Load Packages

In [1]:
```
# 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
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay
from sklearn.metrics import accuracy_score, cohen_kappa_score, classification_report
import joblib
```

Load CSVs

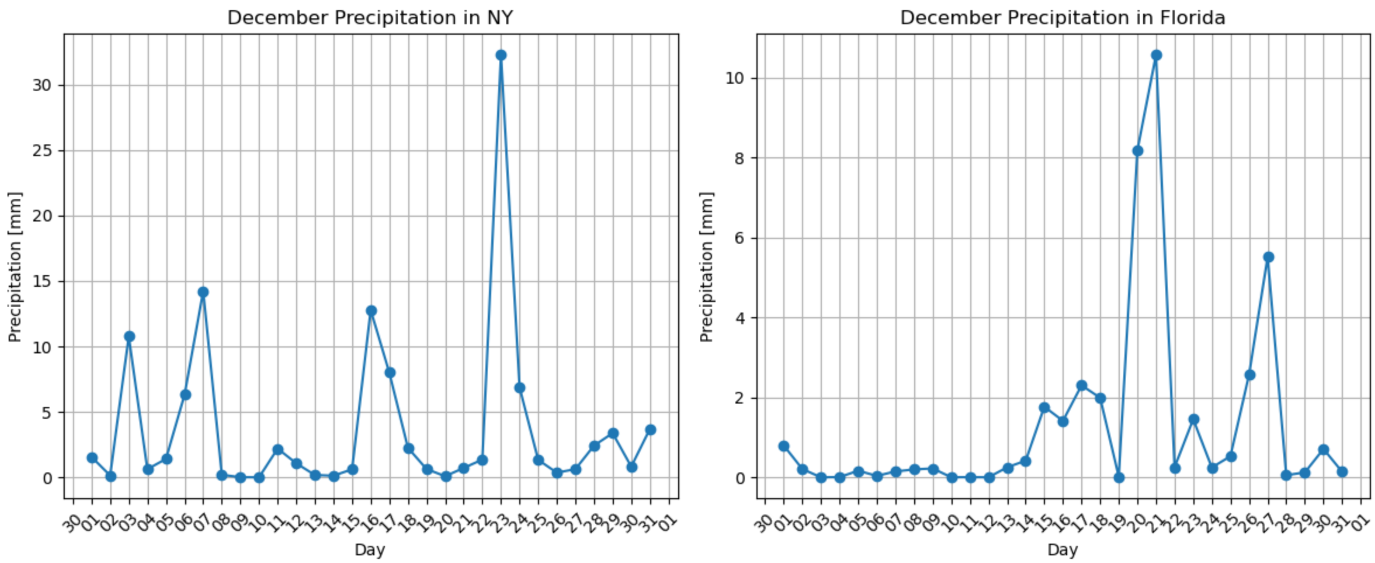
In [2]:
```
ny = pd.read_csv(f'CSVafterClean2/12.csv')
fl = pd.read_csv(f'CSVafterClean3/12.csv')
```

Precipitation vs Time

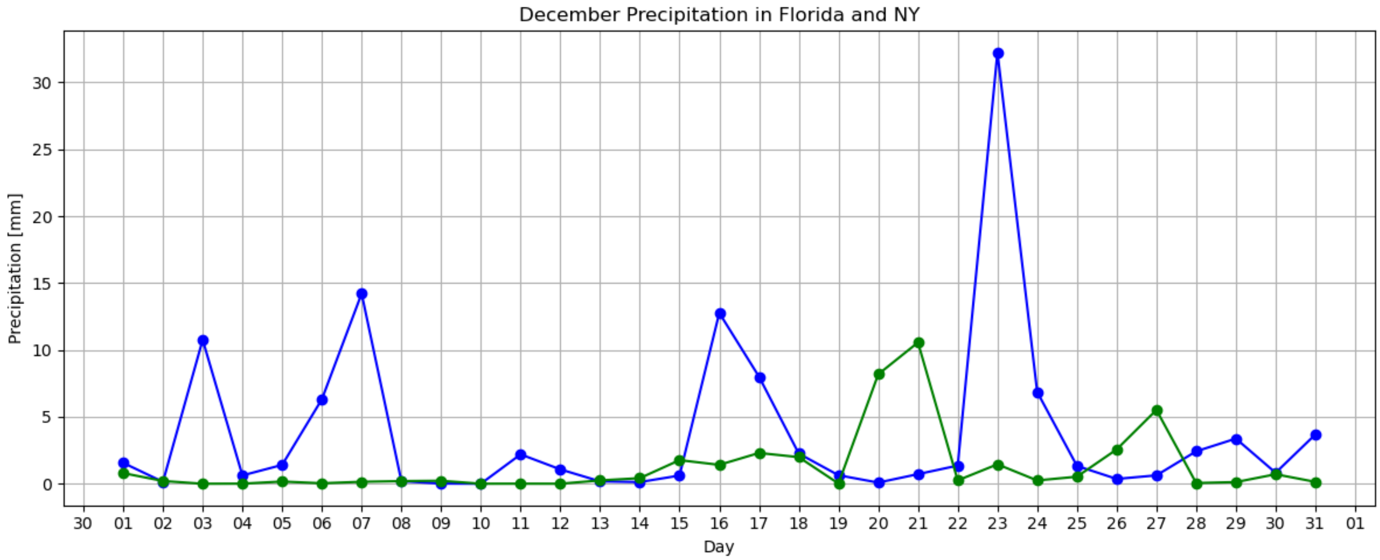
In [3]:
```
#initialize dfs
ny_snip = ny
fl_snip = fl

# 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()
```



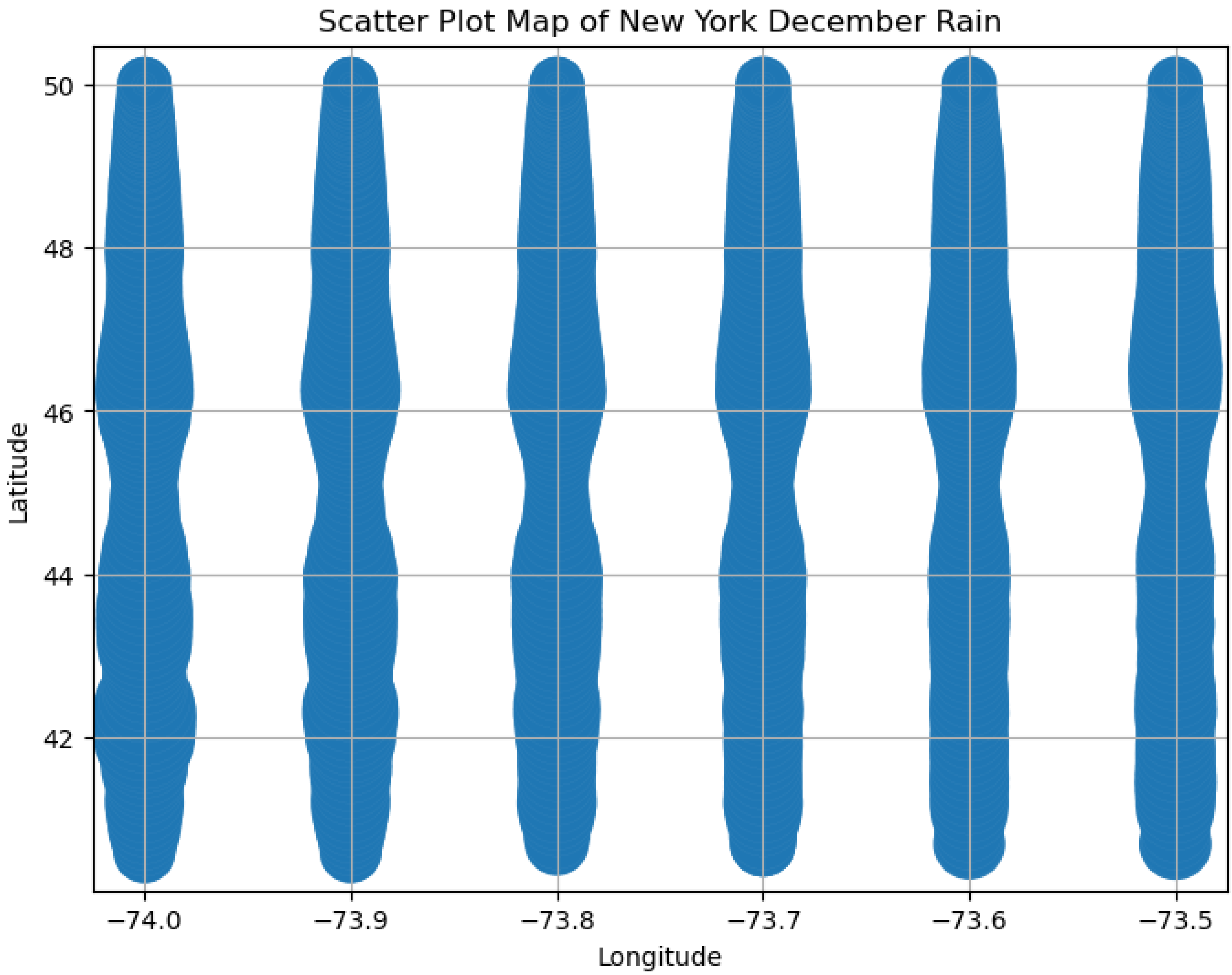
In [5]:
```
# Create subplots with two line graphs
plt.figure(figsize=(12, 5))  # Adjust the figure size as needed

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()
```



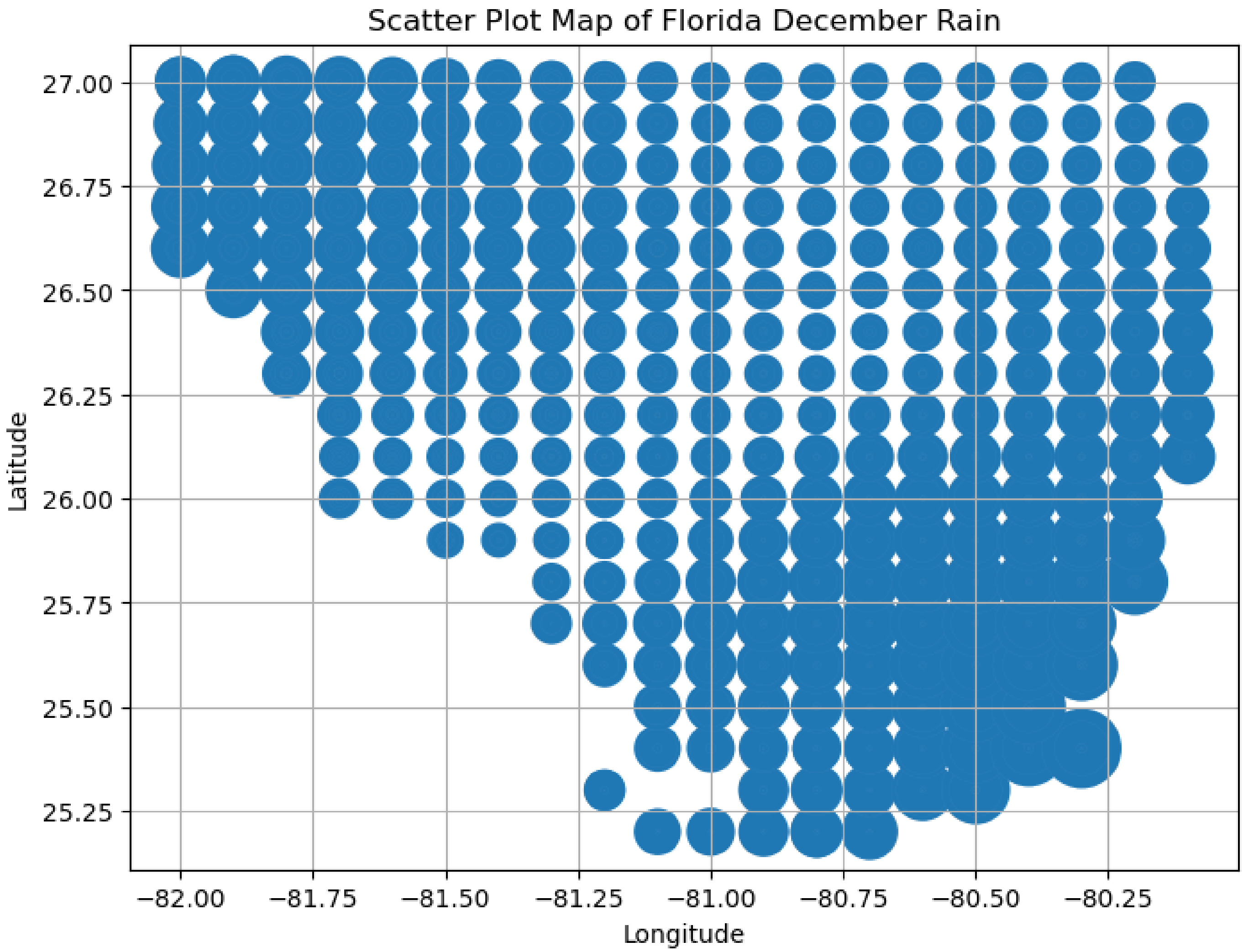
Spatial Distribution

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
```

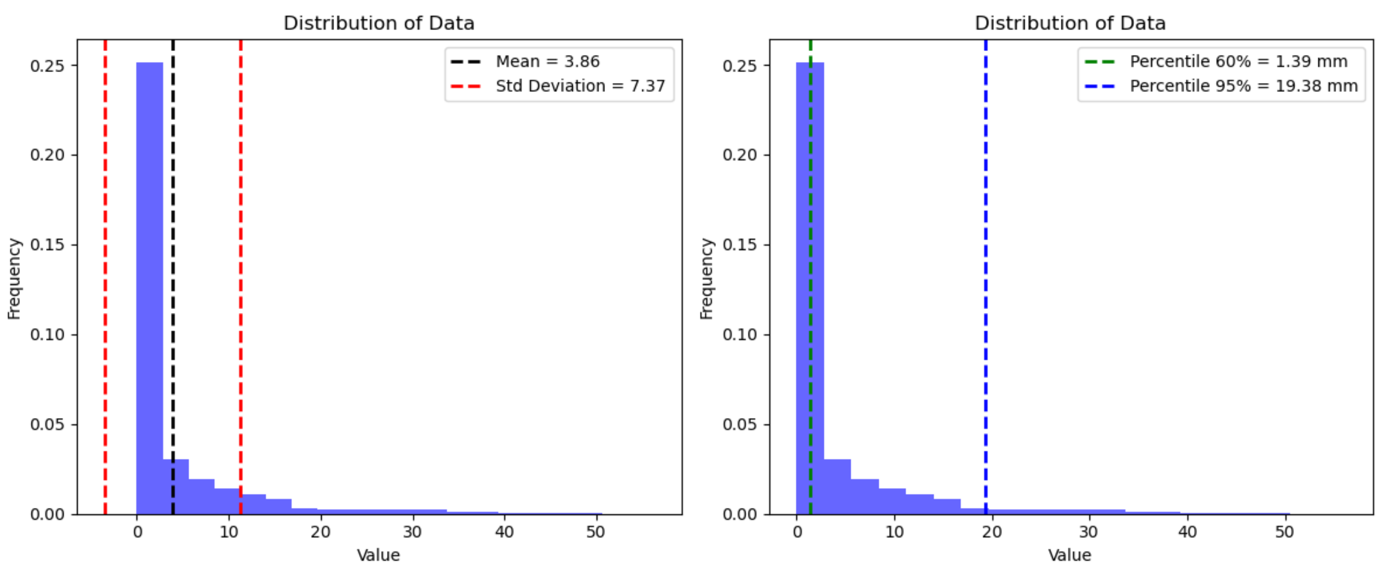


Group Categorically

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")
```

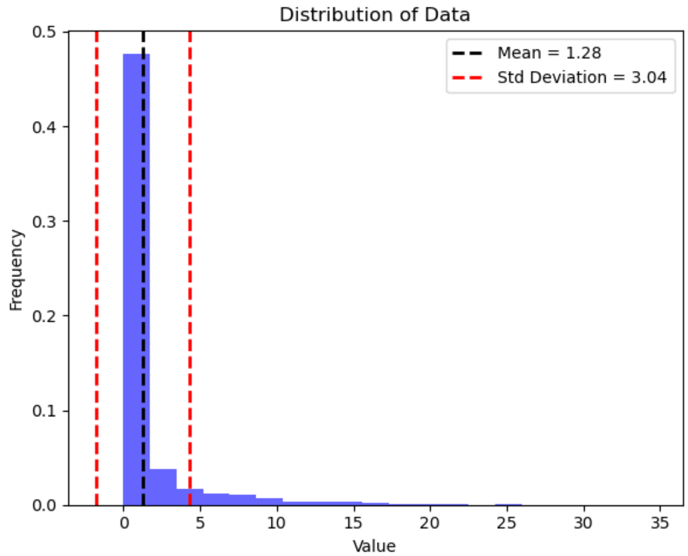
```
    plt.subplot(1, 2, 2)  # 1 row, 2 columns, subplot 2
    plt.hist(df, bins=20, density=True, alpha=0.6, color='b')
    plt.axvline(percentile_a, color='g', linestyle='dashed', linewidth=2, label=f"Percen
    plt.axvline(percentile_b, color='b', linestyle='dashed', linewidth=2, label=f"Percen
    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
```

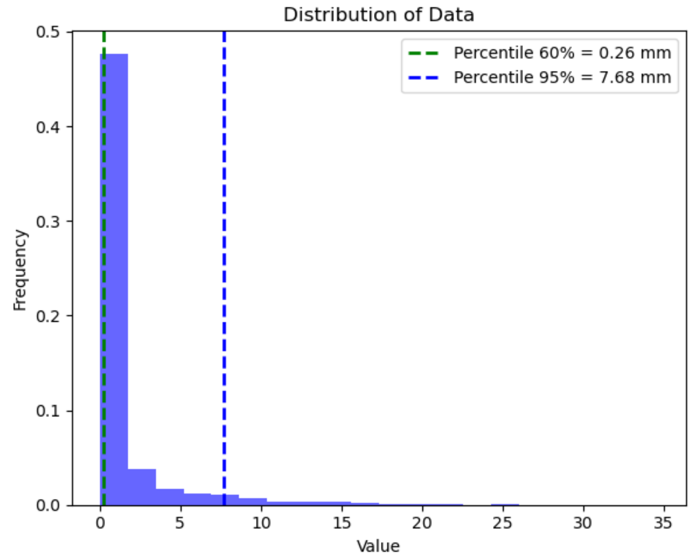
In [8]:
```
ny['nxtpr_cat'] = catAn(ny)
```




```
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 Exploration

In [10]:
```python
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]:
```python
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

        #Categorize neural net results to compare it to the classifiers
    # Calculate the percentiles
    a = 0.6
    b = 0.95
    percentile_a = df['nn_pred'].quantile(a)
    percentile_b = df['nn_pred'].quantile(b)

    dfa = df['nn_pred']

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

    df['nnCat'] = nnCat

    return df
```

In [14]:
```
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 621us/step
271/271 [==============================] - 0s 609us/step
```

Data Exploration

In [15]:
```
pred_ny.dtypes
```

Out[15]:
```
next_day_prcp_total             float64
nxtpr_cat                      category
time                     datetime64[ns]
nn_pred                         float32
rf_pred                          object
xg_pred                           int64
nnCat                          category
dtype: object
```

In [16]:
```
pred_fl.dtypes
```

Out[16]:
```
next_day_prcp_total             float64
nxtpr_cat                      category
time                     datetime64[ns]
nn_pred                         float32
rf_pred                          object
xg_pred                           int64
nnCat                          category
dtype: object
```

In [17]:
```
print(pred_ny['nnCat'].describe())
print(pred_ny['nxtpr_cat'].describe())
print(pred_ny['xg_pred'].describe())
print(pred_ny['rf_pred'].describe())
print(pred_ny['next_day_prcp_total'].describe())
print(pred_ny['nn_pred'].describe())
```

```
count     17422
unique        3
top           0
freq      10453
Name: nnCat, dtype: object
count     17422
unique        3
top           0
freq      10454
Name: nxtpr_cat, dtype: object
count    17422.000000
mean         0.345024
std          0.497573
min          0.000000
25%          0.000000
50%          0.000000
75%          1.000000
max          2.000000
Name: xg_pred, dtype: float64
count     17422
unique        3
top           0
freq      12235
Name: rf_pred, dtype: object
count    1.742200e+04
mean     3.858676e+00
std      7.373894e+00
min     -3.469447e-15
25%      2.401292e-02
50%      4.964994e-01
75%      3.910462e+00
max      5.620139e+01
Name: next_day_prcp_total, dtype: float64
```

```
count    17422.000000
mean         1.143511
std          2.020737
min         -5.456779
25%          0.066277
50%          0.722711
75%          2.049328
max         15.614716
Name: nn_pred, dtype: float64
```

In [18]:
```
pred_fl.describe()
```

Out[18]:

	next_day_prcp_total	nn_pred	xg_pred
count	8.649000e+03	8649.000000	8649.000000
mean	1.282288e+00	1.234443	0.383281
std	3.036130e+00	1.268596	0.506939
min	-3.469447e-15	-2.586165	0.000000
25%	5.285096e-03	0.341753	0.000000
50%	1.178576e-01	1.002364	0.000000
75%	7.948784e-01	1.909153	1.000000
max	3.463482e+01	7.717388	2.000000

In [19]:
```
pred_ny.describe()
```

Out[19]:

	next_day_prcp_total	nn_pred	xg_pred
count	1.742200e+04	17422.000000	17422.000000
mean	3.858676e+00	1.143511	0.345024
std	7.373894e+00	2.020737	0.497573
min	-3.469447e-15	-5.456779	0.000000
25%	2.401292e-02	0.066277	0.000000
50%	4.964994e-01	0.722711	0.000000
75%	3.910462e+00	2.049328	1.000000
max	5.620139e+01	15.614716	2.000000

In [20]:
```
pred_ny
```

Out[20]:

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

17419	3.285482	1	2022-12-29	-1.607829	0	1	0
17420	1.258963	0	2022-12-30	2.423182	1	1	1
17421	0.165100	0	2022-12-31	4.790707	1	1	2

17422 rows × 7 columns

In [21]:
```
pred_fl
```

Out[21]:

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

8649 rows × 7 columns

In [22]:
```
pred_ny.dtypes
```

Out[22]:
```
next_day_prcp_total             float64
nxtpr_cat                      category
time                     datetime64[ns]
nn_pred                         float32
rf_pred                          object
xg_pred                           int64
nnCat                          category
dtype: object
```

In [23]:
```
# Check for NA values in 'nnCat' column
nnCat_na = pred_ny['nnCat'].isna().sum()

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

# 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 nnCat: {nnCat_na}')
print(f'NA values in nn_pred: {nn_pred_na}')
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 nnCat: 0
NA values in nn_pred: 0
NA values in xg_pred: 0
NA values in rf_pred: 0
NA values in nxtpr_cat: 0
```

In [24]:

```
# Check for NA values in 'nnCat' column
nnCat_na = pred_fl['nnCat'].isna().sum()

# Check for NA values in 'nn_pred' column
nn_pred_na = pred_fl['nn_pred'].isna().sum()

# Check for NA values in 'xg_pred' column
xg_pred_na = pred_fl['xg_pred'].isna().sum()

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

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

print(f'NA values in nnCat: {nnCat_na}')
print(f'NA values in nn_pred: {nn_pred_na}')
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}')
```

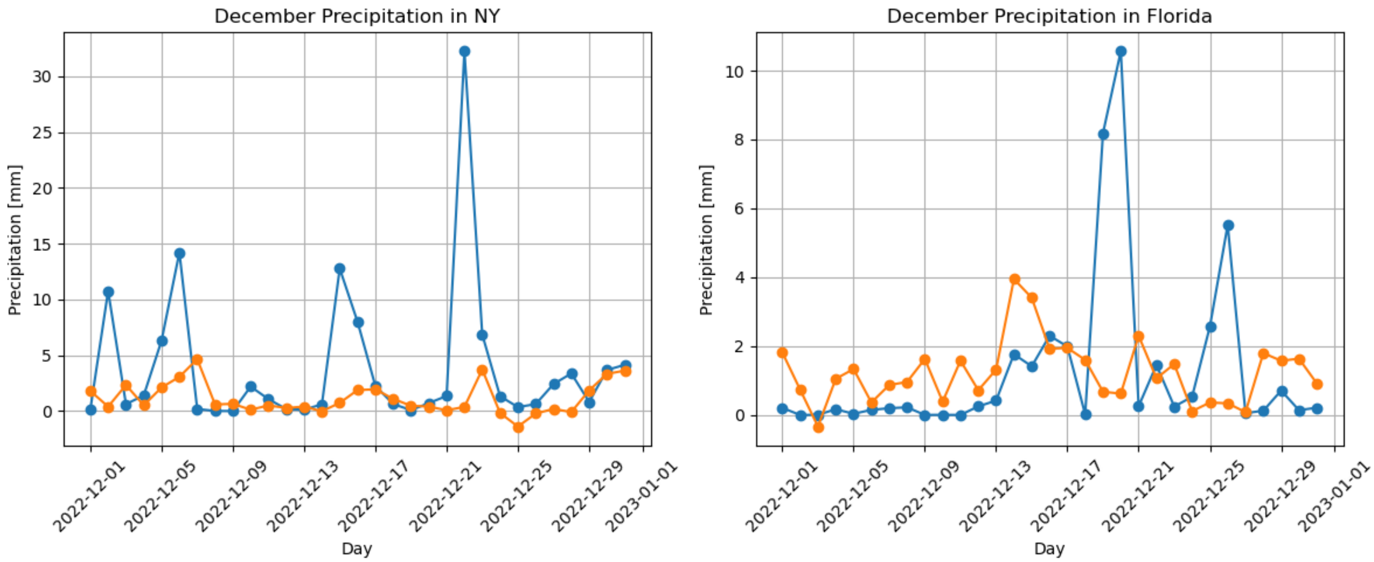
```
NA values in nnCat: 0
NA values in nn_pred: 0
NA values in xg_pred: 0
NA values in rf_pred: 0
NA values in nxtpr_cat: 0
```

Evaluate Neural Network Regression

In [25]:

```
# 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()
```

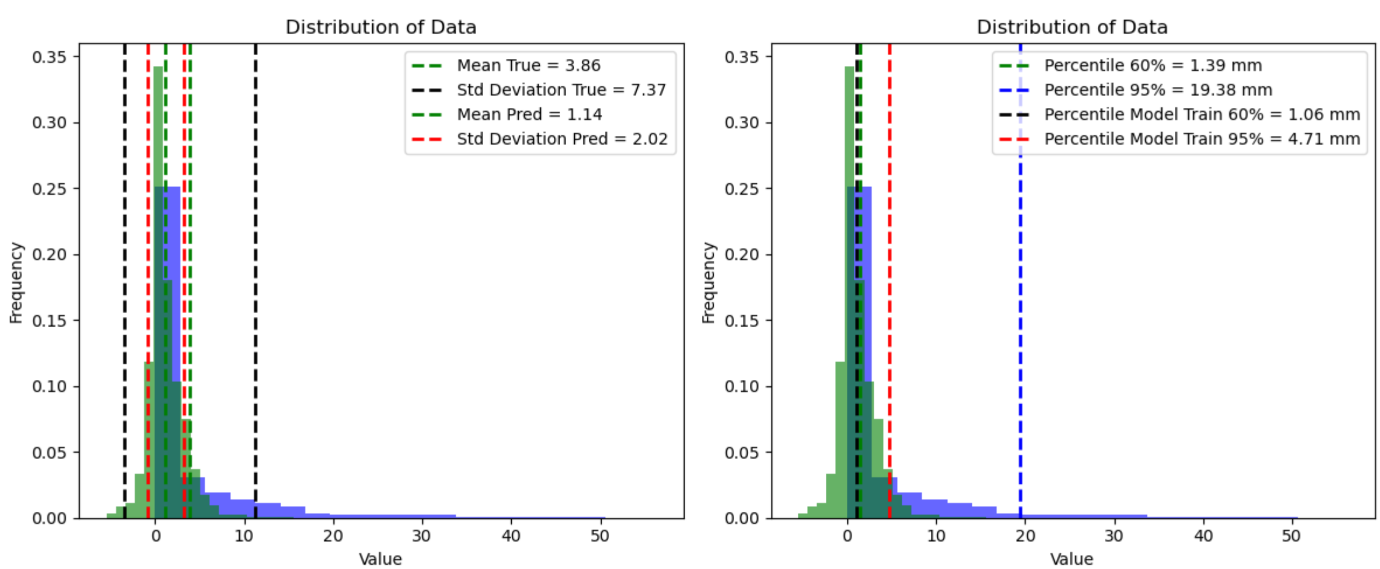


In [26]:

```
def compare(df, model):
    if model == 'nn':
            df1 = df['next_day_prcp_total']
            df2 = df['nn_pred']
            bins = 20
    if model == 'nnCat':
            df1 = df['nxtpr_cat']
            df2 = df['nnCat']
            bins = 3
    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 = dfp.quantile(a)  #model was trained on 0.649, but this is standardized, n
    percBpred = dfp.quantile(b)  #model was trained on 4.408, but this is standardized, n
    # 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)
```

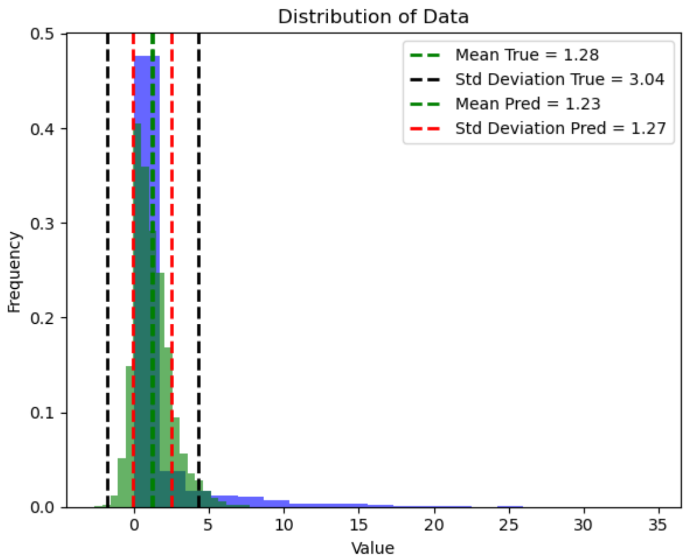
```python
    # Create subplots with two histograms
    if model == 'nn':
        plt.figure(figsize=(12, 5))  # Adjust the figure size as needed

        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}")
```

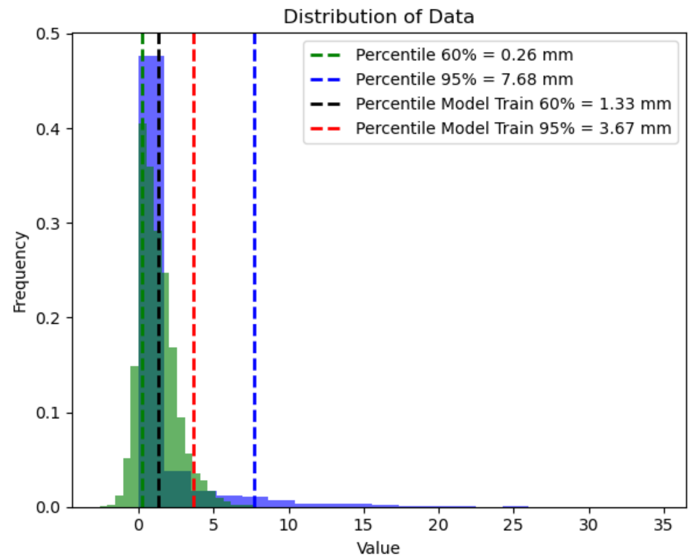
In [27]:
```python
compare(pred_ny, 'nn')
```



```
Category 0 is from 0 to 1.063 mm of rain
Number of data points below the 60.0% percentile: 9856
Category 1 is from 1.063 mm of rain to 4.709 mm of rain
Number of data points in the 60.0% to 95.0% range: 3596
Category 2 is from 4.709 mm of rain to the maximum
Number of data points above the 95.0% percentile: 3970
```

In [28]:
```
compare(pred_fl, 'nn')
```






```
Category 0 is from 0 to 1.333 mm of rain
Number of data points below the 60.0% percentile: 6917
Category 1 is from 1.333 mm of rain to 3.668 mm of rain
Number of data points in the 60.0% to 95.0% range: 825
Category 2 is from 3.668 mm of rain to the maximum
Number of data points above the 95.0% percentile: 907
```

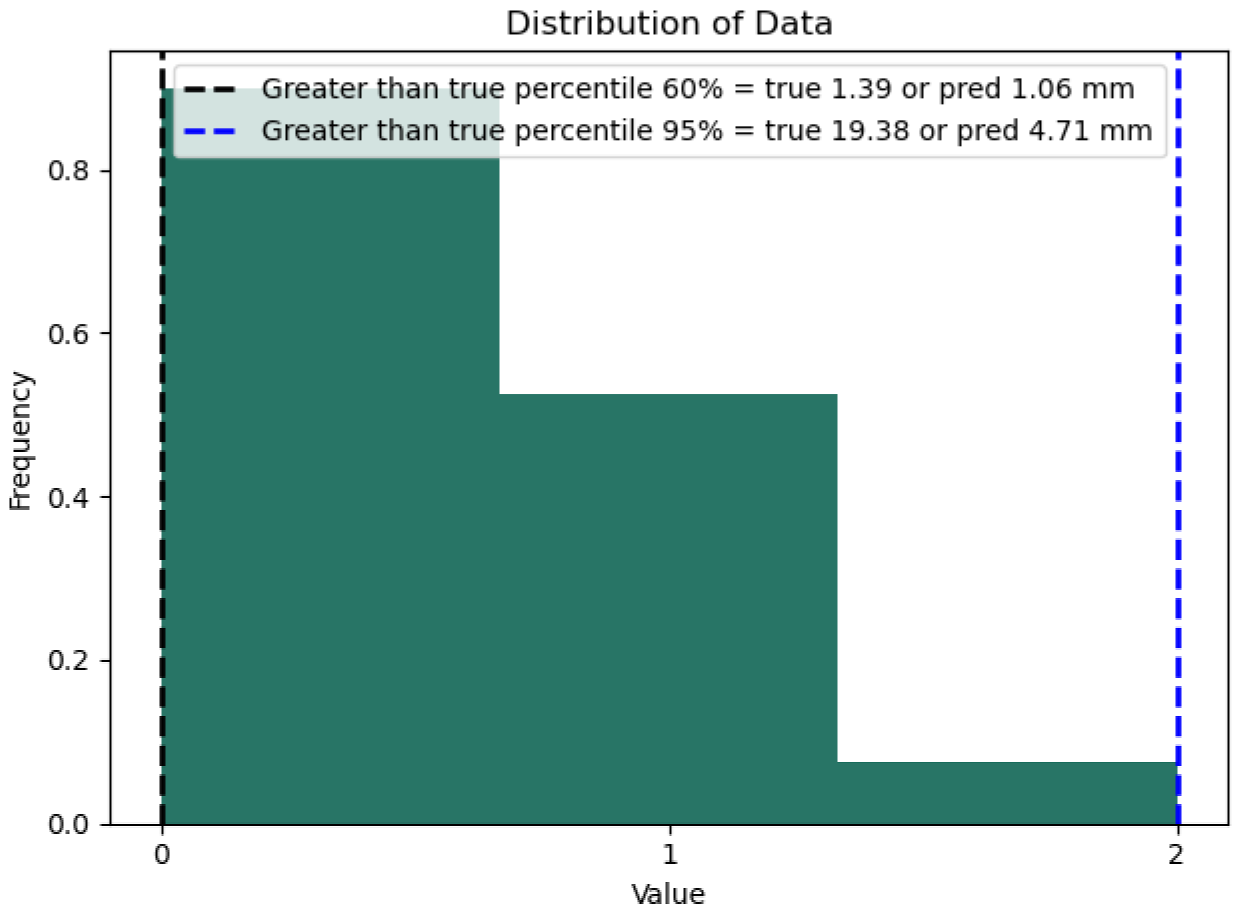
Regression Discussion:

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

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 Neural Network Classifier

In [29]:
```
compare(pred_ny, 'nnCat')
```



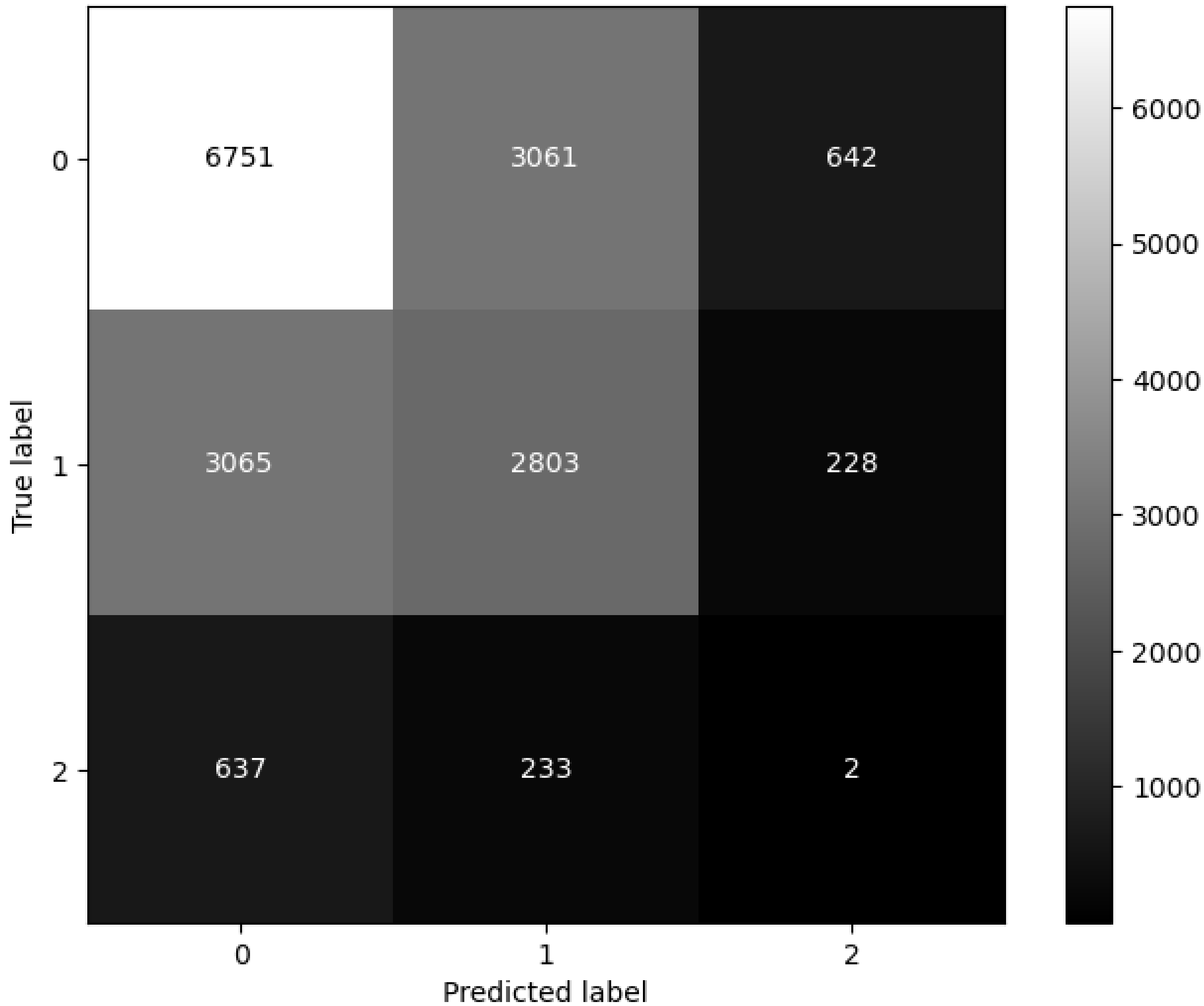

```
Category 0 is from 0 to 1.063 mm of rain
Number of data points below the 60.0% percentile: 9856
Category 1 is from 1.063 mm of rain to 4.709 mm of rain
Number of data points in the 60.0% to 95.0% range: 3596
Category 2 is from 4.709 mm of rain to the maximum
Number of data points above the 95.0% percentile: 3970
```

In [30]:

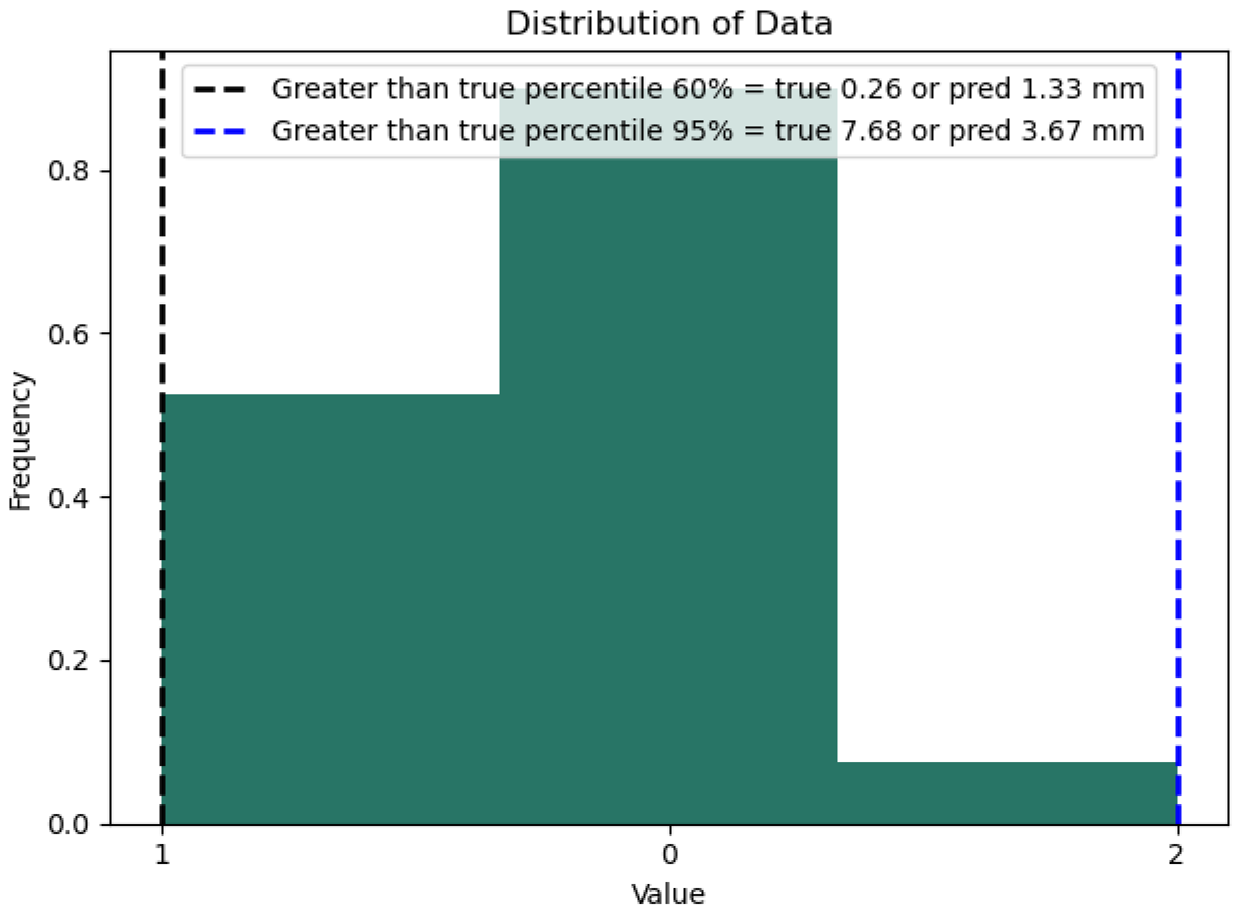
```python
# Extract true labels and predicted labels
y_test_category = pred_ny['nxtpr_cat']
y_pred = pred_ny['nnCat']

#Metrics
accuracy = accuracy_score(y_test_category, y_pred)
coh_kap = cohen_kappa_score(y_test_category, y_pred)
print("Accuracy = {}".format(accuracy))
print("Cohen's Kappa = {}".format(coh_kap))
print(classification_report(y_test_category,y_pred,digits=5))

# Create a confusion matrix
cm = confusion_matrix(y_test_category, y_pred, labels=np.unique(y_test_category))

# Create a ConfusionMatrixDisplay
disp = ConfusionMatrixDisplay(confusion_matrix=cm)

# Display the confusion matrix with custom colors
fig, ax = plt.subplots(figsize=(8, 6))
disp.plot(cmap='gray', ax=ax)

plt.show()
```

```
Accuracy = 0.5485018941568133
Cohen's Kappa = 0.12334274416376279
              precision    recall  f1-score   support

           0    0.64584   0.64578   0.64581     10454
           1    0.45973   0.45981   0.45977      6096
```

```
           2    0.00229   0.00229   0.00229       872

    accuracy                        0.54850     17422
   macro avg    0.36929   0.36929   0.36929     17422
weighted avg    0.54851   0.54850   0.54851     17422
```



In [31]:
```
compare(pred_fl, 'nnCat')
```

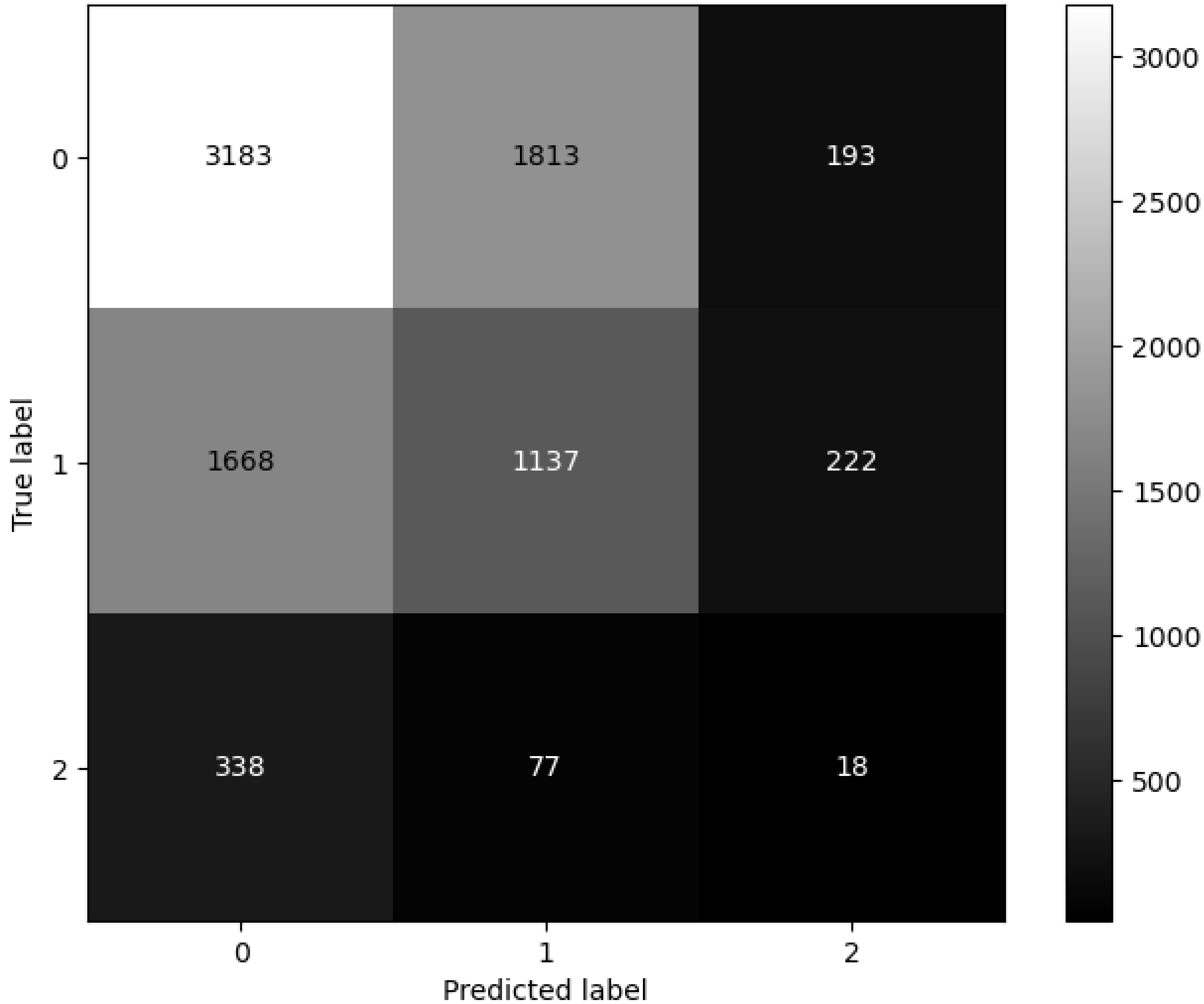



```
Category 0 is from 0 to 1.333 mm of rain
Number of data points below the 60.0% percentile: 6917
Category 1 is from 1.333 mm of rain to 3.668 mm of rain
Number of data points in the 60.0% to 95.0% range: 825
Category 2 is from 3.668 mm of rain to the maximum
Number of data points above the 95.0% percentile: 907
```

In [32]:
```
# Extract true labels and predicted labels
y_test_category = pred_fl['nxtpr_cat']
y_pred = pred_fl['nnCat']


#Metrics
accuracy = accuracy_score(y_test_category, y_pred)
coh_kap = cohen_kappa_score(y_test_category, y_pred)
print("Accuracy = {}".format(accuracy))
print("Cohen's Kappa = {}".format(coh_kap))
print(classification_report(y_test_category,y_pred,digits=5))

# Create a confusion matrix
cm = confusion_matrix(y_test_category, y_pred, labels=np.unique(y_test_category))

# Create a ConfusionMatrixDisplay
disp = ConfusionMatrixDisplay(confusion_matrix=cm)

# Display the confusion matrix with custom colors
fig, ax = plt.subplots(figsize=(8, 6))
disp.plot(cmap='gray', ax=ax)

plt.show()
```

```
Accuracy = 0.5015608740894901
Cohen's Kappa = 0.03227217277091887
              precision    recall  f1-score   support

           0    0.61341   0.61341   0.61341      5189
```

```
           1     0.37562   0.37562   0.37562      3027
           2     0.04157   0.04157   0.04157       433

    accuracy                         0.50156      8649
   macro avg     0.34353   0.34353   0.34353      8649
weighted avg     0.50156   0.50156   0.50156      8649
```

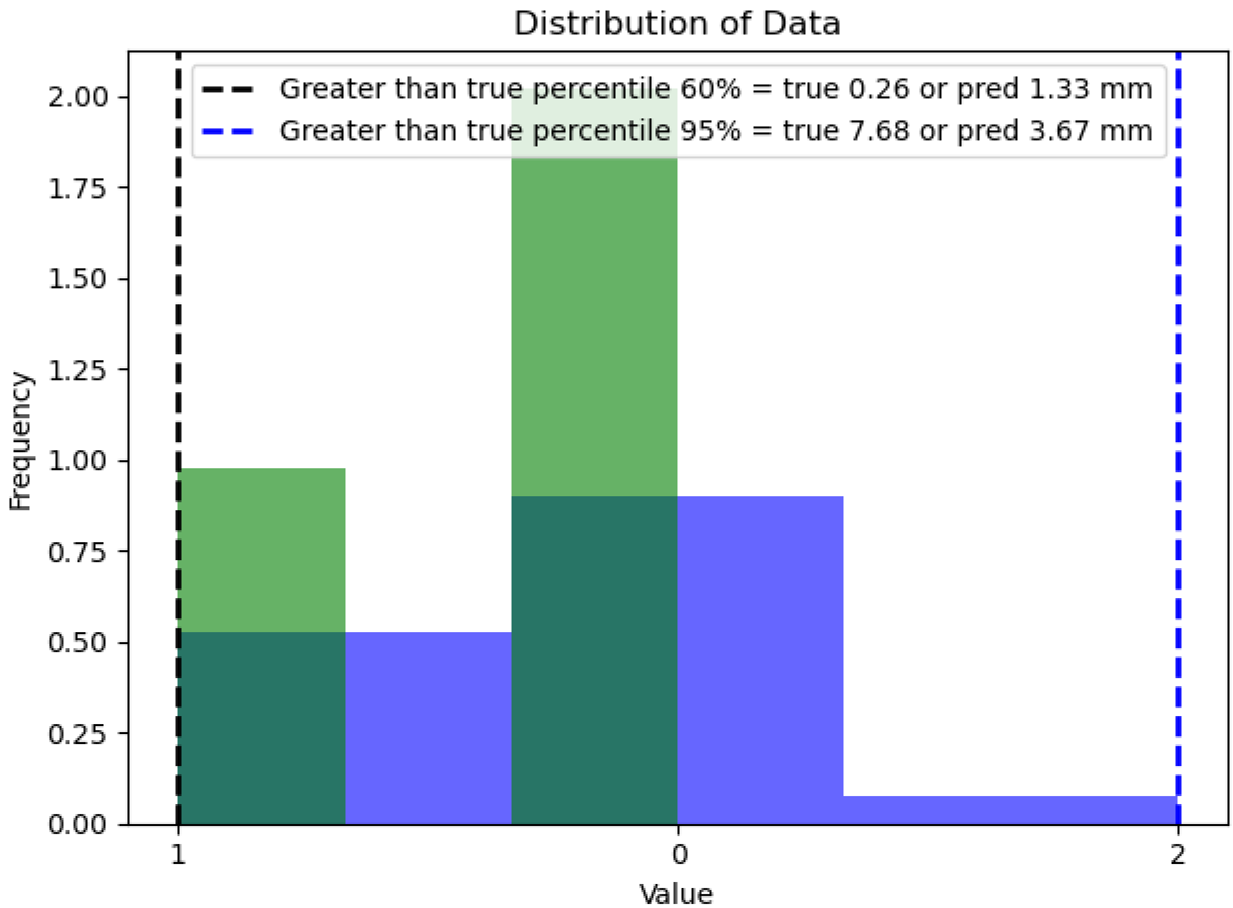


Neural Net Classifier Confusion Matrix Note

It is actually to be expected that the classifier would have an imbalanced confusion matrix because the data was grouped into bins based on 60% and the 95% of data.

Evaluate Random Forest & XGBoost Classifiers

In [33]:
```
compare(pred_fl, 'rf')
```




```
Category 0 is from 0 to 1.333 mm of rain
Number of data points below the 60.0% percentile: 6917
Category 1 is from 1.333 mm of rain to 3.668 mm of rain
Number of data points in the 60.0% to 95.0% range: 825
Category 2 is from 3.668 mm of rain to the maximum
Number of data points above the 95.0% percentile: 907
```

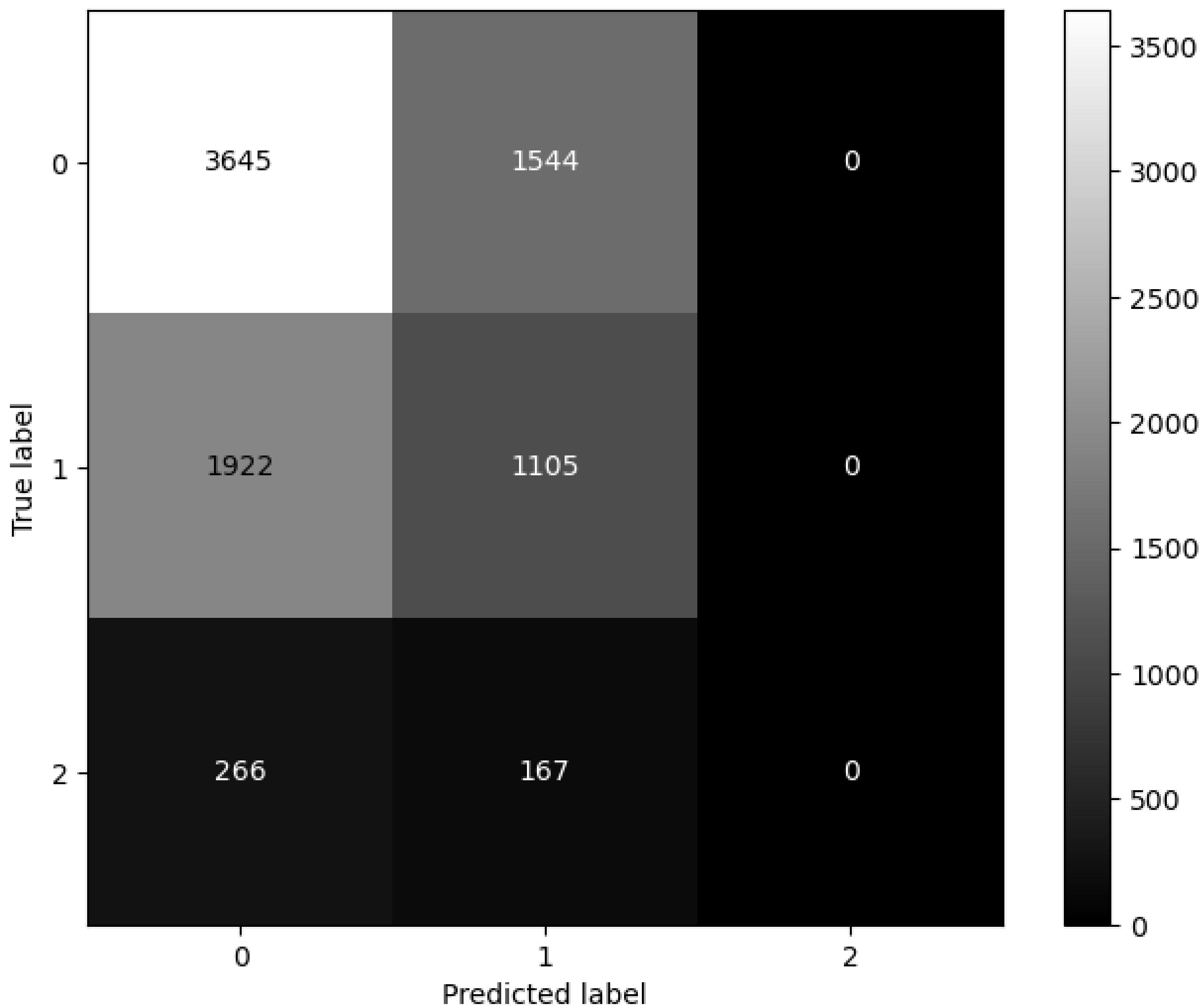
In [34]:

```python
# Extract true labels and predicted labels
y_test_category = pred_fl['nxtpr_cat']
y_pred = pred_fl['rf_pred']

#Metrics
accuracy = accuracy_score(y_test_category, y_pred)
coh_kap = cohen_kappa_score(y_test_category, y_pred)
print("Accuracy = {}".format(accuracy))
print("Cohen's Kappa = {}".format(coh_kap))
print(classification_report(y_test_category,y_pred,digits=5))

# Create a confusion matrix
cm = confusion_matrix(y_test_category, y_pred, labels=np.unique(y_test_category))

# Create a ConfusionMatrixDisplay
disp = ConfusionMatrixDisplay(confusion_matrix=cm)

# Display the confusion matrix with custom colors
fig, ax = plt.subplots(figsize=(8, 6))
disp.plot(cmap='gray', ax=ax)

plt.show()
```

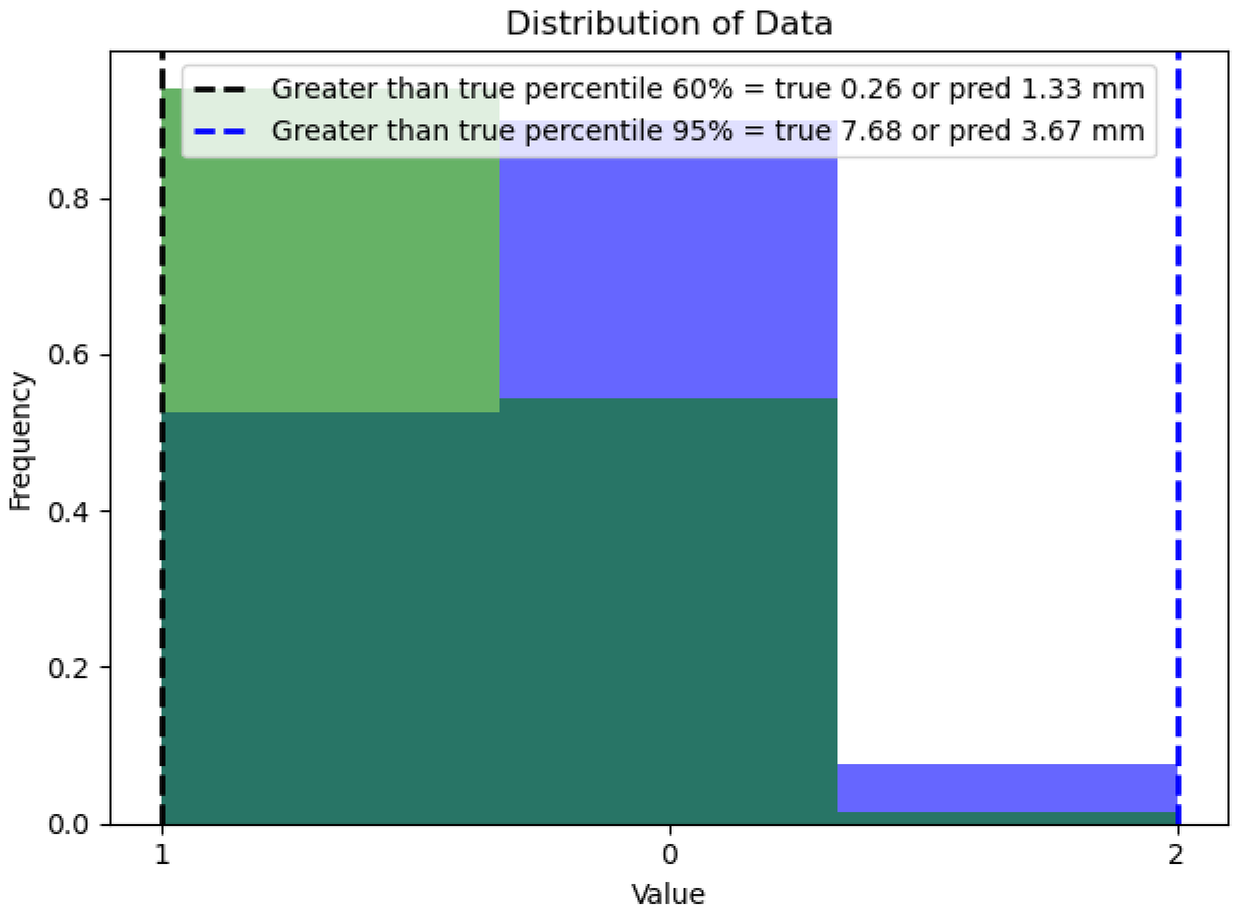
```
Accuracy = 0.54919643889467
Cohen's Kappa = 0.06362242602349577
              precision    recall  f1-score   support

           0    0.62489   0.70245   0.66140      5189
           1    0.39240   0.36505   0.37823      3027
```

```
           2    0.00000   0.00000   0.00000       433

    accuracy                        0.54920      8649
   macro avg    0.33910   0.35583   0.34654      8649
weighted avg    0.51224   0.54920   0.52919      8649
```

```
C:\Users\yepesim\AppData\Roaming\Python\Python39\site-packages\sklearn\metrics\_classifi
cation.py:1469: UndefinedMetricWarning: Precision and F-score are ill-defined and being
set to 0.0 in labels with no predicted samples. Use `zero_division` parameter to control
this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
C:\Users\yepesim\AppData\Roaming\Python\Python39\site-packages\sklearn\metrics\_classifi
cation.py:1469: UndefinedMetricWarning: Precision and F-score are ill-defined and being
set to 0.0 in labels with no predicted samples. Use `zero_division` parameter to control
this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
C:\Users\yepesim\AppData\Roaming\Python\Python39\site-packages\sklearn\metrics\_classifi
cation.py:1469: UndefinedMetricWarning: Precision and F-score are ill-defined and being
set to 0.0 in labels with no predicted samples. Use `zero_division` parameter to control
this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```



In [35]:
```
compare(pred_fl, 'xg')
```



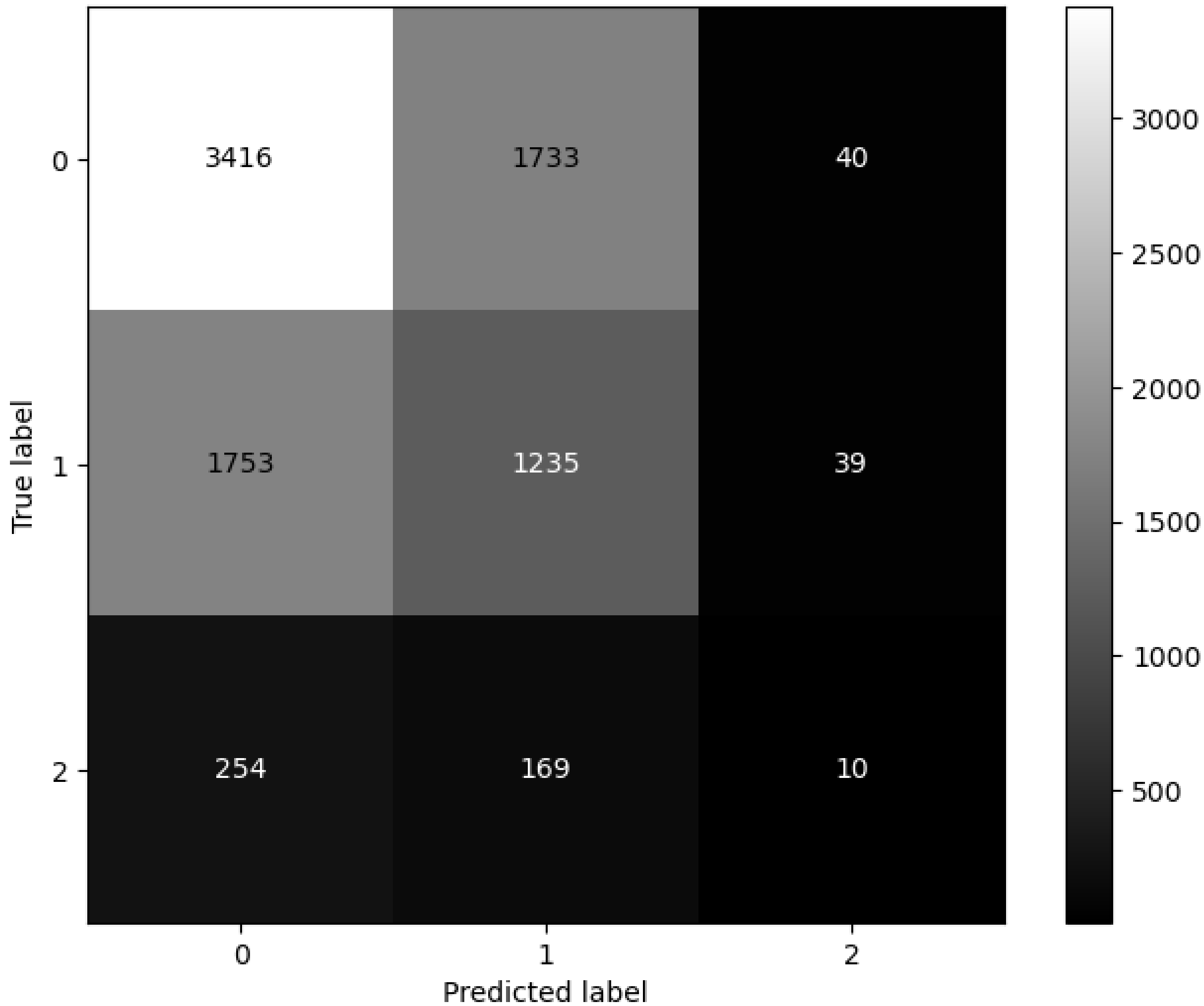

```
Category 0 is from 0 to 1.333 mm of rain
Number of data points below the 60.0% percentile: 6917
Category 1 is from 1.333 mm of rain to 3.668 mm of rain
Number of data points in the 60.0% to 95.0% range: 825
Category 2 is from 3.668 mm of rain to the maximum
Number of data points above the 95.0% percentile: 907
```

In [36]:

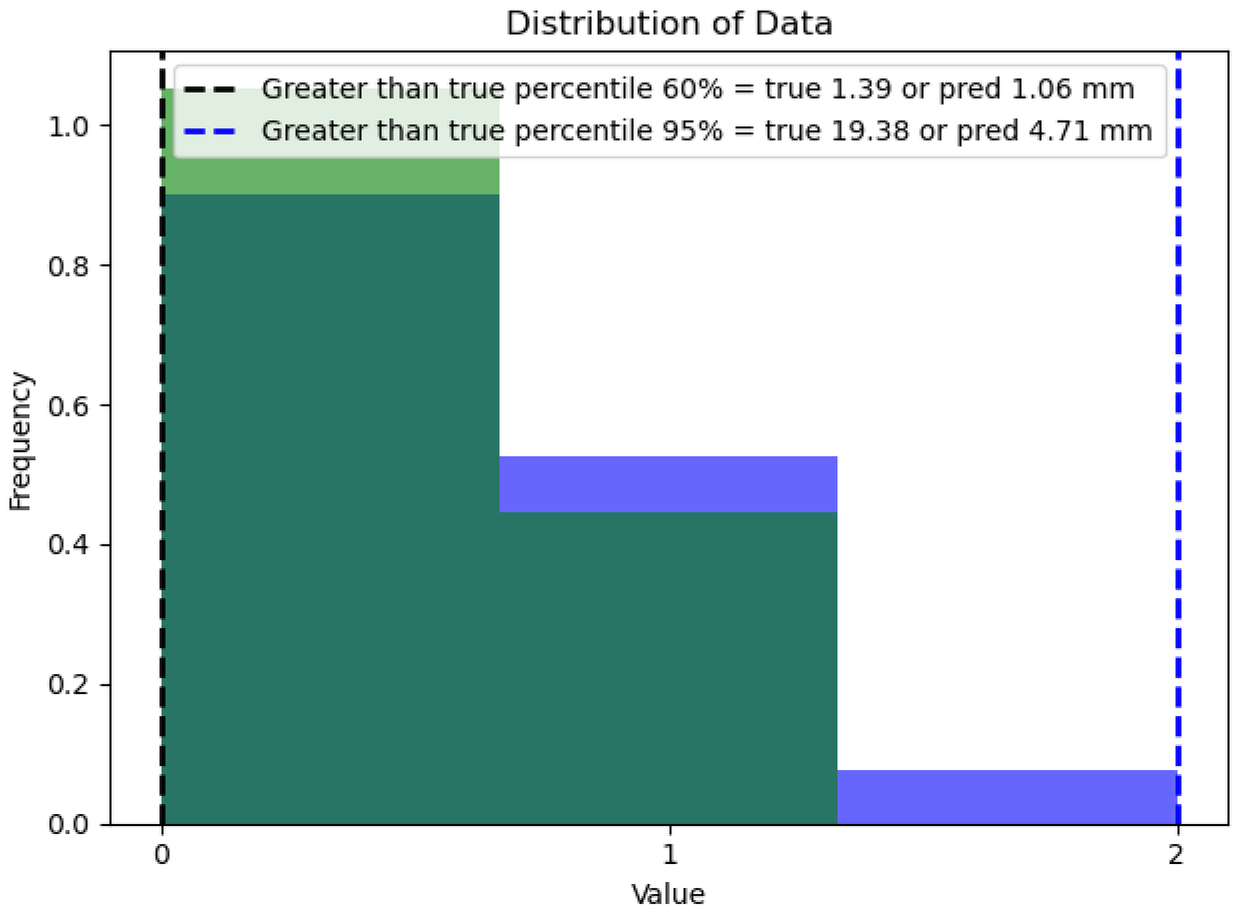
```
# Extract true labels and predicted labels
#coh_kap and classification report gave error:
#ValueError: Mix of label input types (string and number)
#therefore added as type int
y_test_category = pred_fl['nxtpr_cat'].astype(int)
y_pred = pred_fl['xg_pred'].astype(int)

#Metrics
accuracy = accuracy_score(y_test_category, y_pred)
coh_kap = cohen_kappa_score(y_test_category, y_pred)
print("Accuracy = {}".format(accuracy))
print("Cohen's Kappa = {}".format(coh_kap))
print(classification_report(y_test_category,y_pred,digits=5))

# Create a confusion matrix
cm = confusion_matrix(y_test_category, y_pred, labels=np.unique(y_test_category))

# Create a ConfusionMatrixDisplay
disp = ConfusionMatrixDisplay(confusion_matrix=cm)

# Display the confusion matrix with custom colors
fig, ax = plt.subplots(figsize=(8, 6))
disp.plot(cmap='gray', ax=ax)

plt.show()
```

```
Accuracy = 0.5389062319343276
Cohen's Kappa = 0.0710674293928596
              precision    recall  f1-score   support
```

0	0.62991	0.65832	0.64380	5189
1	0.39369	0.40799	0.40071	3027
2	0.11236	0.02309	0.03831	433
accuracy			0.53891	8649
macro avg	0.37865	0.36314	0.36094	8649
weighted avg	0.52133	0.53891	0.52841	8649



In [37]:
```
compare(pred_ny, 'rf')
```



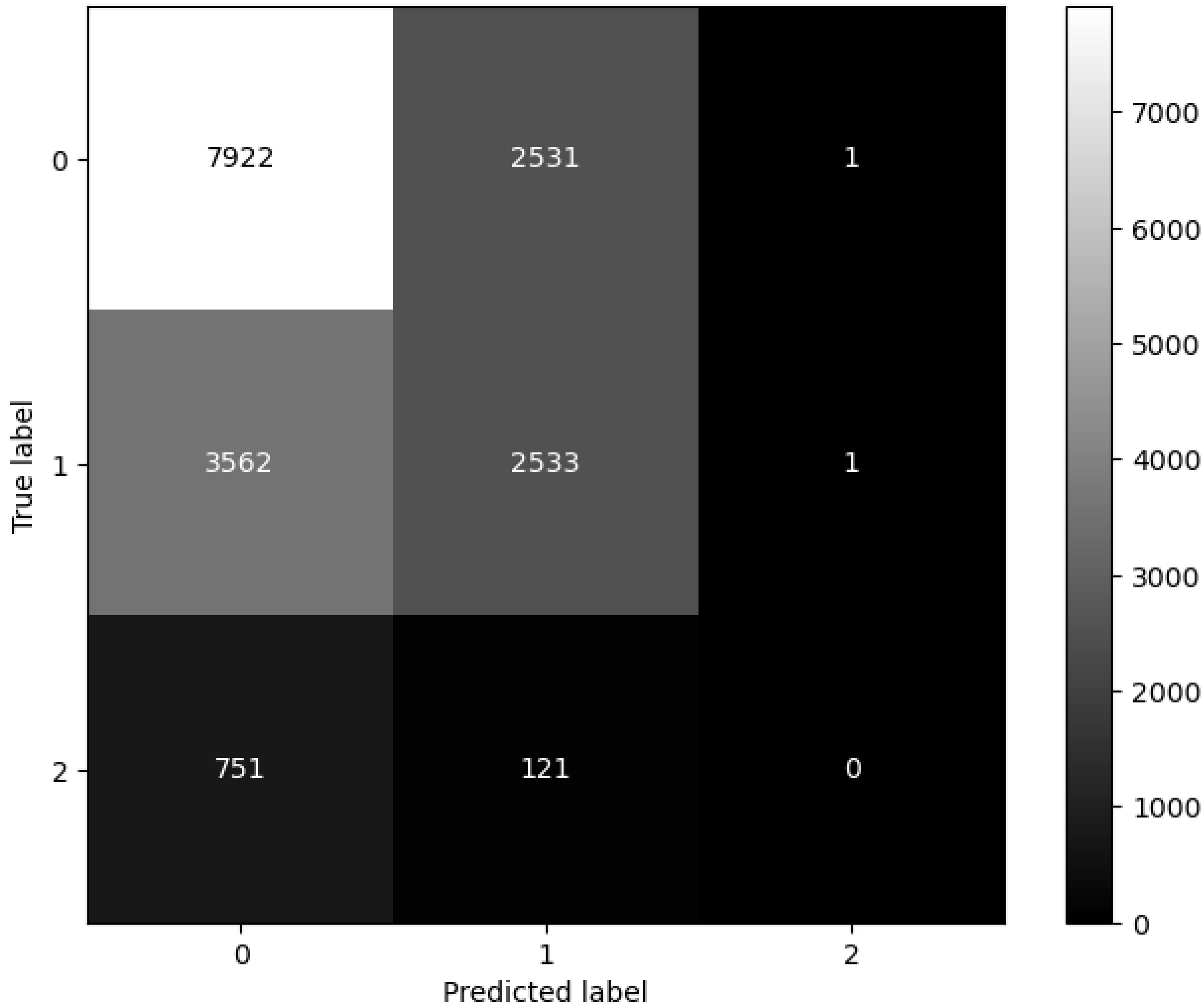

```
Category 0 is from 0 to 1.063 mm of rain
Number of data points below the 60.0% percentile: 9856
Category 1 is from 1.063 mm of rain to 4.709 mm of rain
Number of data points in the 60.0% to 95.0% range: 3596
Category 2 is from 4.709 mm of rain to the maximum
Number of data points above the 95.0% percentile: 3970
```

In [38]:

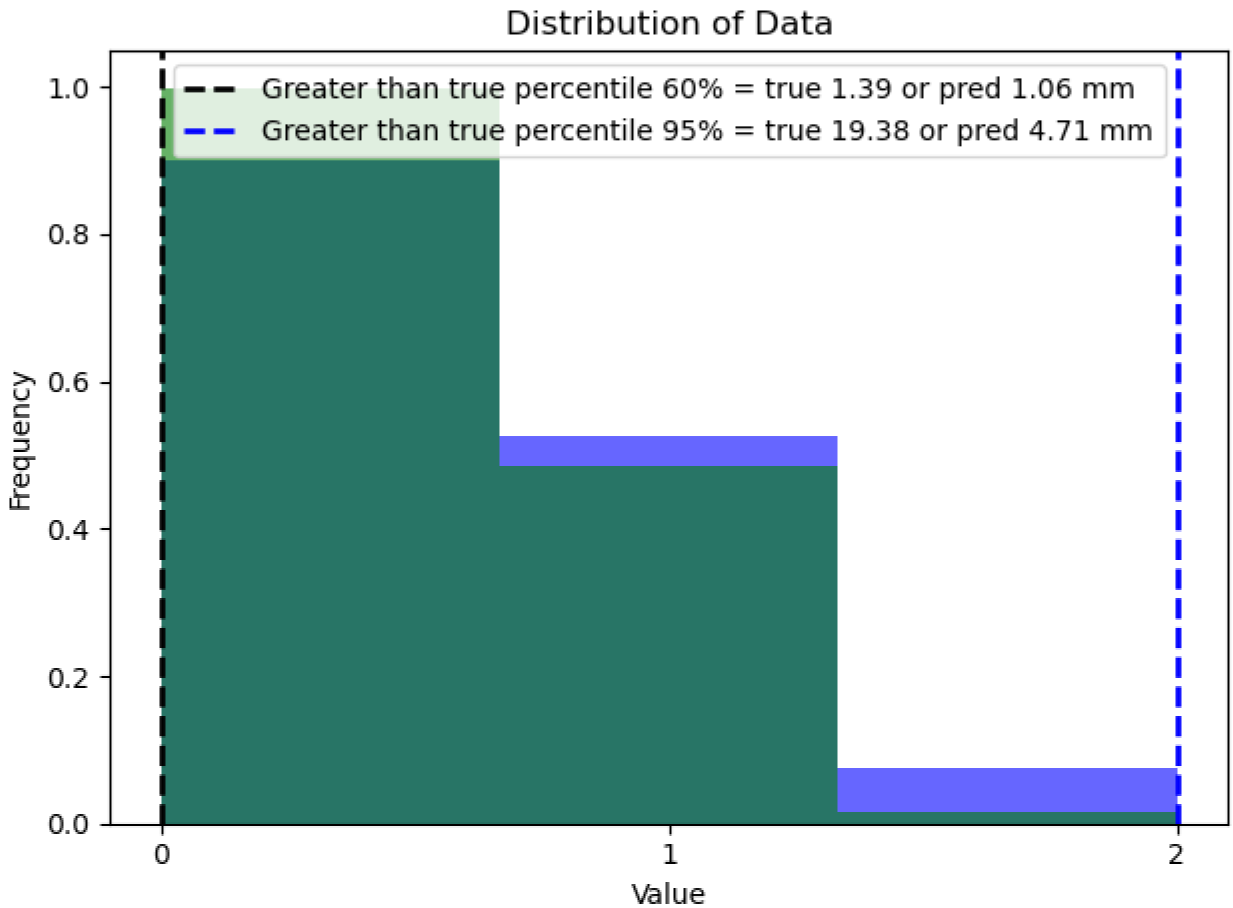
```python
# Extract true labels and predicted labels
y_test_category = pred_ny['nxtpr_cat']
y_pred = pred_ny['rf_pred']

#Metrics
accuracy = accuracy_score(y_test_category, y_pred)
coh_kap = cohen_kappa_score(y_test_category, y_pred)
print("Accuracy = {}".format(accuracy))
print("Cohen's Kappa = {}".format(coh_kap))
print(classification_report(y_test_category,y_pred,digits=5))

# Create a confusion matrix
cm = confusion_matrix(y_test_category, y_pred, labels=np.unique(y_test_category))

# Create a ConfusionMatrixDisplay
disp = ConfusionMatrixDisplay(confusion_matrix=cm)

# Display the confusion matrix with custom colors
fig, ax = plt.subplots(figsize=(8, 6))
disp.plot(cmap='gray', ax=ax)

plt.show()
```

```
Accuracy = 0.6001033176443578
Cohen's Kappa = 0.15715935677255555
              precision    recall  f1-score   support

           0    0.64749   0.75780   0.69831     10454
           1    0.48852   0.41552   0.44907      6096
```

```
           2    0.00000   0.00000   0.00000       872

    accuracy                        0.60010     17422
   macro avg    0.37867   0.39110   0.38246     17422
weighted avg    0.55946   0.60010   0.57615     17422
```



In [39]:
```
compare(pred_ny, 'xg')
```



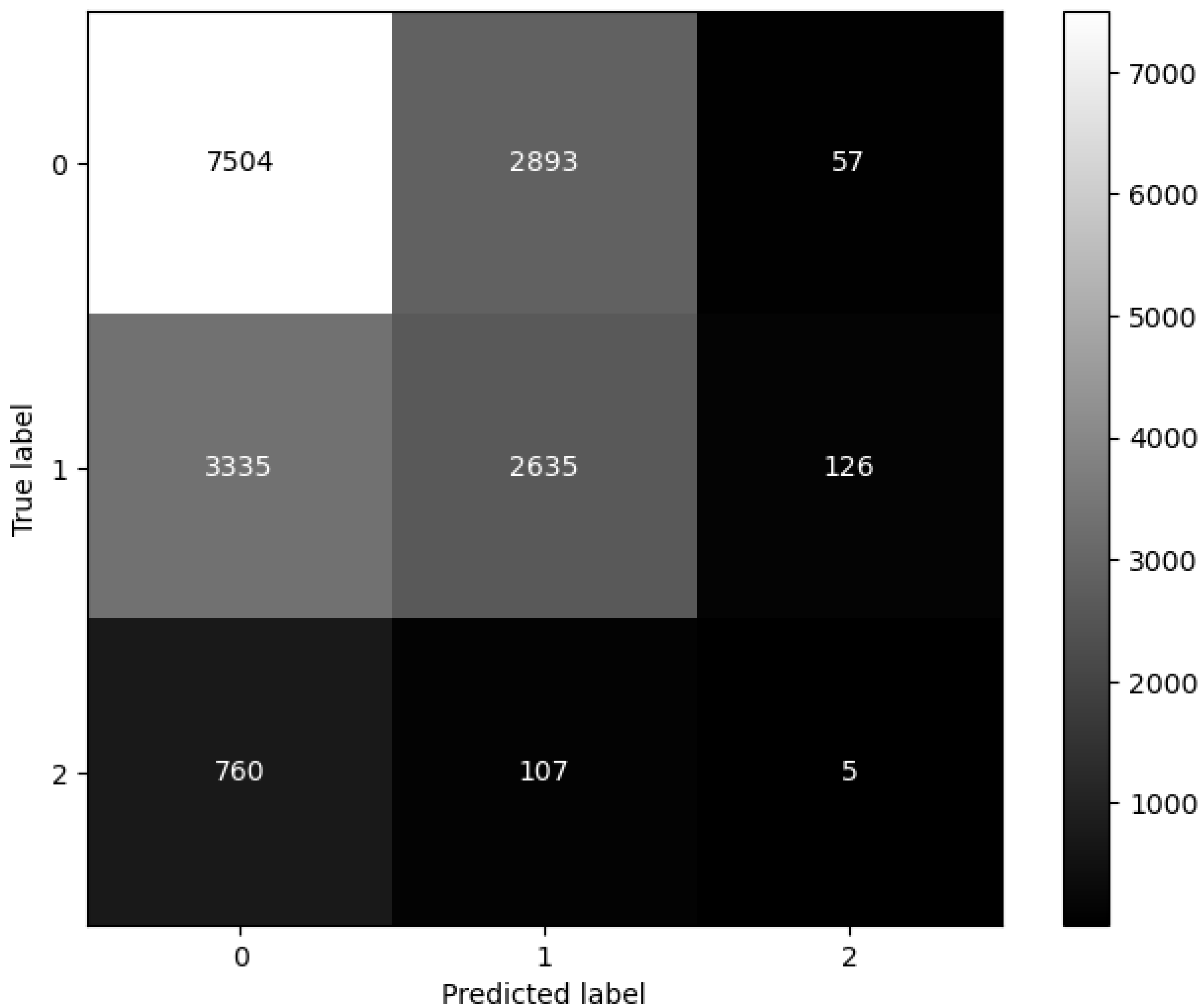

```
Category 0 is from 0 to 1.063 mm of rain
Number of data points below the 60.0% percentile: 9856
Category 1 is from 1.063 mm of rain to 4.709 mm of rain
Number of data points in the 60.0% to 95.0% range: 3596
Category 2 is from 4.709 mm of rain to the maximum
Number of data points above the 95.0% percentile: 3970
```

In [40]:

```python
# Extract true labels and predicted labels
#coh_kap and classification report gave error:
#ValueError: Mix of label input types (string and number)
#therefore added as type int
y_test_category = pred_ny['nxtpr_cat'].astype(int)
y_pred = pred_ny['xg_pred'].astype(int)

#Metrics
accuracy = accuracy_score(y_test_category, y_pred)
coh_kap = cohen_kappa_score(y_test_category, y_pred)
print("Accuracy = {}".format(accuracy))
print("Cohen's Kappa = {}".format(coh_kap))
print(classification_report(y_test_category,y_pred,digits=5))

# Create a confusion matrix
cm = confusion_matrix(y_test_category, y_pred, labels=np.unique(y_test_category))

# Create a ConfusionMatrixDisplay
disp = ConfusionMatrixDisplay(confusion_matrix=cm)

# Display the confusion matrix with custom colors
fig, ax = plt.subplots(figsize=(8, 6))
disp.plot(cmap='gray', ax=ax)

plt.show()
```

```
Accuracy = 0.582252324646998
Cohen's Kappa = 0.14184218249258462
              precision    recall  f1-score   support
```

```
           0     0.64695   0.71781   0.68054     10454
           1     0.46761   0.43225   0.44924      6096
           2     0.02660   0.00573   0.00943       872

    accuracy                         0.58225     17422
   macro avg     0.38039   0.38527   0.37974     17422
weighted avg     0.55315   0.58225   0.56602     17422
```



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.

From the confusion matrix's F1 score (accuracy indicator), for class 0 the Random Forest model was the most accurate, for class 1 and 2, both the Neural Net and the XGBoost models were comparable. Random Forest was the worst accurate for class 2.

Though, visually the **neural network classifier** is the best, **XGBoost classifier** ranked across all classes based on the f1 score is the most accurate.

Further Work

```
- Increasing number of epochs
- Try without outlier removal to see if it is actually beneficial (especially
since the prediction category bins are 95% and 60%)
```

- Try different percentiles
- Conserve lat and lon (might not work NYC)
- Add previous prcp total feature. This would make it more of a temporal model which would likely improve results since the prcptotal current day's total precipitation is a feature with high importance. This would require further data processing: need to download the previous year's last month in order to calculate the first day of the first month's previous day's precipitation.
- Add neural net classifier classification report to model building code
- Understand classifier data type discrepancy (for XGBoost int64)