1. Data Generation

In [1]:
```
import os
os.environ['TF_CPP_MIN_LOG_LEVEL'] = '3'
import pandas as pd
import numpy as np
import pickle
import ast

# Plotting libraries
import matplotlib.pyplot as plt
import matplotlib.cm as cm
import seaborn as sns
%matplotlib inline
```

In [2]:
```
# Universial data folder
# Inside, we have the CSV for each weather station, and the satellite imagery c
# shall be generated and stored inside a sub-folder

data_path = 'data_dir/'
csv_path = 'combined_dataset/'
```

In [3]:
```
# Get list of all CSV files
all_files = os.listdir(data_path + csv_path)

# Filter out the CSV files
csv_files = [file for file in all_files if file.endswith('.csv')]

# Now csv_files list contains all the names of csv files

# To get the full path of these csv files
csv_file_paths = [os.path.join(data_path, csv_path, file) for file in csv_files
```

In [4]:
```
# Inspection purpose
len(csv_file_paths)
```

Out[4]:
```
5
```

In [5]:
```
csv_file_paths
```

Out[5]:
```
['data_dir/combined_dataset/Take_2_2006Fall_2017Spring_GOES_meteo_combined_148
15.csv',
 'data_dir/combined_dataset/Take_2_2006Fall_2017Spring_GOES_meteo_combined_148
50.csv',
 'data_dir/combined_dataset/Take_2_2006Fall_2017Spring_GOES_meteo_combined_148
19.csv',
 'data_dir/combined_dataset/Take_2_2006Fall_2017Spring_GOES_meteo_combined_048
46.csv',
 'data_dir/combined_dataset/Take_2_2006Fall_2017Spring_GOES_meteo_combined_148
45.csv']
```

`TO-DO`:

Change the index number for `csv_file_paths` to switch weather stations.

In [6]:
```
file_idx = 1
```

In [7]:
```
df_single_station = pd.read_csv(csv_file_paths[file_idx])

filename_curr = csv_file_paths[file_idx]
station_code = filename_curr[-9:-4]
```

In [8]:
```
# Inspection purpose
df_single_station.head(5)
```

Out[8]:

	Date_UTC	Time_UTC	Date_CST	Time_CST	File_name_for_1D_lake	File_nam
0	2006-10-01	00:00	2006-09-30	18:00	goes11.2006.10.01.0000.v01.nc-var1-t0.csv	T_goes11.2006.10.0
1	2006-10-01	01:00	2006-09-30	19:00	goes11.2006.10.01.0100.v01.nc-var1-t0.csv	T_goes11.2006.10.0
2	2006-10-01	02:00	2006-09-30	20:00	goes11.2006.10.01.0200.v01.nc-var1-t0.csv	T_goes11.2006.10.0
3	2006-10-01	03:00	2006-09-30	21:00	goes11.2006.10.01.0300.v01.nc-var1-t0.csv	T_goes11.2006.10.0
4	2006-10-01	04:00	2006-09-30	22:00	goes11.2006.10.01.0400.v01.nc-var1-t0.csv	T_goes11.2006.10.0

5 rows × 31 columns

Change column names for easier access.

In [9]:
```
# Check if 'Unnamed: 18' is in the DataFrame's columns
if 'Unnamed: 18' in df_single_station.columns:
    # Drop the column
    df_single_station = df_single_station.drop(columns=['Unnamed: 18'])
#     print('Dropped the empty column.')
else:
    print('Empty column does not exist.')

# Check if 'does_snow_24_120' is in the DataFrame's columns
if 'does_snow_24_120' in df_single_station.columns:
    # Drop the column
    df_single_station = df_single_station.drop(columns=['does_snow_24_120'])
#     print('Dropped the <does_snow_24_120> column.')
```

```
else:
    print('The <does_snow_24_120> column does not exist.')

# Check if 'precip_work_zone' is in the DataFrame's columns
if 'precip_work_zone' in df_single_station.columns:
    # Drop the column
    df_single_station = df_single_station.drop(columns=['precip_work_zone'])
#     print('Dropped the <precip_work_zone> column.')
else:
    print('The <precip_work_zone> column does not exist.')

# Check if 'is_snow_precip' is in the DataFrame's columns
if 'is_snow_precip' in df_single_station.columns:
    # Drop the column
    df_single_station = df_single_station.drop(columns=['is_snow_precip'])
#     print('Dropped the <is_snow_precip> column.')
else:
    print('The <is_snow_precip> column does not exist.')

# Check if 'is_precip' is in the DataFrame's columns
if 'is_precip' in df_single_station.columns:
    # Drop the column
    df_single_station = df_single_station.drop(columns=['is_precip'])
#     print('Dropped the <is_precip> column.')
else:
    print('The <is_precip> column does not exist.')

# Check if 'Wind Chill (F)' is in the DataFrame's columns
if 'Wind Chill (F)' in df_single_station.columns:
    # Drop the column
    df_single_station = df_single_station.drop(columns=['Wind Chill (F)'])
#     print('Dropped the <Wind Chill (F)> column.')
else:
    print('The <Wind Chill (F)> column does not exist.')

# Check if 'Heat Index (F)' is in the DataFrame's columns
if 'Heat Index (F)' in df_single_station.columns:
    # Drop the column
    df_single_station = df_single_station.drop(columns=['Heat Index (F)'])
#     print('Dropped the <Heat Index (F)> column.')
else:
    print('The <Heat Index (F)> column does not exist.')
```

In [10]:

```
# Renaming
df_single_station.rename(columns={ "Temp (F)": "Temp_F", "RH (%)": "RH_pct",
                   "Dewpt (F)" : "Dewpt_F", "Wind Spd (mph)" : "Wind_Spd_mph",
                   "Wind Direction (deg)" : "Wind_Direction_deg", "Peak Wind Gu
                   "Low Cloud Ht (ft)" : "Low_Cloud_Ht_ft", "Med Cloud Ht (ft)'
                   "High Cloud Ht (ft)" : "High_Cloud_Ht_ft", "Visibility (mi)'
                   "Atm Press (hPa)" : "Atm_Press_hPa", "Sea Lev Press (hPa)" :
                   "Altimeter (hPa)" : "Altimeter_hPa", "Precip (in)" : "Precip
                   "Wind Chill (F)" : "Wind_Chill_F", "Heat Index (F)" : "Heat_
                   } , inplace = True)
```

In [11]:

```
def missing_values(df):
    total_null = df.isna().sum()
    percent_null = total_null / df.count() # Total count of null values / Total
    missing_data = pd.concat([total_null, percent_null], axis = 1, keys = ['Tot
    return missing_data
```

```
missing_values_before = missing_values(df_single_station)
missing_values_before
```

Out[11]:

	Total Null	Percentage Null
Date_UTC	0	0.000000
Time_UTC	0	0.000000
Date_CST	0	0.000000
Time_CST	0	0.000000
File_name_for_1D_lake	0	0.000000
File_name_for_2D_lake	0	0.000000
Lake_data_1D	0	0.000000
data_usable	0	0.000000
cloud_count	0	0.000000
cloud_exist	0	0.000000
Temp_F	239	0.004991
RH_pct	239	0.004991
Dewpt_F	239	0.004991
Wind_Spd_mph	239	0.004991
Wind_Direction_deg	239	0.004991
Peak_Wind_Gust_mph	239	0.004991
Low_Cloud_Ht_ft	239	0.004991
Med_Cloud_Ht_ft	239	0.004991
High_Cloud_Ht_ft	239	0.004991
Visibility_mi	239	0.004991
Atm_Press_hPa	239	0.004991
Sea_Lev_Press_hPa	239	0.004991
Altimeter_hPa	239	0.004991
Precip_in	239	0.004991

In [12]:

```
# Replace any m, M values to nan (float type)
df_single_station['Temp_F'] = df_single_station['Temp_F'].replace(['m', 'M'], f

# Then, replace those nan values with the last numerical value in the column
df_single_station['Temp_F'] = df_single_station['Temp_F'].fillna(method='ffill'
```

In [13]:

```
# Replace any m, M values to nan (float type)
df_single_station['RH_pct'] = df_single_station['RH_pct'].replace(['m', 'M'], f

# Then, replace those nan values with the last numerical value in the column
df_single_station['RH_pct'] = df_single_station['RH_pct'].fillna(method='ffill'
```

In [14]:
```
# Replace any m, M values to nan (float type)
df_single_station['Dewpt_F'] = df_single_station['Dewpt_F'].replace(['m', 'M'],

# Then, replace those nan values with the last numerical value in the column
df_single_station['Dewpt_F'] = df_single_station['Dewpt_F'].fillna(method='ffil
```

In [15]:
```
# Replace any m, M values to nan (float type)
df_single_station['Wind_Spd_mph'] = df_single_station['Wind_Spd_mph'].replace([

# Then, replace those nan values with the last numerical value in the column
df_single_station['Wind_Spd_mph'] = df_single_station['Wind_Spd_mph'].fillna(me
```

In [16]:
```
# Replace any m, M values to nan (float type)
df_single_station['Wind_Direction_deg'] = df_single_station['Wind_Direction_deg

# Then, replace those nan values with the last numerical value in the column
df_single_station['Wind_Direction_deg'] = df_single_station['Wind_Direction_deg
```

> "Peak Wind Gust" refers to the highest instantaneous wind speed recorded during a specific period, typically over the course of a day. It represents the maximum force of wind experienced at a location and is usually caused by high-pressure systems or storms.

Therefore, we further replace any of the `NaN` values in the column `Peak_Wind_Gust_mph` with the value that is in the column `Wind_Spd_mph`.

In [17]:
```
# Replace any m, M values to nan (float type)
df_single_station['Peak_Wind_Gust_mph'] = df_single_station['Peak_Wind_Gust_mph

# Then, replace those nan values with the last numerical value in the column
df_single_station['Peak_Wind_Gust_mph'] = df_single_station['Peak_Wind_Gust_mph

df_single_station['Peak_Wind_Gust_mph'] = df_single_station['Peak_Wind_Gust_mph
```

In [18]:
```
# Replace any m, M values to nan (float type)
df_single_station['Low_Cloud_Ht_ft'] = df_single_station['Low_Cloud_Ht_ft'].rep

# Then, replace those nan values with the last numerical value in the column
df_single_station['Low_Cloud_Ht_ft'] = df_single_station['Low_Cloud_Ht_ft'].fil
```

In [19]:
```
# Replace any m, M values to nan (float type)
df_single_station['Med_Cloud_Ht_ft'] = df_single_station['Med_Cloud_Ht_ft'].rep

# Then, replace those nan values with the last numerical value in the column
df_single_station['Med_Cloud_Ht_ft'] = df_single_station['Med_Cloud_Ht_ft'].fil

df_single_station['Med_Cloud_Ht_ft'] = df_single_station['Med_Cloud_Ht_ft'].fil
```

In [20]:
```
# Replace any m, M values to nan (float type)
df_single_station['High_Cloud_Ht_ft'] = df_single_station['High_Cloud_Ht_ft'].r

# Then, replace those nan values with the last numerical value in the column
df_single_station['High_Cloud_Ht_ft'] = df_single_station['High_Cloud_Ht_ft'].f
```

```
df_single_station['High_Cloud_Ht_ft'] = df_single_station['High_Cloud_Ht_ft'].f
```

In [21]:
```
# Replace any m, M values to nan (float type)
df_single_station['Visibility_mi'] = df_single_station['Visibility_mi'].replace

# Then, replace those nan values with the last numerical value in the column
df_single_station['Visibility_mi'] = df_single_station['Visibility_mi'].fillna(
```

In [22]:
```
# Replace any m, M values to nan (float type)
df_single_station['Atm_Press_hPa'] = df_single_station['Atm_Press_hPa'].replace

# Then, replace those nan values with the last numerical value in the column
df_single_station['Atm_Press_hPa'] = df_single_station['Atm_Press_hPa'].fillna(
```

In [23]:
```
# Replace any m, M values to nan (float type)
df_single_station['Sea_Lev_Press_hPa'] = df_single_station['Sea_Lev_Press_hPa']

# Then, replace those nan values with the last numerical value in the column
df_single_station['Sea_Lev_Press_hPa'] = df_single_station['Sea_Lev_Press_hPa']
```

In [24]:
```
# Replace any m, M values to nan (float type)
df_single_station['Altimeter_hPa'] = df_single_station['Altimeter_hPa'].replace

# Then, replace those nan values with the last numerical value in the column
df_single_station['Altimeter_hPa'] = df_single_station['Altimeter_hPa'].fillna(
```

In [25]:
```
# Replace any m, M values to nan (float type)
df_single_station['Precip_in'] = df_single_station['Precip_in'].replace(['m', '

# Then, replace those nan values with the last numerical value in the column
df_single_station['Precip_in'].fillna(0.00, inplace = True)
```

After all the patch work, let's see how the situation is now with missing values.

In [26]:
```
missing_values_after = missing_values(df_single_station)
missing_values_after
```

Out[26]:

	Total Null	Percentage Null
Date_UTC	0	0.0
Time_UTC	0	0.0
Date_CST	0	0.0
Time_CST	0	0.0
File_name_for_1D_lake	0	0.0
File_name_for_2D_lake	0	0.0
Lake_data_1D	0	0.0
data_usable	0	0.0
cloud_count	0	0.0
cloud_exist	0	0.0
Temp_F	0	0.0
RH_pct	0	0.0
Dewpt_F	0	0.0
Wind_Spd_mph	0	0.0
Wind_Direction_deg	0	0.0
Peak_Wind_Gust_mph	0	0.0
Low_Cloud_Ht_ft	0	0.0
Med_Cloud_Ht_ft	0	0.0
High_Cloud_Ht_ft	0	0.0
Visibility_mi	0	0.0
Atm_Press_hPa	0	0.0
Sea_Lev_Press_hPa	0	0.0
Altimeter_hPa	0	0.0
Precip_in	0	0.0

In [27]:
```
df_daytime_only = df_single_station.loc[(df_single_station['Time_UTC'] >= '14:(
                        & (df_single_station['Time_UTC'] <= '21:00')]
df_daytime_only  = df_daytime_only .reset_index(drop=True)
# df_daytime_only.head(10)
```

---

2. Cloud Image Generation

We will try to generate the images based on the 1-D lake data.

In [28]:
```
df_lat_lon = pd.read_csv('data_dir/lat_long_1D_labels_for_plotting.csv')
df_lat_lon.head(5)
```

Out[28]:

	latitude	longitude
0	41.78	-87.54
1	41.78	-87.50
2	41.78	-87.46
3	41.78	-87.42
4	41.78	-87.38

In [29]:
```
lat_lst = df_lat_lon['latitude'].to_list()
lon_lst = df_lat_lon['longitude'].to_list()
```

1-D Lake Imagery Data Conversion

In [30]:
```
def rectify(crap_string):
    return [0.0 if el == 'nan' else float(el) for el in crap_string.strip('][')
```

3. Feature Engineering for Snowfall Events

The fundamental criteria are the temperature to be below 32 F in the local area, and the precipitation larger than 0.01 inch.

In [31]:
```
df_daytime_only.loc[(df_daytime_only['Temp_F'] <= 32) & (df_daytime_only['Preci
df_daytime_only.loc[(df_daytime_only['Temp_F'] > 32) | (df_daytime_only['Precip
# df_daytime_only.head(5)
```

In [32]:
```
df_daytime_only = df_daytime_only.drop(['Date_UTC', 'Time_UTC', 'Date_CST', 'Ti
df_daytime_only = df_daytime_only.reset_index(drop=True)
# df_daytime_only.head()
```

In [33]:
```
df_daytime_only = df_daytime_only.drop(['data_usable', 'cloud_count', 'cloud_ex
df_daytime_only = df_daytime_only.reset_index(drop=True)
```

In [34]:
```
# Summary
df_daytime_only.describe()
```

Out[34]:

	Temp_F	RH_pct	Dewpt_F	Wind_Spd_mph	Wind_Direction_deg	Peak_
count	16040.000000	16040.000000	16040.000000	16040.000000	16040.000000	
mean	35.412594	68.103491	25.379988	8.313529	183.465087	
std	14.920630	15.099017	13.649343	4.870364	113.074909	
min	-13.000000	10.000000	-20.000000	0.000000	0.000000	
25%	25.000000	58.000000	16.000000	5.000000	80.000000	
50%	34.000000	70.000000	25.000000	8.000000	210.000000	
75%	45.000000	79.000000	34.000000	11.000000	270.000000	
max	88.000000	100.000000	67.000000	32.000000	360.000000	

In [35]:

```
df_daytime_only.LES_Snowfall.value_counts()
```

Out[35]:

```
0.0    15696
1.0      344
Name: LES_Snowfall, dtype: int64
```

I reckon it looks alright? We can then work on checking the correlations between the features.

---

4. Correlations Between Features

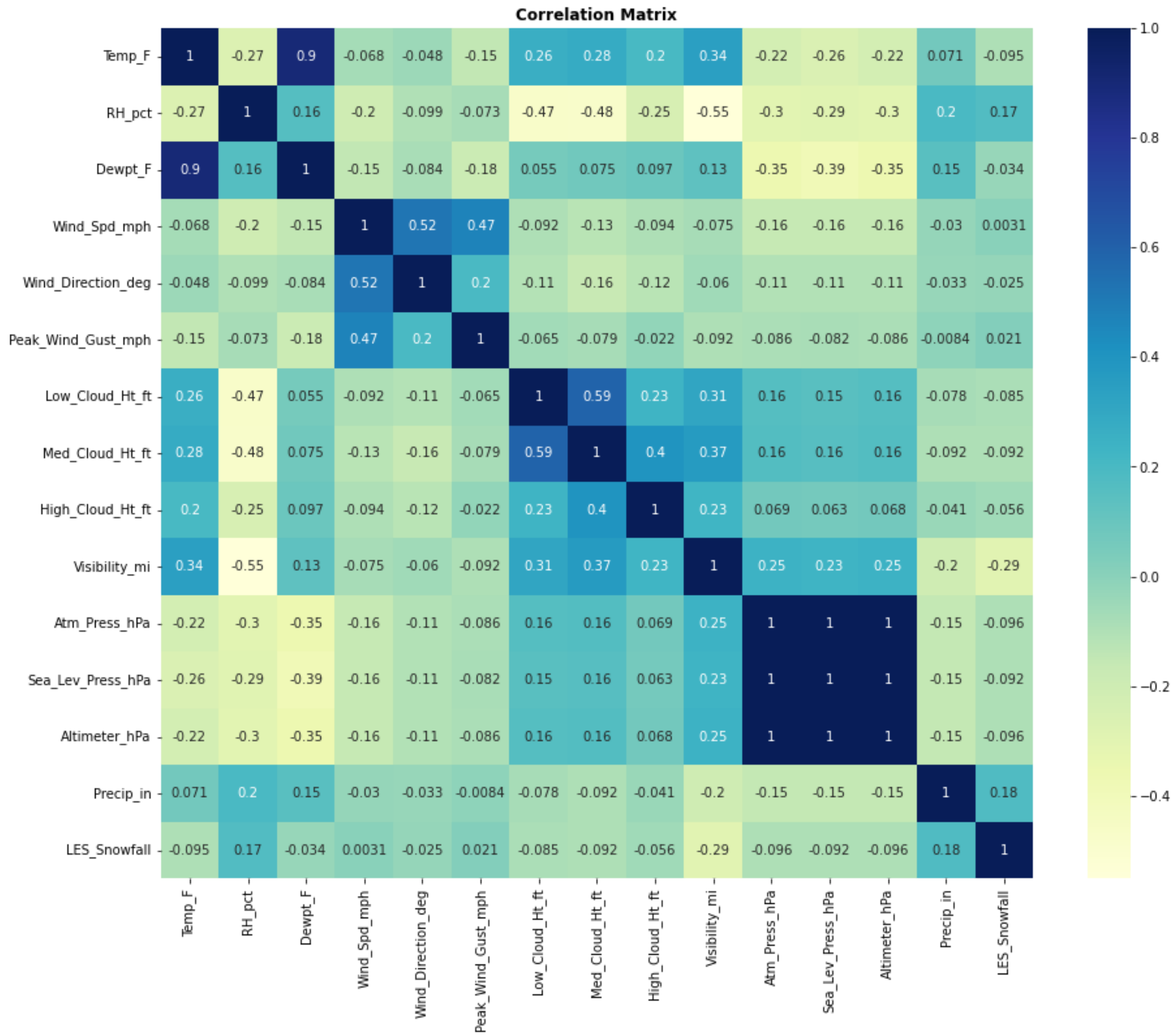
In [36]:

```
# Correlation
correlation_matrix = df_daytime_only.corr(method = 'pearson')
plt.subplots(figsize=(15,12))

# Heatmap
sns.heatmap(correlation_matrix, annot = True, cmap = "YlGnBu")
plt.title("Correlation Matrix", size = 12, weight = 'bold')
```

```
/tmp/ipykernel_7582/3056942574.py:2: FutureWarning: The default value of numer
ic_only in DataFrame.corr is deprecated. In a future version, it will default
to False. Select only valid columns or specify the value of numeric_only to si
lence this warning.
  correlation_matrix = df_daytime_only.corr(method = 'pearson')
```

Out[36]:

```
Text(0.5, 1.0, 'Correlation Matrix')
```



Observations from the above correlation plots:

- Few features are very heavily correated with each other (score >= 0.50)
    - **Temp_F** is highly correlated with **Dewpt_F**
    - **Wind_Spd_mph** is highly correlated with **Wind_Direction_deg**
    - **Atm_Press_hPa**, **Sea_Lev_Press_hPa**, and **Altimeter_hPa** are highly correlated to each other
- We also note some strong `negative correlation`, but all of them are greater than -0.5, hence we do not drop those features

We can drop the above columns since they imply to the same information, and keeping them as features will increase the model size.

But before doing this, let's work on **Atm_Press_hPa**, **Sea_Lev_Press_hPa**, and **Altimeter_hPa**, to see what is actually going on.

They are not identical to each other, but by nature, we know that they should be highly correlated. So, we are going to drop:

- **Dewpt_F**

- **Sea_Lev_Press_hPa** and **Altimeter_hPa**

We are being a little bit conservative here at the moment. The threshold for what constitutes "high" correlation can depend on the specific context and the dataset, but a common rule of thumb is to consider variables with a correlation coefficient above 0.8 or 0.9 to be highly correlated. However, there's no hard and fast rule, and the specific requirements of your project might necessitate a different threshold.

In [37]:
```
df_daytime_only = df_daytime_only.drop(['Dewpt_F', 'Sea_Lev_Press_hPa', 'Altime
df_daytime_only = df_daytime_only.reset_index(drop=True)

# Information about dataset shape
print('Total observations: ', df_daytime_only.shape[0])
print('Total number of features: ', df_daytime_only.shape[1])
df_daytime_only.head()
```

```
Total observations:  16040
Total number of features:  15
```

Out[37]:

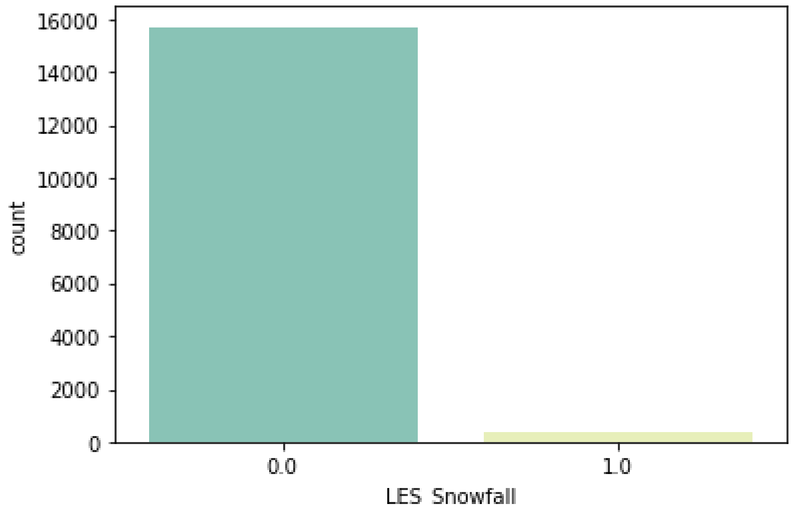
	File_name_for_1D_lake	File_name_for_2D_lake	Lake_data_1D	Temp_F	RH_pc
0	goes11.2006.10.01.1400.v01.nc-var1-t0.csv	T_goes11.2006.10.01.1400.v01.nc-var1-t0.csv.csv	[0.067499995, 0.07, 0.0625, 0.06, 0.0725, 0.06...	48.0	92.
1	goes11.2006.10.01.1500.v01.nc-var1-t0.csv	T_goes11.2006.10.01.1500.v01.nc-var1-t0.csv.csv	[0.067499995, 0.067499995, 0.06, 0.06, 0.05749...	55.0	59.
2	goes11.2006.10.01.1600.v01.nc-var1-t0.csv	T_goes11.2006.10.01.1600.v01.nc-var1-t0.csv.csv	[0.0725, 0.067499995, 0.07, 0.07, 0.067499995,...	55.0	61.
3	goes11.2006.10.01.1700.v01.nc-var1-t0.csv	T_goes11.2006.10.01.1700.v01.nc-var1-t0.csv.csv	[0.067499995, 0.067499995, 0.067499995, 0.07, ...	58.0	55.
4	goes11.2006.10.01.1800.v01.nc-var1-t0.csv	T_goes11.2006.10.01.1800.v01.nc-var1-t0.csv.csv	[0.085, 0.085, 0.0875, 0.0725, 0.0775, 0.0775,...	56.0	59.

In [38]:
```
df_daytime_only['LES_Snowfall'].value_counts()
```

Out[38]:
```
0.0    15696
1.0      344
Name: LES_Snowfall, dtype: int64
```

In [39]:
```
sns.countplot(x = df_daytime_only['LES_Snowfall'], palette=["#7fcdbb", "#edf8b1
```

Out[39]:
```
<Axes: xlabel='LES_Snowfall', ylabel='count'>
```



5. Feature Engineering: Precipitation

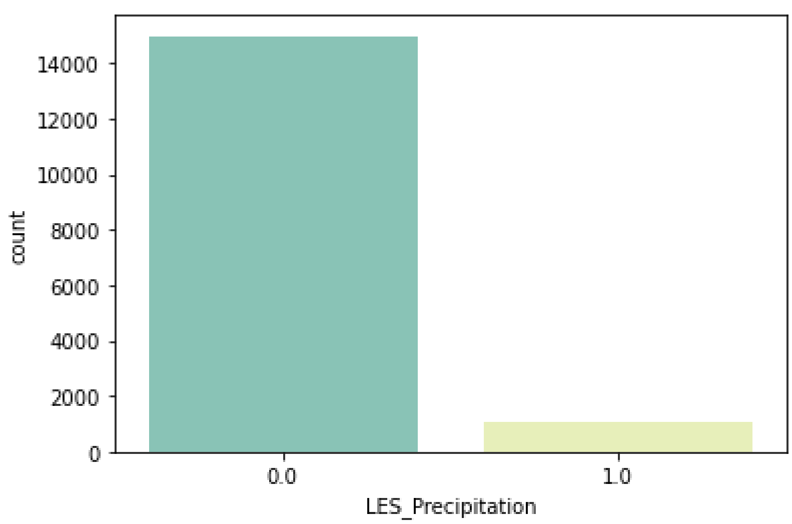
Adding a New Column For Precipitation

There is no fancy masking being applied yet. We will do that in another experiment.

In [40]:
```
df_daytime_only.loc[df_daytime_only['Precip_in'] > 0, 'LES_Precipitation'] = 1
df_daytime_only.loc[df_daytime_only['Precip_in'] <= 0, 'LES_Precipitation'] = (
# df_daytime_only
```

In [41]:
```
sns.countplot(x = df_daytime_only['LES_Precipitation'], palette=["#7fcdbb", "#e
```

Out[41]:
```
<Axes: xlabel='LES_Precipitation', ylabel='count'>
```



In [42]:
```
import tensorflow as tf
from tensorflow import keras
from tensorflow.keras import layers

import io
```

```
import imageio
from IPython.display import Image, display
from ipywidgets import widgets, Layout, HBox
```

In [43]:
```
from tqdm import tqdm
import cv2

images = []
for idx in tqdm(range(df_daytime_only.shape[0])):
# for idx in tqdm(range(7)):
    # im shape -> (64, 64)
    im = cv2.imread('data_dir/lake-michigan-images-64/' + str(idx) + '.png')
    # im = cv2.imread('/content/lake-michigan-images-64/' + str(idx) + '.png')
    # Storing 1 channel, since the images are grayscale, and cropping
    images.append(im[8:-8,8:-8,0])
    # images shape -> (35, 64, 64)
```

```
100%|██████████| 16040/16040 [00:00<00:00, 18119.56it/s]
```

6. Predicting rain from past imagery *and* meteo

In this section, we will build the network with ConvLSTM2D for meteorological imagery data,

In [44]:
```
meteo_les = df_single_station.drop(
    [ 'Date_UTC', 'Time_UTC', 'Date_CST', 'Time_CST', 'File_name_for_1D_lake',
     'Lake_data_1D', 'Dewpt_F', 'Sea_Lev_Press_hPa', 'Altimeter_hPa', 'data_usa
       'cloud_exist' ], axis=1)
```

In [45]:
```
meteo_les.head()
```

Out[45]:

	Temp_F	RH_pct	Wind_Spd_mph	Wind_Direction_deg	Peak_Wind_Gust_mph	Low_Cloud_Ht
0	51.0	92.0	0.0	0.0	0.0	370
1	48.0	96.0	0.0	0.0	0.0	370
2	49.0	92.0	3.0	220.0	3.0	370
3	48.0	100.0	0.0	0.0	0.0	250
4	50.0	92.0	3.0	180.0	3.0	700

In [46]:
```
len(meteo_les)
```

Out[46]:
```
48121
```

In [47]:
```
meteo_train_batched = tf.keras.preprocessing.timeseries_dataset_from_array(mete
                                                                            sampling_rat
```

In [48]:
```
for batch in meteo_train_batched:
    meteo_train = batch
    print(meteo_train.shape)
    print('--')
```

```
(1685, 72, 11)
--
```

Next, we load the validation portion.

In [49]:
```
meteo_val_batched = tf.keras.preprocessing.timeseries_dataset_from_array(meteo_
                                                                          sampling_rat
```

In [50]:
```
meteo_val = None
for batch in meteo_val_batched:
    meteo_val = batch
    print(meteo_val.shape)
    print('--')
```

```
(310, 72, 11)
--
```

For the imagery data, $8 \times 3 \ = \ 24$ images per input sequence, and time step is 8 images.

In [51]:
```
cloud_train_batched = tf.keras.preprocessing.timeseries_dataset_from_array(imag
                                                                            samp
```

In [52]:
```
cloud_train = None
for batch in cloud_train_batched:
    cloud_train = batch
    cloud_train = np.expand_dims(cloud_train, axis=-1)
    print(cloud_train.shape)
    cloud_train = cloud_train / 255
    print('--')
```

```
(1685, 24, 48, 48, 1)
--
```

And test data:

In [53]:
```
cloud_val_batched = tf.keras.preprocessing.timeseries_dataset_from_array(images
                                                                          sampli
```

In [54]:
```
cloud_val = None
for batch in cloud_val_batched:
    cloud_val = batch
    cloud_val = np.expand_dims(cloud_val, axis=-1)
    print(cloud_val.shape)
    cloud_val = cloud_val / 255
    print('--')
```

```
(310, 24, 48, 48, 1)
--
```

Final rain classification label

Finally, let's create our label:

This is how much precipitation in 72 hours:

In [55]:
```
rain_train = []
for batch in meteo_train:
```

```
    batch =batch
    batch = np.expand_dims(batch, axis=0)
    for i in range(batch.shape[0]):
        rain_train.append(sum(batch[i,0:23,-1]))
#                   rain_train.append(sum(batch[i,:,-1].numpy()))


len(rain_train)
```

Out[55]:
```
1685
```

We use $0.10\ inch$ over the span of 24 hours as the criteria.

In [56]:
```
rain_train_b = [1 if 0.10 <= r else 0 for r in rain_train]
```

In [57]:
```
rain_train_c = np.array(rain_train_b)
rain_train_c.shape
```

Out[57]:
```
(1685,)
```

In [58]:
```
rain_val = []
for batch in meteo_val:
    batch = np.expand_dims(batch, axis=0)
    for i in range(batch.shape[0]):
        rain_val.append(sum(batch[i,0:23,-1]))


len(rain_val)
```

Out[58]:
```
310
```

In [59]:
```
rain_val_b = [1 if 0.10 <= r else 0 for r in rain_val]
```

In [60]:
```
rain_val_c = np.array(rain_val_b)
rain_val_c.shape
```

Out[60]:
```
(310,)
```

Network

Imagery Network

In [61]:
```
cloud_train.shape, rain_train_c.shape, cloud_val.shape, rain_val_c.shape
```

Out[61]:
```
((1685, 24, 48, 48, 1), (1685,), (310, 24, 48, 48, 1), (310,))
```

In [62]:
```
cloud_train.shape[2:]
```

Out[62]:
```
(48, 48, 1)
```

In our network, we will add the custom squeeze-excitation blocks.

In [63]:

```
# from tensorflow.keras.layers import GlobalAveragePooling2D, Reshape, Dense, M

# def se_block(input_tensor, ratio=16):
#     channels = int(input_tensor.shape[-1])

#     # Squeeze step
#     se_tensor = GlobalAveragePooling2D()(input_tensor)
#     se_tensor = Reshape((1, 1, channels))(se_tensor)

#     # Excitation step
#     se_tensor = Dense(channels // ratio, activation='relu')(se_tensor)
#     se_tensor = Dense(channels, activation='sigmoid')(se_tensor)

#     return Multiply()([input_tensor, se_tensor])

from tensorflow.keras.layers import GlobalAveragePooling2D, Reshape, Dense, Mul

# def se_block(input_tensor, ratio=16):
#     channels = int(input_tensor.shape[-1])

#     # Squeeze step
#     se_tensor = TimeDistributed(GlobalAveragePooling2D())(input_tensor)
#     se_tensor = Reshape((1, 1, channels))(se_tensor)

#     # Excitation step
#     se_tensor = TimeDistributed(Dense(channels // ratio, activation='relu'))(
#     se_tensor = TimeDistributed(Dense(channels, activation='sigmoid'))(se_ten

#     return Multiply()([input_tensor, se_tensor])

# from tensorflow.keras import backend as K
# from tensorflow.keras.layers import GlobalAveragePooling2D, Reshape, Multiply

# def se_block(input_tensor, ratio=16):
#     input_shape = input_tensor.shape
#     timesteps, height, width, channels = input_shape[1:]

#     # Break the input tensor into a list of timesteps tensors
#     inputs_per_timestep = [Lambda(lambda x: x[:, i])(input_tensor) for i in r

#     outputs_per_timestep = []
#     for input_per_timestep in inputs_per_timestep:
#         # Squeeze
#         se_tensor = GlobalAveragePooling2D()(input_per_timestep)
#         se_tensor = Dense(channels // ratio, activation='relu')(se_tensor)
#         se_tensor = Dense(channels, activation='sigmoid')(se_tensor)
#         se_tensor = Reshape([1, 1, channels])(se_tensor)

#         # Excite
#         se_tensor = Multiply()([input_per_timestep, se_tensor])

#         outputs_per_timestep.append(se_tensor)

#     # Concatenate the list of timesteps tensors back into a 5D tensor
#     output_tensor = Lambda(lambda x: K.stack(x, axis=1))(outputs_per_timestep

#     return output_tensor

from tensorflow.keras.layers import Layer, GlobalAveragePooling2D, Dense, Resha
```

```
import tensorflow as tf

class SEBlock(Layer):
    def __init__(self, ratio=16, **kwargs):
        self.ratio = ratio
        super(SEBlock, self).__init__(**kwargs)

    def build(self, input_shape):
        self.channels = input_shape[-1]
        self.dense1 = self.add_weight(name='dense1', shape=(self.channels, self
                                      initializer='uniform', trainable=True)
        self.dense2 = self.add_weight(name='dense2', shape=(self.channels // se
                                      initializer='uniform', trainable=True)
        super(SEBlock, self).build(input_shape)

    def call(self, inputs):
        # Get the shape of the input
        shape_tensor = tf.shape(inputs)
        timesteps = shape_tensor[1]
        height = shape_tensor[2]
        width = shape_tensor[3]
        channels = shape_tensor[4]

        # Reshape the input tensor into (batch_size * timesteps, height, width,
        reshaped_inputs = tf.reshape(inputs, (-1, height, width, channels))

        # Squeeze
        se_tensor = GlobalAveragePooling2D()(reshaped_inputs)
        se_tensor = tf.matmul(se_tensor, self.dense1)
        se_tensor = tf.nn.relu(se_tensor)
        se_tensor = tf.matmul(se_tensor, self.dense2)
        se_tensor = tf.nn.sigmoid(se_tensor)
        se_tensor = Reshape((1, 1, self.channels))(se_tensor)

        # Excite
        excited_reshaped_inputs = Multiply()([reshaped_inputs, se_tensor])

        # Reshape back to original shape
        output_tensor = tf.reshape(excited_reshaped_inputs, (-1, timesteps, hei
        return output_tensor
```

This code defines a Squeeze-and-Excitation (SE) block, which is a component that can be added to convolutional neural networks (CNNs) to adaptively recalibrate channel-wise feature responses. The SE block is designed to allow the network to pay more selective attention to informative features during training.

The code includes the following steps:

1. Initialization (**init** method):

ratio: A hyperparameter that controls the reduction dimension in the channel-wise squeeze operation. The constructor initializes the ratio attribute and calls the parent class constructor.

1. Building the Block (build method):

It defines the structure of the SE block by adding trainable weights. self.channels retrieves the number of channels from the input shape. Two dense weight matrices self.dense1 and self.dense2 are created, representing two fully connected (dense) layers. Calling the Block (call method): This method describes the forward computation of the block and includes the following steps:

```
a. Extracting Dimensions:

Extracts the shape of the input tensor, including timesteps,
height, width, and channels.

b. Reshaping the Input:

Reshapes the input tensor to treat each time step as a separate
example, forming a new tensor with shape (batch_size *
timesteps, height, width, channels).

c. Squeeze Operation:

* Applies a Global Average Pooling layer to the reshaped
inputs, reducing the spatial dimensions.
* Multiplies the resulting tensor by the self.dense1 weights
and applies a ReLU activation function.
* Multiplies the resulting tensor by the self.dense2 weights
and applies a sigmoid activation function.
* Reshapes the tensor to have dimensions (1, 1, channels),
preparing it for the excitation step.

d. Excite Operation:

Multiplies the reshaped inputs (from the squeeze operation)
with the se_tensor (from the squeeze step), scaling the
channels based on the information captured by the squeeze
operation.

e. Reshaping Back to Original Shape:

Finally, the excited tensor is reshaped back to the original
shape (batch_size, timesteps, height, width, channels).
```

Therefore, the SE block takes an input tensor and applies a "squeeze" operation to capture global information about each channel and then an "excitation" operation to re-weight the channels. It's particularly useful for enhancing the representational power of a CNN by allowing it to emphasize the most informative channels for a given task. The code provided is a modified version to work with sequences of 2D images (as might be used with ConvLSTM2D layers), extending the typical SE block to handle this additional time dimension.

In [64]:

```
# Construct the input layer with no definite frame size (None below could be re

from tensorflow.keras.layers import MultiHeadAttention
inp = layers.Input(shape=(None, *cloud_train.shape[2:]))
print("layers.Input(shape=", inp.shape)

# x = layers.ConvLSTM2D(
#     filters=64,
#     kernel_size=(5, 5),
#     strides=(2, 2),
#     padding="same",
#     return_sequences=True,
#     activation="relu",
# )(inp)
x = layers.ConvLSTM2D(
    filters=96,
    kernel_size=(9, 9),
    strides=(1, 1),
    padding="same",
    return_sequences=True,
    activation="relu",
)(inp)
# x = layers.Dropout(0.3)(x)
x = layers.BatchNormalization()(x)
# x = layers.ConvLSTM2D(
#     filters=64,
#     kernel_size=(7, 7),
#     strides=(1, 1),
#     padding="same",
#     return_sequences=True,
#     activation="relu",
# # )(inp)
# )(x)
# Add the SE block here
# x = se_block(x)
x = SEBlock()(x)
# x = layers.SqueezeAndExciteBlock(64)(x)
# x = layers.Dropout(0.3)(x)
# x = layers.BatchNormalization()(x)
x = layers.ConvLSTM2D(
    filters=64,
    kernel_size=(7, 7),
    strides=(1, 1),
    padding="same",
    return_sequences=True,
    activation="relu",
# )(inp)
)(x)
print("ConvLSTM2D filters=64, kernel_size=(5, 5), return_sequences=True", x.sha

# x = layers.Dropout(0.3)(x)
x = layers.BatchNormalization()(x)

print("BatchNormalization", x.shape)

# Save the shape before attention
shape_before_attention = tf.shape(x)
time_steps = shape_before_attention[1]
height_width_channels = shape_before_attention[2] * shape_before_attention[3] *
```

```
# Reshape for attention (flattening spatial dimensions)
x_flattened = tf.reshape(x, (-1, time_steps, height_width_channels))

# Apply MultiHeadAttention
attention = MultiHeadAttention(num_heads=2, key_dim=64)
x_attention = attention(x_flattened, x_flattened)

# Reshape back to original shape
x_after_attention = tf.reshape(x_attention, shape_before_attention)
x = layers.ConvLSTM2D(
    filters=64,
    kernel_size=(5, 5),
    strides=(2, 2),
    padding="same",
    return_sequences=True,
    activation="relu",
)(x)
x = layers.BatchNormalization()(x)
x = SEBlock()(x)

x = layers.ConvLSTM2D(
    filters=64,
    kernel_size=(5, 5),
    strides=(1, 1),
    padding="same",
    return_sequences=True,
    activation="relu",
)(x)

# Save the shape before attention
shape_before_attention = tf.shape(x)
time_steps = shape_before_attention[1]
height_width_channels = shape_before_attention[2] * shape_before_attention[3] *

# Reshape for attention (flattening spatial dimensions)
x_flattened = tf.reshape(x, (-1, time_steps, height_width_channels))

# Apply MultiHeadAttention
attention = MultiHeadAttention(num_heads=2, key_dim=64)
x_attention = attention(x_flattened, x_flattened)

# Reshape back to original shape
x_after_attention = tf.reshape(x_attention, shape_before_attention)

x = layers.ConvLSTM2D(
    filters=64,
    kernel_size=(3, 3),
    strides=(2, 2),
    padding="same",
    return_sequences=True,
    activation="relu",
)(x)
# x = layers.Dropout(0.3)(x)
x = layers.BatchNormalization()(x)
x = SEBlock()(x)
x = layers.ConvLSTM2D(
    filters=32,
    kernel_size=(3, 3),
    strides=(1, 1),
```

```
    padding="same",
    return_sequences=True,
    activation="relu",
)(x)
x = SEBlock()(x)
# x = squeeze_excite_block(32,x)
print("ConvLSTM2D filters=64, kernel_size=(3, 3), return_sequences=True", x.sha
x = layers.BatchNormalization()(x)
print("BatchNormalization", x.shape)

# Save the shape before attention
shape_before_attention = tf.shape(x)
time_steps = shape_before_attention[1]
height_width_channels = shape_before_attention[2] * shape_before_attention[3] *

# Reshape for attention (flattening spatial dimensions)
x_flattened = tf.reshape(x, (-1, time_steps, height_width_channels))

# Apply MultiHeadAttention
attention = MultiHeadAttention(num_heads=2, key_dim=64)
x_attention = attention(x_flattened, x_flattened)

# Reshape back to original shape
x_after_attention = tf.reshape(x_attention, shape_before_attention)
x = layers.ConvLSTM2D(
    filters=32,
    kernel_size=(1, 1),
    strides=(2, 2),
    padding="same",
    return_sequences=True,
    activation="relu",
)(x)
print("ConvLSTM2D filters=64, kernel_size=(1, 1), return_sequences=True", x.sha
x = layers.Conv3D(
    filters=24, kernel_size=(3, 3, 3), activation="sigmoid", padding="same"
)(x)

print("Conv3D kernel_size=(3, 3, 3)", x.shape)
x = layers.ConvLSTM2D(
    filters=24,
    kernel_size=(1, 1),
    strides=(2, 2),
    padding="same",
    return_sequences=False,
    activation="relu",
)(x)
# x = layers.Dropout(0.3)(x)
print("ConvLSTM2D filters=1, kernel_size=(1, 1), return_sequences=False", x.sha
x = layers.BatchNormalization()(x)
print("BatchNormalization", x.shape)

#x = layers.Dense(1)(x)
#print("Dense", x.shape)
x = GlobalAveragePooling2D()(x)
print("GlobalAveragePooling2D", x.shape)
```

```
layers.Input(shape= (None, None, 48, 48, 1)
ConvLSTM2D filters=64, kernel_size=(5, 5), return_sequences=True (None, None,
48, 48, 64)
BatchNormalization (None, None, 48, 48, 64)
ConvLSTM2D filters=64, kernel_size=(3, 3), return_sequences=True (None, None,
12, 12, 32)
BatchNormalization (None, None, 12, 12, 32)
ConvLSTM2D filters=64, kernel_size=(1, 1), return_sequences=True (None, None,
6, 6, 32)
Conv3D kernel_size=(3, 3, 3) (None, None, 6, 6, 24)
ConvLSTM2D filters=1, kernel_size=(1, 1), return_sequences=False (None, 3, 3,
24)
BatchNormalization (None, 3, 3, 24)
GlobalAveragePooling2D (None, 24)
```

Meteo network

In [65]:
```
meteo_train.shape, rain_train_c.shape, meteo_val.shape, rain_val_c.shape
```

Out[65]:
```
(TensorShape([1685, 72, 11]), (1685,), TensorShape([310, 72, 11]), (310,))
```

In [66]:
```
meteo_train.shape[1:]
```

Out[66]:
```
TensorShape([72, 11])
```

In [67]:
```
# RNN = layers.LSTM
# hidden_size = 8
# data_shape = (24, 11)
# data = layers.Input(shape= data_shape)
# meteo_inp = layers.Input(shape=(None, *meteo_train.shape[1:]))
# print("layers.Input(shape=", meteo_inp.shape)
# lstm1 = RNN(hidden_size, input_shape=(24, data_shape[1]), return_sequences= T
# lstm2 = RNN(hidden_size, input_shape=(24, hidden_size), return_sequences= Fal
# lstm2.shape
```

In [68]:
```
# RNN = layers.LSTM
# hidden_size = 24
# data_shape = (72, 11)
# data = layers.Input(shape= data_shape)
# meteo_inp = layers.Input(shape=(None, *meteo_train.shape[1:]))
# print("layers.Input(shape=", meteo_inp.shape)
# print(data_shape[1])
# lstm1 = RNN(hidden_size, input_shape=(48, data_shape[1]), return_sequences= T
# lstm2 = RNN(hidden_size, input_shape=(48, hidden_size), return_sequences= Fal
# lstm2.shape
```

In [69]:
```
from tensorflow.keras.layers import Add

from tensorflow.keras.layers import Bidirectional
from tensorflow.keras.layers import Dropout, BatchNormalization

# from tensorflow.keras.layers import Add

RNN = layers.LSTM
hidden_size = 24
data_shape = (72, 11)
```

```python
data = layers.Input(shape=data_shape)
meteo_inp = layers.Input(shape=(None, *meteo_train.shape[1:]))
print("layers.Input(shape=", meteo_inp.shape)

lstm1 = Bidirectional(RNN(hidden_size, return_sequences=True))(data)

lstm2 = Bidirectional(RNN(hidden_size, return_sequences=True))(lstm1)
lstm2 = Add()([lstm1, lstm2]) # Residual connection

lstm3 = Bidirectional(RNN(hidden_size, return_sequences=True))(lstm2)
lstm3 = Add()([lstm2, lstm3]) # Residual connection

lstm4 = Bidirectional(RNN(hidden_size, return_sequences=True))(lstm3)
lstm4 = Add()([lstm3, lstm4]) # Residual connection

lstm5 = Bidirectional(RNN(hidden_size, return_sequences=False))(lstm4)

# Continue to build the rest of your model
```

```
layers.Input(shape= (None, None, 72, 11)
```

Imagery + meteo

Our final classification into rain or no rain, based on a balanced amount of information from both imagery and meteo:

In [70]:
```python
# Flatten the output of CNN
#flattened = layers.Flatten()(conv6)

# Connect the CNN output and RNN output to a dense layer with 1 neuron for fina
final = layers.Concatenate(axis=1)([lstm5, x])
print("layers.Concatenate(axis=1)([lstm5, x])", final.shape)
out = layers.Dense(1, activation='sigmoid')(final)
print("layers.Dense(1)", out.shape)
```

```
layers.Concatenate(axis=1)([lstm5, x]) (None, 72)
layers.Dense(1) (None, 1)
```

In [71]:
```python
# Using both, images and numerical data as input
#inp = layers.Input(shape=(None, *cloud_train.shape[2:]))
#data = layers.Input(shape= (24, 11))
model = keras.models.Model([inp, data], out)
#model = keras.models.Model(inp, x)

# Build model
model.compile(loss=keras.losses.binary_crossentropy, optimizer=keras.optimizers
model.summary()
```

```
Model: "model"
__________________________________________________________________________________________________
 Layer (type)                   Output Shape         Param #     Connected to
==================================================================================================
 input_1 (InputLayer)           [(None, None, 48, 4  0           []
                                8, 1)]

 conv_lstm2d (ConvLSTM2D)       (None, None, 48, 48  3017472     ['input_1[0]
[0]']
                                , 96)

 batch_normalization (BatchNorm  (None, None, 48, 48  384        ['conv_lstm2d
[0][0]']
 alization)                     , 96)

 se_block (SEBlock)             (None, None, 48, 48  1152        ['batch_norma
lization[0][0]']
                                , 96)

 conv_lstm2d_1 (ConvLSTM2D)     (None, None, 48, 48  2007296     ['se_block[0]
[0]']
                                , 64)

 batch_normalization_1 (BatchNo  (None, None, 48, 48  256        ['conv_lstm2d
_1[0][0]']
 rmalization)                   , 64)

 conv_lstm2d_2 (ConvLSTM2D)     (None, None, 24, 24  819456      ['batch_norma
lization_1[0][0]']
                                , 64)

 batch_normalization_2 (BatchNo  (None, None, 24, 24  256        ['conv_lstm2d
_2[0][0]']
 rmalization)                   , 64)

 se_block_1 (SEBlock)           (None, None, 24, 24  512         ['batch_norma
lization_2[0][0]']
                                , 64)

 conv_lstm2d_3 (ConvLSTM2D)     (None, None, 24, 24  819456      ['se_block_1
[0][0]']
                                , 64)

 conv_lstm2d_4 (ConvLSTM2D)     (None, None, 12, 12  295168      ['conv_lstm2d
_3[0][0]']
                                , 64)

 batch_normalization_3 (BatchNo  (None, None, 12, 12  256        ['conv_lstm2d
_4[0][0]']
 rmalization)                   , 64)

 input_2 (InputLayer)           [(None, 72, 11)]     0           []

 se_block_2 (SEBlock)           (None, None, 12, 12  512         ['batch_norma
lization_3[0][0]']
                                , 64)

 bidirectional (Bidirectional)  (None, 72, 48)       6912        ['input_2[0]
```

```
[0]']

 conv_lstm2d_5 (ConvLSTM2D)     (None, None, 12, 12  110720      ['se_block_2
[0][0]']
                                , 32)

 bidirectional_1 (Bidirectional  (None, 72, 48)      14016       ['bidirection
al[0][0]']
 )

 se_block_3 (SEBlock)           (None, None, 12, 12  128         ['conv_lstm2d
_5[0][0]']
                                , 32)

 add (Add)                      (None, 72, 48)      0           ['bidirection
al[0][0]',
                                                                  'bidirection
al_1[0][0]']

 batch_normalization_4 (BatchNo  (None, None, 12, 12  128        ['se_block_3
[0][0]']
 rmalization)                   , 32)

 bidirectional_2 (Bidirectional  (None, 72, 48)      14016       ['add[0][0]']
 )

 conv_lstm2d_6 (ConvLSTM2D)     (None, None, 6, 6,   8320        ['batch_norma
lization_4[0][0]']
                                32)

 add_1 (Add)                    (None, 72, 48)      0           ['add[0][0]',
                                                                  'bidirection
al_2[0][0]']

 conv3d (Conv3D)                (None, None, 6, 6,   20760       ['conv_lstm2d
_6[0][0]']
                                24)

 bidirectional_3 (Bidirectional  (None, 72, 48)      14016       ['add_1[0]
[0]']
 )

 conv_lstm2d_7 (ConvLSTM2D)     (None, 3, 3, 24)     4704        ['conv3d[0]
[0]']

 add_2 (Add)                    (None, 72, 48)      0           ['add_1[0]
[0]',
                                                                  'bidirection
al_3[0][0]']

 batch_normalization_5 (BatchNo  (None, 3, 3, 24)    96          ['conv_lstm2d
_7[0][0]']
 rmalization)

 bidirectional_4 (Bidirectional  (None, 48)          14016       ['add_2[0]
[0]']
 )

 global_average_pooling2d (Glob  (None, 24)          0           ['batch_norma
lization_5[0][0]']
```

```
 alAveragePooling2D)

 concatenate (Concatenate)      (None, 72)           0           ['bidirection
al_4[0][0]',
                                                                   'global_aver
age_pooling2d[0][0]'
                                                                  ]

 dense (Dense)                  (None, 1)            73          ['concatenate
[0][0]']

==============================================================================
====================
Total params: 7,170,081
Trainable params: 7,169,393
Non-trainable params: 688
______________________________________________________________________________
____________________
```

Training

In [72]:
```python
cloud_train.shape, meteo_train.shape
```

Out[72]:
```
((1685, 24, 48, 48, 1), TensorShape([1685, 72, 11]))
```

In [72]:

In [72]:

In [72]:

In [72]:

In [72]:

In [72]:

In [72]:

In [72]:

In [74]:
```python
# Define some callbacks to improve training
# early_stopping = keras.callbacks.EarlyStopping(monitor="val_loss", patience=2
reduce_lr = keras.callbacks.ReduceLROnPlateau(monitor="val_loss", patience=15)

# Define modifiable training hyperparameters
epochs = 60
batch_size = 16

from datetime import datetime
now = datetime.now()
current_time = now.strftime("%H:%M:%S")
print("Started training at", current_time)

# Fit the model to the training data
```

```
history = model.fit(
    [cloud_train, meteo_train],
    rain_train_c,
    batch_size=batch_size,
    epochs=epochs,
    validation_data=([cloud_val, meteo_val], rain_val_c),
    # callbacks=[early_stopping, reduce_lr],
    callbacks=[reduce_lr],
)
```

```
Started training at 20:24:51
Epoch 1/60
106/106 [==============================] - 175s 1s/step - loss: 0.3995 - accur
acy: 0.8593 - val_loss: 0.4190 - val_accuracy: 0.8452 - lr: 0.0010
Epoch 2/60
106/106 [==============================] - 122s 1s/step - loss: 0.3618 - accur
acy: 0.8742 - val_loss: 0.4020 - val_accuracy: 0.8452 - lr: 0.0010
Epoch 3/60
106/106 [==============================] - 123s 1s/step - loss: 0.3517 - accur
acy: 0.8742 - val_loss: 0.3756 - val_accuracy: 0.8452 - lr: 0.0010
Epoch 4/60
106/106 [==============================] - 123s 1s/step - loss: 0.3397 - accur
acy: 0.8742 - val_loss: 0.3702 - val_accuracy: 0.8452 - lr: 0.0010
Epoch 5/60
106/106 [==============================] - 122s 1s/step - loss: 0.3349 - accur
acy: 0.8748 - val_loss: 0.3614 - val_accuracy: 0.8452 - lr: 0.0010
Epoch 6/60
106/106 [==============================] - 123s 1s/step - loss: 0.3247 - accur
acy: 0.8754 - val_loss: 0.3733 - val_accuracy: 0.8452 - lr: 0.0010
Epoch 7/60
106/106 [==============================] - 123s 1s/step - loss: 0.3146 - accur
acy: 0.8754 - val_loss: 0.3507 - val_accuracy: 0.8548 - lr: 0.0010
Epoch 8/60
106/106 [==============================] - 123s 1s/step - loss: 0.3108 - accur
acy: 0.8789 - val_loss: 0.3670 - val_accuracy: 0.8581 - lr: 0.0010
Epoch 9/60
106/106 [==============================] - 122s 1s/step - loss: 0.3072 - accur
acy: 0.8783 - val_loss: 0.3828 - val_accuracy: 0.8387 - lr: 0.0010
Epoch 10/60
106/106 [==============================] - 123s 1s/step - loss: 0.2957 - accur
acy: 0.8813 - val_loss: 0.3478 - val_accuracy: 0.8677 - lr: 0.0010
Epoch 11/60
106/106 [==============================] - 123s 1s/step - loss: 0.2909 - accur
acy: 0.8801 - val_loss: 0.4382 - val_accuracy: 0.8452 - lr: 0.0010
Epoch 12/60
106/106 [==============================] - 123s 1s/step - loss: 0.3002 - accur
acy: 0.8825 - val_loss: 0.3535 - val_accuracy: 0.8484 - lr: 0.0010
Epoch 13/60
106/106 [==============================] - 123s 1s/step - loss: 0.2859 - accur
acy: 0.8813 - val_loss: 0.3438 - val_accuracy: 0.8516 - lr: 0.0010
Epoch 14/60
106/106 [==============================] - 123s 1s/step - loss: 0.3063 - accur
acy: 0.8742 - val_loss: 0.3337 - val_accuracy: 0.8516 - lr: 0.0010
Epoch 15/60
106/106 [==============================] - 123s 1s/step - loss: 0.2800 - accur
acy: 0.8878 - val_loss: 0.4764 - val_accuracy: 0.8452 - lr: 0.0010
Epoch 16/60
106/106 [==============================] - 123s 1s/step - loss: 0.2775 - accur
acy: 0.8872 - val_loss: 0.4257 - val_accuracy: 0.8452 - lr: 0.0010
Epoch 17/60
106/106 [==============================] - 123s 1s/step - loss: 0.2874 - accur
acy: 0.8849 - val_loss: 0.3959 - val_accuracy: 0.8419 - lr: 0.0010
Epoch 18/60
106/106 [==============================] - 122s 1s/step - loss: 0.2835 - accur
acy: 0.8825 - val_loss: 0.4051 - val_accuracy: 0.8452 - lr: 0.0010
Epoch 19/60
106/106 [==============================] - 123s 1s/step - loss: 0.2968 - accur
acy: 0.8718 - val_loss: 0.3456 - val_accuracy: 0.8516 - lr: 0.0010
Epoch 20/60
106/106 [==============================] - 122s 1s/step - loss: 0.2848 - accur
```

```
acy: 0.8807 - val_loss: 0.3428 - val_accuracy: 0.8548 - lr: 0.0010
Epoch 21/60
106/106 [==============================] - 123s 1s/step - loss: 0.2662 - accur
acy: 0.8908 - val_loss: 0.3709 - val_accuracy: 0.8645 - lr: 0.0010
Epoch 22/60
106/106 [==============================] - 123s 1s/step - loss: 0.2811 - accur
acy: 0.8849 - val_loss: 0.3590 - val_accuracy: 0.8548 - lr: 0.0010
Epoch 23/60
106/106 [==============================] - 123s 1s/step - loss: 0.2812 - accur
acy: 0.8813 - val_loss: 0.3347 - val_accuracy: 0.8645 - lr: 0.0010
Epoch 24/60
106/106 [==============================] - 123s 1s/step - loss: 0.2615 - accur
acy: 0.8866 - val_loss: 0.3272 - val_accuracy: 0.8742 - lr: 0.0010
Epoch 25/60
106/106 [==============================] - 122s 1s/step - loss: 0.2714 - accur
acy: 0.8866 - val_loss: 0.3781 - val_accuracy: 0.8484 - lr: 0.0010
Epoch 26/60
106/106 [==============================] - 123s 1s/step - loss: 0.2692 - accur
acy: 0.8896 - val_loss: 0.3485 - val_accuracy: 0.8613 - lr: 0.0010
Epoch 27/60
106/106 [==============================] - 123s 1s/step - loss: 0.2731 - accur
acy: 0.8878 - val_loss: 0.3452 - val_accuracy: 0.8484 - lr: 0.0010
Epoch 28/60
106/106 [==============================] - 122s 1s/step - loss: 0.2460 - accur
acy: 0.8944 - val_loss: 0.3417 - val_accuracy: 0.8516 - lr: 0.0010
Epoch 29/60
106/106 [==============================] - 123s 1s/step - loss: 0.2628 - accur
acy: 0.8902 - val_loss: 0.3529 - val_accuracy: 0.8548 - lr: 0.0010
Epoch 30/60
106/106 [==============================] - 123s 1s/step - loss: 0.2557 - accur
acy: 0.8950 - val_loss: 0.3352 - val_accuracy: 0.8613 - lr: 0.0010
Epoch 31/60
106/106 [==============================] - 123s 1s/step - loss: 0.2538 - accur
acy: 0.8979 - val_loss: 0.3513 - val_accuracy: 0.8613 - lr: 0.0010
Epoch 32/60
106/106 [==============================] - 123s 1s/step - loss: 0.2429 - accur
acy: 0.9033 - val_loss: 0.3803 - val_accuracy: 0.8452 - lr: 0.0010
Epoch 33/60
106/106 [==============================] - 122s 1s/step - loss: 0.2567 - accur
acy: 0.8955 - val_loss: 0.3302 - val_accuracy: 0.8613 - lr: 0.0010
Epoch 34/60
106/106 [==============================] - 123s 1s/step - loss: 0.2338 - accur
acy: 0.9033 - val_loss: 0.3502 - val_accuracy: 0.8419 - lr: 0.0010
Epoch 35/60
106/106 [==============================] - 123s 1s/step - loss: 0.2315 - accur
acy: 0.9033 - val_loss: 0.3750 - val_accuracy: 0.8742 - lr: 0.0010
Epoch 36/60
106/106 [==============================] - 123s 1s/step - loss: 0.2600 - accur
acy: 0.8920 - val_loss: 0.3512 - val_accuracy: 0.8516 - lr: 0.0010
Epoch 37/60
106/106 [==============================] - 123s 1s/step - loss: 0.2325 - accur
acy: 0.9098 - val_loss: 0.3931 - val_accuracy: 0.8419 - lr: 0.0010
Epoch 38/60
106/106 [==============================] - 123s 1s/step - loss: 0.2554 - accur
acy: 0.8914 - val_loss: 0.3452 - val_accuracy: 0.8677 - lr: 0.0010
Epoch 39/60
106/106 [==============================] - 123s 1s/step - loss: 0.2316 - accur
acy: 0.8991 - val_loss: 0.3678 - val_accuracy: 0.8548 - lr: 0.0010
Epoch 40/60
106/106 [==============================] - 123s 1s/step - loss: 0.2005 - accur
```

```
acy: 0.9139 - val_loss: 0.3704 - val_accuracy: 0.8581 - lr: 0.0001
Epoch 41/60
106/106 [==============================] - 123s 1s/step - loss: 0.1897 - accur
acy: 0.9175 - val_loss: 0.3707 - val_accuracy: 0.8581 - lr: 0.0001
Epoch 42/60
106/106 [==============================] - 123s 1s/step - loss: 0.1830 - accur
acy: 0.9217 - val_loss: 0.3657 - val_accuracy: 0.8613 - lr: 0.0001
Epoch 43/60
106/106 [==============================] - 123s 1s/step - loss: 0.1768 - accur
acy: 0.9270 - val_loss: 0.3657 - val_accuracy: 0.8548 - lr: 0.0001
Epoch 44/60
106/106 [==============================] - 123s 1s/step - loss: 0.1702 - accur
acy: 0.9306 - val_loss: 0.3623 - val_accuracy: 0.8548 - lr: 0.0001
Epoch 45/60
106/106 [==============================] - 123s 1s/step - loss: 0.1655 - accur
acy: 0.9282 - val_loss: 0.3723 - val_accuracy: 0.8581 - lr: 0.0001
Epoch 46/60
106/106 [==============================] - 122s 1s/step - loss: 0.1580 - accur
acy: 0.9353 - val_loss: 0.3750 - val_accuracy: 0.8452 - lr: 0.0001
Epoch 47/60
106/106 [==============================] - 123s 1s/step - loss: 0.1543 - accur
acy: 0.9365 - val_loss: 0.3709 - val_accuracy: 0.8419 - lr: 0.0001
Epoch 48/60
106/106 [==============================] - 122s 1s/step - loss: 0.1510 - accur
acy: 0.9407 - val_loss: 0.3719 - val_accuracy: 0.8516 - lr: 0.0001
Epoch 49/60
106/106 [==============================] - 123s 1s/step - loss: 0.1457 - accur
acy: 0.9401 - val_loss: 0.3772 - val_accuracy: 0.8452 - lr: 0.0001
Epoch 50/60
106/106 [==============================] - 123s 1s/step - loss: 0.1416 - accur
acy: 0.9442 - val_loss: 0.3888 - val_accuracy: 0.8548 - lr: 0.0001
Epoch 51/60
106/106 [==============================] - 123s 1s/step - loss: 0.1376 - accur
acy: 0.9466 - val_loss: 0.3896 - val_accuracy: 0.8452 - lr: 0.0001
Epoch 52/60
106/106 [==============================] - 123s 1s/step - loss: 0.1320 - accur
acy: 0.9478 - val_loss: 0.3909 - val_accuracy: 0.8484 - lr: 0.0001
Epoch 53/60
106/106 [==============================] - 123s 1s/step - loss: 0.1279 - accur
acy: 0.9472 - val_loss: 0.3977 - val_accuracy: 0.8452 - lr: 0.0001
Epoch 54/60
106/106 [==============================] - 123s 1s/step - loss: 0.1253 - accur
acy: 0.9531 - val_loss: 0.3853 - val_accuracy: 0.8548 - lr: 0.0001
Epoch 55/60
106/106 [==============================] - 123s 1s/step - loss: 0.1204 - accur
acy: 0.9561 - val_loss: 0.3876 - val_accuracy: 0.8516 - lr: 1.0000e-05
Epoch 56/60
106/106 [==============================] - 123s 1s/step - loss: 0.1182 - accur
acy: 0.9573 - val_loss: 0.3889 - val_accuracy: 0.8516 - lr: 1.0000e-05
Epoch 57/60
106/106 [==============================] - 123s 1s/step - loss: 0.1166 - accur
acy: 0.9555 - val_loss: 0.3904 - val_accuracy: 0.8516 - lr: 1.0000e-05
Epoch 58/60
106/106 [==============================] - 122s 1s/step - loss: 0.1156 - accur
acy: 0.9561 - val_loss: 0.3919 - val_accuracy: 0.8548 - lr: 1.0000e-05
Epoch 59/60
106/106 [==============================] - 123s 1s/step - loss: 0.1155 - accur
acy: 0.9579 - val_loss: 0.3922 - val_accuracy: 0.8548 - lr: 1.0000e-05
Epoch 60/60
106/106 [==============================] - 123s 1s/step - loss: 0.1147 - accur
```

```
acy: 0.9585 - val_loss: 0.3929 - val_accuracy: 0.8484 - lr: 1.0000e-05
```

That looks pretty good :-) It looks like I can keep on training, too! The first couple epoch took too long since I was running out of memory (forgot to close other notebooks), so the memory overflew into the RAM off from the GPU.

This is running on an A100. ;)

Let's look at accuracy:

In [75]:
```
cloud_val.shape, tf.convert_to_tensor(cloud_val).shape, meteo_val.shape
```

Out[75]:
```
((310, 24, 48, 48, 1),
 TensorShape([310, 24, 48, 48, 1]),
 TensorShape([310, 72, 11]))
```

In [76]:
```
# Select a random example from the cloud imagery validation dataset
# This approach didn't work initially
example_index = np.random.choice(range(len(cloud_val)), size=1)[0]
print("Picked index", example_index,"from validation dataset.")
example_clouds = tf.convert_to_tensor(cloud_val[example_index]) # all 8 frames

# Select the same example from the meteo validation dataset
example_meteo = meteo_val[example_index]

# input
#np.expand_dims([example_clouds, example_meteo], axis=0)
# [example_clouds, example_meteo]
```

```
Picked index 291 from validation dataset.
```

In [77]:
```
# pred_input_combo = np.expand_dims([example_clouds, example_meteo], axis = 0)
```

In [78]:
```
# pred_input_combo = np.array(pred_input_combo, dtype=object)
```

In [79]:
```
# tf.convert_to_tensor(pred_input_combo, dtype=tf.float32)
```

In [80]:
```
# model.predict(pred_input_combo)
```

In [ ]:
```

```

In [81]:
```
pred = model([cloud_val, meteo_val])

# Convert to array
pred = np.array(pred)

# Assigning class based on prediction
pred[pred >= 0.5] = 1
pred[pred < 0.5] = 0
#pred[pred != 1] = 0

# Class-wise accuracy
classwise1 = ((np.array(pred)[:,0] == np.array(rain_val_c))*(rain_val_c==1)).su
classwise0 = ((np.array(pred)[:,0] == np.array(rain_val_c))*(rain_val_c==0)).su
```

In [82]:
```
print('')
rain_val_series = pd.Series(rain_val_c)
value_counts = rain_val_series.value_counts()
value_counts
print('')
```

```
0    262
1     48
dtype: int64
```

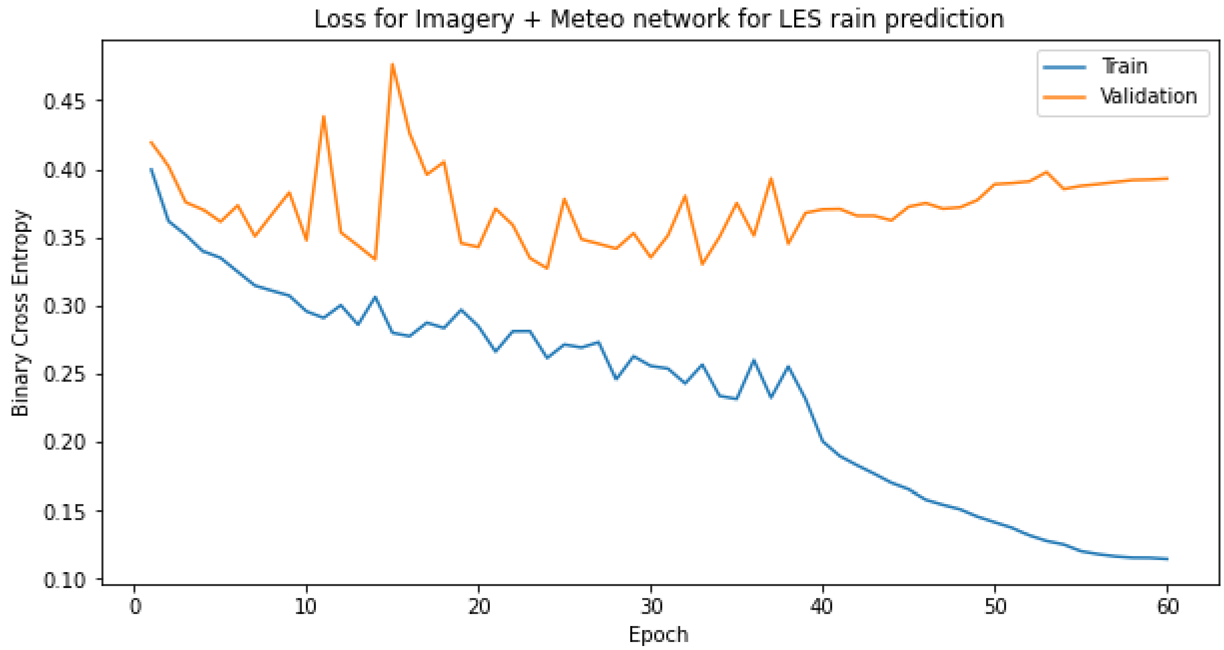
In [83]:
```
# Plot
```

In [ ]:
```
```

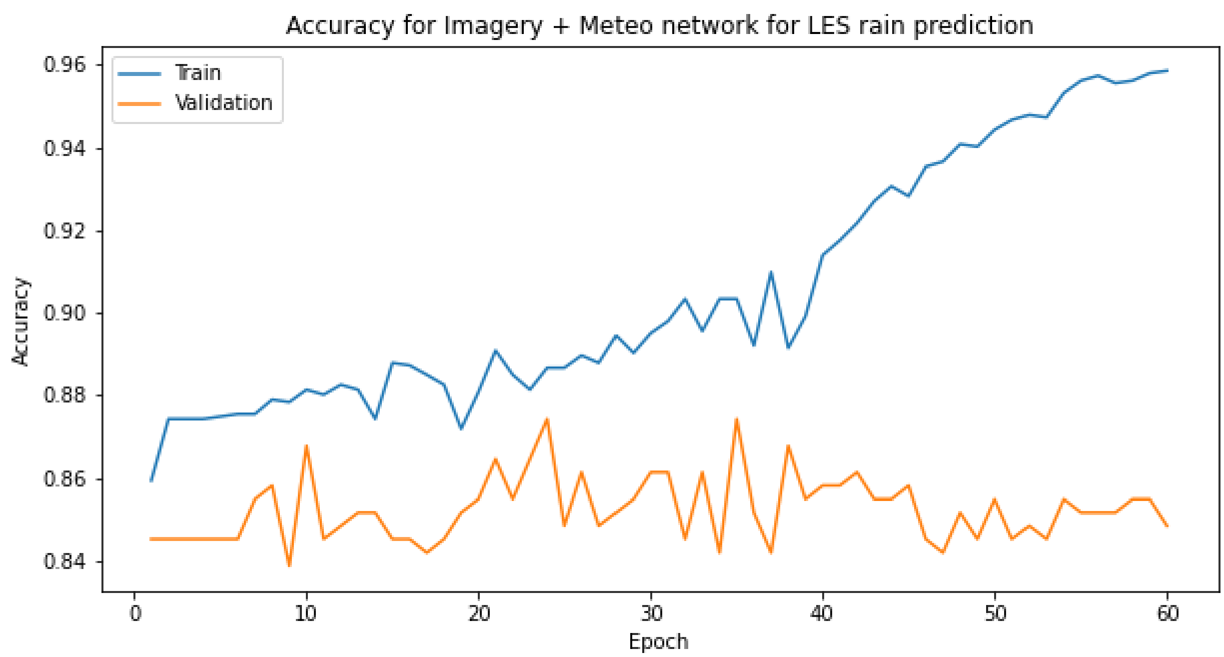
In [85]:
```
print(f'Total Accuracy: \t {((np.array(pred)[:,0] == np.array(rain_val_c)).sum(
print('-'*30)
print('--Class wise Accuracy of Test--')
print('-'*30)
print(f'Class 0: \t {classwise0*100:.3f}')
print(f'Class 1: \t {classwise1*100:.3f}')

######################################

#Note: Class 0: Non-LES Precip
#     Class 1: LES Precip
```

```
Total Accuracy:          84.839
------------------------------
--Class wise Accuracy of Test--
------------------------------
Class 0:         90.458
Class 1:         54.167
```

In [90]:
```
import matplotlib.pyplot as plt
%matplotlib inline
plt.figure(figsize=(10, 5))
plt.plot(history.history['val_loss'], label='Validation')
plt.plot(history.history['loss'], label='Train')
plt.legend()
plt.xlabel('Epochs')
plt.ylabel('Binary Cross Entropy')
plt.title('Loss for Imagery + Meteo network for LES rain prediction')
```



In [93]:
```
import matplotlib.pyplot as plt
%matplotlib inline
plt.figure(figsize=(10, 5))
plt.plot(history.history['val_accuracy'], label='Validation')
plt.plot(history.history['accuracy'], label='Train')
plt.legend()
plt.xlabel('Epochs')
plt.ylabel('Binary Cross Entropy')
plt.title('Loss for Imagery + Meteo network for LES rain prediction')
```



In [ ]:

In [ ]:

In [ ]:

In [ ]:

In [ ]:

In [ ]:

In [ ]:

In [ ]:

In [ ]:

In [ ]:

In [ ]: