Global Temperature vs Precipitation Project

In [1]:

```
#from IPython.core.interactiveshell import InteractiveShell
#InteractiveShell.ast_node_interactivity = "all"

import pandas as pd
import numpy as np
import matplotlib
import copy

from pprint import pprint

import seaborn as sns
import missingno as msno


# First let's import the package
# pyplot is the interface we want to use
import matplotlib.pyplot as plt

# "matplotlib inline" creates static images of plot embedded in the notebook
%matplotlib inline
```

Reading and cleaning the data set

In [2]:

```
# Let's begin with checking the data first
# df = pd.read_csv('Traffic_Crashes_-_Crashes.csv')
df1900 = pd.read_csv('air_temp.1900', sep='\s+',  names=["Longitude", "Latitude", "Jan", "Feb", "Mar", "Apr", "May",
                                                         "Jun", "Jul", "Aug", "Sep", "Oct", "Nov", "Dec"])

df1900.info()
df1900.head()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 85794 entries, 0 to 85793
Data columns (total 14 columns):
 #   Column     Non-Null Count  Dtype  
---  ------     --------------  -----  
 0   Longitude  85794 non-null  float64
 1   Latitude   85794 non-null  float64
 2   Jan        85794 non-null  float64
 3   Feb        85794 non-null  float64
 4   Mar        85794 non-null  float64
 5   Apr        85794 non-null  float64
```

```
 6   May        85794 non-null  float64
 7   Jun        85794 non-null  float64
 8   Jul        85794 non-null  float64
 9   Aug        85794 non-null  float64
 10  Sep        85794 non-null  float64
 11  Oct        85794 non-null  float64
 12  Nov        85794 non-null  float64
 13  Dec        85794 non-null  float64
dtypes: float64(14)
memory usage: 9.2 MB
```

Out[2]:

	Longitude	Latitude	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
0	-179.75	71.25	-26.9	-19.0	-22.6	-22.4	-8.0	-0.8	2.6	0.3	-2.9	-9.2	-12.0	-23.7
1	-179.75	68.75	-28.7	-21.2	-24.5	-24.4	-8.0	0.0	3.9	0.9	-2.8	-10.9	-13.8	-26.8
2	-179.75	68.25	-29.3	-22.0	-25.4	-25.2	-8.7	0.0	4.1	0.9	-3.5	-11.8	-14.8	-27.8
3	-179.75	67.75	-28.1	-20.8	-24.3	-24.3	-7.4	2.5	7.2	3.5	-2.1	-11.3	-14.4	-27.3
4	-179.75	67.25	-30.1	-23.3	-26.8	-26.7	-9.1	2.2	7.5	3.1	-3.9	-14.3	-17.5	-30.4

In [3]:

```
df1901 = pd.read_csv('air_temp.1901', sep='\s+', names=["Longitude", "Latitude", "Jan", "Feb", "Mar", "Apr", "May", "Jun"
df1901.info()
df1901.head()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 85794 entries, 0 to 85793
Data columns (total 14 columns):
 #   Column     Non-Null Count  Dtype  
---  ------     --------------  -----  
 0   Longitude  85794 non-null  float64
 1   Latitude   85794 non-null  float64
 2   Jan        85794 non-null  float64
 3   Feb        85794 non-null  float64
 4   Mar        85794 non-null  float64
 5   Apr        85794 non-null  float64
 6   May        85794 non-null  float64
 7   Jun        85794 non-null  float64
 8   Jul        85794 non-null  float64
 9   Aug        85794 non-null  float64
 10  Sep        85794 non-null  float64
 11  Oct        85794 non-null  float64
 12  Nov        85794 non-null  float64
 13  Dec        85794 non-null  float64
dtypes: float64(14)
memory usage: 9.2 MB
```

Out[3]:

	Longitude	Latitude	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
0	-179.75	71.25	-31.0	-27.5	-28.0	-16.6	-9.2	0.1	1.7	0.8	-0.8	-7.5	-14.8	-18.8
1	-179.75	68.75	-33.4	-30.0	-30.6	-17.6	-8.9	0.7	2.9	1.4	-0.9	-8.9	-16.0	-20.5
2	-179.75	68.25	-34.1	-30.9	-31.7	-18.2	-9.5	0.6	3.2	1.5	-1.5	-9.7	-16.8	-21.4
3	-179.75	67.75	-32.9	-29.8	-30.9	-17.0	-8.1	3.1	6.2	4.0	-0.1	-9.2	-16.3	-20.7
4	-179.75	67.25	-34.9	-32.3	-33.8	-19.2	-9.7	2.7	6.6	3.6	-1.8	-12.2	-19.3	-23.6

In [4]:

```
horizontal_stack = pd.concat([df1900, df1901], axis=1)
horizontal_stack.info()
horizontal_stack.head()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 85794 entries, 0 to 85793
Data columns (total 28 columns):
 #   Column     Non-Null Count  Dtype  
---  ------     --------------  -----  
 0   Longitude  85794 non-null  float64
 1   Latitude   85794 non-null  float64
 2   Jan        85794 non-null  float64
 3   Feb        85794 non-null  float64
 4   Mar        85794 non-null  float64
 5   Apr        85794 non-null  float64
 6   May        85794 non-null  float64
 7   Jun        85794 non-null  float64
 8   Jul        85794 non-null  float64
 9   Aug        85794 non-null  float64
 10  Sep        85794 non-null  float64
 11  Oct        85794 non-null  float64
 12  Nov        85794 non-null  float64
 13  Dec        85794 non-null  float64
 14  Longitude  85794 non-null  float64
 15  Latitude   85794 non-null  float64
 16  Jan        85794 non-null  float64
 17  Feb        85794 non-null  float64
 18  Mar        85794 non-null  float64
 19  Apr        85794 non-null  float64
 20  May        85794 non-null  float64
 21  Jun        85794 non-null  float64
 22  Jul        85794 non-null  float64
 23  Aug        85794 non-null  float64
 24  Sep        85794 non-null  float64
 25  Oct        85794 non-null  float64
 26  Nov        85794 non-null  float64
```

```
 27  Dec         85794 non-null  float64
dtypes: float64(28)
memory usage: 18.3 MB
```

Out[4]:

	Longitude	Latitude	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	...	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
0	-179.75	71.25	-26.9	-19.0	-22.6	-22.4	-8.0	-0.8	2.6	0.3	...	-28.0	-16.6	-9.2	0.1	1.7	0.8	-0.8	-7.5	-14.8	-18.8
1	-179.75	68.75	-28.7	-21.2	-24.5	-24.4	-8.0	0.0	3.9	0.9	...	-30.6	-17.6	-8.9	0.7	2.9	1.4	-0.9	-8.9	-16.0	-20.5
2	-179.75	68.25	-29.3	-22.0	-25.4	-25.2	-8.7	0.0	4.1	0.9	...	-31.7	-18.2	-9.5	0.6	3.2	1.5	-1.5	-9.7	-16.8	-21.4
3	-179.75	67.75	-28.1	-20.8	-24.3	-24.3	-7.4	2.5	7.2	3.5	...	-30.9	-17.0	-8.1	3.1	6.2	4.0	-0.1	-9.2	-16.3	-20.7
4	-179.75	67.25	-30.1	-23.3	-26.8	-26.7	-9.1	2.2	7.5	3.1	...	-33.8	-19.2	-9.7	2.7	6.6	3.6	-1.8	-12.2	-19.3	-23.6

5 rows × 28 columns

Finding Mean Monthly Temperature for all locations:

In [38]:

```
# Finding the mean temperature of all months over these 115 years
# means[0] = mean of all January temperatures for a location
# .
# .
# .
# means[11] = mean of all December temperatures for a location


# Open each of the 115 files and add headers to them. Then we concatenate them.
df = pd.read_csv('air_temp.1900', sep='\s+', names=["Longitude", "Latitude", "Jan", "Feb", "Mar", "Apr",
                                                     "May", "Jun", "Jul", "Aug", "Sep", "Oct",
                                                     "Nov", "Dec"])

# We start with finding the mean for the month of January
means = []
means.append(df["Jan"])
means[0]

# This for loop goes from files of year 1901 to 2014
for x in range(1901,2015):
    yearS = str(x)
    tempDf = pd.read_csv('air_temp.'+yearS, sep='\s+', names=["Longitude", "Latitude", "Jan", "Feb", "Mar", "Apr",
                                                     "May", "Jun", "Jul", "Aug", "Sep", "Oct",
                                                     "Nov", "Dec"])
    # Appending every January to the list of means and finding its average
    neans = []
    neans.append(tempDf["Jan"])
```

```python
    neans[0]
    means[0] = [(g + h) / 2 for g, h in zip(means[0], neans[0])]

# Let's look at the first 10 locations and their mean of January temperature over these 115 years
print('Number of locations', len(means[0]))
print('First 10 locations mean of January temperature over these 115 years', means[0][:10] )
```

```
Number of locations 85794
First 10 locations mean of January temperature over these 115 years [-20.96137796198625, -24.45661837395835, -25.13148242
6337037, -24.033856462913093, -26.06643366000808, -22.15940931684048, -17.85112352212908, -17.9250874739215, -18.96867812
4794337, 28.941589688074693]
```

In [39]:

```python
# Now let's find the mean for the month of February
means.append(df["Feb"])

# This for loop goes from files of year 1901 to 2014
for x in range(1901,2015):
    yearS = str(x)
    tempDf = pd.read_csv('air_temp.'+yearS, sep='\s+', names=["Longitude", "Latitude", "Jan", "Feb", "Mar", "Apr",
                                                    "May", "Jun", "Jul", "Aug", "Sep", "Oct",
                                                    "Nov", "Dec"])
    neans = []
    neans.append(tempDf["Feb"])
    neans[0]
    means[1] = [(g + h) / 2 for g, h in zip(means[1], neans[0])]

print('First 10 locations and their mean of February temperature over these 115 years', means[1][:10] )
```

```
First 10 locations and their mean of February temperature over these 115 years [-20.779783236809827, -24.331992323388192,
-25.416651118350963, -24.64637796694462, -27.391093202909516, -23.008203378518125, -17.784674004420168, -16.8465436075628
22, -17.44647308741829, 28.7546216415445]
```

In [40]:

```python
# Now let's find the mean for all of the remaining months
listMonths = ["Mar", "Apr", "May", "Jun", "Jul", "Aug", "Sep", "Oct", "Nov", "Dec"]
for m in listMonths:
    means.append(df[m])

# This for loop goes from files of year 1901 to 2014
for x in range(1901,2015):
    yearS = str(x)
    tempDf = pd.read_csv('air_temp.'+yearS, sep='\s+', names=["Longitude", "Latitude", "Jan", "Feb", "Mar", "Apr",
                                                    "May", "Jun", "Jul", "Aug", "Sep", "Oct",
                                                    "Nov", "Dec"])

    # Appending every month to the list of means and finding its average
    neans = []
    for m in listMonths:
```

```python
        neans.append(tempDf[m])

    for i in range(2,12):
        means[i] = [(g + h) / 2 for g, h in zip(means[i], neans[i-2])]
```

In [41]:

```python
# Converting all these means of months to list of columns
tempp = list(zip(means[0],means[1],means[2],means[3],means[4],means[5],means[6],means[7],means[8],means[9]
        ,means[10],means[11] ) )
```

In [42]:

```python
# Let's look at our final dataframe where every column has the monthly mean temperature (in C) for that location
# Every row is a new location
dfTemp = pd.DataFrame(tempp, columns = ["Jan", "Feb", "Mar", "Apr",
                                         "May", "Jun", "Jul", "Aug", "Sep", "Oct",
                                         "Nov", "Dec"])


dfTemp
```

Out[42]:

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	
0	-20.961378	-20.779783	-19.675764	-14.790577	-5.732376	0.135406	3.152787	3.225932	0.135928	-4.684637	-9.416071	-18.1
1	-24.456618	-24.331992	-23.543032	-16.092644	-6.216872	0.726472	3.691958	3.264084	-0.171904	-6.644039	-12.713751	-21.2
2	-25.131482	-25.416651	-24.716702	-16.879098	-7.093584	0.708316	3.854926	3.230236	-0.916411	-7.677704	-14.062823	-22.2
3	-24.033856	-24.646378	-24.136576	-15.999113	-5.939159	3.164843	6.835533	5.678750	0.305764	-7.387230	-14.039276	-21.7
4	-26.066434	-27.391093	-27.065579	-18.487692	-7.898725	2.703818	7.072001	5.160881	-1.741065	-10.623888	-17.517930	-24.8
...	...	...	...	...	...	...	...	...	...	...	...	
85789	-26.463595	-40.683517	-52.579954	-55.379404	-55.807754	-54.853559	-59.087699	-56.469397	-55.209656	-48.277740	-35.060065	-25.5
85790	-27.124657	-41.571104	-53.739873	-56.269398	-57.174633	-55.735657	-60.054656	-57.688047	-56.440033	-49.348712	-35.752015	-26.1
85791	-27.232112	-42.150392	-54.230889	-56.695314	-57.873331	-56.092594	-60.519794	-58.166734	-56.951290	-49.948798	-36.002803	-26.3
85792	-27.196750	-42.375904	-54.335810	-56.658709	-57.935848	-55.935078	-60.454131	-58.170307	-56.905594	-50.349672	-36.119418	-26.2
85793	-27.096628	-42.534882	-54.032129	-56.255701	-57.715741	-55.434006	-60.061958	-57.965854	-56.579379	-50.706742	-36.491473	-26.2

85794 rows × 12 columns

Finding Mean Monthly Precipitation for all locations:

In [43]:

```
# Finding the mean precipitation of all months over these 115 years
# means[0] = mean of all January precipitation for a location
# .
# .
# .
# means[11] = mean of all December precipitation for a location
ef = pd.read_csv('precip.1900', sep='\s+', names=["Longitude", "Latitude", "Jan", "Feb", "Mar", "Apr",
                                                    "May", "Jun", "Jul", "Aug", "Sep", "Oct",
                                                    "Nov", "Dec"])
avgsP = []
avgsP.append(ef["Jan"])
avgsP[0]

# This for loop goes from files of year 1901 to 2014
for x in range(1901,2015):
    yearS = str(x)
    tempDf = pd.read_csv('precip.'+yearS, sep='\s+', names=["Longitude", "Latitude", "Jan", "Feb", "Mar", "Apr",
                                                    "May", "Jun", "Jul", "Aug", "Sep", "Oct",
                                                    "Nov", "Dec"])
    # Appending every January to the list of means and finding its average
    neans = []
    neans.append(tempDf["Jan"])
    neans[0]
    avgsP[0] = [(g + h) / 2 for g, h in zip(avgsP[0], neans[0])]
```

In [44]:

```
# Now let's find the mean for all of the remaining months
listMonths = ["Feb", "Mar", "Apr", "May", "Jun", "Jul", "Aug", "Sep", "Oct", "Nov", "Dec"]
for m in listMonths:
    avgsP.append(ef[m])
# means[0]

# This for loop goes from files of year 1901 to 2014
for x in range(1901,2015):
    yearS = str(x)
    tempDf = pd.read_csv('precip.'+yearS, sep='\s+', names=["Longitude", "Latitude", "Jan", "Feb", "Mar", "Apr",
                                                    "May", "Jun", "Jul", "Aug", "Sep", "Oct",
                                                    "Nov", "Dec"])
    # Appending every month to the list of means and finding its average
    neans = []
    for m in listMonths:
        neans.append(tempDf[m])
    for i in range(1,12):
        avgsP[i] = [(g + h) / 2 for g, h in zip(avgsP[i], neans[i-1])]
```

In [45]:

```
# Converting all these means of months to list of columns
```

```
precipp = list(zip(avgsP[0],avgsP[1],avgsP[2],avgsP[3],avgsP[4],avgsP[5],avgsP[6],avgsP[7],avgsP[8],avgsP[9]
        ,avgsP[10],avgsP[11] ) )


# Let's look at our final dataframe where every column has the monthly mean precipiation (in mm) for that location
# Every row is a new location
dfPrecip = pd.DataFrame(precipp, columns = ["Jan", "Feb", "Mar", "Apr",
                                            "May", "Jun", "Jul", "Aug", "Sep", "Oct",
                                            "Nov", "Dec"])


dfPrecip
```

Out[45]:

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	
0	17.906886	11.710341	1.247260e+01	4.905435	3.059161	5.958738e+00	1.024784e+01	1.200584e+01	1.559985e+01	1.147546e+01	10.2
1	27.772241	22.034911	1.751727e+01	9.456831	23.178640	1.534989e+01	2.868153e+01	3.378672e+01	4.942416e+01	4.055705e+01	30.8
2	28.057248	25.427971	1.857660e+01	9.217719	29.491328	1.529094e+01	3.255547e+01	3.415742e+01	4.155990e+01	4.043054e+01	31.8
3	30.724294	31.681006	2.110698e+01	10.539274	37.674670	1.769305e+01	4.213071e+01	3.787658e+01	3.814262e+01	3.952282e+01	34.3
4	33.887307	38.706987	2.434751e+01	12.559512	42.270961	2.022752e+01	5.418735e+01	4.210935e+01	3.707040e+01	3.738716e+01	39.2
...	...	...	...	...	...	...	...	...	...	...	
85789	0.050000	0.009071	2.372787e-07	0.010156	0.022266	3.439163e-09	2.270498e-07	9.894113e-10	3.434279e-09	2.443962e-05	0.0
85790	0.100000	0.006238	2.258466e-07	0.009570	0.021680	2.372254e-09	1.434443e-07	7.513912e-10	2.667238e-09	1.224385e-05	0.0
85791	0.100000	0.004395	3.908398e-04	0.009180	0.021289	1.491885e-09	8.368202e-08	5.254227e-10	1.902378e-09	4.835544e-08	0.0
85792	0.100098	0.002478	3.125206e-03	0.008594	0.021289	8.120668e-10	4.784343e-08	2.965450e-10	1.144090e-09	4.806924e-08	0.0
85793	0.100902	0.002246	6.250100e-03	0.008008	0.021289	2.587613e-10	1.197063e-08	1.055027e-10	3.799821e-10	1.201745e-08	0.0

85794 rows × 12 columns

Putting all Temperature data together for all locations for our EDA:

In [12]:

```
# Open each of the 115 files and add headers to them. Then we concatenate them.
df = pd.read_csv('air_temp.1900', sep='\s+', names=["Longitude", "Latitude", "Jan 1900", "Feb 1900", "Mar 1900", "Apr 190
                                            "May 1900", "Jun 1900", "Jul 1900", "Aug 1900", "Sep 1900", "Oct 190
                                            "Nov 1900", "Dec 1900"])


# This for loop goes from files of year 1901 to 2014
```

```python
for x in range(1901,2015):
    yearS = str(x)
    tempDf = pd.read_csv('air_temp.'+yearS, sep='\s+', names=["Longitude", "Latitude", "Jan "+yearS, "Feb "+yearS, "Mar "
                                                    "Apr "+yearS, "May "+yearS, "Jun "+yearS, "Jul "+yearS,
                                                    "Aug "+yearS, "Sep "+yearS, "Oct "+yearS, "Nov "+yearS,
                                                    "Dec "+yearS])

    df = pd.concat([df, tempDf], axis=1)

# Removing duplicate columns (of latitude and longitude)
df1 = df.loc[:, ~df.columns.duplicated()]

df1.info()
df1.head()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 85794 entries, 0 to 85793
Columns: 1382 entries, Longitude to Dec 2014
dtypes: float64(1382)
memory usage: 904.6 MB
```

Out[12]:

	Longitude	Latitude	Jan 1900	Feb 1900	Mar 1900	Apr 1900	May 1900	Jun 1900	Jul 1900	Aug 1900	...	Mar 2014	Apr 2014	May 2014	Jun 2014	Jul 2014	Aug 2014	Sep 2014	Oct 2014	Nov 2014	De 201
0	-179.75	71.25	-26.9	-19.0	-22.6	-22.4	-8.0	-0.8	2.6	0.3	...	-19.0	-15.2	-5.1	-0.7	2.9	4.8	0.9	-3.5	-5.3	-19
1	-179.75	68.75	-28.7	-21.2	-24.5	-24.4	-8.0	0.0	3.9	0.9	...	-22.7	-16.1	-6.0	-0.2	4.0	5.0	0.9	-5.3	-8.8	-22
2	-179.75	68.25	-29.3	-22.0	-25.4	-25.2	-8.7	0.0	4.1	0.9	...	-24.1	-16.9	-7.0	-0.2	4.1	4.9	0.2	-6.6	-10.0	-22
3	-179.75	67.75	-28.1	-20.8	-24.3	-24.3	-7.4	2.5	7.2	3.5	...	-23.6	-15.9	-5.8	2.3	7.1	7.3	1.5	-6.6	-9.9	-21
4	-179.75	67.25	-30.1	-23.3	-26.8	-26.7	-9.1	2.2	7.5	3.1	...	-26.4	-18.2	-7.7	1.8	7.3	6.7	-0.5	-10.1	-13.3	-24

5 rows × 1382 columns

In [14]:
```python
df1 = df.loc[:, ~df.columns.duplicated()]
```

In [20]:
```python
df1.isnull().values.any()
```

Out[20]:
```
False
```

We thus see that we have no null values in our data set.
Also, given the way our dataset is defined, all of the 85794 locations are unique

In [10]:

```
df1.info()
df1.head(20)
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 85794 entries, 0 to 85793
Columns: 1382 entries, Longitude to Dec 2014
dtypes: float64(1382)
memory usage: 904.6 MB
```

Out[10]:

	Longitude	Latitude	Jan 1900	Feb 1900	Mar 1900	Apr 1900	May 1900	Jun 1900	Jul 1900	Aug 1900	...	Mar 2014	Apr 2014	May 2014	Jun 2014	Jul 2014	Aug 2014	Sep 2014	Oct 2014	Nov 2014	D 20
0	-179.75	71.25	-26.9	-19.0	-22.6	-22.4	-8.0	-0.8	2.6	0.3	...	-19.0	-15.2	-5.1	-0.7	2.9	4.8	0.9	-3.5	-5.3	-1
1	-179.75	68.75	-28.7	-21.2	-24.5	-24.4	-8.0	0.0	3.9	0.9	...	-22.7	-16.1	-6.0	-0.2	4.0	5.0	0.9	-5.3	-8.8	-2
2	-179.75	68.25	-29.3	-22.0	-25.4	-25.2	-8.7	0.0	4.1	0.9	...	-24.1	-16.9	-7.0	-0.2	4.1	4.9	0.2	-6.6	-10.0	-2
3	-179.75	67.75	-28.1	-20.8	-24.3	-24.3	-7.4	2.5	7.2	3.5	...	-23.6	-15.9	-5.8	2.3	7.1	7.3	1.5	-6.6	-9.9	-2
4	-179.75	67.25	-30.1	-23.3	-26.8	-26.7	-9.1	2.2	7.5	3.1	...	-26.4	-18.2	-7.7	1.8	7.3	6.7	-0.5	-10.1	-13.3	-2
5	-179.75	66.75	-26.1	-18.7	-22.6	-22.9	-6.1	4.3	9.6	5.8	...	-22.1	-14.1	-5.0	3.5	8.9	9.0	2.1	-6.7	-9.2	-1
6	-179.75	66.25	-21.6	-13.4	-17.2	-18.9	-3.5	4.7	9.9	7.1	...	-16.7	-9.8	-2.6	3.4	9.0	10.2	4.1	-3.0	-4.7	-1
7	-179.75	65.75	-20.6	-12.0	-16.7	-17.8	-2.9	5.7	11.1	8.7	...	-16.8	-8.9	-1.4	5.3	11.2	12.3	5.7	-1.5	-4.0	-1
8	-179.75	65.25	-20.8	-12.2	-16.7	-18.2	-2.7	5.9	11.6	9.1	...	-17.4	-9.3	-0.6	6.4	12.7	13.2	6.3	-1.6	-4.6	-1
9	-179.75	-16.75	27.2	27.2	27.1	26.7	25.1	24.4	24.1	24.8	...	28.8	27.8	27.1	26.6	24.2	24.5	26.6	27.1	27.7	2
10	-179.75	-84.75	-20.2	-30.2	-39.3	-43.4	-44.7	-45.5	-48.7	-48.9	...	-40.7	-42.3	-40.3	-44.3	-49.8	-44.9	-41.5	-36.3	-27.3	-1
11	-179.75	-85.25	-25.1	-36.0	-45.7	-49.7	-50.9	-51.4	-54.9	-54.4	...	-47.3	-48.4	-46.6	-50.1	-55.6	-50.8	-48.0	-42.6	-32.5	-2
12	-179.75	-85.75	-23.9	-35.5	-45.8	-49.7	-50.7	-50.9	-54.7	-53.8	...	-47.5	-48.3	-46.6	-49.4	-55.1	-50.5	-48.3	-42.5	-31.5	-2
13	-179.75	-86.25	-25.4	-37.3	-48.3	-52.1	-53.0	-53.0	-57.1	-55.6	...	-50.2	-50.5	-49.1	-51.4	-57.2	-52.7	-50.9	-45.0	-33.0	-2
14	-179.75	-86.75	-26.5	-38.8	-50.1	-53.8	-54.7	-54.7	-58.9	-57.0	...	-52.1	-52.1	-51.0	-52.9	-58.8	-54.6	-52.9	-46.7	-34.2	-2
15	-179.75	-87.25	-27.2	-39.6	-51.3	-54.9	-55.7	-55.6	-60.0	-58.1	...	-53.5	-53.0	-52.2	-53.7	-59.6	-56.1	-54.5	-47.9	-34.9	-2
16	-179.75	-87.75	-27.7	-40.4	-52.2	-55.7	-56.7	-56.6	-60.9	-58.9	...	-54.5	-53.6	-53.3	-54.6	-60.4	-57.3	-55.7	-48.8	-35.4	-2
17	-179.75	-88.25	-28.2	-41.1	-53.4	-56.8	-57.7	-57.7	-62.1	-59.8	...	-55.8	-54.5	-54.6	-55.4	-61.4	-58.5	-57.2	-49.9	-36.1	-2
18	-179.75	-88.75	-28.3	-41.5	-53.9	-57.3	-58.1	-58.2	-62.6	-60.3	...	-56.4	-54.8	-55.1	-55.7	-61.8	-59.3	-57.9	-50.5	-36.4	-2
19	-179.75	-89.25	-28.1	-41.4	-54.1	-57.3	-58.1	-58.4	-62.6	-60.3	...	-56.6	-54.6	-55.2	-55.5	-61.7	-59.4	-58.0	-50.8	-36.7	-2

20 rows × 1382 columns

In [14]:
```
df1.to_csv("cleaned_MonthlyAirTemperature_Jan1900_to_Dec2014.csv", index=False, header=True)
```

In [15]:
```
df1.describe()
```

Out[15]:

	Longitude	Latitude	Jan 1900	Feb 1900	Mar 1900	Apr 1900	May 1900	Jun 1900	Jul 1900	Aug 1
count	85794.000000	85794.000000	85794.000000	85794.000000	85794.000000	85794.000000	85794.000000	85794.000000	85794.000000	85794.00
mean	18.436540	1.060109	-8.415361	-9.044871	-8.795384	-6.884105	-3.749948	-1.542897	-1.246522	-1.60
std	88.008337	57.848430	22.194745	23.872740	26.675315	28.543110	29.495691	30.559122	32.252617	31.79
min	-179.750000	-89.750000	-60.300000	-53.000000	-58.000000	-65.600000	-66.600000	-69.300000	-70.000000	-71.40
25%	-62.250000	-71.750000	-26.900000	-28.800000	-27.900000	-28.500000	-28.000000	-29.400000	-32.700000	-32.80
50%	28.250000	19.250000	-14.100000	-15.300000	-8.600000	-1.100000	6.400000	11.300000	13.500000	12.20
75%	93.750000	52.250000	13.300000	16.400000	18.000000	18.700000	19.600000	21.300000	22.600000	22.50
max	179.750000	83.250000	37.300000	37.700000	38.600000	37.500000	36.700000	38.100000	39.400000	38.10

8 rows × 1382 columns

Putting all Precipitation data together for all locations for our EDA:

In [21]:
```
ef = pd.read_csv('precip.1900', sep='\s+', names=["Longitude", "Latitude", "Jan 1900", "Feb 1900", "Mar 1900", "Apr 1900"

for x in range(1901,2015):
    yearS = str(x)
    tempEf = pd.read_csv('precip.'+yearS, sep='\s+', names=["Longitude", "Latitude", "Jan "+yearS, "Feb "+yearS, "Mar "+y
    ef = pd.concat([ef, tempEf], axis=1)

ef.info()
ef.head()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 85794 entries, 0 to 85793
Columns: 1610 entries, Longitude to Dec 2014
dtypes: float64(1610)
memory usage: 1.0 GB
```

Out[21]:

	Longitude	Latitude	Jan 1900	Feb 1900	Mar 1900	Apr 1900	May 1900	Jun 1900	Jul 1900	Aug 1900	...	Mar 2014	Apr 2014	May 2014	Jun 2014	Jul 2014	Aug 2014	Sep 2014	Oct 2014	Nov 2014	De 201
0	-179.75	71.25	0.0	1.4	1.9	5.5	6.3	12.7	7.7	37.1	...	10.9	6.9	0.0	5.0	7.3	6.8	22.2	10.2	11.1	8
1	-179.75	68.75	12.2	5.6	6.2	10.9	9.7	19.6	17.7	53.8	...	18.6	7.4	31.5	8.2	27.3	23.3	53.7	40.0	40.7	31
2	-179.75	68.25	11.7	7.1	6.2	11.4	9.1	21.2	18.9	56.0	...	20.7	6.5	44.1	8.6	31.5	25.3	45.5	39.6	42.2	32
3	-179.75	67.75	15.1	11.4	8.0	13.6	9.3	25.2	24.2	61.3	...	24.3	7.4	61.1	11.5	39.9	30.4	43.3	36.9	44.6	33
4	-179.75	67.25	20.6	16.7	10.5	16.3	9.5	29.9	30.0	67.0	...	28.5	9.1	72.0	13.3	49.8	36.6	44.7	30.6	49.2	35

5 rows × 1610 columns

In [22]:

```
ef1 = ef.loc[:, ~ef.columns.duplicated()]
```

In [23]:

```
ef1.isnull().values.any()
```

Out[23]:

```
False
```

We thus see that we have no null values in our data set.

Also, given the way our dataset is defined, all of the 85794 locations are unique

In [18]:

```
ef1.info()
ef1.head(20)
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 85794 entries, 0 to 85793
Columns: 1382 entries, Longitude to Dec 2014
dtypes: float64(1382)
memory usage: 904.6 MB
```

Out[18]:

	Longitude	Latitude	Jan 1900	Feb 1900	Mar 1900	Apr 1900	May 1900	Jun 1900	Jul 1900	Aug 1900	...	Mar 2014	Apr 2014	May 2014	Jun 2014	Jul 2014	Aug 2014	Sep 2014	Oct 2014	Nov 2014
0	-179.75	71.25	0.0	1.4	1.9	5.5	6.3	12.7	7.7	37.1	...	10.9	6.9	0.0	5.0	7.3	6.8	22.2	10.2	11.1
1	-179.75	68.75	12.2	5.6	6.2	10.9	9.7	19.6	17.7	53.8	...	18.6	7.4	31.5	8.2	27.3	23.3	53.7	40.0	40.7
2	-179.75	68.25	11.7	7.1	6.2	11.4	9.1	21.2	18.9	56.0	...	20.7	6.5	44.1	8.6	31.5	25.3	45.5	39.6	42.2
3	-179.75	67.75	15.1	11.4	8.0	13.6	9.3	25.2	24.2	61.3	...	24.3	7.4	61.1	11.5	39.9	30.4	43.3	36.9	44.6
4	-179.75	67.25	20.6	16.7	10.5	16.3	9.5	29.9	30.0	67.0	...	28.5	9.1	72.0	13.3	49.8	36.6	44.7	30.6	49.2

	Longitude	Latitude	Jan 1900	Feb 1900	Mar 1900	Apr 1900	May 1900	Jun 1900	Jul 1900	Aug 1900	...	Mar 2014	Apr 2014	May 2014	Jun 2014	Jul 2014	Aug 2014	Sep 2014	Oct 2014	Nov 2014
5	-179.75	66.75	18.9	16.6	9.9	15.3	11.4	34.3	38.9	77.8	...	29.4	7.2	86.8	12.5	63.6	49.1	52.3	22.7	50.3
6	-179.75	66.25	14.6	14.7	8.9	14.2	15.5	40.9	54.2	94.6	...	29.8	5.9	97.3	15.2	81.5	66.4	62.1	19.6	49.7
7	-179.75	65.75	10.5	12.5	5.7	9.1	9.1	36.4	41.8	87.7	...	24.2	6.0	71.1	18.5	61.8	51.6	51.5	19.0	37.5
8	-179.75	65.25	10.4	10.1	5.6	6.9	6.9	34.7	34.8	82.1	...	22.0	8.7	46.9	24.1	47.6	39.9	44.5	24.7	30.1
9	-179.75	-16.75	384.3	341.8	401.9	214.0	43.2	189.9	65.7	244.9	...	278.9	202.1	250.7	157.1	103.2	103.6	61.0	276.2	237.6
10	-179.75	-84.75	49.4	49.4	0.0	13.8	1.6	30.5	0.0	16.2	...	8.9	2.3	11.5	0.0	0.0	0.0	0.0	16.6	15.4
11	-179.75	-85.25	48.9	47.5	0.0	10.6	0.0	32.6	0.0	17.4	...	5.3	0.8	7.7	0.0	0.0	0.0	0.0	11.0	9.7
12	-179.75	-85.75	47.9	45.3	0.0	7.4	0.0	33.2	0.0	17.8	...	2.5	0.0	4.5	0.0	0.0	0.0	0.0	6.4	5.2
13	-179.75	-86.25	47.6	44.8	0.0	6.3	0.0	33.4	0.0	18.2	...	1.9	0.0	3.7	0.0	0.0	0.0	0.0	5.1	4.1
14	-179.75	-86.75	46.0	42.0	0.0	3.5	0.0	32.7	0.0	17.9	...	0.0	0.0	0.6	0.0	0.0	0.0	0.0	0.9	0.0
15	-179.75	-87.25	45.5	41.6	0.0	2.7	0.0	32.3	0.0	18.1	...	0.0	0.0	0.1	0.0	0.0	0.0	0.0	0.0	0.0
16	-179.75	-87.75	45.2	41.3	0.0	2.3	0.0	31.8	0.0	18.1	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
17	-179.75	-88.25	44.9	41.3	0.0	1.8	0.0	31.4	0.0	18.1	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
18	-179.75	-88.75	44.6	41.2	0.0	1.5	0.0	30.9	0.0	18.2	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
19	-179.75	-89.25	44.5	41.2	0.0	0.3	0.0	30.8	0.0	18.2	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0

20 rows × 1382 columns

In [ ]:

```
ef1.to_csv("cleaned_MonthlyPrecipitation_Jan1900_to_Dec2014.csv", index=False, header=True)
```

In [19]:

```
ef1.describe()
```

Out[19]:

	Longitude	Latitude	Jan 1900	Feb 1900	Mar 1900	Apr 1900	May 1900	Jun 1900	Jul 1900	Aug '
count	85794.000000	85794.000000	85794.000000	85794.000000	85794.000000	85794.000000	85794.000000	85794.000000	85794.000000	85794.00
mean	18.436540	1.060109	48.431712	43.624701	41.093362	42.824277	38.047119	51.056387	52.437842	54.54
std	88.008337	57.848430	72.010699	60.525697	66.856413	67.345912	63.442895	80.688875	89.439978	77.32

	Longitude	Latitude	Jan 1900	Feb 1900	Mar 1900	Apr 1900	May 1900	Jun 1900	Jul 1900	Aug 1
min	-179.750000	-89.750000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.00
25%	-62.250000	-71.750000	7.300000	5.600000	0.000000	3.000000	0.000000	5.800000	0.000000	11.70
50%	28.250000	19.250000	26.000000	23.600000	14.300000	17.600000	16.000000	30.300000	19.100000	30.40
75%	93.750000	52.250000	54.000000	51.300000	50.300000	47.800000	43.300000	59.200000	71.400000	70.60
max	179.750000	83.250000	1003.200000	780.900000	742.100000	1633.700000	1107.800000	2661.900000	3213.700000	1347.30

8 rows × 1382 columns

EDA with our Data set:

In [24]:

```
# Let's plot the trends in mean monthly Precipitation in the year 1900 vs the mean of all years vs the year 2014


new1 = ef1.describe()
new1 = new1.astype(float)
listMonths = ["Jan", "Feb", "Mar", "Apr", "May", "Jun", "Jul", "Aug", "Sep", "Oct", "Nov", "Dec"]
for m in listMonths:
    listY = []
    # List of January months
    for x in range(1900,2015):
        yearS = str(x)
        month = m+ " " + yearS
        listY.append(month)

    # print(listY)
    # new1.convert_objects(convert_numeric=True).head()

    # Add mean columns of January
    new1["Avg"+m] = new1[listY].mean(axis=1)

#     new1["AvgJan"]
```

In [26]:

```
# Printing out mean monthly precipitation of mean of all years
meanPrecip = []
for m in listMonths:
    meanPrecip.append(new1["Avg"+m]["mean"])
```

```
meanPrecip
```

Out[26]:
```
[42.25716171496803,
 39.798554261928366,
 44.54618102411183,
 41.08075519621867,
 44.487637840287086,
 47.59720119274637,
 54.73063843524126,
 54.23993534563627,
 47.70267724204953,
 45.07384985876216,
 42.42358377144084,
 42.42554916681169]
```

In [42]:
```
# # Printing out mean monthly precipitation of year 1900
Precip1900 = []
for m in listMonths:
    Precip1900.append(new1[m+" 1900"]["mean"])

Precip1900
```

Out[42]:
```
[48.43171200783357,
 43.62470102804501,
 41.0933620066675,
 42.824276755950514,
 38.047118679627914,
 51.056387393058245,
 52.43784180711939,
 54.547067393990176,
 46.45499102501364,
 43.18918805510856,
 41.580483483693506,
 45.19333286709998]
```

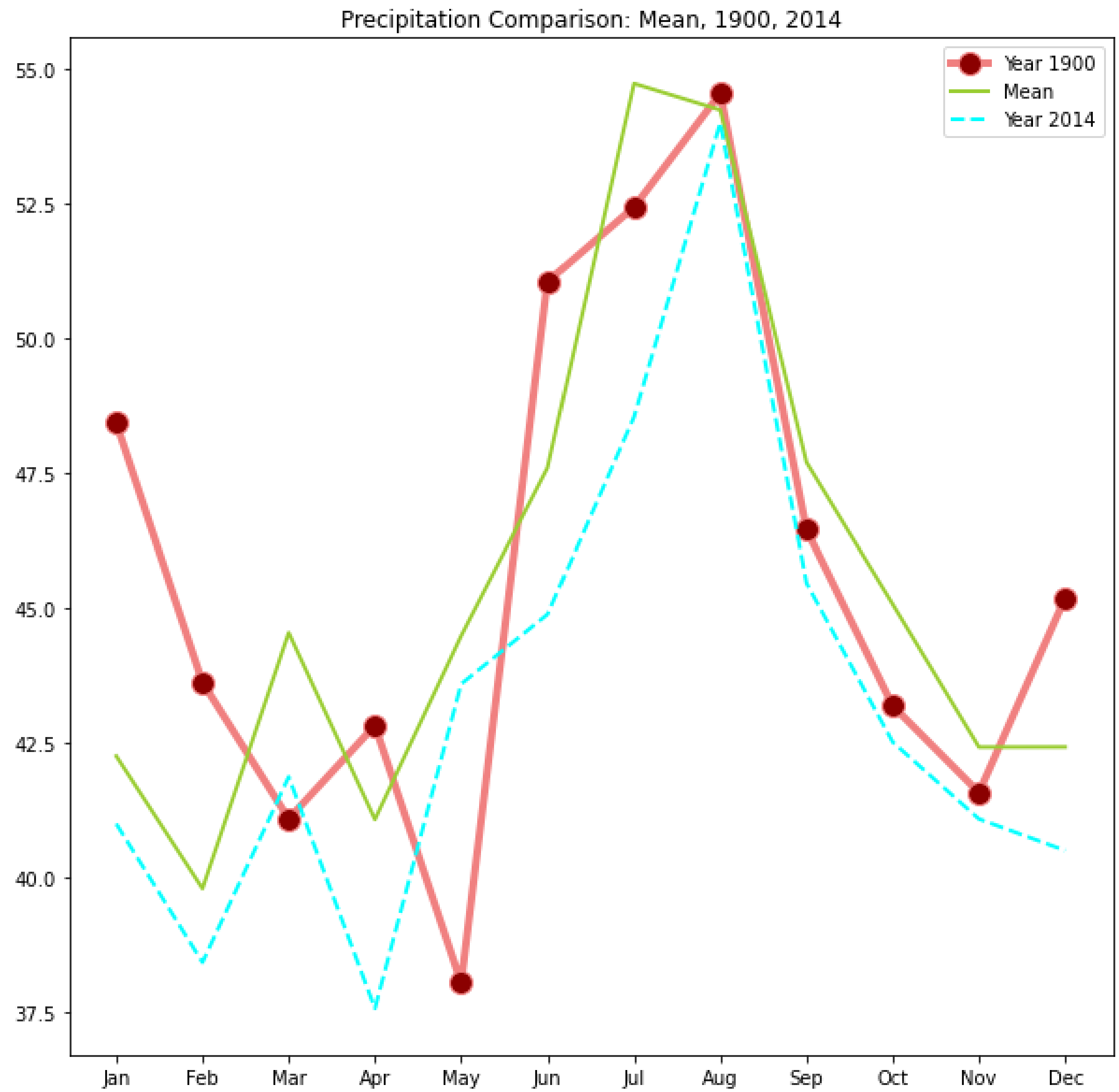
In [43]:
```
# # Printing out mean monthly precipitation of year 2014
Precip2014 = []
for m in listMonths:
    Precip2014.append(new1[m+" 2014"]["mean"])

Precip2014
```

Out[43]:
```
[41.00000699349686,
 38.42854045737573,
 41.87192810686132,
 37.57269739142694,
 43.59436440776849,
```

```
44.88581369326578,
48.54476769937399,
54.003677413340164,
45.46583793738552,
42.51642655663561,
41.08969508357368,
40.504176282725794]
```

In [66]:

```
# Plotting the mean monthly Precipitation in the year 1900 vs the mean of all years vs the year 2014
plt.figure(figsize=(10, 10))
plt.title("Precipitation Comparison: Mean, 1900, 2014")

plt.plot(listMonths,Precip1900, label="Year 1900",marker='o',markerfacecolor='darkred',markersize=12,color='lightcoral',
         linewidth=4)

plt.plot(listMonths,meanPrecip, label="Mean",marker='',color='yellowgreen',
         linewidth=2)

plt.plot(listMonths,Precip2014, label="Year 2014",marker='',color='cyan',
         linewidth=2, linestyle = "dashed")

# plt.label("Year 1900")
plt.legend()
fig1 = plt.gcf()
plt.show()


fig1.savefig('precippppp.png', bbox_inches='tight')
```



In [27]:

```
# Now let's plot the trends in mean monthly Temperature in the year 1900 vs the mean of all years vs the year 2014


new2 = df1.describe()
new2 = new2.astype(float)
listMonths = ["Jan", "Feb", "Mar", "Apr", "May", "Jun", "Jul", "Aug", "Sep", "Oct", "Nov", "Dec"]
for m in listMonths:
    listY = []
```

```
    # List of January months
    for x in range(1900,2015):
        yearS = str(x)
        month = m+ " " + yearS
        listY.append(month)

    # print(listY)
    # new1.convert_objects(convert_numeric=True).head()

    # Add mean columns of January
    new2["Avg"+m] = new2[listY].mean(axis=1)

#     new1["AvgJan"]
```

In [28]:

```
# Printing out mean monthly temperature of mean of all years
meanTemp = []
for m in listMonths:
    meanTemp.append(new2["Avg"+m]["mean"])

print (meanTemp)

# Printing out mean monthly temperature of year 1900
Temp1900 = []
for m in listMonths:
    Temp1900.append(new2[m+" 1900"]["mean"])

print(Temp1900)

# Printing out mean monthly temperature of year 2014
Temp2014 = []
for m in listMonths:
    Temp2014.append(new2[m+" 2014"]["mean"])

Temp2014
```

```
[-7.436555348453474, -9.073614634042505, -9.1744681648965, -6.910142981519938, -3.9133071736039082, -1.551567201922502, -
0.6835402698678623, -1.4546657666341318, -3.102605198904147, -4.666632844498097, -5.694412237199119, -6.320863189986943]
[-8.415361214070925, -9.0448714362311, -8.795384292607785, -6.884104949064119, -3.7499475487796783, -1.5428969391798921,
-1.2465219012984567, -1.6077895890155576, -2.9789390866494023, -4.2512215306431225, -5.945491526213908, -6.30959391099600
9]
```

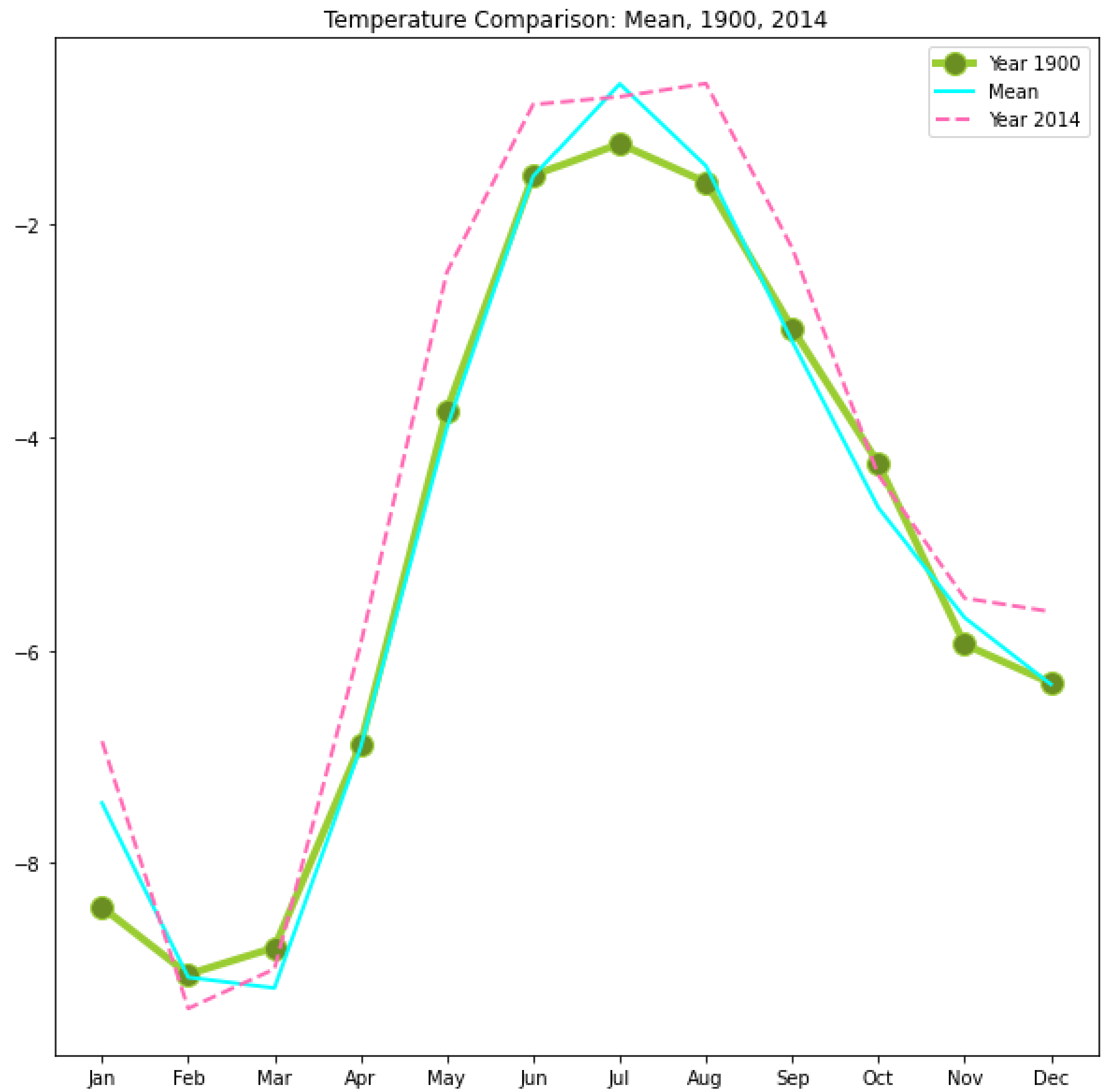
Out[28]:

```
[-6.855600624752311,
 -9.36664218943026,
 -8.996130265519659,
 -5.943503042170706,
 -2.4533627060167467,
 -0.8774891018019868,
```

```
-0.8037356924726528,
-0.6801419679697651,
-2.226570622654268,
-4.361294496118648,
-5.511663985826508,
-5.637958365386899]
```

In [67]:

```python
# Plotting the mean monthly Temperature in the year 1900 vs the mean of all years vs the year 2014
plt.figure(figsize=(10, 10))
plt.title("Temperature Comparison: Mean, 1900, 2014")

plt.plot(listMonths,Temp1900, label="Year 1900",marker='o',markerfacecolor='olivedrab',markersize=12,color='yellowgreen',
         linewidth=4)

plt.plot(listMonths,meanTemp, label="Mean",marker='',color='cyan',
         linewidth=2)

plt.plot(listMonths,Temp2014, label="Year 2014",marker='',color='hotpink',
         linewidth=2, linestyle = "dashed")

# plt.label("Year 1900")
plt.legend()
fig2 = plt.gcf()

plt.show()

fig2.savefig('tempppppp.png', bbox_inches='tight')
```



Executing our model using Linear Regression:

In [46]:
```
# Find the mean annual precipitation for every location

dfPrecip['mean'] = dfPrecip.mean(axis=1)
dfPrecip
```

Out[46]:

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	
0	17.906886	11.710341	1.247260e+01	4.905435	3.059161	5.958738e+00	1.024784e+01	1.200584e+01	1.559985e+01	1.147546e+01	10.2
1	27.772241	22.034911	1.751727e+01	9.456831	23.178640	1.534989e+01	2.868153e+01	3.378672e+01	4.942416e+01	4.055705e+01	30.8
2	28.057248	25.427971	1.857660e+01	9.217719	29.491328	1.529094e+01	3.255547e+01	3.415742e+01	4.155990e+01	4.043054e+01	31.8
3	30.724294	31.681006	2.110698e+01	10.539274	37.674670	1.769305e+01	4.213071e+01	3.787658e+01	3.814262e+01	3.952282e+01	34.3
4	33.887307	38.706987	2.434751e+01	12.559512	42.270961	2.022752e+01	5.418735e+01	4.210935e+01	3.707040e+01	3.738716e+01	39.2
...	...	...	...	...	...	...	...	...	...	...	
85789	0.050000	0.009071	2.372787e-07	0.010156	0.022266	3.439163e-09	2.270498e-07	9.894113e-10	3.434279e-09	2.443962e-05	0.0
85790	0.100000	0.006238	2.258466e-07	0.009570	0.021680	2.372254e-09	1.434443e-07	7.513912e-10	2.667238e-09	1.224385e-05	0.0
85791	0.100000	0.004395	3.908398e-04	0.009180	0.021289	1.491885e-09	8.368202e-08	5.254227e-10	1.902378e-09	4.835544e-08	0.0
85792	0.100098	0.002478	3.125206e-03	0.008594	0.021289	8.120668e-10	4.784343e-08	2.965450e-10	1.144090e-09	4.806924e-08	0.0
85793	0.100902	0.002246	6.250100e-03	0.008008	0.021289	2.587613e-10	1.197063e-08	1.055027e-10	3.799821e-10	1.201745e-08	0.0

85794 rows × 13 columns

Finding best train-test split

In [52]:

```python
from sklearn.model_selection import train_test_split
from sklearn import datasets, linear_model
from sklearn.metrics import mean_squared_error, r2_score

mse = []
possible_splits = [0.10,0.15,0.20,0.25,0.30]
for sz in possible_splits:
    # Finding the best train-test split
    X_train, X_test, y_train, y_test = train_test_split(dfTemp, dfPrecip['mean'], test_size=sz)

    # Linear Regression
    # Create linear regression object
    regr = linear_model.LinearRegression()

    # Train the model using the training sets
    regr.fit(X_train, y_train)
```

```
    my_pred = regr.predict(X_test)

    # The mean squared error
    current_mse = mean_squared_error(y_test, my_pred)
    mse.append(current_mse)
    print('Mean squared error: %.2f'
          % current_mse)
```

```
Mean squared error: 1775.05
Mean squared error: 1808.93
Mean squared error: 1751.75
Mean squared error: 1817.26
Mean squared error: 1770.22
```

In [60]:
```
# Finding the best split
n = np.argmin(mse)

print ('The best test size for train-test split is', possible_splits[n])
```

```
The best test size for train-test split is 0.2
```

Training our model with the 80-20 split

In [62]:
```
from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(dfTemp, dfPrecip['mean'], test_size=0.20)
```

In [48]:
```
#  Right now our dataset looks like this:
#        X = X_train   + X_test
# 80K rows = 60k rows + 20k rows

#        y = y_train   + y_test
# 80K rows = 60k rows + 20k rows
```

In [50]:
```
from sklearn import datasets, linear_model

# Linear Regression
# Create linear regression object
regr = linear_model.LinearRegression()

# Train the model using the training sets
regr.fit(X_train, y_train)
```

Out[50]:
```
LinearRegression()
```

Prediciting on our model

In [64]:
```
my_pred = regr.predict(X_test)
```

Analyzing the results

In [66]:
```
from sklearn.metrics import mean_squared_error, r2_score

# The coefficients
print('Coefficients: \n', regr.coef_)
# The mean squared error
print('Mean squared error: %.2f'
      % mean_squared_error(y_test, my_pred))
# The coefficient of determination: 1 is perfect prediction
print('Coefficient of determination: %.2f'
      % r2_score(y_test, my_pred))
```

```
Coefficients: 
 [-2.28791131  4.57552108 -2.26940253  1.89933999 -1.58942057 -0.76093129
  3.0483552   1.00016227 -3.03739748  0.06332089 -1.73389818  2.45792963]
Mean squared error: 1785.76
Coefficient of determination: 0.34
```

In [90]:
```
import statsmodels.api as sm
from scipy import stats


diabetes = datasets.load_diabetes()
X = dfTemp
y = dfPrecip['mean']

X2 = sm.add_constant(X)
est = sm.OLS(y, X2)
est2 = est.fit()
print(est2.summary())
```

```
                            OLS Regression Results                            
==============================================================================
Dep. Variable:                   mean   R-squared:                       0.342
Model:                            OLS   Adj. R-squared:                  0.342
Method:                 Least Squares   F-statistic:                     3714.
Date:                Tue, 27 Apr 2021   Prob (F-statistic):               0.00
Time:                        18:49:47   Log-Likelihood:            -4.4355e+05
No. Observations:               85794   AIC:                         8.871e+05
```

```
Df Residuals:                   85781   BIC:                         8.873e+05
Df Model:                          12
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const         56.9556      0.293    194.397      0.000      56.381      57.530
Jan           -2.2737      0.097    -23.553      0.000      -2.463      -2.085
Feb            4.5432      0.111     41.049      0.000       4.326       4.760
Mar           -2.2279      0.125    -17.781      0.000      -2.473      -1.982
Apr            1.8786      0.127     14.841      0.000       1.631       2.127
May           -1.5960      0.119    -13.373      0.000      -1.830      -1.362
Jun           -0.7114      0.136     -5.239      0.000      -0.978      -0.445
Jul            2.9740      0.143     20.756      0.000       2.693       3.255
Aug            0.9925      0.141      7.035      0.000       0.716       1.269
Sep           -2.9911      0.177    -16.852      0.000      -3.339      -2.643
Oct            0.0591      0.136      0.434      0.665      -0.208       0.326
Nov           -1.6936      0.112    -15.138      0.000      -1.913      -1.474
Dec            2.4070      0.097     24.819      0.000       2.217       2.597
==============================================================================
Omnibus:                    39683.307   Durbin-Watson:                   0.199
Prob(Omnibus):                  0.000   Jarque-Bera (JB):           466974.787
Skew:                           1.923   Prob(JB):                         0.00
Kurtosis:                      13.763   Cond. No.                         198.
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
```

Observation: We see that only the mean temperatures in February, April, July, August, and December have an impact on the mean precipitation. This is because the t-values of these variables are considerably bigger than 0. The mean squared error on this model is also the least among all the other models.

Thus our Equation for Linear regression model looks like this:

(without including random error)

```
**y = -2.2737 * X1 + 4.5432 * X2 - 2.2279 * X3 + 1.8786 * X4  - 1.5960 * X5  - 0.7114 * X6  +

       2.9740 * X7 + 0.9925 * X8 - 2.9911 * X9 + 0.0591 * X10 - 1.6936 * X11 + 2.4070 * X12 + 56.9556**
```

Here,

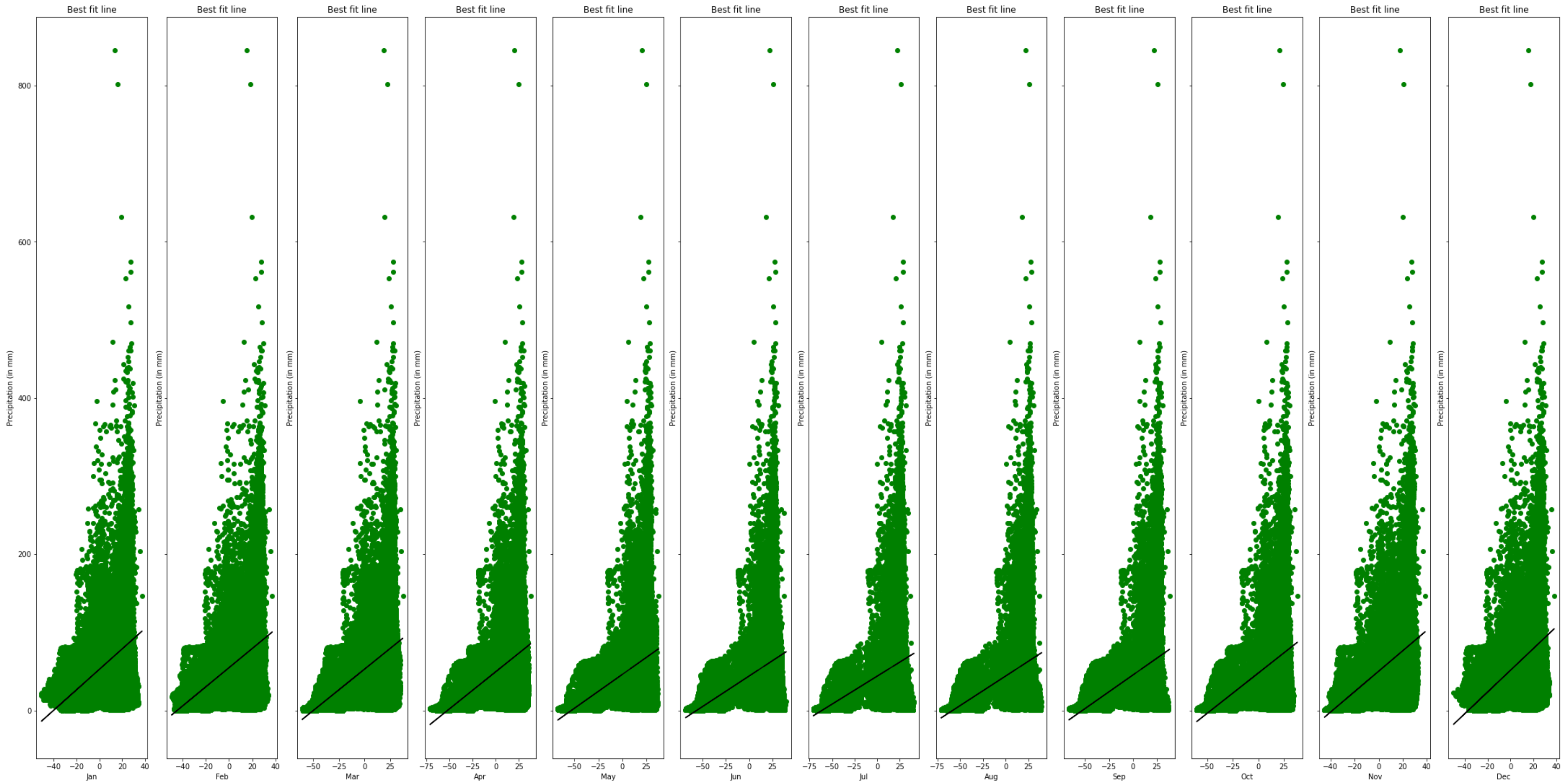
y = Annual mean precipitation

X1 = Monthly mean temperature in January
X2 = Monthly mean temperature in February
X3 = Monthly mean temperature in March
X4 = Monthly mean temperature in April
X5 = Monthly mean temperature in May
X6 = Monthly mean temperature in June
X7 = Monthly mean temperature in July
X8 = Monthly mean temperature in August
X9 = Monthly mean temperature in Sepetember
X10 = Monthly mean temperature in October
X11 = Monthly mean temperature in November
X12 = Monthly mean temperature in December

Plotting our linear regression for each feature

In [77]:

```
# Plotting our linear regression for every feature
# Reference: https://stackoverflow.com/a/52464283

train_copy =pd.get_dummies(X_train)
train_copy=train_copy.fillna(0)
clf = linear_model.LinearRegression()

fig, axes = plt.subplots(1,len(train_copy.columns.values),sharey=True,constrained_layout=True,figsize=(30,15))

for i,e in enumerate(train_copy.columns):
  clf.fit(train_copy[e].values[:,np.newaxis], y_train)
  axes[i].set_title("Best fit line")
  axes[i].set_xlabel(str(e))
  axes[i].set_ylabel('Precipitation (in mm)')
  axes[i].scatter(train_copy[e].values[:,np.newaxis], y_train,color='g')
  axes[i].plot(train_copy[e].values[:,np.newaxis],
  clf.predict(train_copy[e].values[:,np.newaxis]),color='k')
```



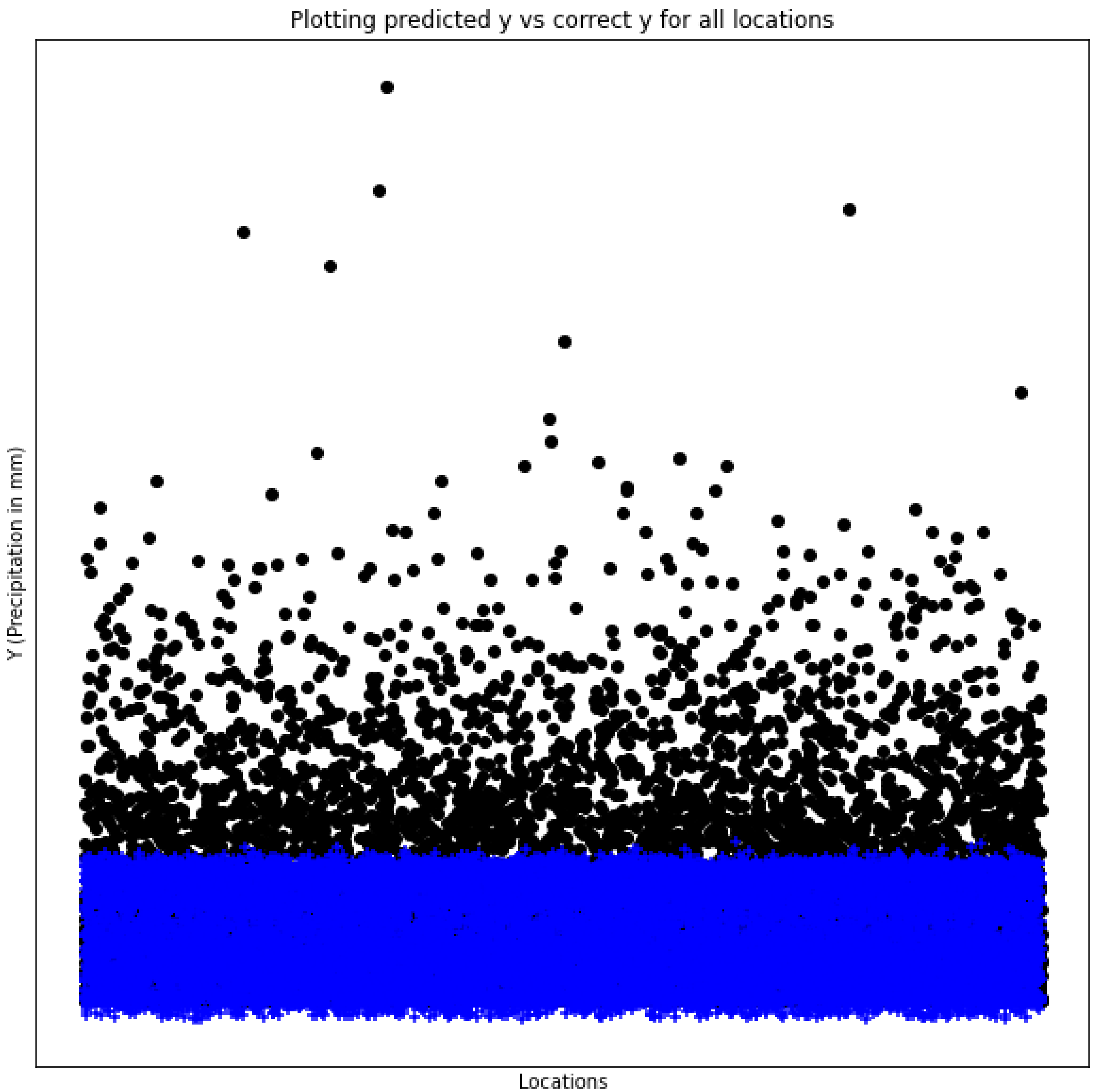
Observation: We see that as the Temperature increases, our linear regression model faces more outliers, which is what accounts for more errors for the model

Plotting our predicted y and actual test y to see how they coincide

In [91]:
```
## Plotting our predicted y and actual test y to see how they coincide
plt.figure(figsize=(10, 10))
print(X_test.shape)
print(y_test.shape)
print(my_pred.shape)

myListMonths = ["Jan", "Feb", "Mar", "Apr", "May", "Jun", "Jul", "Aug", "Sep", "Oct", "Nov", "Dec"]
myEx = list(range(1,17160))

print(len(myEx))
```

```python
# Plot outputs
plt.scatter(myEx, y_test,  color='black')
plt.scatter(myEx, my_pred, color='blue',marker='+')
plt.xlabel('Locations')
plt.ylabel('Y (Precipitation in mm)')
plt.title('Plotting predicted y vs correct y for all locations')
plt.xticks(())
plt.yticks(())

plt.show()
```

```
(17159, 12)
(17159,)
(17159,)
17159
```



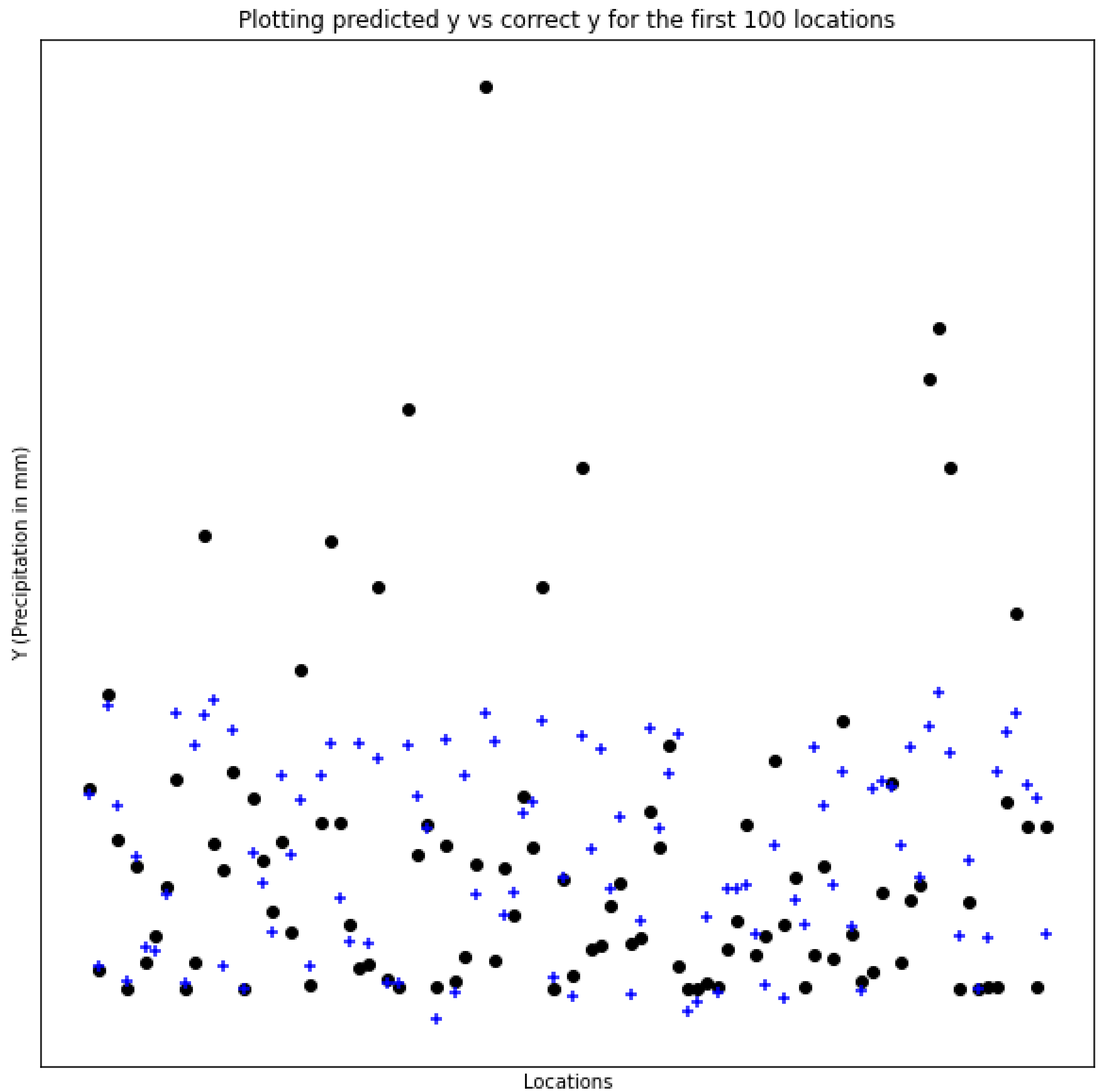
Observation: We do see that values in the lower range are better predicted. Let's take only the first 100 values for a better view

In [100…

```
plt.figure(figsize=(10, 10))
print(X_test.shape)
print(y_test.shape)
print(my_pred.shape)

myListMonths = ["Jan", "Feb", "Mar", "Apr", "May", "Jun", "Jul", "Aug", "Sep", "Oct", "Nov", "Dec"]
```

```python
myEx = list(range(1,17160))

print(len(myEx))

# Plot outputs
plt.scatter(myEx[:100], y_test[:100],  color='black')
plt.scatter(myEx[:100], my_pred[:100], color='blue', marker='+')
plt.xlabel('Locations')
plt.ylabel('Y (Precipitation in mm)')
plt.title('Plotting predicted y vs correct y for the first 100 locations')
plt.xticks(())
plt.yticks(())
plt.show()
```

```
(17159, 12)
(17159,)
(17159,)
17159
```



Observation: We thus see that the model predicts the values correctly for those locations who have a lower precipitation value. As the value increase and as there are more outliers, the model somewhat fails to predict those values correctly

Common FAQs for this model:

What are the features of the model? Why?

The features of the model are each of the months of January, February, March, April, May, June, July, August, Sepetember, October, November, and December. The reason for choosing these features is because the trends in annual precipitation vary vastly with respect to monthly temperature depending on which month of the year it is.
A small practical example of this could be that these days we experience more fluctuations in precipitation in some months, when all of the months have almost same changes in temperature due to global warming

How was the data cleaned? We checked if there are any null values, and while there were not any, we did spot some 0 values, which means the data was already cleaned before usage

Conclusion:

Mean Annual Precipitations is influenced by the mean monthly temperatures in the months of February, April, July, August, and December. Therefore, it might be more probable to experience sudden, unexpected or excessive rainfall in these months over a year. Lastly, there is a relationship between the global mean monthly temperatures and annual precipitation based on the results of our model. In conclusion, our findings would be extremely helpful in deciding the plan of action taken by humans in order to protect from the dangers of climate change.