Weather forecasting at Ria Arousa

This dataset is focused on meteorological stations at Ria Arousa (Spain). The meteorological stations is: Cortegada at latitude: 42.626 N and longitude: 8.784 W. diro: wind direction (degrees) gustdirectiono: gust direction (degees) gustspeedo: gust speed (m/s) spdo: speed (m/s) stddiro: standard deviation direction (degrees) stdspdo: standard deviation speed (m/s) gustspdmaxhourbeforeo: max gust speed an hour before (m/s) temp: Air Temperature in Kelvin at 2 meters.

This data does not show outcomes or predicts storms or clam weather. The idea is to cluster the data and figure out what type of weather those clusters tend to predict.

In [1]:
```
!pip install ibm-cos-sdk
```

```
Requirement already satisfied: ibm-cos-sdk in /opt/conda/envs/Python-3.8-mai
n/lib/python3.8/site-packages (2.7.0)
Requirement already satisfied: ibm-cos-sdk-s3transfer==2.7.0 in /opt/conda/en
vs/Python-3.8-main/lib/python3.8/site-packages (from ibm-cos-sdk) (2.7.0)
Requirement already satisfied: ibm-cos-sdk-core==2.7.0 in /opt/conda/envs/Pyt
hon-3.8-main/lib/python3.8/site-packages (from ibm-cos-sdk) (2.7.0)
Requirement already satisfied: jmespath<1.0.0,>=0.7.1 in /opt/conda/envs/Pyth
on-3.8-main/lib/python3.8/site-packages (from ibm-cos-sdk) (0.10.0)
Requirement already satisfied: docutils<0.16,>=0.10 in /opt/conda/envs/Python
-3.8-main/lib/python3.8/site-packages (from ibm-cos-sdk-core==2.7.0->ibm-cos-
sdk) (0.15.2)
Requirement already satisfied: requests<3.0,>=2.18 in /opt/conda/envs/Python-
3.8-main/lib/python3.8/site-packages (from ibm-cos-sdk-core==2.7.0->ibm-cos-s
dk) (2.25.1)
Requirement already satisfied: python-dateutil<3.0.0,>=2.1 in /opt/conda/env
s/Python-3.8-main/lib/python3.8/site-packages (from ibm-cos-sdk-core==2.7.0->
ibm-cos-sdk) (2.8.1)
Requirement already satisfied: six>=1.5 in /opt/conda/envs/Python-3.8-main/li
b/python3.8/site-packages (from python-dateutil<3.0.0,>=2.1->ibm-cos-sdk-core
==2.7.0->ibm-cos-sdk) (1.15.0)
Requirement already satisfied: certifi>=2017.4.17 in /opt/conda/envs/Python-
3.8-main/lib/python3.8/site-packages (from requests<3.0,>=2.18->ibm-cos-sdk-c
ore==2.7.0->ibm-cos-sdk) (2021.10.8)
Requirement already satisfied: chardet<5,>=3.0.2 in /opt/conda/envs/Python-3.
8-main/lib/python3.8/site-packages (from requests<3.0,>=2.18->ibm-cos-sdk-cor
e==2.7.0->ibm-cos-sdk) (3.0.4)
Requirement already satisfied: urllib3<1.27,>=1.21.1 in /opt/conda/envs/Pytho
n-3.8-main/lib/python3.8/site-packages (from requests<3.0,>=2.18->ibm-cos-sdk
-core==2.7.0->ibm-cos-sdk) (1.26.6)
Requirement already satisfied: idna<3,>=2.5 in /opt/conda/envs/Python-3.8-mai
n/lib/python3.8/site-packages (from requests<3.0,>=2.18->ibm-cos-sdk-core==2.
7.0->ibm-cos-sdk) (2.8)
```

In [2]:
```
import numpy as np, pandas as pd, matplotlib.pyplot as plt, seaborn as sns, os
#os.chdir('data')
#from colorsetup import colors, palette
#sns.set_palette(palette)
%matplotlib inline
import os, types
import pandas as pd
from botocore.client import Config
import ibm_boto3
```

In [3]:
```
import seaborn as sns
coloribm = {"Magenta 100":"2A0A16", "Magenta 90":"57002B", "Magenta 80":"760A3A", "Magenta 70":"A11950", "Magenta 60":"D12765", "Magenta 50":"EE538B", "Magenta 40":"FA75A6", "Magenta 30":"FFA0C2", "Magenta 20":"FFCFE1", "Magenta 10":"FFF0F6", "Purple 100":"1E1033", "Purple 90":"38146B", "Purple 80":"4F2196", "Purple 70":"6E32C9", "Purple 60":"8A3FFC", "Purple 50":"A66EFA", "Purple 40":"BB8EFF", "Purple 30":"D0B0FF", "Purple 20":"E6D6FF", "Purple 10":"F7F1FF", "Blue 100":"051243", "Blue 90":"061F80", "Blue 80":"0530AD", "Blue 70":"054ADA", "Blue 60":"0062FF", "Blue 50":"408BFC", "Blue 40":"6EA6FF", "Blue 30":"97C1FF", "Blue 20":"C9DEFF", "Blue 10":"EDF4FF", "Teal 100":"081A1C", "Teal 90":"003137", "Teal 80":"004548", "Teal 70":"006161", "Teal 60":"007D79", "Teal 50":"009C98", "Teal 40":"00BAB6", "Teal 30":"20D5D2", "Teal 20":"92EEEE", "Teal 10":"DBFBFB", "Gray 100":"171717", "Gray 90":"282828", "Gray 80":"3D3D3D", "Gray 70":"565656", "Gray 60":"6F6F6F", "Gray 50":"8C8C8C", "Gray 40":"A4A4A4", "Gray 30":"BEBEBE", "Gray 20":"DCDCDC", "Gray 10":"F3F3F3"}
colors = []
colornum = 60
for i in [f'Blue {colornum}', f'Teal {colornum}', f'Magenta {colornum}', f'Purple {colornum}', f'Gray {colornum}']:
    colors.append(f'#{coloribm[i]}')
palette = sns.color_palette(colors)
```

In [4]:
```
pip install colour
```

```
Collecting colour
  Downloading colour-0.1.5-py2.py3-none-any.whl (23 kB)
Installing collected packages: colour
Successfully installed colour-0.1.5
Note: you may need to restart the kernel to use updated packages.
```

In [5]:
```
import warnings
warnings.simplefilter(action='ignore', category=FutureWarning)
```

In [6]:

```
import os, types
import pandas as pd
from botocore.client import Config
import ibm_boto3

def __iter__(self): return 0

# @hidden_cell
# The following code accesses a file in your IBM Cloud Object Storage. It includes your credentials.
# You might want to remove those credentials before you share the notebook.

if os.environ.get('RUNTIME_ENV_LOCATION_TYPE') == 'external':
    endpoint_931d06c29a624816bb257512bafae77d = 'https://s3.us.cloud-object-storage.appdomain.cloud'
else:
    endpoint_931d06c29a624816bb257512bafae77d = 'https://s3.private.us.cloud-object-storage.appdomain.cloud'

client_931d06c29a624816bb257512bafae77d = ibm_boto3.client(service_name='s3',
    ibm_api_key_id='PrzXlU7pJtv48uceZsBxlgeqNbtXs52zcsFOpP7jvh8V',
    ibm_auth_endpoint="https://iam.cloud.ibm.com/oidc/token",
    config=Config(signature_version='oauth'),
    endpoint_url=endpoint_931d06c29a624816bb257512bafae77d)

body = client_931d06c29a624816bb257512bafae77d.get_object(Bucket='weatherforecastingatriaarousa-donotdelete-pr-m2yl5thxtuh8gt',Key='cortegada_data.csv')['Body']
# add missing __iter__ method, so pandas accepts body as file-like object
if not hasattr(body, "__iter__"): body.__iter__ = types.MethodType( __iter__, body )

df_data_1 = pd.read_csv(body)
df_data_1.head()

data = df_data_1
```

In [7]:

```
data.shape
```

Out[7]:

```
(90432, 24)
```

In [8]:
```
data.head()
```

Out[8]:

	time	dir0	mod0	wind_gust0	mslp0	temp0	rh0	visibility(
0	1/3/2010 0:00	166.244751	10.572862	12.931561	100673.8125	286.756073	0.880696	3036.57348(
1	1/3/2010 1:00	160.286255	13.737501	15.760801	100422.6406	287.255737	0.822041	20635.62695(
2	1/3/2010 2:00	174.143463	15.747597	23.766697	100389.8672	287.624176	0.817438	24036.58789(
3	1/3/2010 3:00	173.907684	17.533861	25.642481	100312.4219	287.766388	0.830344	22438.73047(
4	1/3/2010 4:00	173.191208	17.138390	25.355106	100236.6563	287.971619	0.838364	24040.59766(

5 rows × 24 columns

In [9]:
```
data_del = data.drop(['HGT5000', 'HGT8500', 'T5000', 'T8500', 'time', 'swflx0'
, 'shflx0', 'cfl0', 'cfm0'], axis=1)
```

In [10]:
```
data_del.head()
```

Out[10]:

	dir0	mod0	wind_gust0	mslp0	temp0	rh0	visibility0	lh
0	166.244751	10.572862	12.931561	100673.8125	286.756073	0.880696	3036.573486	82.336
1	160.286255	13.737501	15.760801	100422.6406	287.255737	0.822041	20635.626950	128.879
2	174.143463	15.747597	23.766697	100389.8672	287.624176	0.817438	24036.587890	139.651
3	173.907684	17.533861	25.642481	100312.4219	287.766388	0.830344	22438.730470	139.857
4	173.191208	17.138390	25.355106	100236.6563	287.971619	0.838364	24040.597660	118.182

Pre_Processing Data Check for data types, Null Values, check for standard distribution dir: Predicted wind direction at 10 meters. From North direction clockwise. Units are degrees. Unlike dir_o no variable wind is forecasted (no -1 values)

mod: Wind intensity forecasted at 10 meters. Units are meters per second.

wind_gust: Wind gust at 10 meters. Units are meters per second.

mslp: Sea Level Pressure in pascals

temp: Air Temperature in Kelvin at 2 meters

rh: Relative Humidity. Units fraction

visibility: Visibility in the air. Units meters. Minimum visibility 26.028316 meters. Maximum visibility 24235.000000

lhflx: Surface downward latent heat flux. Units, watts per square meters.

lwflx: Surface downward latent heat flux. Units: W m-2

conv_prec: Total accumulated convective rainfall between each model output. Every hour in our case.

prec: Total accumulated rainfall between each model output. In our case, every hour. Units kilograms per meter squared.

cape: Convective available potential energy. Units: Jules per kilogram.

cfl: Cloud area fraction at low atmosphere layer. I found 1251 samples with values higher than 1 !! Perhaps, we wouldn’t trust this feature so much.

cfm: Cloud area fraction at mid atmosphere layer. Also, I found 37 samples with values higher than 1.

cfh: Cloud cover at high levels. Units fraction

cft: Cloud cover at low and mid-levels. Units fraction

In [11]:
```
data_del.dtypes
```

Out[11]:
```
dir0           float64
mod0           float64
wind_gust0     float64
mslp0          float64
temp0          float64
rh0            float64
visibility0    float64
lhflx0         float64
lwflx0         float64
conv_prec0     float64
prec0          float64
cape0          float64
cin0           float64
cfh0           float64
cft0           float64
dtype: object
```

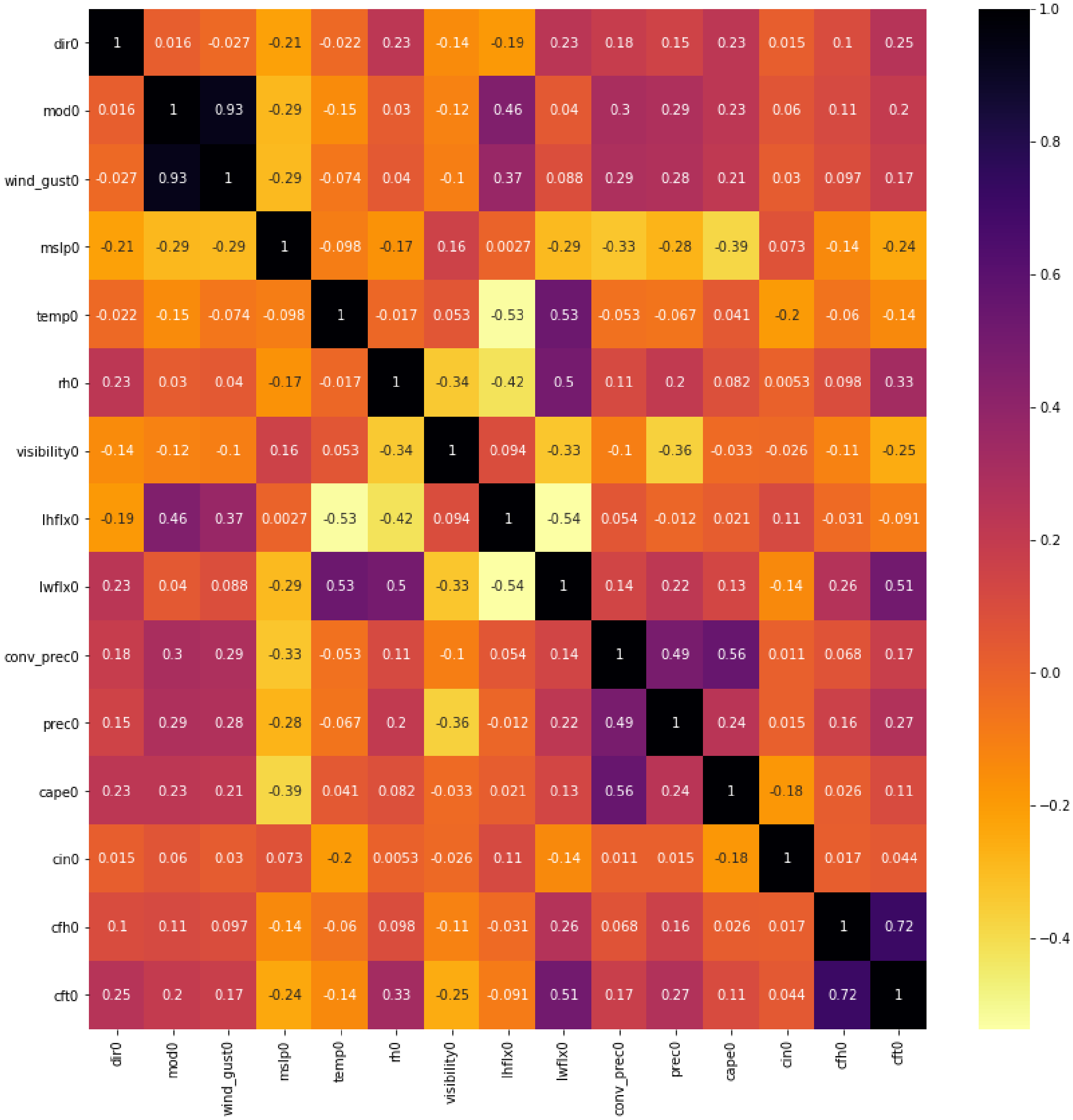
Ensuring that data all are float types or else, one hot encoding is required.

In [12]:
```
data_del.isnull().values.any()
```

Out[12]:
```
False
```

Heat Map to demonstrating correleations between columns of data.

In [13]:
```
plt.figure(figsize=(14,14))
p=sns.heatmap(data_del.corr(), annot=True,cmap ='inferno_r') # seaborn has very simple solution for heatmap
```



High correlations exist between:

wind_gust0 & mod0

lwflx & temp0

conv_prec & cape

cfh & cft

In [14]:

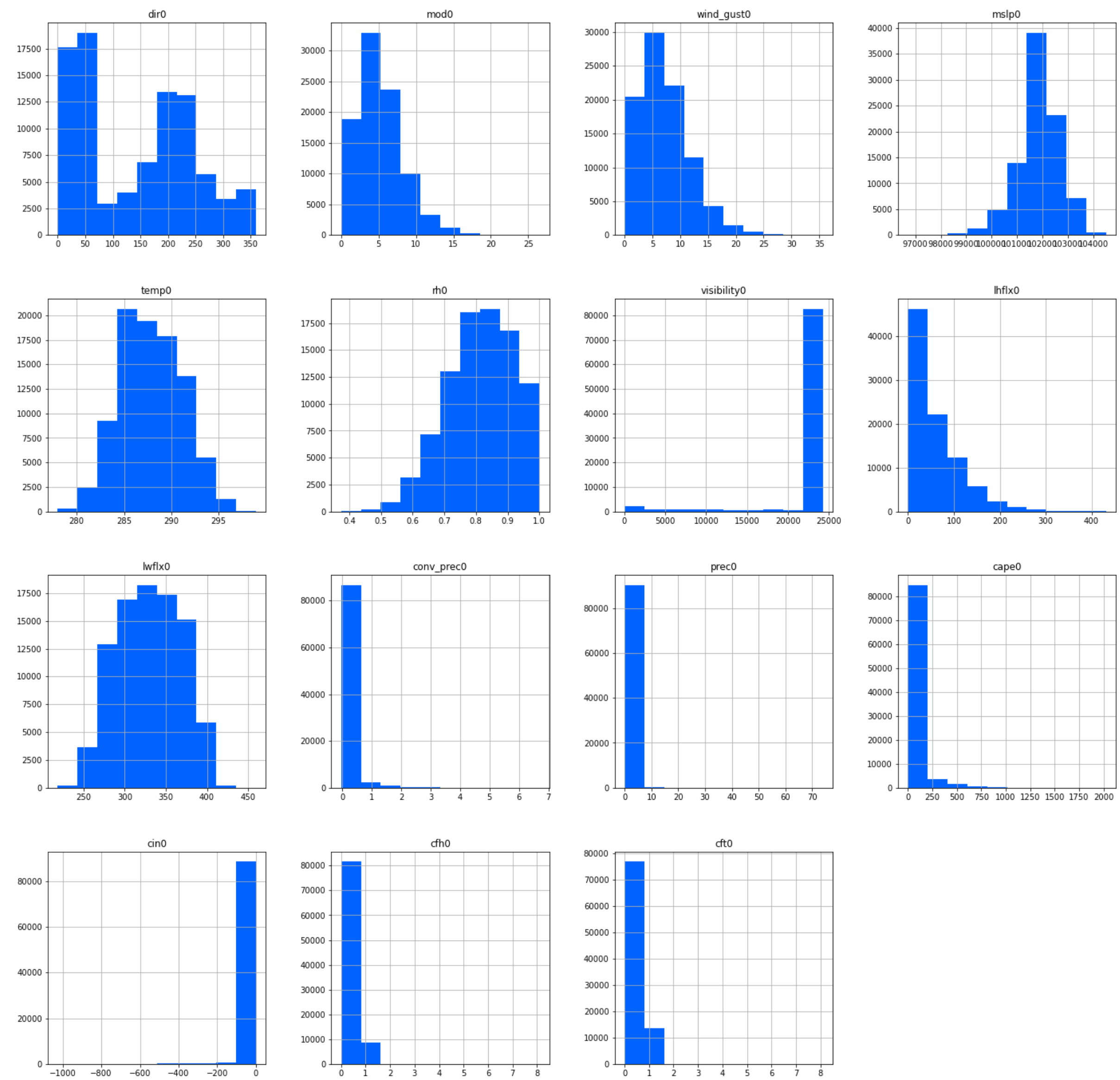
```python
# The correlation matrix
### BEGIN SOLUTION
float_columns = [x for x in data_del.columns]
corr_mat = data_del[float_columns].corr()

# Strip out the diagonal values for the next step
for x in range(len(float_columns)):
    corr_mat.iloc[x,x] = 0.0

# Pairwise maximal correlations
corr_mat.abs().idxmax()
```

Out[14]:

```
dir0                  cft0
mod0            wind_gust0
wind_gust0            mod0
mslp0                cape0
temp0               lwflx0
rh0                 lwflx0
visibility0          prec0
lhflx0              lwflx0
lwflx0              lhflx0
conv_prec0           cape0
prec0           conv_prec0
cape0           conv_prec0
cin0                 temp0
cfh0                  cft0
cft0                  cfh0
dtype: object
```

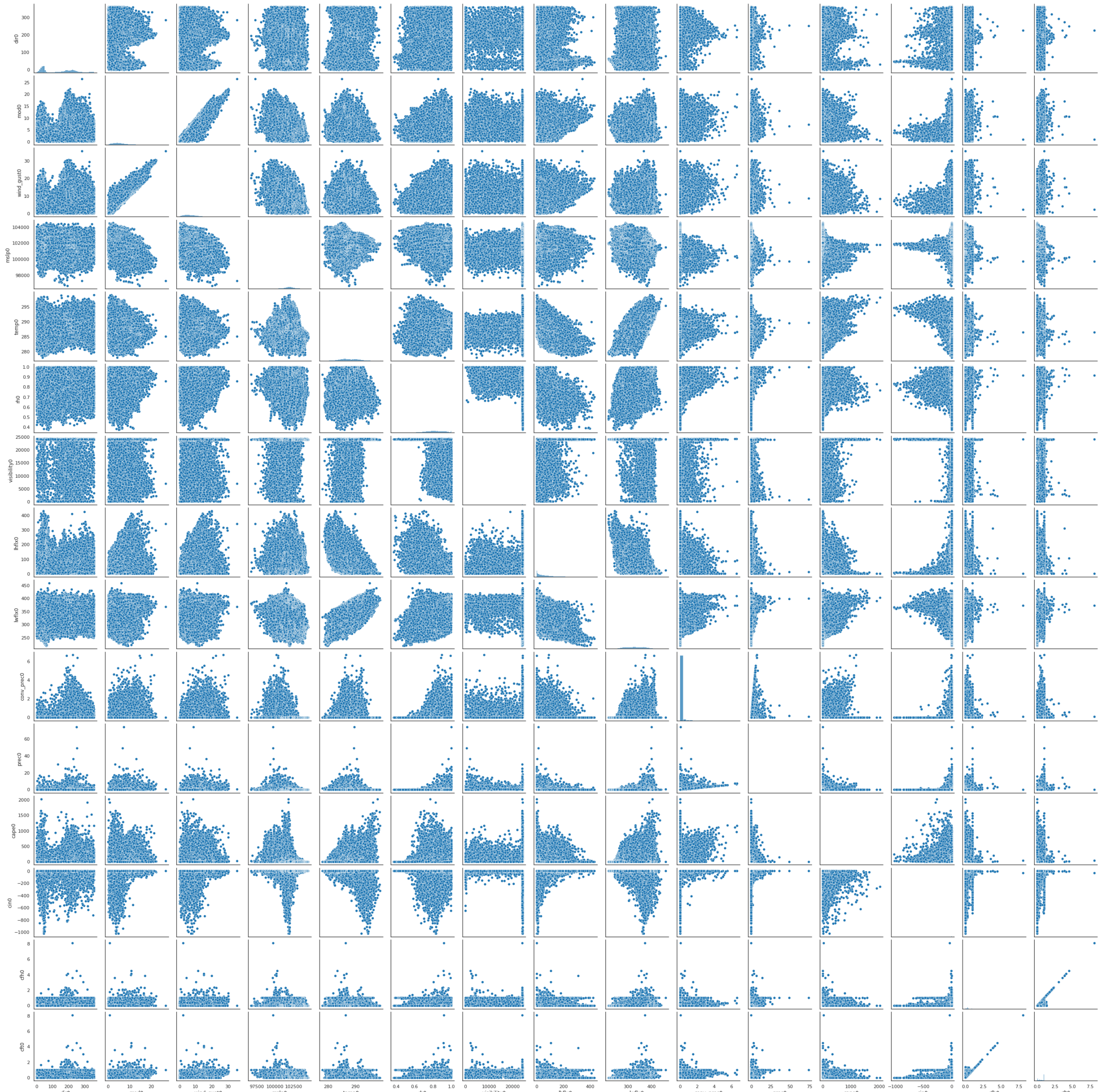
```
In [15]: data_del.hist(color=colors[0], figsize=(24, 24))
```

```
Out[15]: array([[<AxesSubplot:title={'center':'dir0'}>,
                 <AxesSubplot:title={'center':'mod0'}>,
                 <AxesSubplot:title={'center':'wind_gust0'}>,
                 <AxesSubplot:title={'center':'mslp0'}>],
                [<AxesSubplot:title={'center':'temp0'}>,
                 <AxesSubplot:title={'center':'rh0'}>,
                 <AxesSubplot:title={'center':'visibility0'}>,
                 <AxesSubplot:title={'center':'lhflx0'}>],
                [<AxesSubplot:title={'center':'lwflx0'}>,
                 <AxesSubplot:title={'center':'conv_prec0'}>,
                 <AxesSubplot:title={'center':'prec0'}>,
                 <AxesSubplot:title={'center':'cape0'}>],
                [<AxesSubplot:title={'center':'cin0'}>,
                 <AxesSubplot:title={'center':'cfh0'}>,
                 <AxesSubplot:title={'center':'cft0'}>, <AxesSubplot:>]],
               dtype=object)
```



Some of the data above are not normally distributed.

In [16]:
```
sns.set_context('notebook')
sns.set_style('white')
sns.pairplot(data_del);
```



A value is normalized as follows: y = (x – min) / (max – min)

Standardizing a dataset involves rescaling the distribution of values so that the mean of observed values is 0 and the standard deviation is 1. A value is standardized as follows:

y = (x – mean) / standard_deviation

In [17]:
```
skew_columns = data_del.skew().sort_values(ascending=False)

skew_columns = skew_columns.loc[skew_columns > 0.75]
skew_columns
```

Out[17]:
```
prec0          18.241951
conv_prec0      6.332812
cape0           4.698357
cfh0            2.308762
lhflx0          1.519432
cft0            1.119474
mod0            0.934429
wind_gust0      0.931469
dtype: float64
```

In [18]:
```
skew_columns2 = data_del.skew().sort_values(ascending=False)

skew_columns2 = skew_columns2.loc[skew_columns2 < 0.0]
skew_columns2
```

Out[18]:
```
lwflx0        -0.027799
rh0           -0.364057
mslp0         -0.570461
visibility0   -3.696142
cin0          -9.835984
dtype: float64
```

In [19]:
```
data_del.head()
```

Out[19]:

	dir0	mod0	wind_gust0	mslp0	temp0	rh0	visibility0	lh
0	166.244751	10.572862	12.931561	100673.8125	286.756073	0.880696	3036.573486	82.336
1	160.286255	13.737501	15.760801	100422.6406	287.255737	0.822041	20635.626950	128.879
2	174.143463	15.747597	23.766697	100389.8672	287.624176	0.817438	24036.587890	139.651
3	173.907684	17.533861	25.642481	100312.4219	287.766388	0.830344	22438.730470	139.857
4	173.191208	17.138390	25.355106	100236.6563	287.971619	0.838364	24040.597660	118.182

In [20]:
```
data_del.index
```

Out[20]:
```
RangeIndex(start=0, stop=90432, step=1)
```

LOG TRANSFORMATION BEFORE SO WE GET STANDARDIZED DISTRIBUTION

In [21]:
```
# The log transformations

data_del_log = np.log1p(data_del)
```

In [22]:

```
data_del_log.head() #still a pandas dataframe
```

Out[22]:

	dir0	mod0	wind_gust0	mslp0	temp0	rh0	visibility0	lhflx0	lwflx0
0	5.119458	2.448663	2.634157	11.519651	5.662113	0.631642	8.018814	4.422890	5.930765
1	5.083181	2.690395	2.819043	11.517153	5.663848	0.599957	9.934823	4.866609	5.927356
2	5.165605	2.818255	3.209500	11.516827	5.665125	0.597428	10.087374	4.946287	5.933128
3	5.164258	2.919599	3.282507	11.516055	5.665618	0.604504	10.018588	4.947752	5.938271
4	5.160154	2.898031	3.271662	11.515299	5.666328	0.608876	10.087541	4.780652	5.940176

In [23]:

```
data_del_log_MMS = data_del_log
```

In [24]:

```
from sklearn.preprocessing import MinMaxScaler

MMS = MinMaxScaler()
for col in data_del_log_MMS.columns:
    data_del_log_MMS[col] = MMS.fit_transform(data_del_log_MMS[[col]]).squeeze
()
```

In [25]:

```
data_del_log_MMS
```

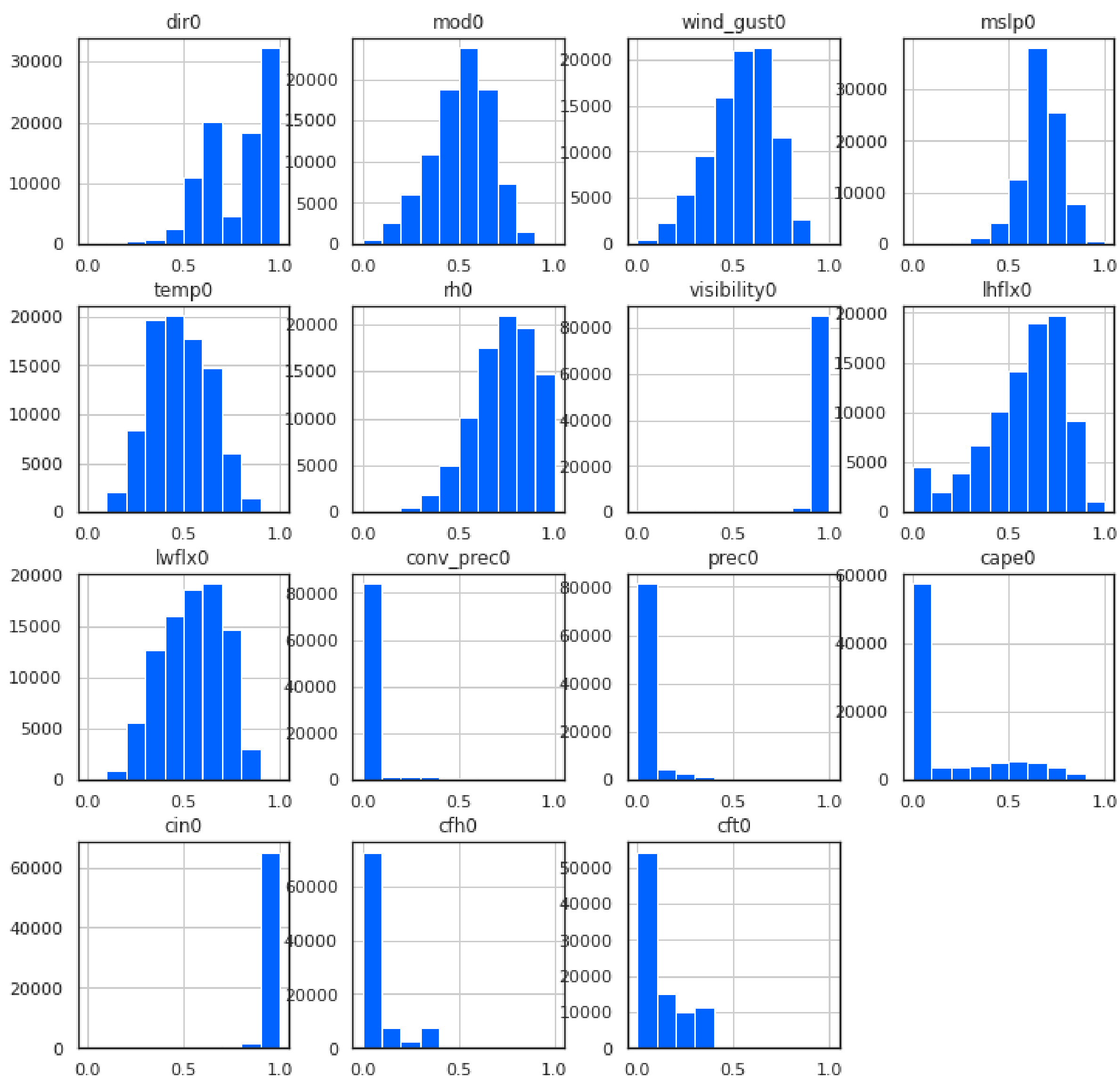
Out[25]:

	dir0	mod0	wind_gust0	mslp0	temp0	rh0	visibility0	lhflx0	lw
0	0.869207	0.738046	0.730572	0.518395	0.426986	0.836097	0.693883	0.731723	0.727
1	0.863040	0.811286	0.782106	0.486192	0.450954	0.751661	0.976302	0.803992	0.722
2	0.877052	0.850025	0.890938	0.481984	0.468600	0.744921	0.998788	0.816969	0.730
3	0.876823	0.880730	0.911287	0.472035	0.475406	0.763778	0.988649	0.817208	0.737
4	0.876125	0.874195	0.908264	0.462294	0.485221	0.775430	0.998813	0.789992	0.740
...	...	...	...	...	...	...	...	...	...
90427	0.899460	0.493926	0.548361	0.688854	0.519841	0.939961	0.998838	0.393143	0.675
90428	0.886810	0.405201	0.483917	0.688856	0.497887	0.970865	0.998816	0.369281	0.568
90429	0.882076	0.417456	0.481844	0.690491	0.486007	0.990776	0.998786	0.389247	0.770
90430	0.921303	0.417180	0.397207	0.693230	0.477600	0.993861	0.316120	0.415034	0.770
90431	0.933551	0.423195	0.370470	0.694923	0.465633	0.993670	0.317603	0.457901	0.766

90432 rows × 15 columns

In [26]:
```
data_del_log_MMS.hist(color=colors[0], figsize=(12, 12))
```

Out[26]:
```
array([[<AxesSubplot:title={'center':'dir0'}>,
        <AxesSubplot:title={'center':'mod0'}>,
        <AxesSubplot:title={'center':'wind_gust0'}>,
        <AxesSubplot:title={'center':'mslp0'}>],
       [<AxesSubplot:title={'center':'temp0'}>,
        <AxesSubplot:title={'center':'rh0'}>,
        <AxesSubplot:title={'center':'visibility0'}>,
        <AxesSubplot:title={'center':'lhflx0'}>],
       [<AxesSubplot:title={'center':'lwflx0'}>,
        <AxesSubplot:title={'center':'conv_prec0'}>,
        <AxesSubplot:title={'center':'prec0'}>,
        <AxesSubplot:title={'center':'cape0'}>],
       [<AxesSubplot:title={'center':'cin0'}>,
        <AxesSubplot:title={'center':'cfh0'}>,
        <AxesSubplot:title={'center':'cft0'}>, <AxesSubplot:>]],
      dtype=object)
```



In [27]:
```
data_del_log_SS = data_del_log
```

In [28]:
```
from sklearn.preprocessing import StandardScaler
SS = StandardScaler()
for col in data_del_log_SS.columns:
    data_del_log_SS[col] = MMS.fit_transform(data_del_log_SS[[col]]).squeeze()
```

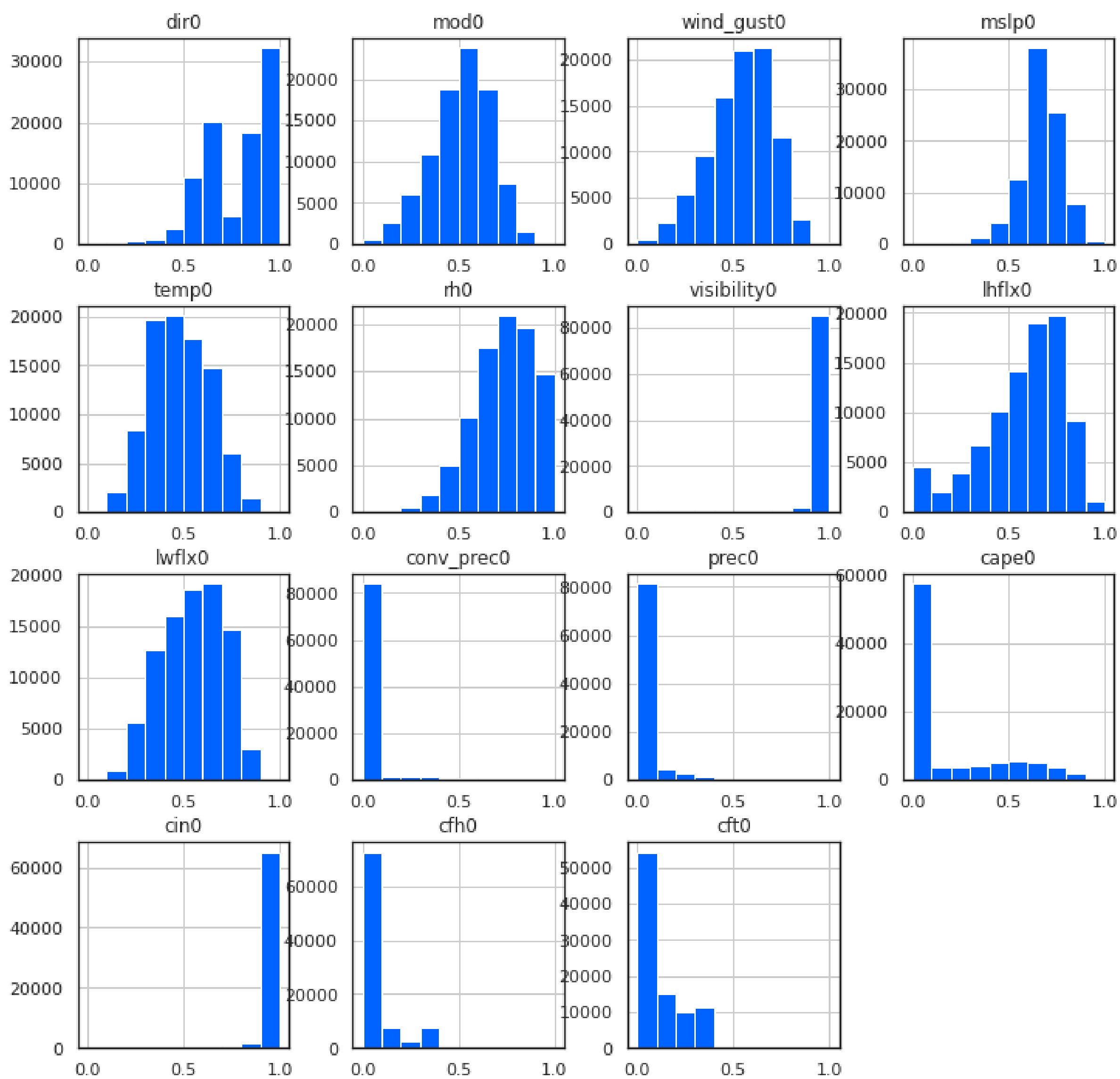
In [29]:
```
data_del_log_SS.head()
```

Out[29]:

	dir0	mod0	wind_gust0	mslp0	temp0	rh0	visibility0	lhflx0	lwflx0
0	0.869207	0.738046	0.730572	0.518395	0.426986	0.836097	0.693883	0.731723	0.727538
1	0.863040	0.811286	0.782106	0.486192	0.450954	0.751661	0.976302	0.803992	0.722929
2	0.877052	0.850025	0.890938	0.481984	0.468600	0.744921	0.998788	0.816969	0.730732
3	0.876823	0.880730	0.911287	0.472035	0.475406	0.763778	0.988649	0.817208	0.737685
4	0.876125	0.874195	0.908264	0.462294	0.485221	0.775430	0.998813	0.789992	0.740261

In [30]:
```python
data_del_log_SS.hist(color=colors[0], figsize=(12, 12))
```

Out[30]:
```
array([[<AxesSubplot:title={'center':'dir0'}>,
        <AxesSubplot:title={'center':'mod0'}>,
        <AxesSubplot:title={'center':'wind_gust0'}>,
        <AxesSubplot:title={'center':'mslp0'}>],
       [<AxesSubplot:title={'center':'temp0'}>,
        <AxesSubplot:title={'center':'rh0'}>,
        <AxesSubplot:title={'center':'visibility0'}>,
        <AxesSubplot:title={'center':'lhflx0'}>],
       [<AxesSubplot:title={'center':'lwflx0'}>,
        <AxesSubplot:title={'center':'conv_prec0'}>,
        <AxesSubplot:title={'center':'prec0'}>,
        <AxesSubplot:title={'center':'cape0'}>],
       [<AxesSubplot:title={'center':'cin0'}>,
        <AxesSubplot:title={'center':'cfh0'}>,
        <AxesSubplot:title={'center':'cft0'}>, <AxesSubplot:>]],
      dtype=object)
```



Fit a K-means clustering model to determine optimal clusters. K-Means models with cluster values ranging from 1 to 20.

Both MinMaxScaler and Standard Scaler produced good results in terms of scaling the data down to a size that does not skew one parameter versus another

In [31]:
```
float_columns = [x for x in data_del_log_MMS.columns]
```

In [32]:
```
float_columns
```

Out[32]:
```
['dir0',
 'mod0',
 'wind_gust0',
 'mslp0',
 'temp0',
 'rh0',
 'visibility0',
 'lhflx0',
 'lwflx0',
 'conv_prec0',
 'prec0',
 'cape0',
 'cin0',
 'cfh0',
 'cft0']
```

In [33]:
```
data_del_log_MMS[float_columns]
```

Out[33]:

	dir0	mod0	wind_gust0	mslp0	temp0	rh0	visibility0	lhflx0	lw
0	0.869207	0.738046	0.730572	0.518395	0.426986	0.836097	0.693883	0.731723	0.727
1	0.863040	0.811286	0.782106	0.486192	0.450954	0.751661	0.976302	0.803992	0.722
2	0.877052	0.850025	0.890938	0.481984	0.468600	0.744921	0.998788	0.816969	0.730
3	0.876823	0.880730	0.911287	0.472035	0.475406	0.763778	0.988649	0.817208	0.737
4	0.876125	0.874195	0.908264	0.462294	0.485221	0.775430	0.998813	0.789992	0.740
...	...	...	...	...	...	...	...	...	
90427	0.899460	0.493926	0.548361	0.688854	0.519841	0.939961	0.998838	0.393143	0.675
90428	0.886810	0.405201	0.483917	0.688856	0.497887	0.970865	0.998816	0.369281	0.568
90429	0.882076	0.417456	0.481844	0.690491	0.486007	0.990776	0.998786	0.389247	0.770
90430	0.921303	0.417180	0.397207	0.693230	0.477600	0.993861	0.316120	0.415034	0.770
90431	0.933551	0.423195	0.370470	0.694923	0.465633	0.993670	0.317603	0.457901	0.766

90432 rows × 15 columns

In [34]:
```
count = np.isinf(data_del_log_MMS).values.sum() # count for any erroneous data
count
```

Out[34]: 0

In [35]:
```
data_del_log_MMS.isnull().values.any()
```

Out[35]: True

In [36]:
```
data_del_log_MMS['cin0'].isnull().values.any()
```

Out[36]: True

Dropping NULL values in dataframe

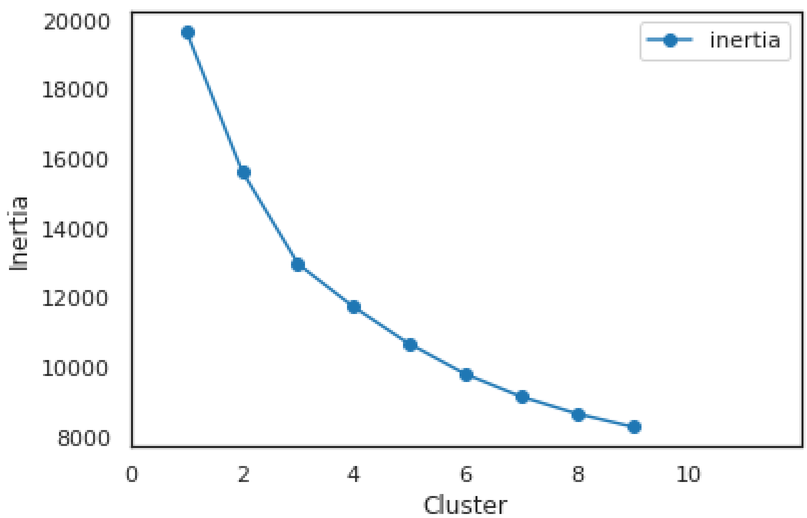
In [37]:
```
data_del_log_MMS = data_del_log_MMS.dropna()
```

In [38]:
```
from sklearn.cluster import KMeans
### BEGIN SOLUTION
kmeans = KMeans(n_clusters=3).fit(data_del_log_MMS[float_columns])
```

KMEANS ALGORITHM FOR UNSUPERVISED LEARNING

In [39]:
```
### BEGIN SOLUTION
# Create and fit a range of models
from sklearn.cluster import KMeans
km_list = list()

for clust in range(1,10):
    km = KMeans(n_clusters=clust, random_state=42)
    km = km.fit(data_del_log_MMS)

    km_list.append(pd.Series({'clusters': clust,
                              'inertia': km.inertia_,
                              'model': km}))
```

```
In [40]: plot_data = (pd.concat(km_list, axis=1)
                      .T
                      [['clusters','inertia']]
                      .set_index('clusters'))

         ax = plot_data.plot(marker='o',ls='-')
         ax.set_xticks(range(0,12,2))
         ax.set_xlim(0,12)
         ax.set(xlabel='Cluster', ylabel='Inertia');
         ### END SOLUTION
```



Conclusion: it appears that the inertia stabilizes after 9 clusters. One can assume these clusters correspond to weather patterns and we could gather these clusters, present to meterological experts and determine the weather for future data.

Fit an Hierarchical Clustering model:

```
In [42]: data_del_log_MMS2=data_del_log_MMS.drop(data_del_log_MMS.index[10000:])
```

PROBLEM: dropped some data - The IBM Cloud Kernal Failed over 3X - reduced data to 10,000 rows

```
In [43]: data_del_log_MMS2.head()
```

Out[43]:

	dir0	mod0	wind_gust0	mslp0	temp0	rh0	visibility0	lhflx0	lwflx0
0	0.869207	0.738046	0.730572	0.518395	0.426986	0.836097	0.693883	0.731723	0.727538
1	0.863040	0.811286	0.782106	0.486192	0.450954	0.751661	0.976302	0.803992	0.722929
2	0.877052	0.850025	0.890938	0.481984	0.468600	0.744921	0.998788	0.816969	0.730732
3	0.876823	0.880730	0.911287	0.472035	0.475406	0.763778	0.988649	0.817208	0.737685
4	0.876125	0.874195	0.908264	0.462294	0.485221	0.775430	0.998813	0.789992	0.740261

In [44]:
```
data_del_log_MMS2.shape
```
Out[44]:
```
(10000, 15)
```

2nd Algorithm - Agglomerative Clustering

In [45]:
```
X = data_del_log_MMS2
```

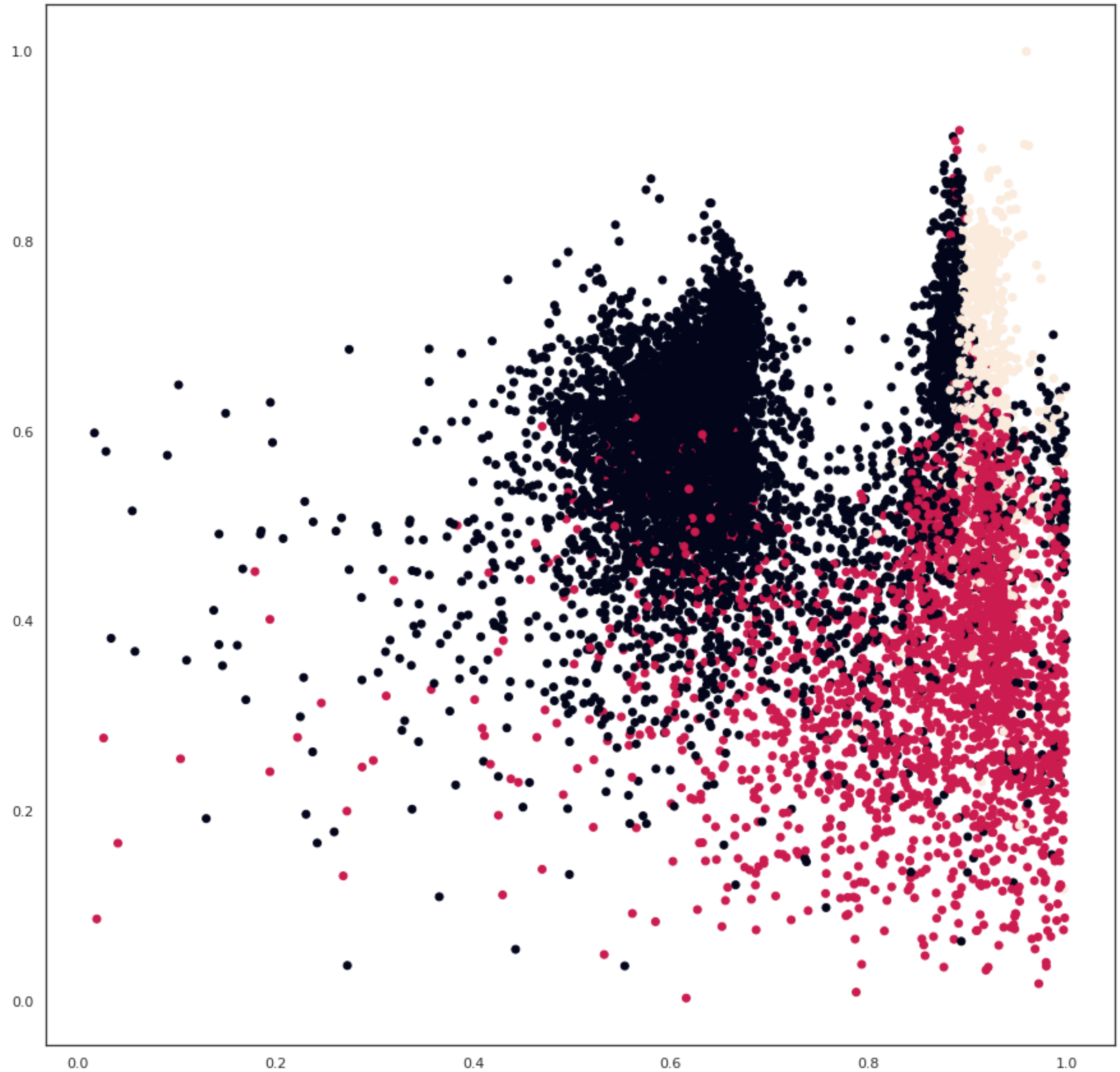
In [50]:
```
from sklearn.cluster import AgglomerativeClustering

cluster = AgglomerativeClustering(n_clusters=3, affinity='euclidean', linkage=
'ward')
cluster.fit_predict(X)
```
Out[50]:
```
array([0, 0, 0, ..., 0, 1, 1])
```

In [51]:
```
print(cluster.labels_)
```
```
[0 0 0 ... 0 1 1]
```

In [52]:
```
cluster.fit(X)
labels = cluster.labels_
```

In [53]:
```
labels[0:300]
```
Out[53]:
```
array([0, 0, 0, 0, 0, 2, 0, 2, 2, 2, 2, 2, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 2, 2, 2,
       2, 2, 2, 2, 2, 2, 2, 2, 0, 0, 0, 0, 0, 0, 0, 0, 2, 2, 2, 2, 2, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 2, 2, 2, 2, 2, 2, 2, 2, 2, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2,
       2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 2, 2, 2, 2, 0, 0, 0, 0, 0, 1])
```

In [54]:
```
plt.figure(figsize=(15,15))
plt.scatter(X.iloc[:,0], X.iloc[:,1], c=labels)
plt.show()
```



The optimal amount of clusters for this data set is 3. There are clearly 3 distinct regions shown in the above graph. If you compare to Kmeans algorithm the elbow on the inertia graph begins at 3 but seems to flatten after 10. However, it is difficult to see how the data is clustered on Kmeans but for Agglomerative Clustering there are 3 clear regions. When the # of clusters is 4 or more, the clusters blur together.

In [55]:
```
from matplotlib import pyplot as plt
from scipy.cluster.hierarchy import dendrogram, linkage
import numpy as np
```

In [56]:
```
# generate the linkage matrix
Z = linkage(X, 'ward')
```

Hierarchical Clustering Dendrogram which will show distances as # of clusters increase.

In [57]:
```
from scipy.cluster.hierarchy import cophenet
from scipy.spatial.distance import pdist

c, coph_dists = cophenet(Z, pdist(X))
c
```

Out[57]: 0.5079123408436517

common linkage methods like 'single', 'complete', 'average', ...

In [58]:
```
Z1 = linkage(X, 'average')
c, coph_dists = cophenet(Z1, pdist(X))
c
```

Out[58]: 0.7178147004071651

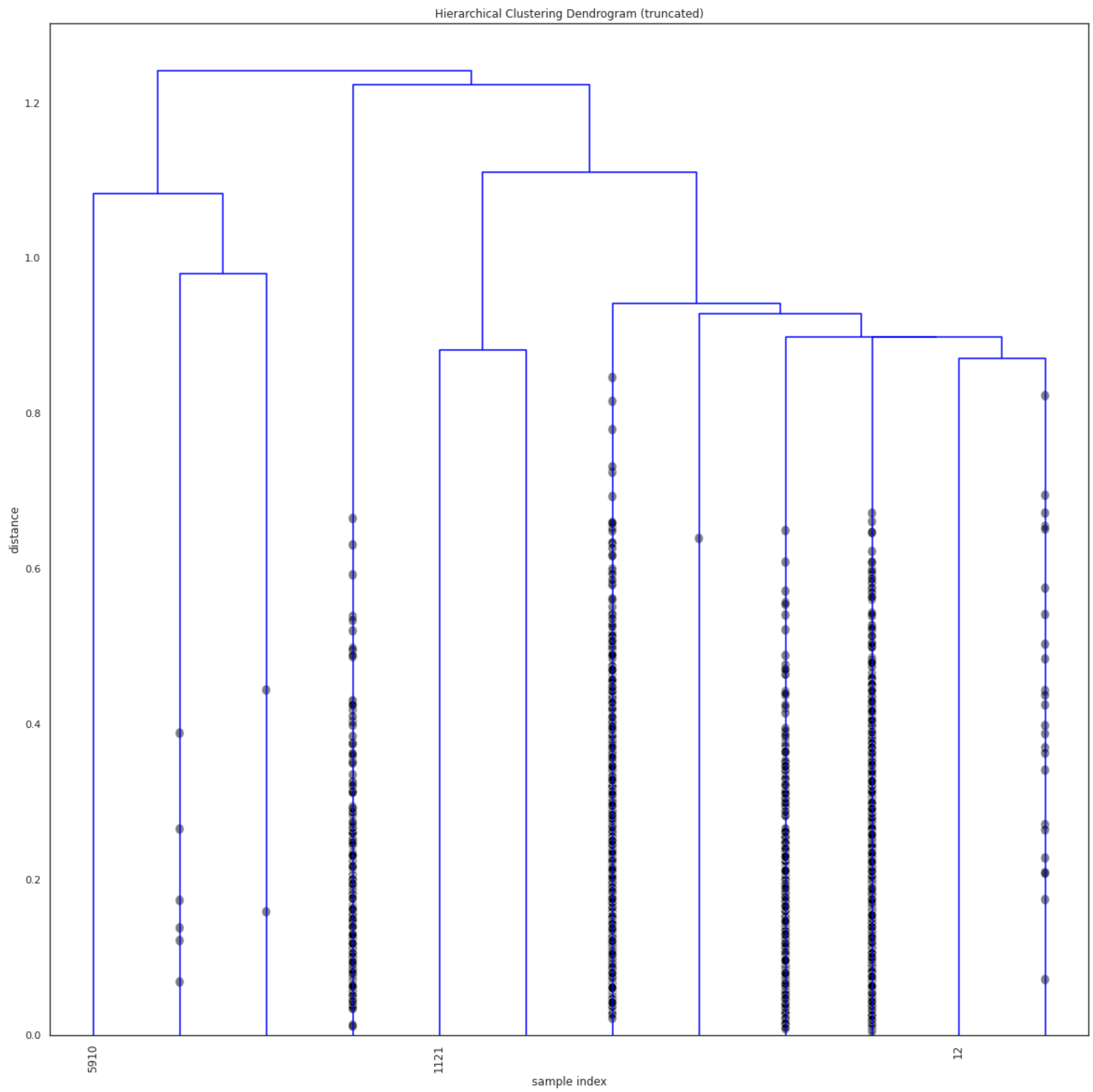
In [59]:
```
Z2 = linkage(X, 'single')
c, coph_dists = cophenet(Z2, pdist(X))
c
```

Out[59]: 0.5835259911046818

In [60]:
```
Z1[0]
```

Out[60]: array([5.72800000e+03, 5.72900000e+03, 4.82989333e-03, 2.00000000e+00])

In [63]:
```
plt.figure(figsize=(20,20))
plt.title('Hierarchical Clustering Dendrogram (truncated)')
plt.xlabel('sample index')
plt.ylabel('distance')
dendrogram(
    Z1,
    truncate_mode='lastp',  # show only the last p merged clusters
    p=12,  # show only the last p merged clusters
    show_leaf_counts=False,  # otherwise numbers in brackets are counts
    leaf_rotation=90.,
    leaf_font_size=12.,
    show_contracted=True,  # to get a distribution impression in truncated bra
nches
)

plt.show()
```



If we draw a horizontal line that passes through longest distance without a horizontal line, we get 5 clusters as shown in the following figure. For optimal prediciton of weather patterns, the optimal number of clusters is 3-4. In this case I would pick 3. Now, I need to analyze the other set of data that I dropped and combine them.

```
In [ ]:
```