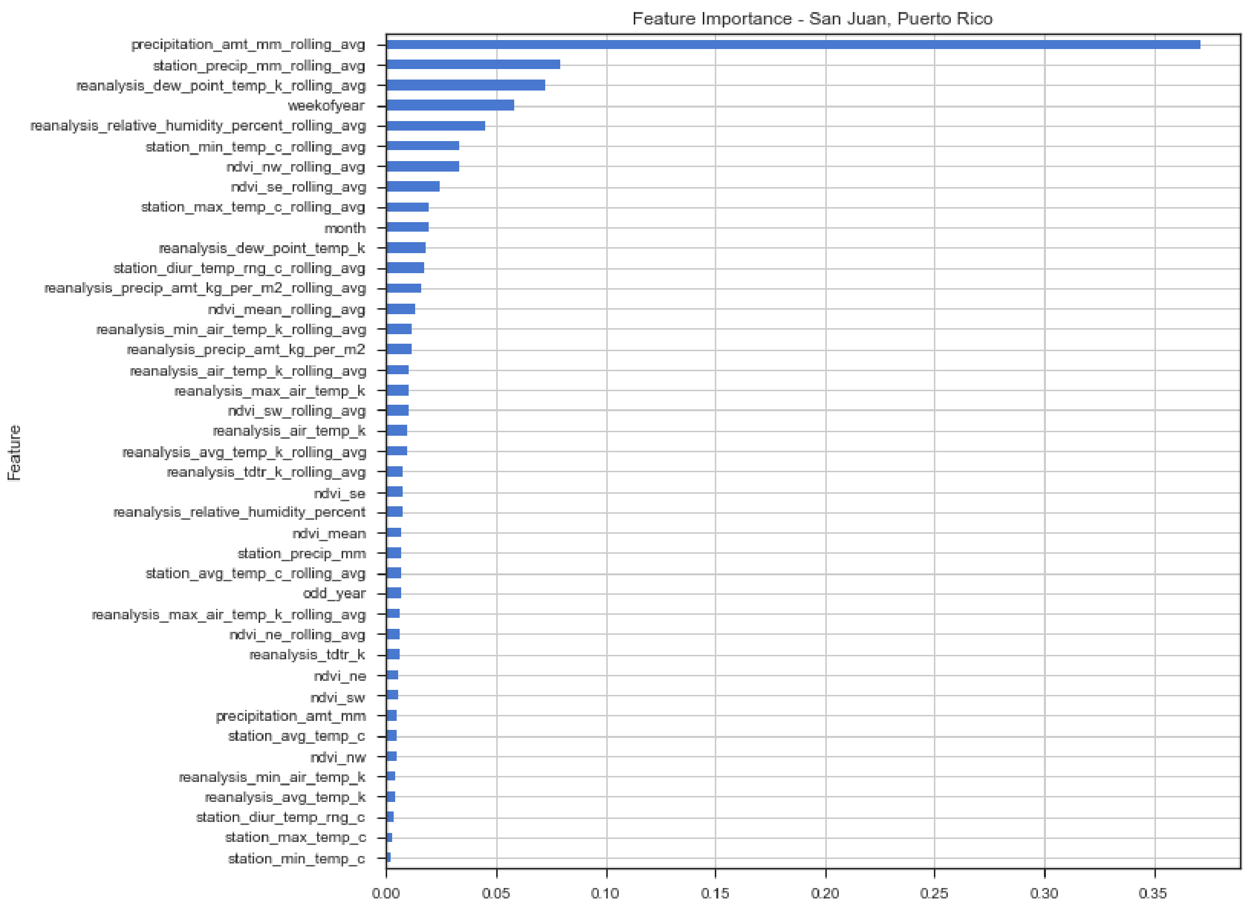
In [118]:
```
from sklearn.feature_selection import RFE

for n in range(1,20,1):

    train_features_sj, test_features_sj, train_outcomes_sj, test_outcomes_
sj = train_test_split(
        data_sj_n,
        data_sj['total_cases'],
        test_size = 0.3
    )

    rfe = RFE(RandomForestRegressor(), n)
    fit = rfe.fit(test_features_sj, test_outcomes_sj)

    train_features_sj, test_features_sj, train_outcomes_sj, test_outcomes_
sj = train_test_split(
        data_sj[data_sj_n.columns[fit.ranking_ == 1]],
        data_sj['total_cases'],
        test_size = 0.3
    )

    rf_reg = RandomForestRegressor()
    rf_preds_sj = rf_reg.fit(train_features_sj, train_outcomes_sj).predict
(test_features_sj)
    print('Features:', n, ', MAE:', mean_absolute_error(test_outcomes_sj,
rf_preds_sj))
```

```
Features: 1 , MAE: 32.35543561284163
Features: 2 , MAE: 21.851879699248123
Features: 3 , MAE: 14.106766917293234
Features: 4 , MAE: 12.383082706766915
Features: 5 , MAE: 9.141729323308272
Features: 6 , MAE: 10.824436090225564
Features: 7 , MAE: 12.757518796992482
Features: 8 , MAE: 12.078571428571427
Features: 9 , MAE: 9.234586466165412
Features: 10 , MAE: 10.472556390977445
Features: 11 , MAE: 11.655639097744363
Features: 12 , MAE: 12.851503759398497
Features: 13 , MAE: 9.752255639097744
Features: 14 , MAE: 11.826315789473686
Features: 15 , MAE: 10.12218045112782
Features: 16 , MAE: 12.781954887218046
Features: 17 , MAE: 11.501127819548874
Features: 18 , MAE: 12.01654135338346
Features: 19 , MAE: 11.009398496240602
```

Random Forest Feature Importance

In [119]:
```
model = RandomForestRegressor()
feature_imp = pd.DataFrame({'Feature' : [], 'Importance' : []})
for i in range(1,10):
    train_features_sj, test_features_sj, train_outcomes_sj, test_outcomes_
sj = train_test_split(
        data_sj_n,
        data_sj['total_cases'],
        test_size = 0.3
    )
    for i in range(1,10):
        model.fit(train_features_sj, train_outcomes_sj)
        imp = pd.DataFrame({'Feature': data_sj_n.columns, 'Importance':mod
el.feature_importances_})
        frames = [feature_imp, imp]
        feature_imp = pd.concat(frames).reset_index(drop = True)
feature_imp = feature_imp.groupby(['Feature'])['Importance'].mean().to_fra
me(name = 'Importance').reset_index()
feature_imp = feature_imp.set_index('Feature')
feature_imp.sort_values(by='Importance').plot(kind='barh', title='Feature
 Importance - San Juan, Puerto Rico', grid = True, legend = False, figsize
=(10,10))
```

Out[119]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x1a25567940>
```



Updating Features

```
In [120]: train_features_sj, test_features_sj, train_outcomes_sj, test_outcomes_sj =
           train_test_split(
              data_sj_n[['precipitation_amt_mm_rolling_avg',
                          'reanalysis_dew_point_temp_k_rolling_avg',
                          'month',
                          'ndvi_nw_rolling_avg',
                          'reanalysis_relative_humidity_percent_rolling_avg',
                          'ndvi_se_rolling_avg']],
              data_sj['total_cases'],
              test_size = 0.3
          )
```

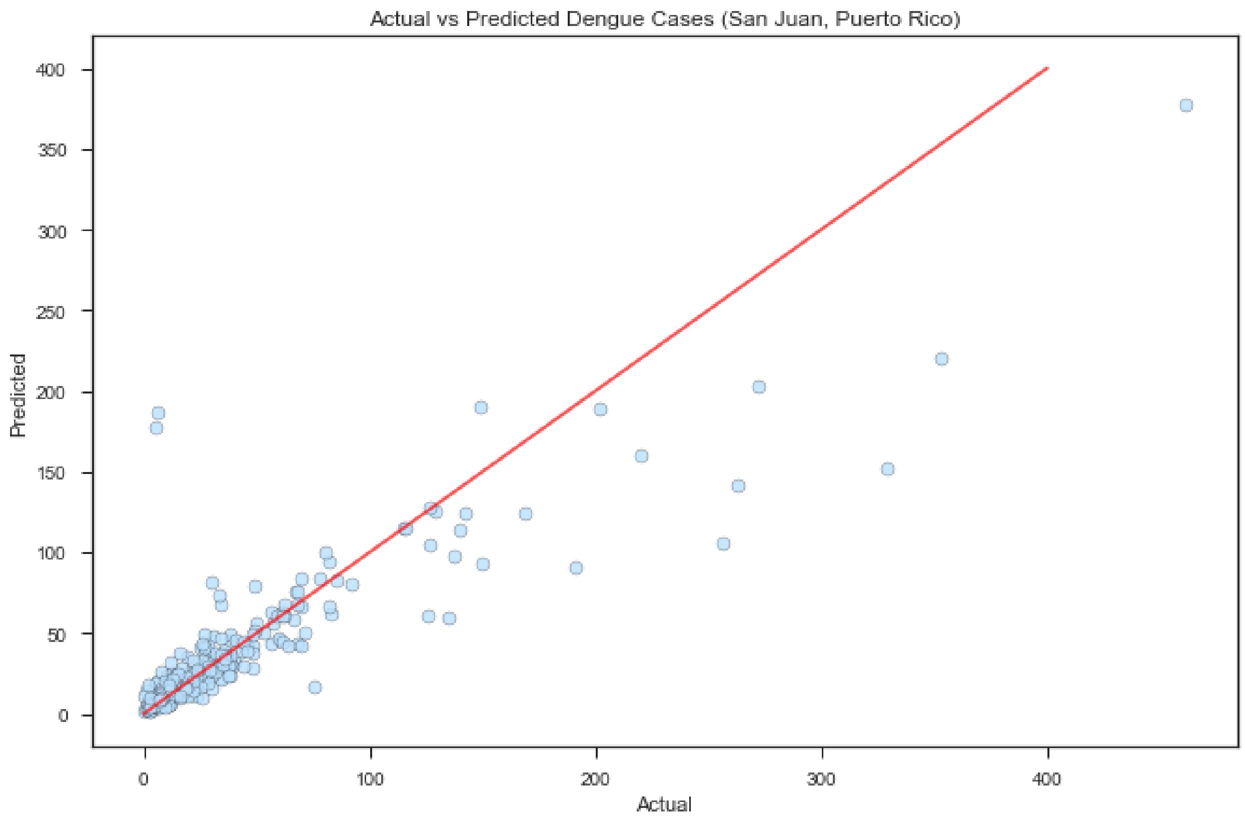
Grid Search & Cross Validation & Mean Absolute Error

```
In [121]: params = {'n_estimators':range(5, 30)}
          folds = KFold(n_splits = 10, shuffle=True)
          grid_search = GridSearchCV(RandomForestRegressor(), param_grid=params, cv=
          folds, scoring='neg_mean_absolute_error')
          rf_preds_sj = grid_search.fit(train_features_sj, train_outcomes_sj).predic
          t(test_features_sj)
          rf_mae_sj = mean_absolute_error(test_outcomes_sj, rf_preds_sj)
          rf_mdae_sj = median_absolute_error(test_outcomes_sj, rf_preds_sj)
          rf_evs_sj = explained_variance_score(test_outcomes_sj, rf_preds_sj)
          print(rf_mae_sj)
```

```
12.363721804511279
```

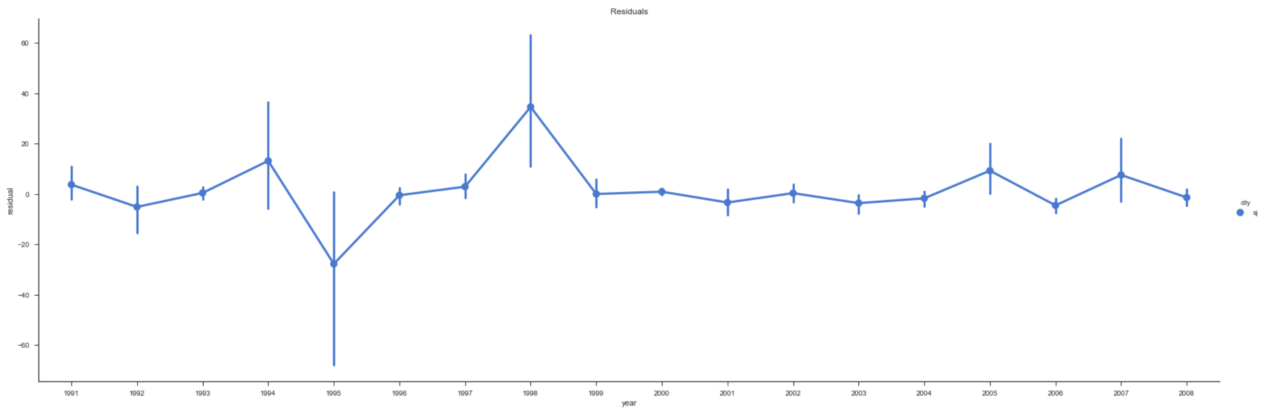
Actual vs Predicted San Juan Random Forest Scatter Plot

```
In [122]: plt.subplots(figsize=(11,7))
          plt.title('Actual vs Predicted Dengue Cases (San Juan, Puerto Rico)')
          plt.xlabel('Actual')
          plt.ylabel('Predicted')
          plt.scatter(test_outcomes_sj, rf_preds_sj, edgecolors = '#1e1e1e', color=
          '#bae1ff', alpha=0.8)
          plt.plot([0, 400], [0, 400], 'red', alpha=0.7)

Out[122]: [<matplotlib.lines.Line2D at 0x1a26f19ac8>]
```



Residuals

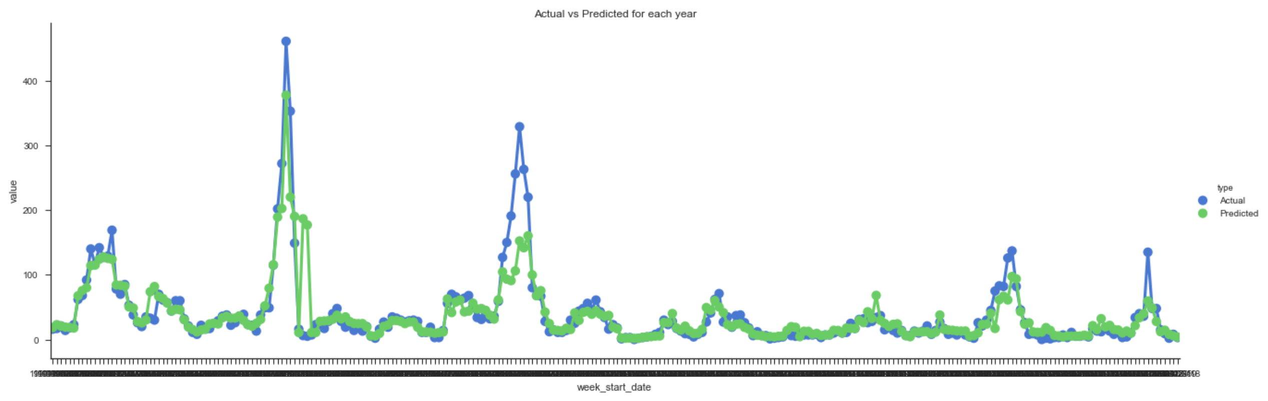
```
In [123]: rf_preds_week_sj = pd.DataFrame(test_features_sj)
          rf_preds_week_sj['Actual'] = test_outcomes_sj.values
          rf_preds_week_sj['Predicted'] = rf_preds_sj
          rf_preds_week_sj = pd.merge(data_sj, rf_preds_week_sj, left_index = True,
          right_index = True)
          plot_d = rf_preds_week_sj.assign(residual=rf_preds_week_sj.Actual - rf_pre
          ds_week_sj .Predicted)
          sns.factorplot(x="year", y="residual", hue="city", size=8, aspect=3,data=p
          lot_d)
          plt.title("Residuals")

Out[123]: Text(0.5,1,'Residuals')
```



Actual Vs Predicted Time Series Line Graph

```
In [124]: plot_d = plot_d.melt(id_vars=['city', 'year', 'weekofyear', 'week_start_da
          te', 'ndvi_ne', 'ndvi_nw',
                 'ndvi_se', 'ndvi_sw', 'precipitation_amt_mm', 'reanalysis_air_temp_
          k',
                 'reanalysis_avg_temp_k', 'reanalysis_dew_point_temp_k',
                 'reanalysis_max_air_temp_k', 'reanalysis_min_air_temp_k',
                 'reanalysis_precip_amt_kg_per_m2',
                 'reanalysis_relative_humidity_percent', 'reanalysis_tdtr_k',
                 'station_avg_temp_c', 'station_diur_temp_rng_c', 'station_max_temp_
          c',
                 'station_min_temp_c', 'station_precip_mm', 'total_cases', 'month_x'
          ,
                 'odd_year', 'ndvi_mean', 'ndvi_mean_rolling_avg', 'ndvi_ne_rolling_
          avg',
                 'ndvi_nw_rolling_avg_x', 'ndvi_se_rolling_avg_x', 'ndvi_sw_rolling_
          avg',
                 'precipitation_amt_mm_rolling_avg_x',
                 'reanalysis_air_temp_k_rolling_avg',
                 'reanalysis_avg_temp_k_rolling_avg',
                 'reanalysis_dew_point_temp_k_rolling_avg_x',
                 'reanalysis_max_air_temp_k_rolling_avg',
                 'reanalysis_min_air_temp_k_rolling_avg',
                 'reanalysis_precip_amt_kg_per_m2_rolling_avg',
                 'reanalysis_relative_humidity_percent_rolling_avg_x',
                 'reanalysis_tdtr_k_rolling_avg', 'station_avg_temp_c_rolling_avg',
                 'station_diur_temp_rng_c_rolling_avg', 'station_max_temp_c_rolling_
          avg',
                 'station_min_temp_c_rolling_avg', 'station_precip_mm_rolling_avg',
                 'precipitation_amt_mm_rolling_avg_y',
                 'reanalysis_dew_point_temp_k_rolling_avg_y', 'month_y',
                 'ndvi_nw_rolling_avg_y',
                 'reanalysis_relative_humidity_percent_rolling_avg_y',
                 'ndvi_se_rolling_avg_y','residual'], var_name='type')

          sns.factorplot(x='week_start_date', y="value", hue="type", data=plot_d, si
          ze = 6, aspect =3)
          plt.title("Actual vs Predicted for each year")
```

```
Out[124]: Text(0.5,1,'Actual vs Predicted for each year')
```



Final Model

```
In [125]: rf_preds_final_sj = rf_reg.fit(train_features_sj, train_outcomes_sj).predi
          ct(
              data_test_sj_n[['precipitation_amt_mm_rolling_avg',
                              'reanalysis_dew_point_temp_k_rolling_avg',
                              'month',
                              'ndvi_nw_rolling_avg',
                              'reanalysis_relative_humidity_percent_rolling_avg',
                              'ndvi_se_rolling_avg']]
          )
```

Submission for San Juan

```
In [126]: submission_sj = data_test_sj[['city', 'year', 'weekofyear']].copy()
          submission_sj['total_cases'] = np.round(rf_preds_final_sj).astype(int)
```

Iquitos Random Forest Regression

Training and Test Data

```
In [127]: train_features_iq, test_features_iq, train_outcomes_iq, test_outcomes_iq =
           train_test_split(
              data_iq_n,
              data_iq['total_cases'],
              test_size = 0.3
          )
```

Feature Selection

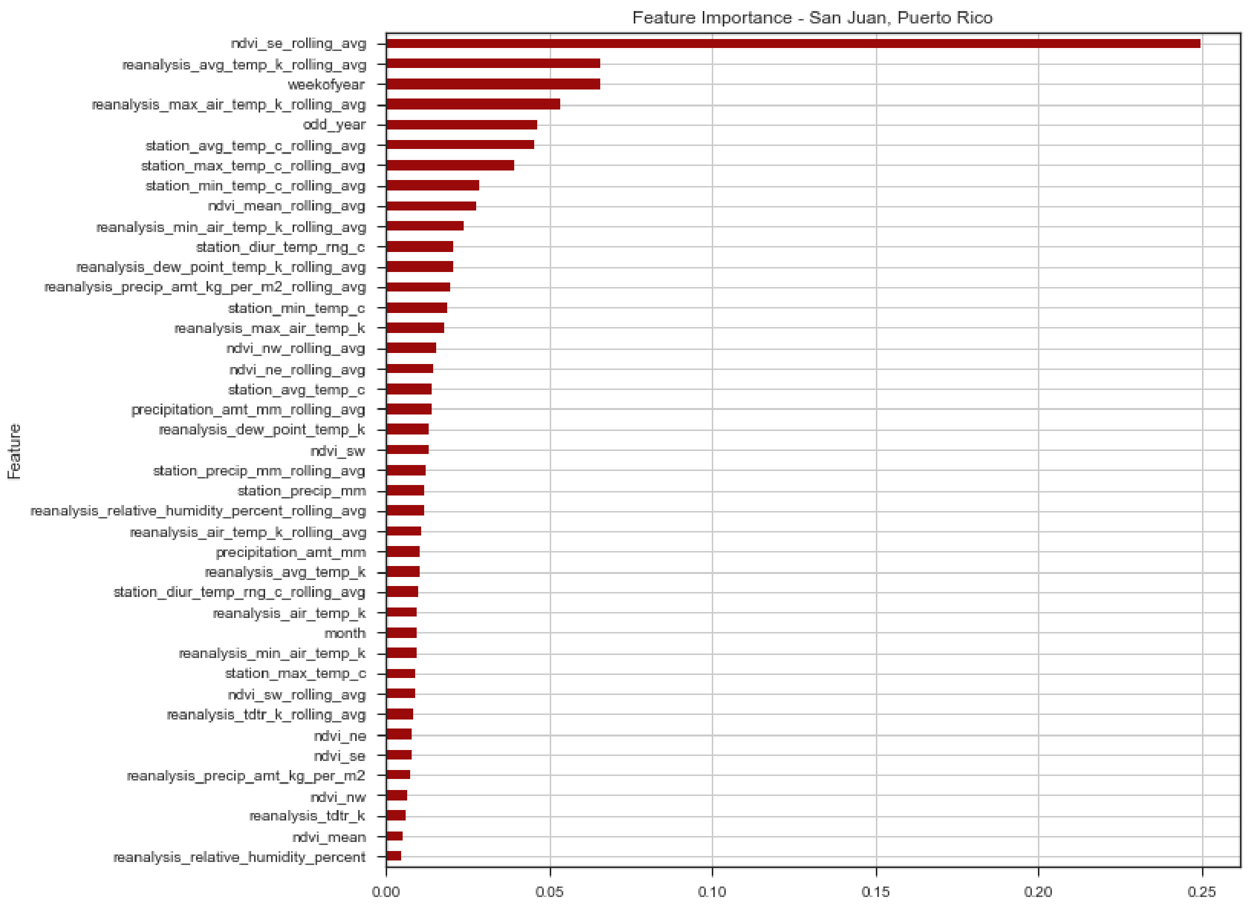
Recursive Feature Elimination

```
In [128]: from sklearn.feature_selection import RFE

          for n in range(1,20,1):

              train_features_iq, test_features_iq, train_outcomes_iq, test_outcomes_
          iq = train_test_split(
                  data_iq_n,
                  data_iq['total_cases'],
                  test_size = 0.3
              )

              rfe = RFE(RandomForestRegressor(), n)
              fit = rfe.fit(test_features_iq, test_outcomes_iq)

              train_features_iq, test_features_iq, train_outcomes_iq, test_outcomes_
          iq = train_test_split(
                  data_iq[data_iq_n.columns[fit.ranking_ == 1]],
                  data_iq['total_cases'],
                  test_size = 0.3
              )

              rf_reg = RandomForestRegressor()
              rf_preds_iq = rf_reg.fit(train_features_iq, train_outcomes_iq).predict
          (test_features_iq)
              print('Features:', n, ', MAE:', mean_absolute_error(test_outcomes_iq,
          rf_preds_iq))
```

```
Features: 1 , MAE: 7.2444444444444445
Features: 2 , MAE: 7.494326241134754
Features: 3 , MAE: 4.5113475177304965
Features: 4 , MAE: 5.922695035460992
Features: 5 , MAE: 4.235460992907802
Features: 6 , MAE: 4.300709219858156
Features: 7 , MAE: 4.180141843971631
Features: 8 , MAE: 4.411347517730497
Features: 9 , MAE: 4.428368794326241
Features: 10 , MAE: 5.15531914893617
Features: 11 , MAE: 4.278723404255318
Features: 12 , MAE: 4.150354609929077
Features: 13 , MAE: 4.182978723404255
Features: 14 , MAE: 3.931205673758865
Features: 15 , MAE: 4.375886524822695
Features: 16 , MAE: 4.2858156028368795
Features: 17 , MAE: 5.041843971631206
Features: 18 , MAE: 4.87872340425532
Features: 19 , MAE: 4.546808510638298
```

Feature Importance

```
In [129]: model = RandomForestRegressor()
          feature_imp = pd.DataFrame({'Feature' : [], 'Importance' : []})
          for i in range(1,10):
              train_features_iq, test_features_iq, train_outcomes_iq, test_outcomes_
          iq = train_test_split(
                  data_iq_n,
                  data_iq['total_cases'],
                  test_size = 0.3
              )
              for i in range(1,10):
                  model.fit(train_features_iq, train_outcomes_iq)
                  imp = pd.DataFrame({'Feature': data_iq_n.columns, 'Importance':mod
          el.feature_importances_})
                  frames = [feature_imp, imp]
                  feature_imp = pd.concat(frames).reset_index(drop = True)
          feature_imp = feature_imp.groupby(['Feature'])['Importance'].mean().to_fra
          me(name = 'Importance').reset_index()
          feature_imp = feature_imp.set_index('Feature')
          feature_imp.sort_values(by='Importance').plot(kind='barh', title='Feature
           Importance - San Juan, Puerto Rico', grid = True, legend = False, color =
           '#9b0a0a', figsize=(10,10))

Out[129]: <matplotlib.axes._subplots.AxesSubplot at 0x1a283f1860>
```



Updating Features

In [130]:
```
train_features_iq, test_features_iq, train_outcomes_iq, test_outcomes_iq =
 train_test_split(
    data_iq_n[['ndvi_se_rolling_avg',
                'reanalysis_avg_temp_k_rolling_avg',
                'weekofyear',
                'station_avg_temp_c_rolling_avg',
                'reanalysis_max_air_temp_k_rolling_avg',
                'odd_year',
                'station_max_temp_c_rolling_avg',
                'reanalysis_min_air_temp_k_rolling_avg']],
    data_iq['total_cases'],
    test_size = 0.3
)
```

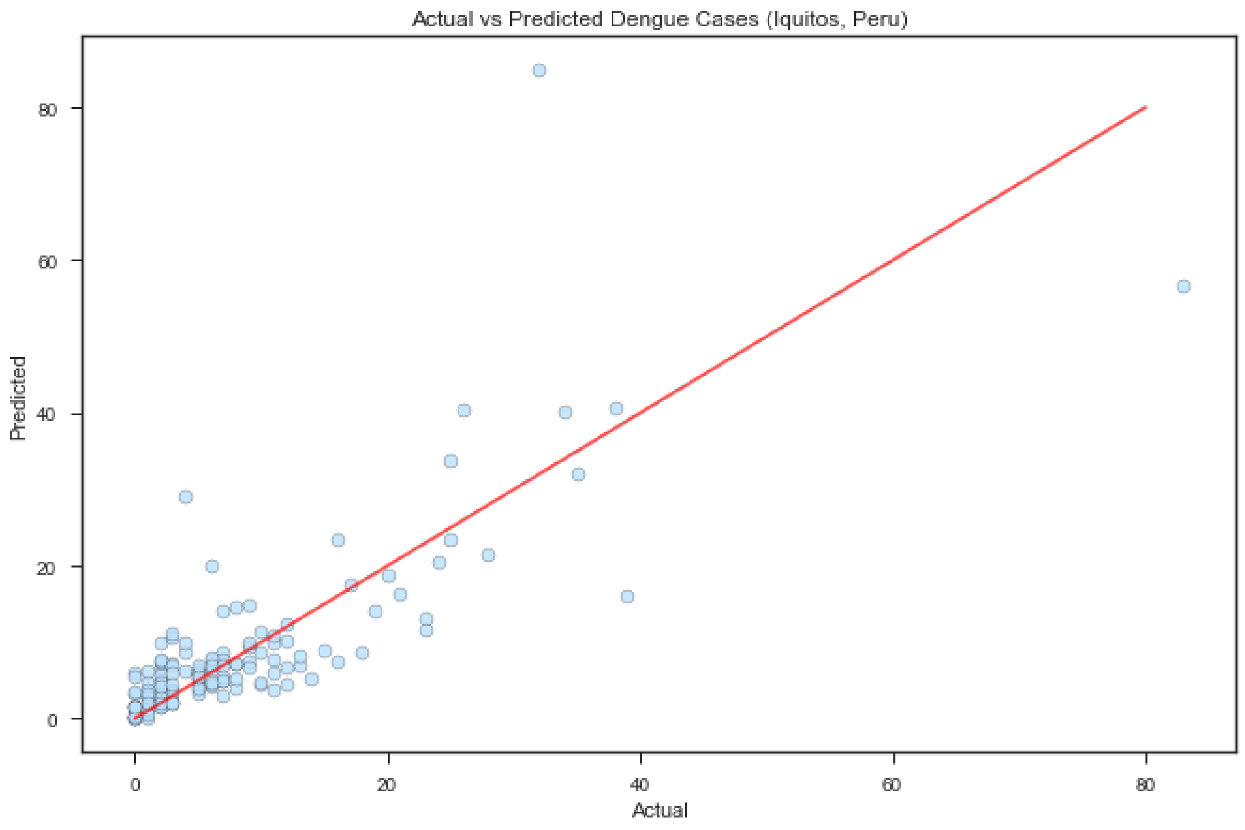
Grid Search & Cross Validation & Mean Absolute Error

In [131]:
```
params = {'n_estimators':range(5, 30)}
folds = KFold(n_splits = 10, shuffle=True)
grid_search = GridSearchCV(RandomForestRegressor(), param_grid=params, cv=
folds, scoring='neg_mean_absolute_error')
rf_preds_iq = grid_search.fit(train_features_iq, train_outcomes_iq).predic
t(test_features_iq)
rf_mae_iq = mean_absolute_error(test_outcomes_iq, rf_preds_iq)
rf_mdae_iq = median_absolute_error(test_outcomes_iq, rf_preds_iq)
rf_evs_iq = explained_variance_score(test_outcomes_iq, rf_preds_iq)
print(rf_mae_iq)
```

```
3.7488716956802057
```

Actual vs Predicted Iquitos Random Forest

```
In [132]: plt.subplots(figsize=(11,7))
          plt.title('Actual vs Predicted Dengue Cases (Iquitos, Peru)')
          plt.xlabel('Actual')
          plt.ylabel('Predicted')
          plt.scatter(test_outcomes_iq, rf_preds_iq, edgecolors = '#1e1e1e', color=
          '#bae1ff', alpha=0.8)
          plt.plot([0, 80], [0, 80], 'red', alpha=0.7)

Out[132]: [<matplotlib.lines.Line2D at 0x1a28681940>]
```

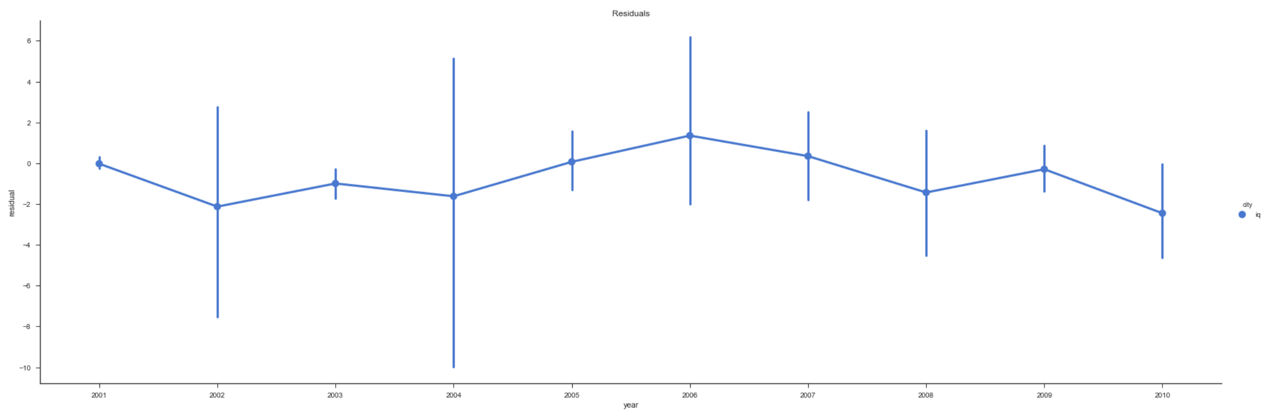


Residuals

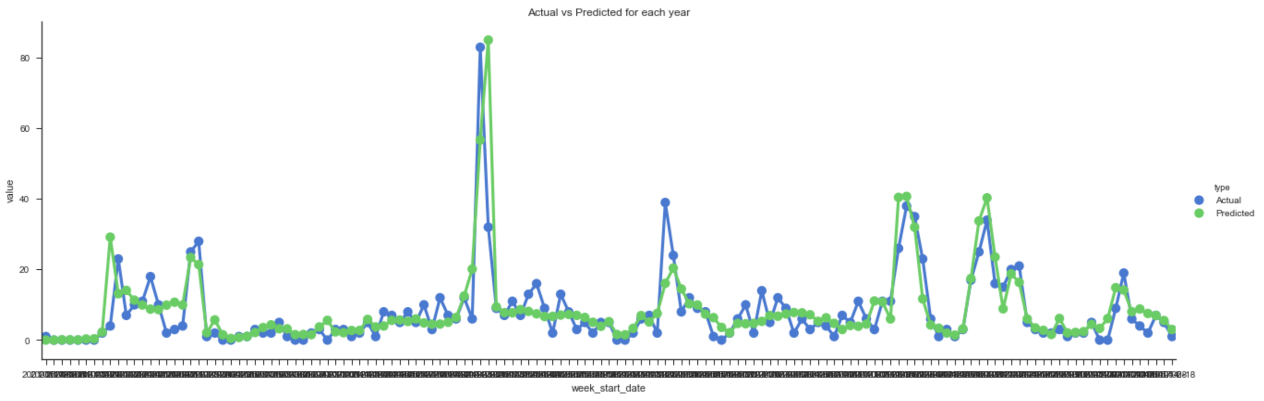
```
In [133]: rf_preds_week_iq = pd.DataFrame(test_features_iq)
          rf_preds_week_iq['Actual'] = test_outcomes_iq.values
          rf_preds_week_iq['Predicted'] = rf_preds_iq
          rf_preds_week_iq = pd.merge(data_iq, rf_preds_week_iq, left_index = True,
          right_index = True)
```

Actual Vs Predicted Time Series Line Graph

```
In [134]: plot_d = rf_preds_week_iq.assign(residual=rf_preds_week_iq.Actual - rf_pre
          ds_week_iq .Predicted)
          sns.factorplot(x="year", y="residual", hue="city", size=8, aspect=3,data=p
          lot_d)
          plt.title("Residuals")

Out[134]: Text(0.5,1,'Residuals')
```



```
In [135]: plot_d = plot_d.melt(id_vars=['city', 'year', 'weekofyear_x', 'week_start_
          date', 'ndvi_ne', 'ndvi_nw',
                 'ndvi_se', 'ndvi_sw', 'precipitation_amt_mm', 'reanalysis_air_temp_
          k',
                 'reanalysis_avg_temp_k', 'reanalysis_dew_point_temp_k',
                 'reanalysis_max_air_temp_k', 'reanalysis_min_air_temp_k',
                 'reanalysis_precip_amt_kg_per_m2',
                 'reanalysis_relative_humidity_percent', 'reanalysis_tdtr_k',
                 'station_avg_temp_c', 'station_diur_temp_rng_c', 'station_max_temp_
          c',
                 'station_min_temp_c', 'station_precip_mm', 'total_cases', 'month',
                 'odd_year_x', 'ndvi_mean', 'ndvi_mean_rolling_avg',
                 'ndvi_ne_rolling_avg', 'ndvi_nw_rolling_avg', 'ndvi_se_rolling_avg_
          x',
                 'ndvi_sw_rolling_avg', 'precipitation_amt_mm_rolling_avg',
                 'reanalysis_air_temp_k_rolling_avg',
                 'reanalysis_avg_temp_k_rolling_avg_x',
                 'reanalysis_dew_point_temp_k_rolling_avg',
                 'reanalysis_max_air_temp_k_rolling_avg_x',
                 'reanalysis_min_air_temp_k_rolling_avg_x',
                 'reanalysis_precip_amt_kg_per_m2_rolling_avg',
                 'reanalysis_relative_humidity_percent_rolling_avg',
                 'reanalysis_tdtr_k_rolling_avg', 'station_avg_temp_c_rolling_avg_x'
          ,
                 'station_diur_temp_rng_c_rolling_avg',
                 'station_max_temp_c_rolling_avg_x', 'station_min_temp_c_rolling_av
          g',
                 'station_precip_mm_rolling_avg', 'ndvi_se_rolling_avg_y',
                 'reanalysis_avg_temp_k_rolling_avg_y', 'weekofyear_y',
                 'station_avg_temp_c_rolling_avg_y',
                 'reanalysis_max_air_temp_k_rolling_avg_y', 'odd_year_y',
                 'station_max_temp_c_rolling_avg_y',
                 'reanalysis_min_air_temp_k_rolling_avg_y','residual'], var_name='ty
          pe')

          sns.factorplot(x='week_start_date', y="value", hue="type", data=plot_d, si
          ze = 6, aspect =3)
          plt.title("Actual vs Predicted for each year")

Out[135]: Text(0.5,1,'Actual vs Predicted for each year')
```



Final Model Submission

In [136]:
```
rf_preds_final_iq = rf_reg.fit(train_features_iq, train_outcomes_iq).predi
ct(
    data_test_iq_n[['ndvi_se_rolling_avg',
                    'reanalysis_avg_temp_k_rolling_avg',
                    'weekofyear',
                    'station_avg_temp_c_rolling_avg',
                    'reanalysis_max_air_temp_k_rolling_avg',
                    'odd_year',
                    'station_max_temp_c_rolling_avg',
                    'reanalysis_min_air_temp_k_rolling_avg']]
)
```

In [137]:
```
submission_iq = data_test_iq[['city', 'year', 'weekofyear']].copy()
submission_iq['total_cases'] = np.round(rf_preds_final_iq).astype(int)
```

In [138]:
```
frames = [submission_sj, submission_iq]
submission = pd.concat(frames)
submission.to_csv('rf.csv', index = False)
```

One Hot Encoding (Adding Dummies) with KNN

We will encode categorical integer features using a one-hot aka one-of-K scheme. we use one hot encoder to perform “binarization” of the category and include it as a feature to train the model. A 1 in a particular column will tell the computer the correct category for that row’s data. In other words, we have created an additional binary column for each category.

Refferred to:

- https://hackernoon.com/what-is-one-hot-encoding-why-and-when-do-you-have-to-use-it-e3c6186d008f (https://hackernoon.com/what-is-one-hot-encoding-why-and-when-do-you-have-to-use-it-e3c6186d008f)
- https://medium.com/@michaeldelsole/what-is-one-hot-encoding-and-how-to-do-it-f0ae272f1179 (https://medium.com/@michaeldelsole/what-is-one-hot-encoding-and-how-to-do-it-f0ae272f1179)

Creating Dummies

In [139]:
```
sj = data_sj.copy()
sj_dum = pd.get_dummies(sj, prefix=['weekofyear', 'month'], columns=['week
ofyear', 'month'])
sj_dum = sj_dum.drop(['city', 'week_start_date'], axis=1)

iq = data_iq.copy()
iq_dum = pd.get_dummies(iq, prefix=['weekofyear', 'month'], columns=['week
ofyear', 'month'])
iq_dum = iq_dum.drop(['city', 'week_start_date'], axis=1)

test_sj = data_test_sj.copy()
test_sj_dum = pd.get_dummies(test_sj, prefix=['weekofyear', 'month'], colu
mns=['weekofyear', 'month'])
test_sj_dum  = test_sj_dum.drop(['city', 'week_start_date'], axis=1)
```

San Juan

```
In [140]: train_features_sj, test_features_sj, train_outcomes_sj, test_outcomes_sj =
           train_test_split(
              sj_dum,
              data_sj['total_cases'],
              test_size = 0.3
          )

          reg = Pipeline([
            ('feature_selection', SelectFromModel(LinearSVC(penalty="l2"))),
            ('classification', KNeighborsRegressor(n_neighbors = 4, weights = 'dista
          nce'))
          ])

          reg = reg.fit(train_features_sj, train_outcomes_sj).predict(test_features_
          sj)
          print(mean_absolute_error(test_outcomes_sj, reg))
```

```
4.735043367947577
```

Iquitos

```
In [141]: train_features_iq, test_features_iq, train_outcomes_iq, test_outcomes_iq =
           train_test_split(
              iq_dum,
              data_iq['total_cases'],
              test_size = 0.3
          )

          reg = Pipeline([
            ('feature_selection', SelectFromModel(LinearSVC(penalty="l2"))),
            ('classification', KNeighborsRegressor(n_neighbors = 4, weights = 'dista
          nce'))
          ])

          reg = reg.fit(train_features_iq, train_outcomes_iq).predict(test_features_
          iq)
          print(mean_absolute_error(test_outcomes_iq, reg))
```

```
5.225599372641924
```

Why did we did not use dummies?

1. We received a better margin of error using KNN (our best model) without dummies on Driven Data
2. We could have worked more on optimizing this but due to time constraints we could not

Comparision of Models

In [142]:
```
algs_mae = pd.DataFrame({'San Juan': [knr_mae_sj, xgb_mae_sj, dt_mae_sj, r
f_mae_sj],
                      'Iquitos': [knr_mae_iq, xgb_mae_iq, dt_mae_iq,rf_mae
_iq]},
                      index=['KNN', 'XGBoost', 'DecisionTree', 'RandomFore
st'])

algs_mdae = pd.DataFrame({'San Juan': [knr_mdae_sj, xgb_mdae_sj, dt_mdae_s
j, rf_mdae_sj],
                      'Iquitos': [knr_mdae_iq, xgb_mdae_iq, dt_mdae_iq,rf_
mdae_iq]},
                      index=['KNN', 'XGBoost', 'DecisionTree', 'RandomFore
st'])

algs_evs = pd.DataFrame({'San Juan': [knr_evs_sj, xgb_evs_sj, dt_evs_sj, r
f_evs_sj],
                      'Iquitos': [knr_evs_iq, xgb_evs_iq, dt_evs_iq,rf_evs
_iq]},
                      index=['KNN', 'XGBoost', 'DecisionTree', 'RandomFore
st'])
```

In [149]:
```
print("Mean Absolute Error")
print("XG Boost has the lowest MAE")
algs_mae
```

```
Mean Absolute Error
XG Boost has the lowest MAE
```

Out[149]:

	San Juan	Iquitos
KNN	9.547511	3.776723
XGBoost	7.587810	4.195427
DecisionTree	13.921697	4.415130
RandomForest	12.363722	3.748872

In [150]:
```
print("Median Absolute Error")
print("Random Forest has the lowest MDAE")
algs_mdae
```

```
Median Absolute Error
Random Forest has the lowest MDAE
```

Out[150]:

	San Juan	Iquitos
KNN	4.527511	2.253439
XGBoost	4.557379	2.438111
DecisionTree	6.000000	2.133333
RandomForest	4.732143	1.727273

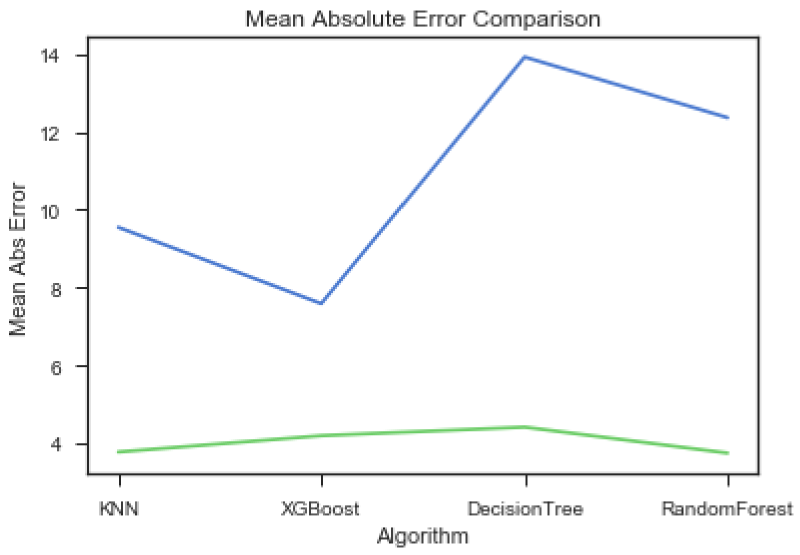
```
In [151]: print("Explained Variance Score")
          print("Decision Tree has the best Explained Variance Score")
          algs_evs

          Explained Variance Score
          Decision Tree has the best Explained Variance Score
```

Out[151]:

	San Juan	Iquitos
KNN	0.853981	0.497566
XGBoost	0.930455	0.582080
DecisionTree	0.677907	0.439068
RandomForest	0.749952	0.548072

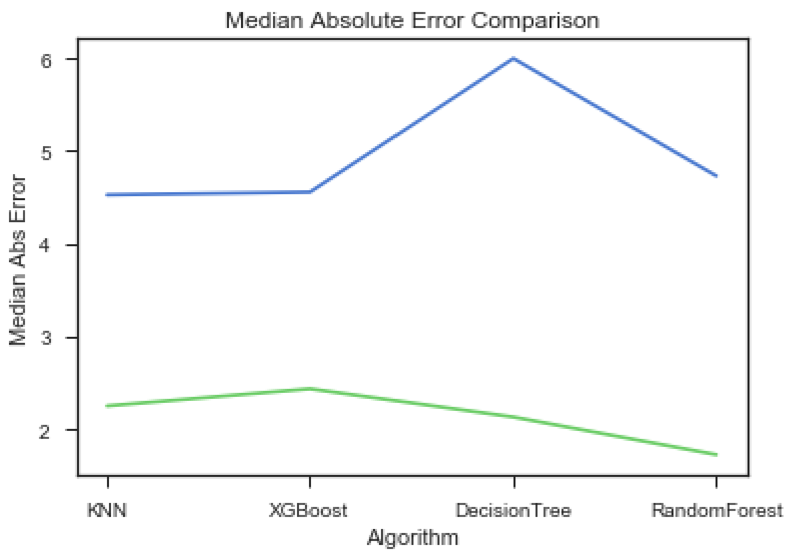
Let us visualize this and see how the models compare to each other.

```
In [143]: plt.subplots(figsize=(6,4))
          plt.plot(algs_mae)
          plt.title('Mean Absolute Error Comparison')
          plt.xlabel('Algorithm')
          plt.ylabel('Mean Abs Error')

Out[143]: Text(0,0.5,'Mean Abs Error')
```



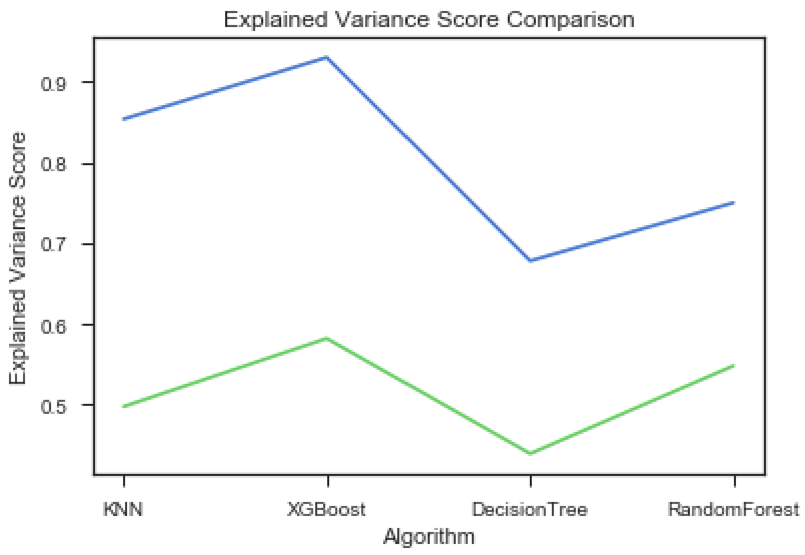
```
In [144]: plt.subplots(figsize=(6,4))
          plt.plot(algs_mdae)
          plt.title('Median Absolute Error Comparison')
          plt.xlabel('Algorithm')
          plt.ylabel('Median Abs Error')
```

```
Out[144]: Text(0,0.5,'Median Abs Error')
```



```
In [145]: plt.subplots(figsize=(6,4))
          plt.plot(algs_evs)
          plt.title('Explained Variance Score Comparison')
          plt.xlabel('Algorithm')
          plt.ylabel('Explained Variance Score')
```

```
Out[145]: Text(0,0.5,'Explained Variance Score')
```



Thank You

Best Model: KNN (Score: 19.4533)