Load Packages

In [15]:
```
# packages used in this tutorial
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import matplotlib.dates as mdates
import seaborn as sns
from sklearn.preprocessing import StandardScaler
import joblib
```

Load CSVs

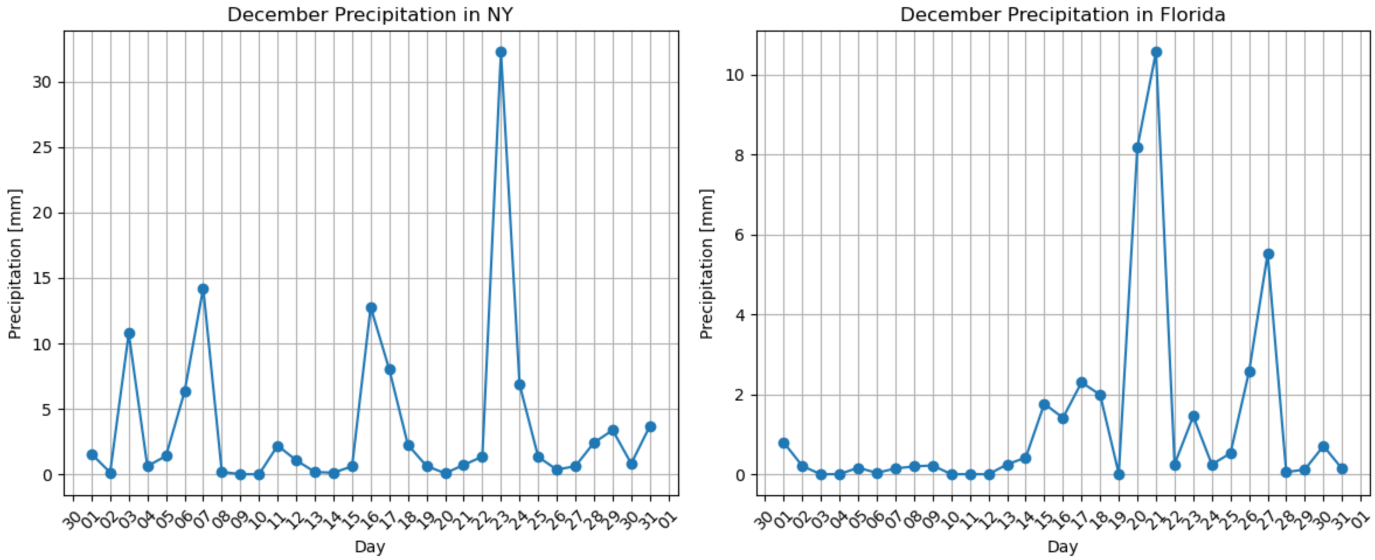
In [2]:
```
ny = pd.read_csv(f'CSVafterClean2/ny_12.csv')
fl = pd.read_csv(f'CSVafterClean3/_12.csv')
```

Precipitation vs Time

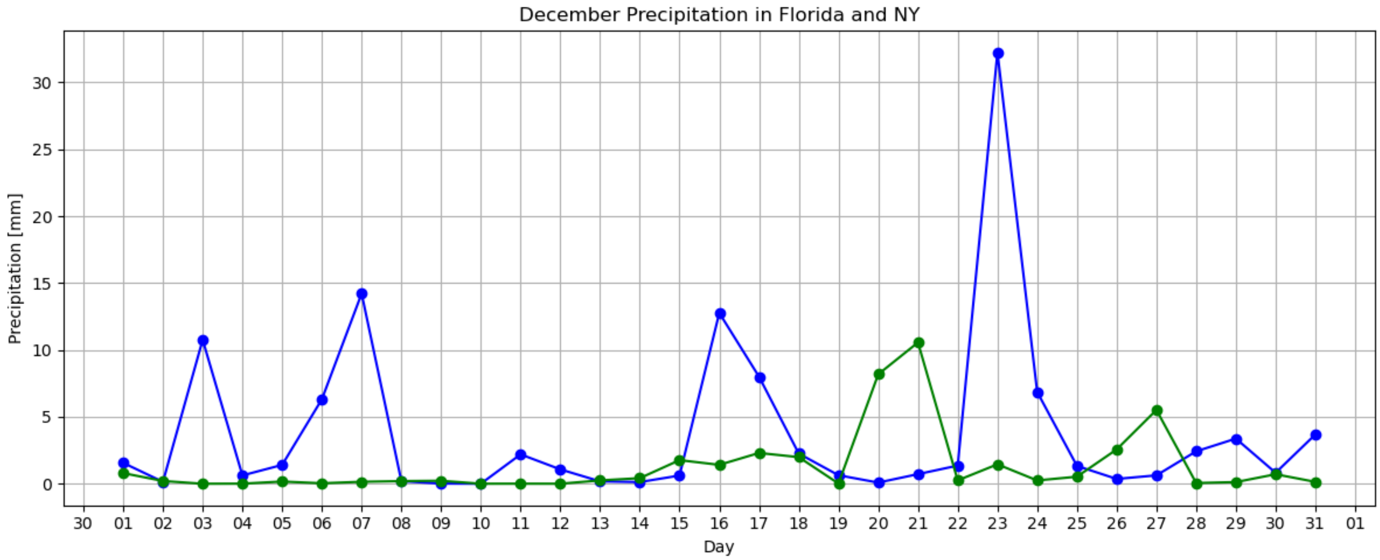
In [3]:
```
#initialize dfs
ny_snip = ny
fl_snip = fl

# Convert 'time' column to datetime
ny_snip['time'] = pd.to_datetime(ny_snip['time'])
fl_snip['time'] = pd.to_datetime(fl_snip['time'])

# Group by date and calculate the average precipitation for each day
ny_snip = ny_snip.groupby(ny_snip['time'].dt.date)['prcp_total'].mean().reset_index()  #c
fl_snip = fl_snip.groupby(fl_snip['time'].dt.date)['prcp_total'].mean().reset_index()

#print('New York',ny_snip)
#print('Florida',fl_snip)
```

In [4]:
```
# Create subplots with two line graphs
plt.figure(figsize=(12, 5))  # Adjust the figure size as needed

plt.subplot(1, 2, 1)  # 1 row, 2 columns, subplot 1
plt.plot(ny_snip['time'], ny_snip['prcp_total'], marker='o', linestyle='-')
plt.xlabel('Day')
plt.ylabel('Precipitation [mm]')
plt.title('December Precipitation in NY')
plt.grid(True)

# Format the x-axis ticks to show one label per day
plt.xticks(rotation=45)  # Rotate x-axis labels for better visibility
# Format the x-axis ticks to show one label per month
plt.gca().xaxis.set_major_formatter(mdates.DateFormatter('%d'))
plt.gca().xaxis.set_major_locator(mdates.DayLocator(interval=1))  # Set tick interval to

plt.subplot(1, 2, 2)  # 1 row, 2 columns, subplot 2
plt.plot(fl_snip['time'], fl_snip['prcp_total'], marker='o', linestyle='-')
plt.xlabel('Day')
plt.ylabel('Precipitation [mm]')
plt.title('December Precipitation in Florida')
plt.grid(True)

# Format the x-axis ticks to show one label per day
plt.xticks(rotation=45)  # Rotate x-axis labels for better visibility
```

```
# Format the x-axis ticks to show one label per month
plt.gca().xaxis.set_major_formatter(mdates.DateFormatter('%d'))
plt.gca().xaxis.set_major_locator(mdates.DayLocator(interval=1))  # Set tick interval to

plt.tight_layout()  # Adjust spacing between subplots
plt.show()
```



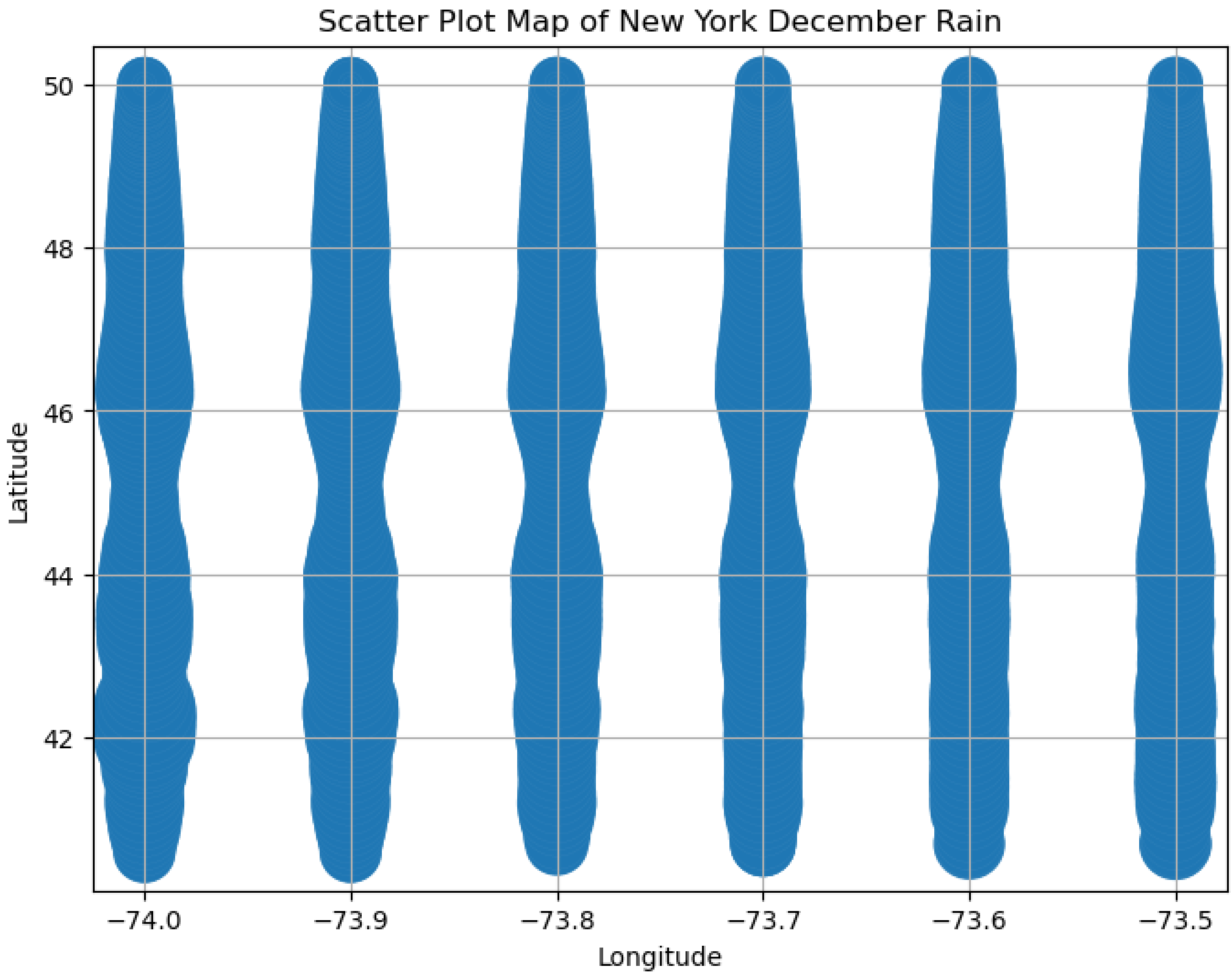
In [5]:
```
# Create subplots with two line graphs
plt.figure(figsize=(12, 5))  # Adjust the figure size as needed

plt.plot(ny_snip['time'], ny_snip['prcp_total'], color = 'b', marker='o', linestyle='-')
plt.xlabel('Day')
plt.ylabel('Precipitation [mm]')
plt.title('December Precipitation in NY')
plt.grid(True)

# Format the x-axis ticks to show one label per month
plt.gca().xaxis.set_major_formatter(mdates.DateFormatter('%d'))
plt.gca().xaxis.set_major_locator(mdates.DayLocator(interval=1))  # Set tick interval to

plt.plot(fl_snip['time'], fl_snip['prcp_total'], color = 'g', marker='o', linestyle='-')
plt.xlabel('Day')
plt.ylabel('Precipitation [mm]')
plt.title('December Precipitation in Florida and NY')
plt.grid(True)

# Format the x-axis ticks to show one label per month
plt.gca().xaxis.set_major_formatter(mdates.DateFormatter('%d'))
plt.gca().xaxis.set_major_locator(mdates.DayLocator(interval=1))  # Set tick interval to

plt.tight_layout()  # Adjust spacing between subplots
plt.show()
```



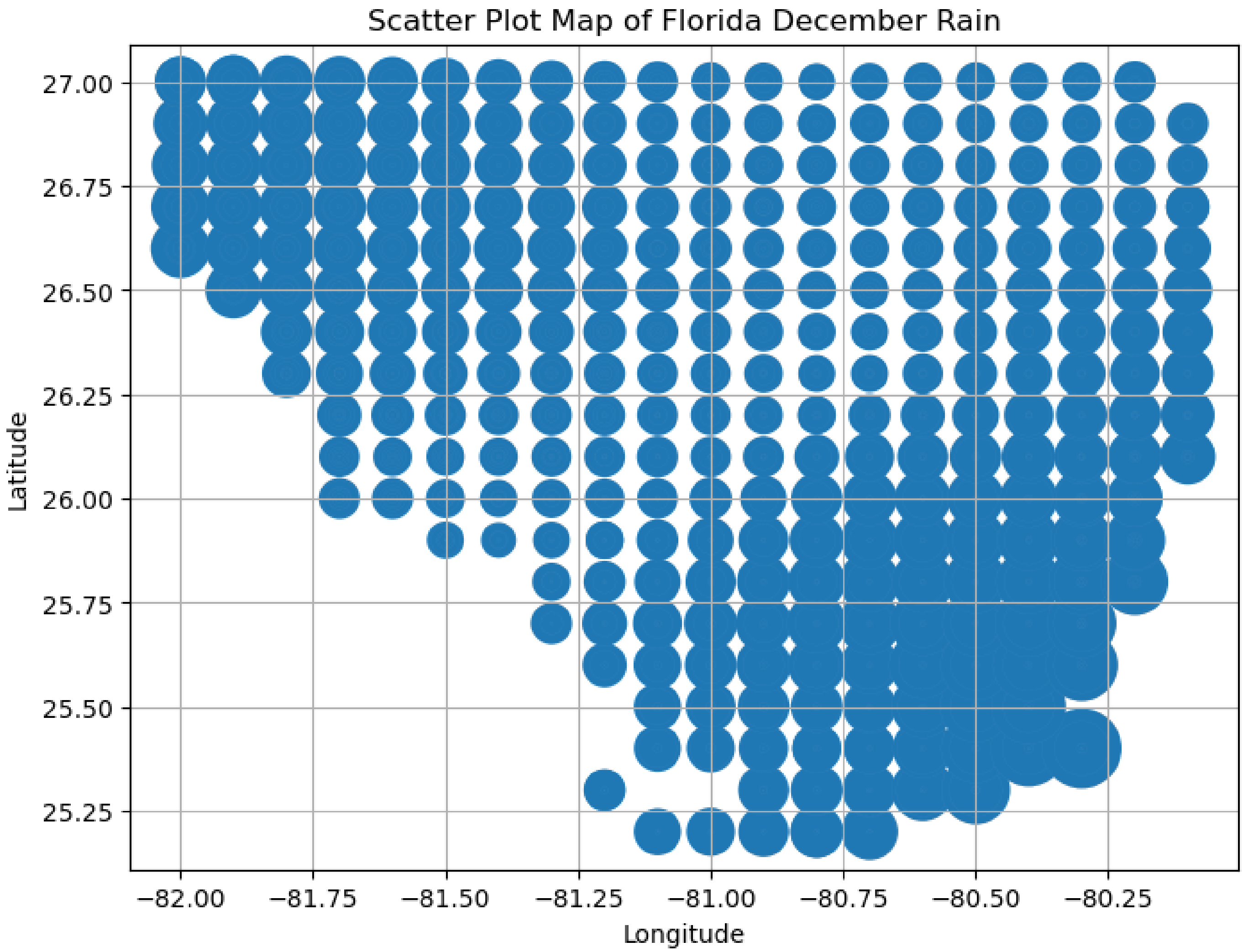
Spatial Distribution

In [6]:
```
locations = {'New York': ny, 'Florida': fl}

for location, df in locations.items():
    plt.figure(figsize=(8, 6))
    sns.scatterplot(x='lon', y='lat', data=df, marker='o', s=df['prcp_total']*30)
    plt.title(f"Scatter Plot Map of {location} December Rain")
    plt.xlabel("Longitude")
    plt.ylabel("Latitude")
    plt.grid(True)
    # Save the plot to a file (optional)
    # plt.savefig(f"CSVafterClean/map_prpc_{location}.png", dpi=300, bbox_inches='tight'
    # Show the plot (optional)
    plt.show()
```

```
C:\Users\yepesim\Anaconda3\envs\PakiMod\lib\site-packages\matplotlib\collections.py:981:
RuntimeWarning: invalid value encountered in sqrt
  scale = np.sqrt(self._sizes) * dpi / 72.0 * self._factor
C:\Users\yepesim\Anaconda3\envs\PakiMod\lib\site-packages\matplotlib\collections.py:981:
RuntimeWarning: invalid value encountered in sqrt
  scale = np.sqrt(self._sizes) * dpi / 72.0 * self._factor
```




```
C:\Users\yepesim\Anaconda3\envs\PakiMod\lib\site-packages\matplotlib\collections.py:981:
RuntimeWarning: invalid value encountered in sqrt
  scale = np.sqrt(self._sizes) * dpi / 72.0 * self._factor
C:\Users\yepesim\Anaconda3\envs\PakiMod\lib\site-packages\matplotlib\collections.py:981:
RuntimeWarning: invalid value encountered in sqrt
  scale = np.sqrt(self._sizes) * dpi / 72.0 * self._factor
```



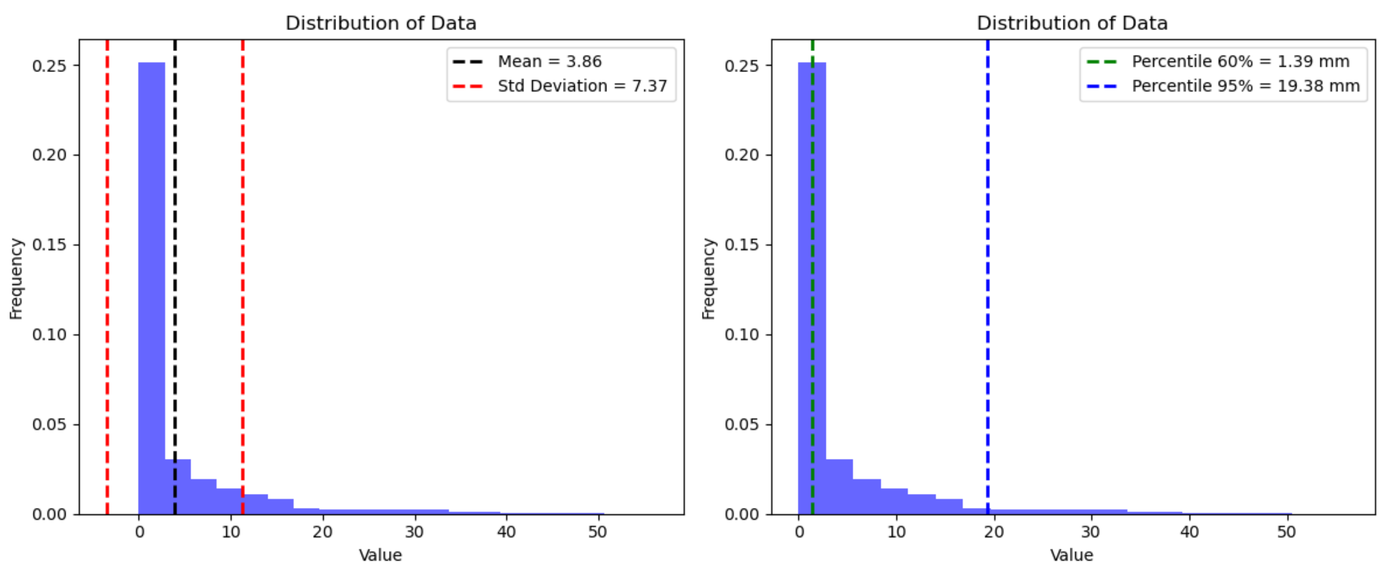
Group Categorically

In [7]:

```
def catAn(df):
    df = df['next_day_prcp_total']
    # Calculate statistics
    mean = np.mean(df)
    std_dev = np.std(df)
    # Calculate the percentiles
    a = 0.6
    b = 0.95
    percentile_a = df.quantile(a)
    percentile_b = df.quantile(b)
    # Count data points within the percentile ranges
    count_below_a = np.sum(df < percentile_a)
    count_a_to_b = np.sum((df >= percentile_a) & (df <= percentile_b))
    count_above_b = np.sum(df > percentile_b)

    # Create subplots with two histograms
    plt.figure(figsize=(12, 5))  # Adjust the figure size as needed

    plt.subplot(1, 2, 1)  # 1 row, 2 columns, subplot 1
    plt.hist(df, bins=20, density=True, alpha=0.6, color='b')
    plt.axvline(mean, color='k', linestyle='dashed', linewidth=2, label=f"Mean = {mean:.
    plt.axvline(mean + std_dev, color='r', linestyle='dashed', linewidth=2, label=f"Std
    plt.axvline(mean - std_dev, color='r', linestyle='dashed', linewidth=2)
    plt.legend()
    plt.title("Distribution of Data")
    plt.xlabel("Value")
    plt.ylabel("Frequency")
```

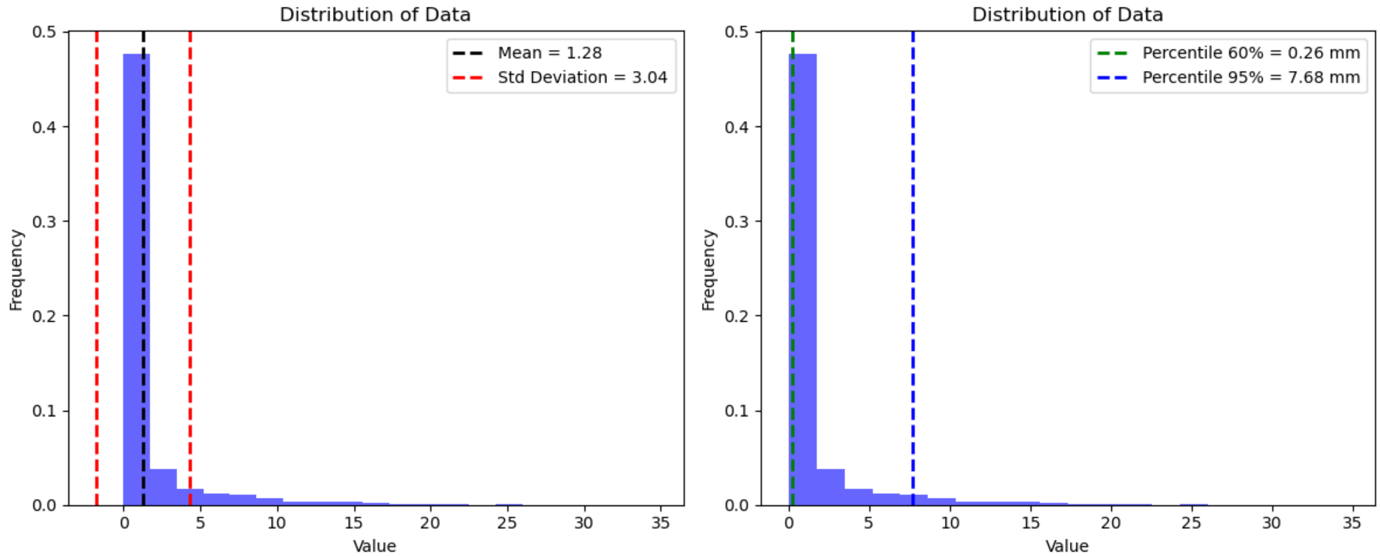
```
    plt.subplot(1, 2, 2)  # 1 row, 2 columns, subplot 2
    plt.hist(df, bins=20, density=True, alpha=0.6, color='b')
    plt.axvline(percentile_a, color='g', linestyle='dashed', linewidth=2, label=f"Percen
    plt.axvline(percentile_b, color='b', linestyle='dashed', linewidth=2, label=f"Percen
    plt.legend()
    plt.title("Distribution of Data")
    plt.xlabel("Value")
    plt.ylabel("Frequency")

    plt.tight_layout()  # Adjust spacing between subplots
    plt.show()

    print('Category 0 is from 0 to ' + str(round(percentile_a, 3)) + ' mm of rain')
    print(f"Number of data points below the {a*100}% percentile: {count_below_a}")
    print('Category 1 is from ' + str(round(percentile_a, 3)) + ' mm of rain to ' + str(
    print(f"Number of data points in the {a*100}% to {b*100}% range: {count_a_to_b}")
    print('Category 2 is from ' + str(round(percentile_b, 3)) + ' mm of rain to the maxi
    print(f"Number of data points above the {b*100}% percentile: {count_above_b}")

    # Create categorical labels based on percentiles
    dfCol = pd.cut(
        df,
        bins=[float('-inf'), percentile_a, percentile_b, float('inf')],
        labels=['0', '1', '2']
    )

    return dfCol
```

In [8]:
```
ny['nxtpr_cat'] = catAn(ny)
```




```
Category 0 is from 0 to 1.391 mm of rain
Number of data points below the 60.0% percentile: 10452
Category 1 is from 1.391 mm of rain to 19.378 mm of rain
Number of data points in the 60.0% to 95.0% range: 6098
Category 2 is from 19.378 mm of rain to the maximum
Number of data points above the 95.0% percentile: 872
```

In [9]:
```
fl['nxtpr_cat'] = catAn(fl)
```




```
Category 0 is from 0 to 0.255 mm of rain
Number of data points below the 60.0% percentile: 5189
Category 1 is from 0.255 mm of rain to 7.678 mm of rain
Number of data points in the 60.0% to 95.0% range: 3027
Category 2 is from 7.678 mm of rain to the maximum
Number of data points above the 95.0% percentile: 433
```

Data

In [10]:
```
print(ny[['next_day_prcp_total', 'nxtpr_cat']])
```

```
       next_day_prcp_total  nxtpr_cat
0                 0.000858          0
1                10.728631          1
2                 0.001715          0
3                 0.001715          0
4                 3.843783          1
...                    ...        ...
17417             1.180921          0
17418            11.342675          1
17419             3.285482          1
17420             1.258963          0
17421             0.165100          0

[17422 rows x 2 columns]
```

In [11]:
```
print(fl[['next_day_prcp_total', 'nxtpr_cat']])
```

```
      next_day_prcp_total  nxtpr_cat
0                0.428093          1
1                0.001057          0
2                0.000529          0
3                0.016912          0
4                0.125785          0
...                   ...        ...
8644             0.228316          0
8645             0.025368          0
8646             0.935990          1
8647             0.420694          1
8648             0.082199          0

[8649 rows x 2 columns]
```

Load Models

In [12]:
```
# Load the Neural Network model using joblib
model_nn = joblib.load("nn_rain_ext.pkl")

# Load the Random Forest model using joblib
model_rf = joblib.load("rf_rain_ext.pkl")

# Load the XGBoost model using joblib
model_xg = joblib.load("xg_rain_ext.pkl")

print("Models Loaded")
```

```
Models Loaded
```

Generate Predictions

In [13]:
```
def gen_pred(df):
    exclude = ['next_day_prcp_total', 'nxtpr_cat', 'time', 'lat', 'lon']
    features = df.loc[:, ~df.columns.isin(exclude)]
    col_names = features.columns
    #standardize features with a standard scaler,
        #since model was trained on standardized features, if you omit this then the mod
        #will output wildly high magnitude quantities
    s_scaler = StandardScaler()
    features = s_scaler.fit_transform(features)
    features = pd.DataFrame(features, columns=col_names)
    pred_nn = model_nn.predict(features)
    pred_rf = model_rf.predict(features)
    pred_xg = model_xg.predict(features)

    df['nn_pred'] = pred_nn # separate assigning it to df as a column bc otherwise the f
    df['rf_pred'] = pred_rf
    df['xg_pred'] = pred_xg

    return df
```

In [16]:
```
pred_ny = ny
pred_fl = fl
pred_ny = gen_pred(pred_ny)
pred_fl = gen_pred(pred_fl)
pred_ny = pred_ny.loc[:,['next_day_prcp_total', 'nxtpr_cat','time','nn_pred','rf_pred','
pred_fl = pred_fl.loc[:,['next_day_prcp_total', 'nxtpr_cat','time','nn_pred','rf_pred','
```

```
545/545 [==============================] - 0s 639us/step
271/271 [==============================] - 0s 657us/step
```

In [17]:
```
pred_ny
```

Out[17]:

	next_day_prcp_total	nxtpr_cat	time	nn_pred	rf_pred	xg_pred
0	0.000858	0	2022-12-01	0.634672	0	1
1	10.728631	1	2022-12-02	-0.045112	0	0
2	0.001715	0	2022-12-03	4.335457	1	0
3	0.001715	0	2022-12-04	2.169055	1	1
4	3.843783	1	2022-12-05	1.781298	1	1
...	...	...	...	...	...	...
17417	1.180921	0	2022-12-27	0.768045	0	0
17418	11.342675	1	2022-12-28	0.537940	0	0
17419	3.285482	1	2022-12-29	-1.607829	0	1

17420	1.258963	0	2022-12-30	2.423182	1	1
17421	0.165100	0	2022-12-31	4.790707	1	1

17422 rows × 6 columns

In [18]:
```
pred_fl
```

Out[18]:

	next_day_prcp_total	nxtpr_cat	time	nn_pred	rf_pred	xg_pred
0	0.428093	1	2022-12-01	0.161013	1	1
1	0.001057	0	2022-12-02	-0.474769	0	1
2	0.000529	0	2022-12-03	0.286668	1	0
3	0.016912	0	2022-12-04	1.496689	0	0
4	0.125785	0	2022-12-05	1.083910	1	1
...	...	...	...	...	...	...
8644	0.228316	0	2022-12-27	0.028671	0	1
8645	0.025368	0	2022-12-28	2.582936	0	0
8646	0.935990	1	2022-12-29	0.283035	1	1
8647	0.420694	1	2022-12-30	2.906575	0	1
8648	0.082199	0	2022-12-31	2.465597	1	1

8649 rows × 6 columns

In [19]:
```
pred_ny.dtypes
```

Out[19]:
```
next_day_prcp_total             float64
nxtpr_cat                      category
time                     datetime64[ns]
nn_pred                         float32
rf_pred                          object
xg_pred                           int64
dtype: object
```

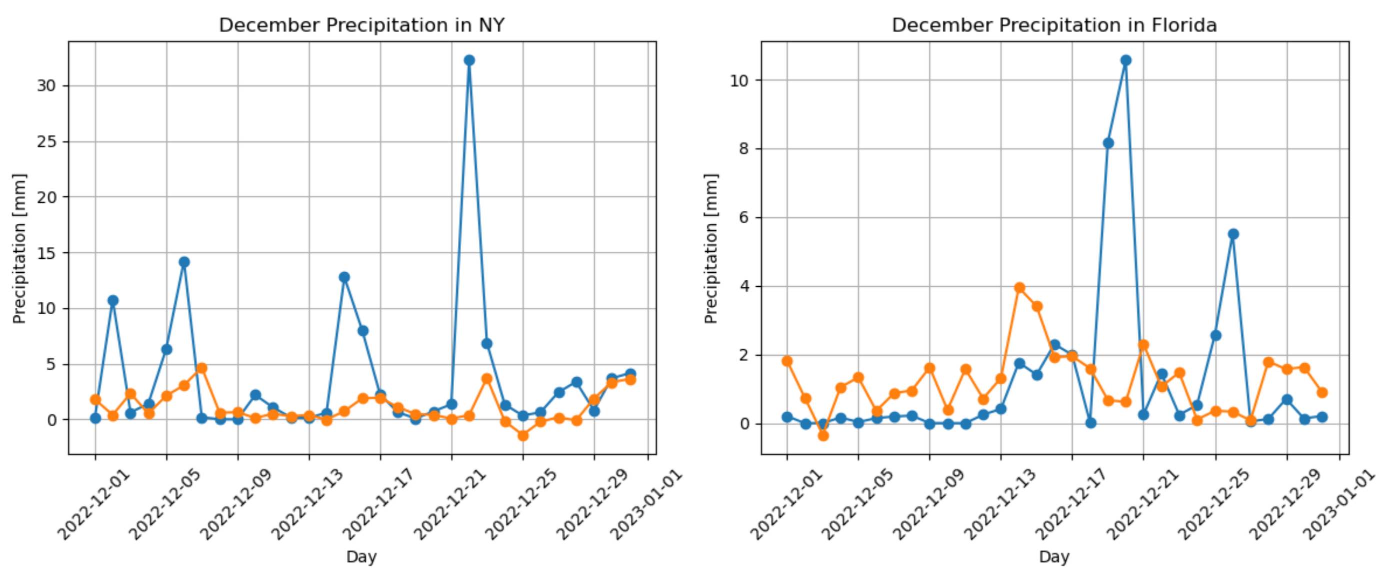
In [20]:
```
# Check for NA values in 'xg_pred' column
xg_pred_na = pred_ny['xg_pred'].isna().sum()

# Check for NA values in 'rf_pred' column
rf_pred_na = pred_ny['rf_pred'].isna().sum()

# Check for NA values in 'nxtpr_cat' column
nxtpr_cat_na = pred_ny['nxtpr_cat'].isna().sum()

print(f'NA values in xg_pred: {xg_pred_na}')
print(f'NA values in rf_pred: {rf_pred_na}')
print(f'NA values in nxtpr_cat: {nxtpr_cat_na}')
```

```
NA values in xg_pred: 0
NA values in rf_pred: 0
NA values in nxtpr_cat: 0
```

Evaluate Neural Network Regression

In [21]:
```
# Initialize DataFrames
ny_snip_pred = pred_ny.copy()
```

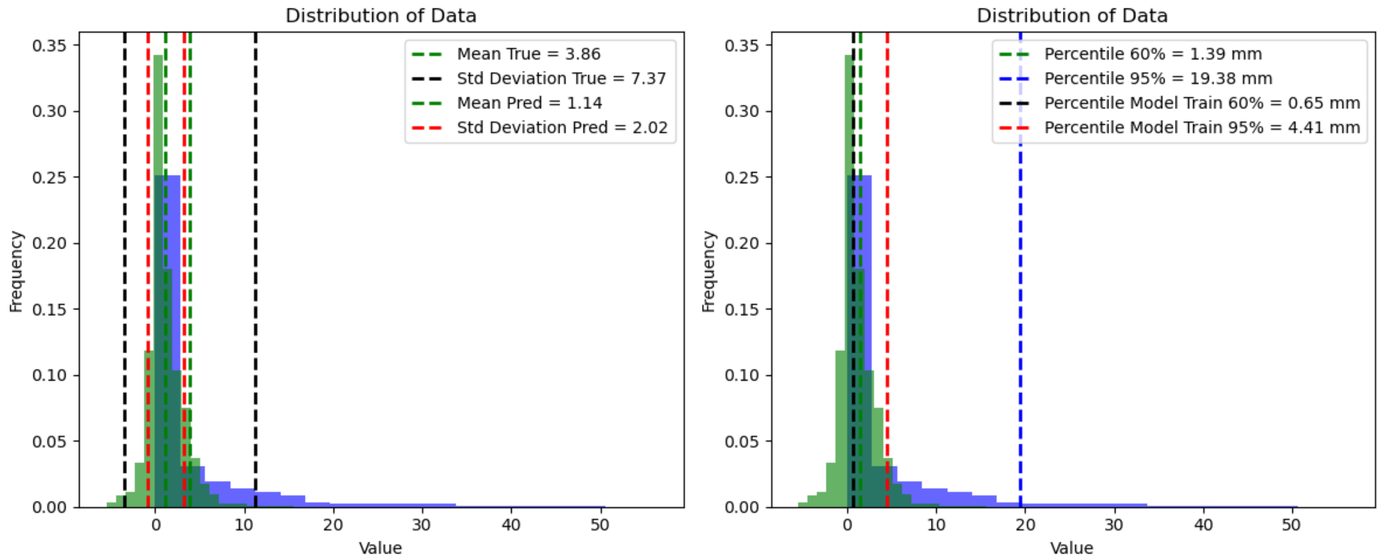
```
fl_snip_pred = pred_fl.copy()

# Convert 'time' column to datetime
ny_snip_pred['time'] = pd.to_datetime(ny_snip_pred['time'])
fl_snip_pred['time'] = pd.to_datetime(fl_snip_pred['time'])

# Group by date and calculate the average precipitation for each day
ny_snip_pred = ny_snip_pred.groupby(ny_snip_pred['time'].dt.date)[['next_day_prcp_total'
fl_snip_pred = fl_snip_pred.groupby(fl_snip_pred['time'].dt.date)[['next_day_prcp_total'

# Create subplots with two line graphs
plt.figure(figsize=(12, 5))

# Plot NY data
plt.subplot(1, 2, 1)
plt.plot(ny_snip_pred['time'], ny_snip_pred['next_day_prcp_total'], marker='o', linestyl
plt.plot(ny_snip_pred['time'], ny_snip_pred['nn_pred'], marker='o', linestyle='-', label
plt.xlabel('Day')
plt.ylabel('Precipitation [mm]')
plt.title('December Precipitation in NY')
plt.grid(True)
plt.xticks(rotation=45)

# Plot FL data
plt.subplot(1, 2, 2)
plt.plot(fl_snip_pred['time'], fl_snip_pred['next_day_prcp_total'], marker='o', linestyl
plt.plot(fl_snip_pred['time'], fl_snip_pred['nn_pred'], marker='o', linestyle='-', label
plt.xlabel('Day')
plt.ylabel('Precipitation [mm]')
plt.title('December Precipitation in Florida')
plt.grid(True)
plt.xticks(rotation=45)

plt.tight_layout()  # Adjust spacing between subplots
plt.show()
```



In [82]:
```
def compare(df, model):
    if model == 'nn':
            df1 = df['next_day_prcp_total']
            df2 = df['nn_pred']
            bins = 20
    if model == 'rf':
            df1 = df['nxtpr_cat']
            df2 = df['rf_pred']
            bins = 3
    if model == 'xg':
            df1 = df['nxtpr_cat']
```

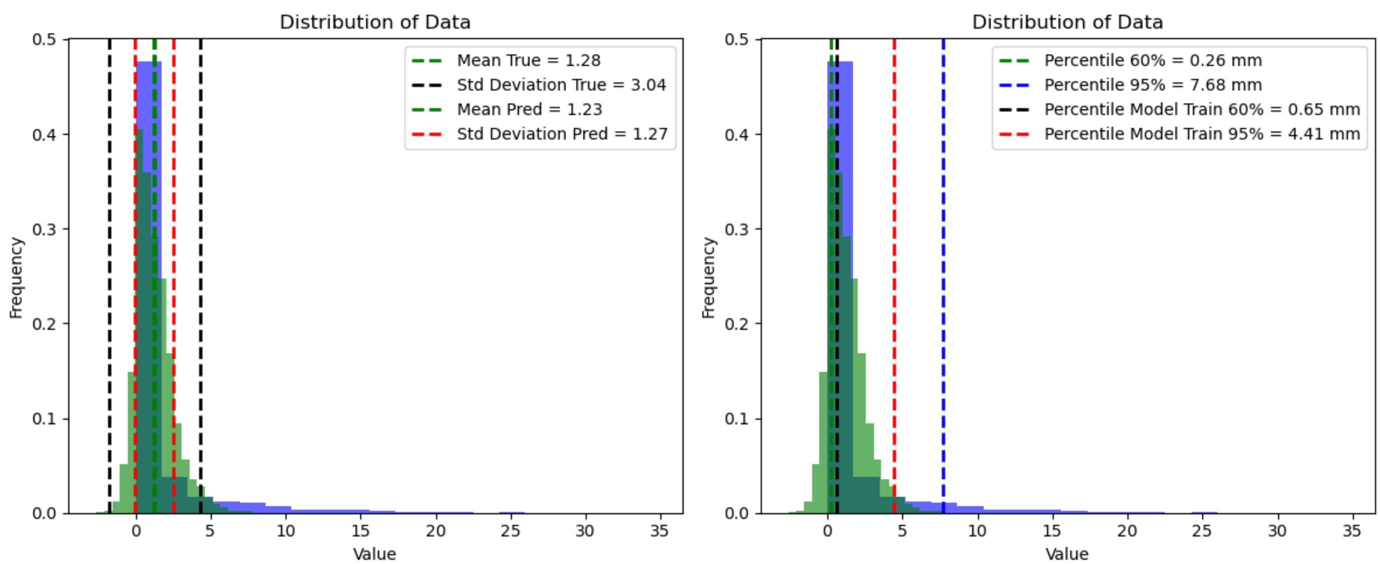
```
        df2 = df['xg_pred']
        bins = 3
# Calculate statistics
dfc = df['next_day_prcp_total']
dfp = df['nn_pred']
mean1 = np.mean(dfc)
std_dev1 = np.std(dfc)
mean2 = np.mean(dfp)
std_dev2 = np.std(dfp)
# Calculate the percentiles
a = 0.6
b = 0.95
percentile_a = dfc.quantile(a)
percentile_b = dfc.quantile(b)
percApred = 0.649 #model was trained on
percBpred = 4.408 #model was trained on
# Count data points within the percentile ranges
count_below_a = np.sum(dfc < percApred)
count_a_to_b = np.sum((dfc >= percApred) & (dfc <= percBpred))
count_above_b = np.sum(dfc > percBpred)

# Create subplots with two histograms
if model == 'nn':
    plt.figure(figsize=(12, 5))  # Adjust the figure size as needed

    plt.subplot(1, 2, 1)  # 1 row, 2 columns, subplot 1
    plt.hist(df1, bins=bins, density=True, alpha=0.6, color='b')
    plt.hist(df2, bins=bins, density=True, alpha=0.6, color='g')
    plt.axvline(mean1, color='g', linestyle='dashed', linewidth=2, label=f"Mean True
    plt.axvline(mean1 + std_dev1, color='k', linestyle='dashed', linewidth=2, label=
    plt.axvline(mean1 - std_dev1, color='k', linestyle='dashed', linewidth=2)
    plt.axvline(mean2, color='g', linestyle='dashed', linewidth=2, label=f"Mean Pred
    plt.axvline(mean2 + std_dev2, color='r', linestyle='dashed', linewidth=2, label=
    plt.axvline(mean2 - std_dev2, color='r', linestyle='dashed', linewidth=2)
    plt.legend()
    plt.title("Distribution of Data")
    plt.xlabel("Value")
    plt.ylabel("Frequency")

    plt.subplot(1, 2, 2)  # 1 row, 2 columns, subplot 2

plt.hist(df1, bins=bins, density=True, alpha=0.6, color='b')
plt.hist(df2, bins=bins, density=True, alpha=0.6, color='g')
if model != 'nn':
    plt.axvline(0, color='k', linestyle='dashed', linewidth=2, label=f"Greater than
    plt.axvline(2, color='b', linestyle='dashed', linewidth=2, label=f"Greater than
if model == 'nn':
    plt.axvline(percentile_a, color='g', linestyle='dashed', linewidth=2, label=f"Pe
    plt.axvline(percentile_b, color='b', linestyle='dashed', linewidth=2, label=f"Pe
    plt.axvline(percApred, color='k', linestyle='dashed', linewidth=2, label=f"Perce
    plt.axvline(percBpred, color='r', linestyle='dashed', linewidth=2, label=f"Perce
plt.legend()
plt.title("Distribution of Data")
plt.xlabel("Value")
plt.ylabel("Frequency")

plt.tight_layout()  # Adjust spacing between subplots
plt.show()

print('Category 0 is from 0 to ' + str(round(percApred, 3)) + ' mm of rain')
print(f"Number of data points below the {a*100}% percentile: {count_below_a}")
print('Category 1 is from ' + str(round(percApred, 3)) + ' mm of rain to ' + str(rou
print(f"Number of data points in the {a*100}% to {b*100}% range: {count_a_to_b}")
print('Category 2 is from ' + str(round(percBpred, 3)) + ' mm of rain to the maximum
print(f"Number of data points above the {b*100}% percentile: {count_above_b}")
```

In [83]:
```
compare(pred_ny, 'nn')
```




```
Category 0 is from 0 to 0.649 mm of rain
Number of data points below the 60.0% percentile: 9141
Category 1 is from 0.649 mm of rain to 4.408 mm of rain
Number of data points in the 60.0% to 95.0% range: 4171
Category 2 is from 4.408 mm of rain to the maximum
Number of data points above the 95.0% percentile: 4110
```

In [84]:
```
compare(pred_fl, 'nn')
```




```
Category 0 is from 0 to 0.649 mm of rain
Number of data points below the 60.0% percentile: 6261
Category 1 is from 0.649 mm of rain to 4.408 mm of rain
Number of data points in the 60.0% to 95.0% range: 1602
Category 2 is from 4.408 mm of rain to the maximum
Number of data points above the 95.0% percentile: 786
```

Regression Discussion:

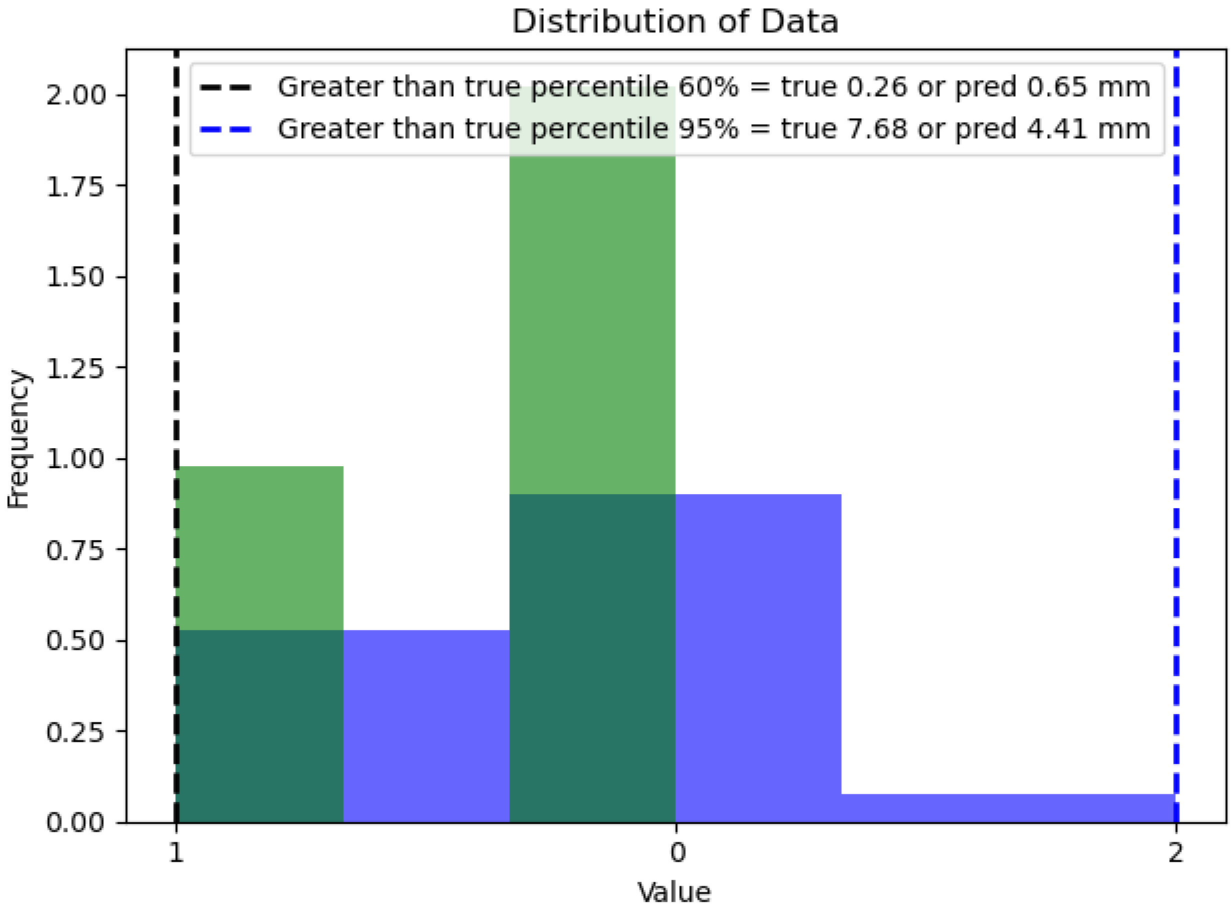
Could above results be due to **outlier removal** during model training? Could performance improve with more epochs? Also, the negative predictions should not be allowed in model building.

Secondly it is a bit of a disconnection between the percentile amounts the model was trained on versus the percentile amount present in the external data, the assumption that justifies the difference is that the location's exact rainfall quantities are not as indicative as the relative distribution of extreme rainfall events

(2/above 95% percentile), moderate rainfall events (1/between 95th and 60th percentile), or low rainfall events (0/below 60th percentile).

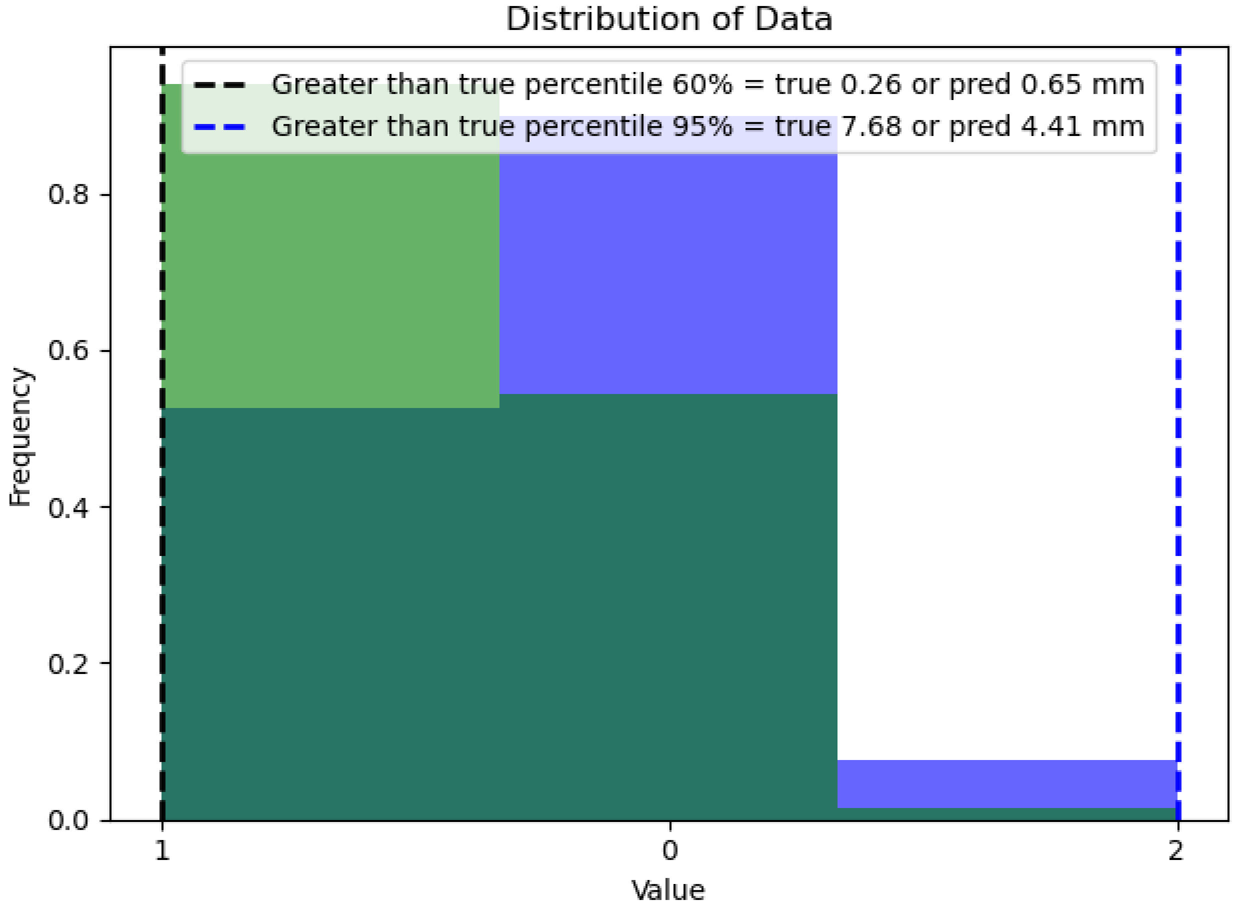
Evaluate Random Forest & XGBoost Classifiers

In [85]:
```
compare(pred_fl, 'rf')
```



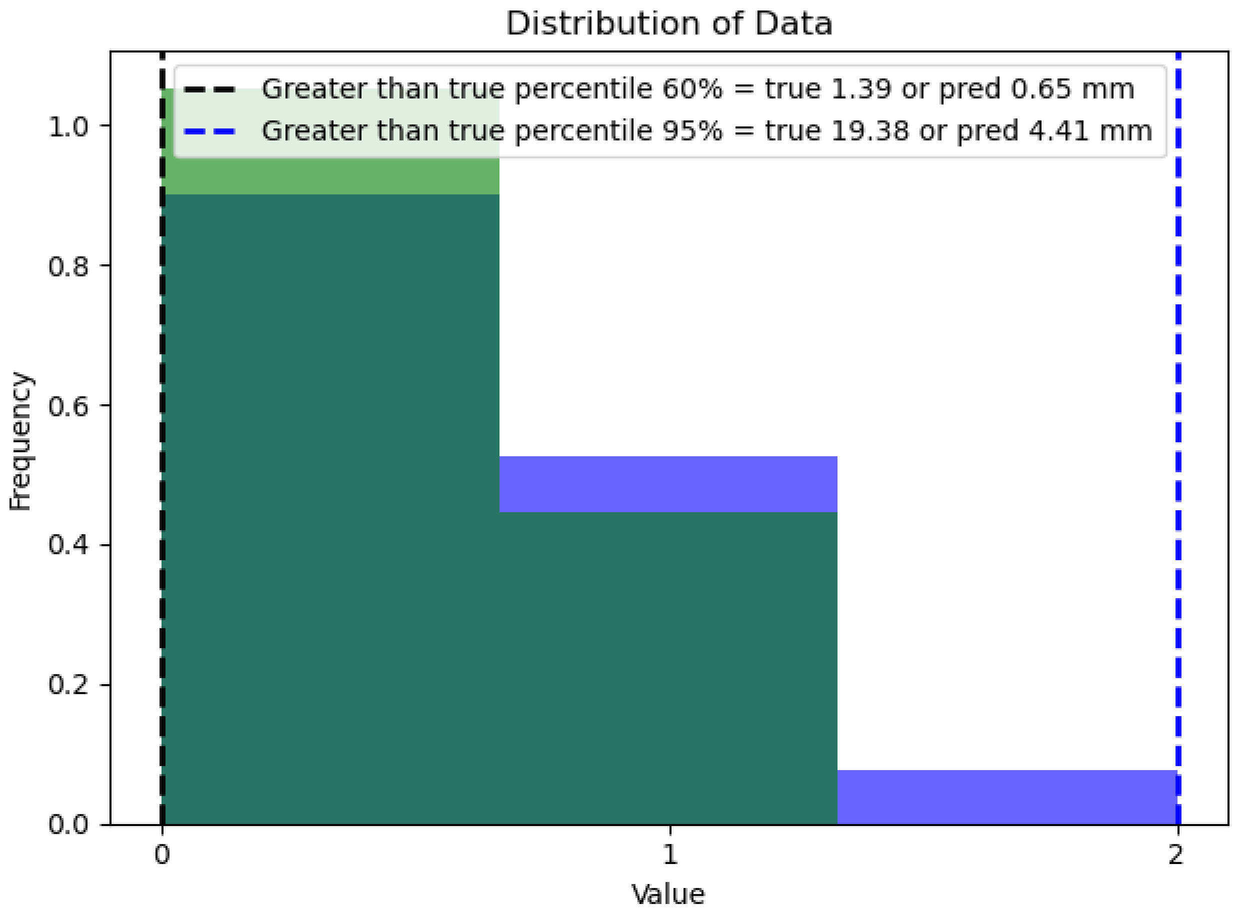

```
Category 0 is from 0 to 0.649 mm of rain
Number of data points below the 60.0% percentile: 6261
Category 1 is from 0.649 mm of rain to 4.408 mm of rain
Number of data points in the 60.0% to 95.0% range: 1602
Category 2 is from 4.408 mm of rain to the maximum
Number of data points above the 95.0% percentile: 786
```

In [86]:
```
compare(pred_fl, 'xg')
```



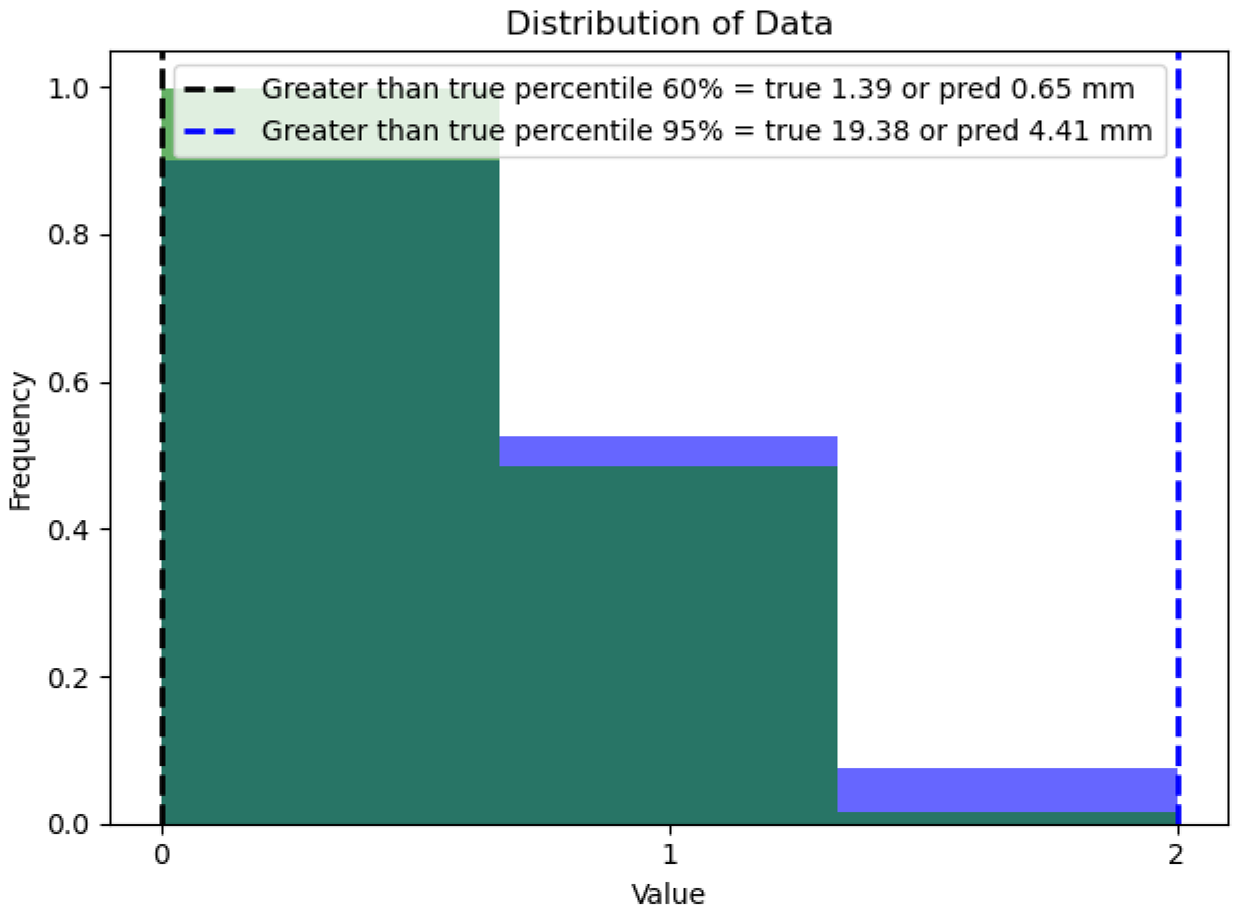

```
Category 0 is from 0 to 0.649 mm of rain
Number of data points below the 60.0% percentile: 6261
Category 1 is from 0.649 mm of rain to 4.408 mm of rain
Number of data points in the 60.0% to 95.0% range: 1602
Category 2 is from 4.408 mm of rain to the maximum
Number of data points above the 95.0% percentile: 786
```

In [87]:
```
compare(pred_ny, 'rf')
```




```
Category 0 is from 0 to 0.649 mm of rain
Number of data points below the 60.0% percentile: 9141
Category 1 is from 0.649 mm of rain to 4.408 mm of rain
Number of data points in the 60.0% to 95.0% range: 4171
Category 2 is from 4.408 mm of rain to the maximum
Number of data points above the 95.0% percentile: 4110
```

In [88]:
```
compare(pred_ny, 'xg')
```




```
Category 0 is from 0 to 0.649 mm of rain
Number of data points below the 60.0% percentile: 9141
Category 1 is from 0.649 mm of rain to 4.408 mm of rain
Number of data points in the 60.0% to 95.0% range: 4171
Category 2 is from 4.408 mm of rain to the maximum
Number of data points above the 95.0% percentile: 4110
```

Classifiers Discussion

Visually, it seems the XGBoost does a better job than Random Forest. Also, it visually seems that both classifiers better predict New York's Rainfall better than South Florida's.

A confusion matrix and F1 score could be implemented to evaluate the classifiers' performance further.