Final

November 12, 2021

1 Component 1 Plotting

timestamp, temperature_site1, and humidity_site1

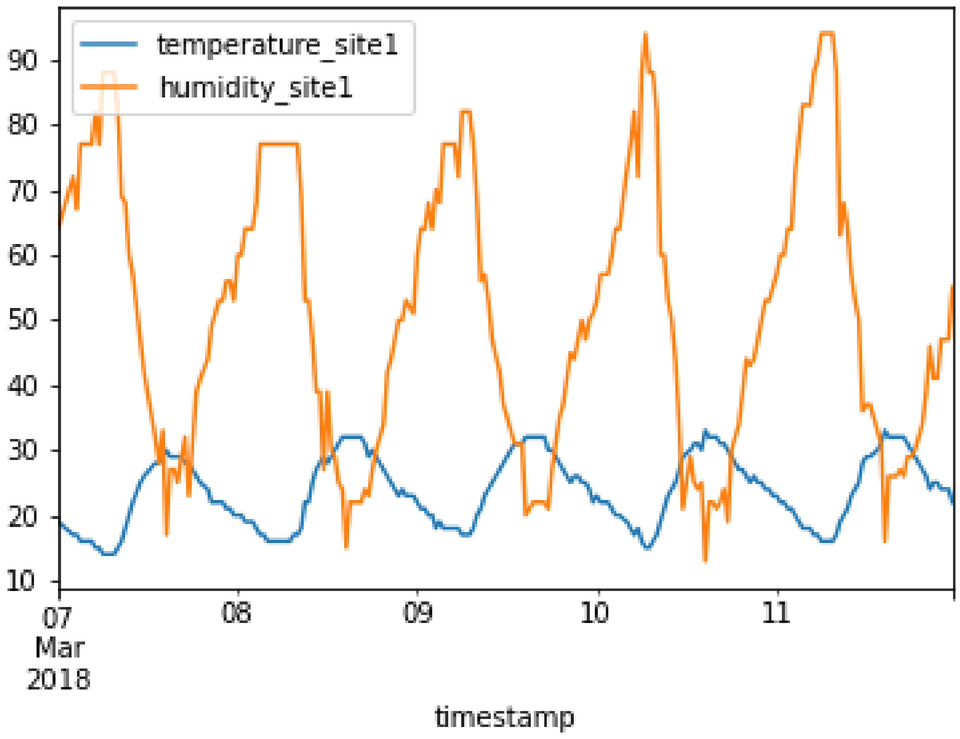
days = 2+4+1 = 7 to 11

[1]:
```
%load_ext lab_black
```

[2]:
```
import pandas as pd
import matplotlib.pyplot as plt
from datetime import datetime as dt
```

Loading and Initial Observations

[3]:
```
df = pd.read_csv(
    "weather_data_2sites-1.csv",
    parse_dates=["timestamp"],
    infer_datetime_format="%yyyy-%m-%dd %H:%M:%S",
).drop(columns=["temperature_site2", "humidity_site2", "Unnamed: 0"])
start_date = "2018-03-07 00:00:00"
end_date = "2018-03-12 00:00:00"
df = df[(df["timestamp"] >= start_date) & (df["timestamp"] < end_date)]
df["date"] = df["timestamp"].dt.date
df["time"] = df["timestamp"].dt.time
df["day"] = df["timestamp"].dt.day
df.reset_index(inplace=True, drop=True)
df.plot(x="timestamp", y=["temperature_site1", "humidity_site1"])
plt.show()
print(df)
```




```
               timestamp  temperature_site1  humidity_site1        date  \
0    2018-03-07 00:00:00               19.0            64.0  2018-03-07
1    2018-03-07 00:30:00               18.5            66.0  2018-03-07
2    2018-03-07 01:00:00               18.0            68.0  2018-03-07
3    2018-03-07 01:30:00               17.5            70.0  2018-03-07
4    2018-03-07 02:00:00               17.0            72.0  2018-03-07
..                   ...                ...             ...         ...
235  2018-03-11 21:30:00               25.0            41.0  2018-03-11
236  2018-03-11 22:00:00               24.0            47.0  2018-03-11
237  2018-03-11 22:30:00               24.0            47.0  2018-03-11
238  2018-03-11 23:00:00               24.0            47.0  2018-03-11
239  2018-03-11 23:30:00               22.0            55.0  2018-03-11

         time  day
```

```
0    00:00:00    7
1    00:30:00    7
2    01:00:00    7
3    01:30:00    7
4    02:00:00    7
..        ...  ...
235  21:30:00   11
236  22:00:00   11
237  22:30:00   11
238  23:00:00   11
239  23:30:00   11

[240 rows x 6 columns]
```

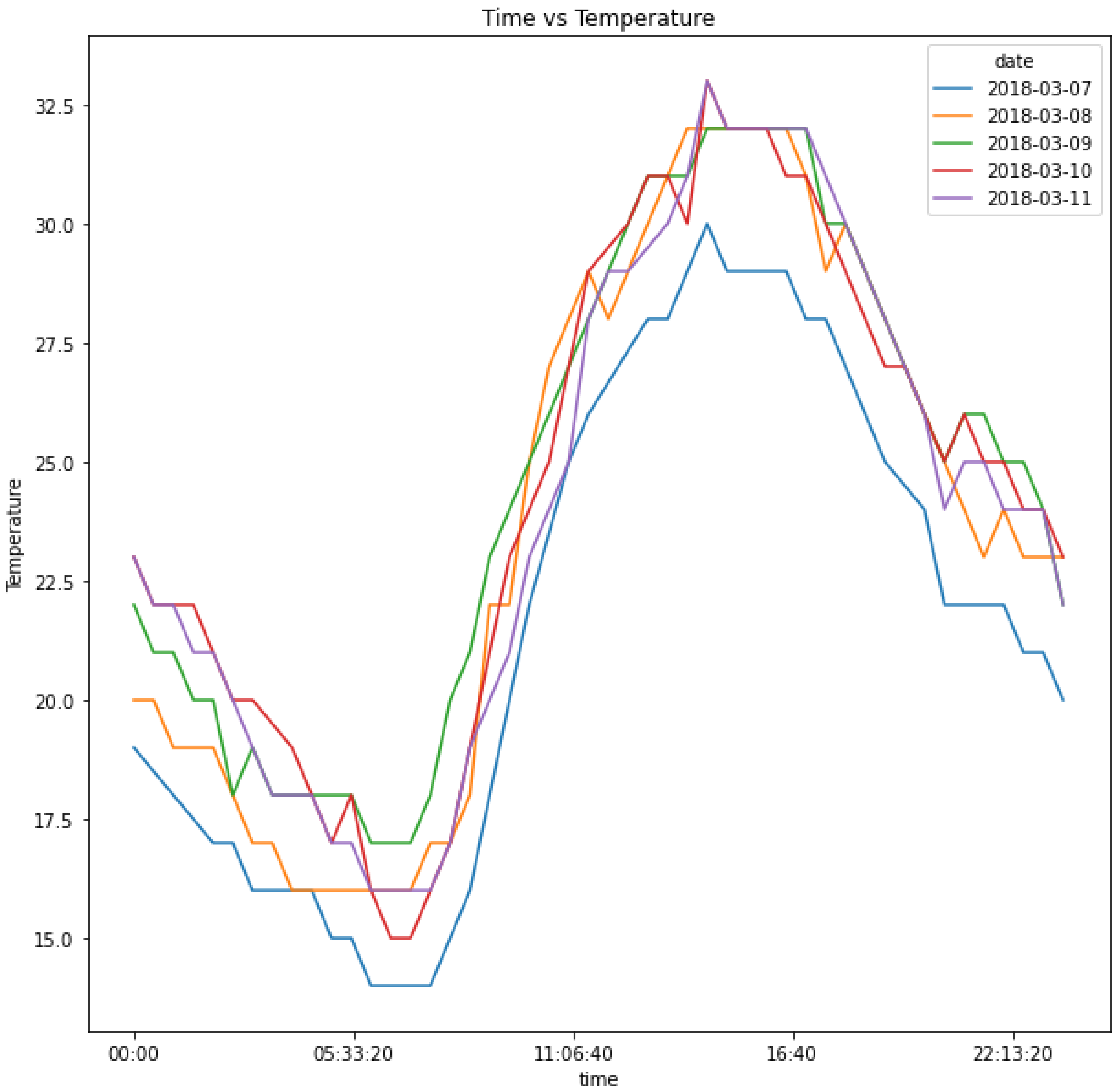
1.1 Line Plots

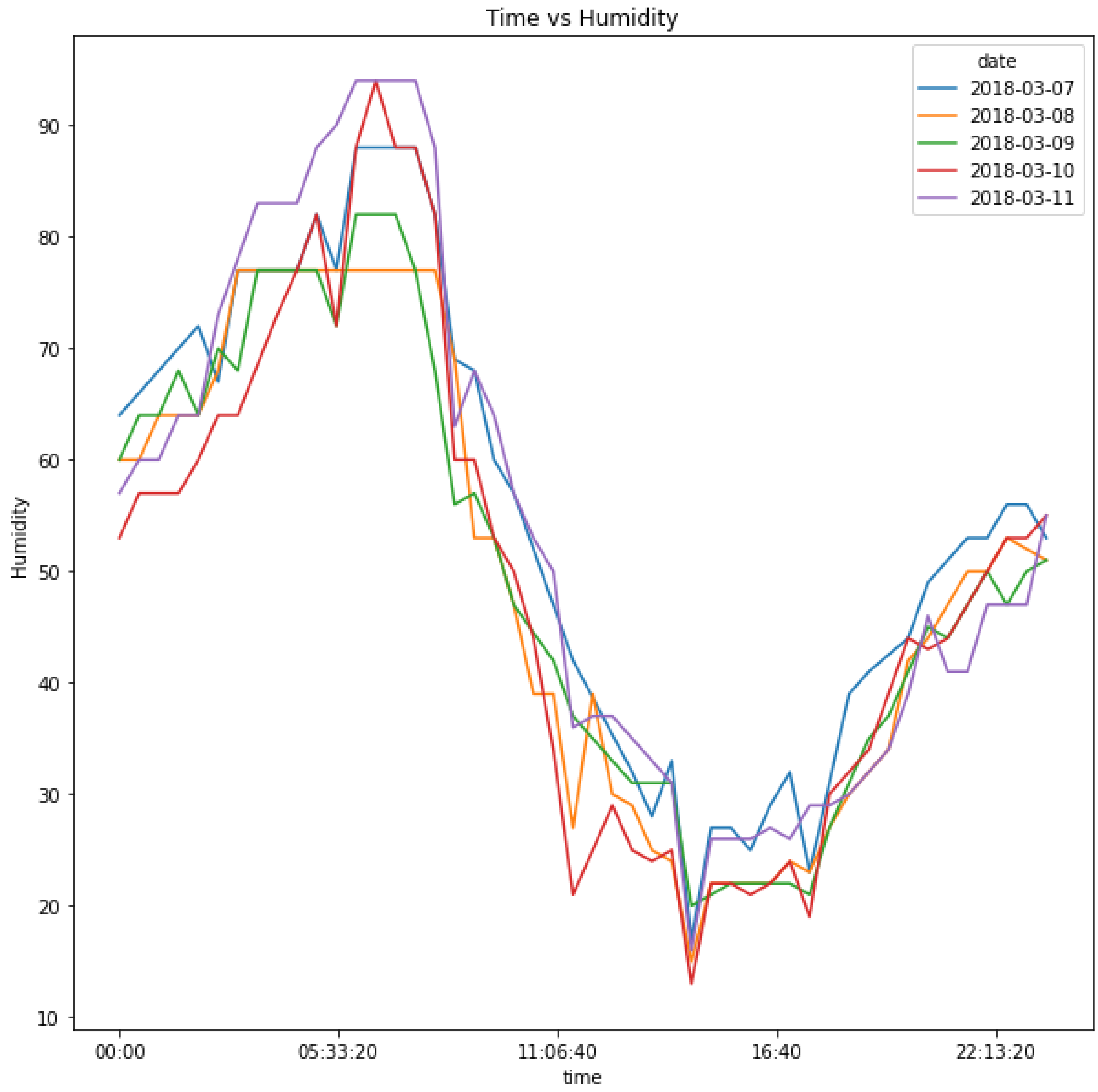
Preprocessing the data for plotting

[4]:
```
k = df[["temperature_site1", "humidity_site1", "date", "time"]]
# k = k.melt(id_vars=['time','temperature_site1','humidity_site1'],value_vars=['date']).set_index([ 'value','time']).
↪unstack('value')
k.set_index(["date", "time"], inplace=True, drop=True)
k = k.unstack("date")
k.head()
```

[4]:
```
         temperature_site1                                                  \
date            2018-03-07 2018-03-08 2018-03-09 2018-03-10 2018-03-11
time
00:00:00              19.0       20.0       22.0       23.0       23.0
00:30:00              18.5       20.0       21.0       22.0       22.0
01:00:00              18.0       19.0       21.0       22.0       22.0
01:30:00              17.5       19.0       20.0       22.0       21.0
02:00:00              17.0       19.0       20.0       21.0       21.0

         humidity_site1
date         2018-03-07 2018-03-08 2018-03-09 2018-03-10 2018-03-11
time
00:00:00           64.0       60.0       60.0       53.0       57.0
00:30:00           66.0       60.0       64.0       57.0       60.0
01:00:00           68.0       64.0       64.0       57.0       60.0
01:30:00           70.0       64.0       68.0       57.0       64.0
02:00:00           72.0       64.0       64.0       60.0       64.0
```

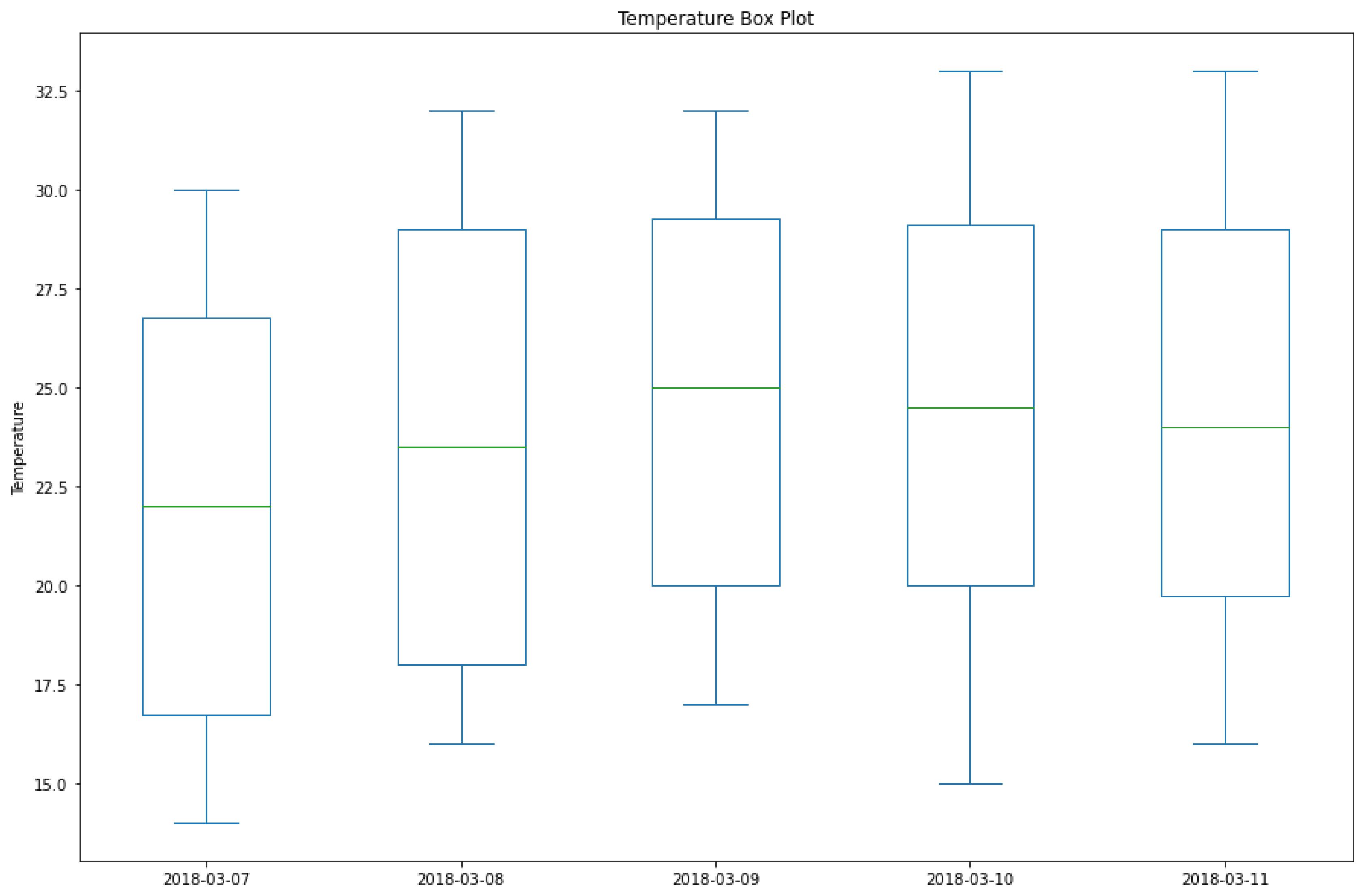
[5]:
```
k["temperature_site1"].plot(
    figsize=(10, 10), ylabel="Temperature", title="Time vs Temperature"
)
k["humidity_site1"].plot(figsize=(10, 10), ylabel="Humidity", title="Time vs Humidity")
plt.show()
```

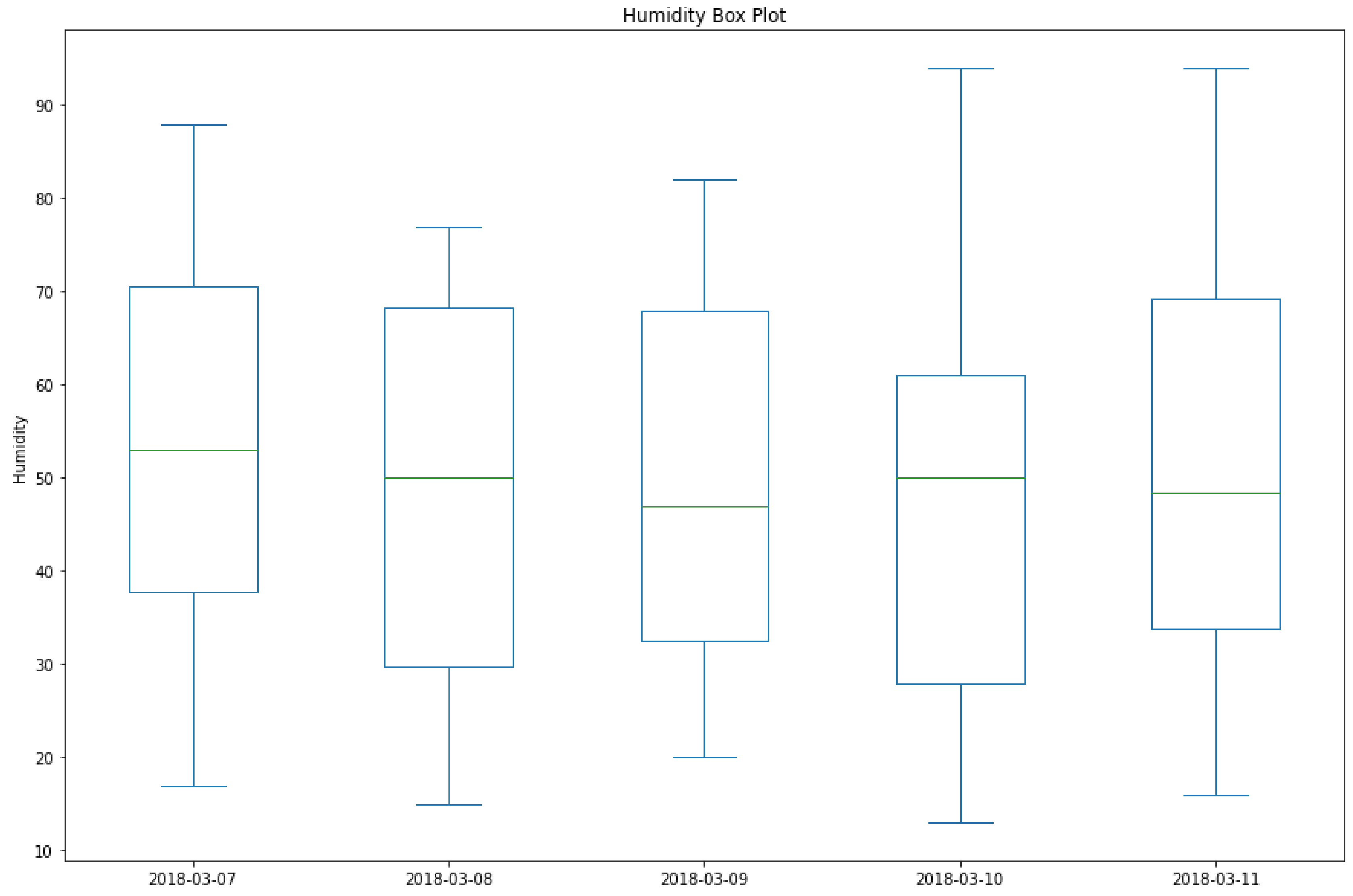

Time vs Temperature
date
2018-03-07
2018-03-08
2018-03-09
2018-03-10
2018-03-11
32.5
30.0
27.5
25.0
22.5
20.0
17.5
15.0
Temperature
00:00
05:33:20
11:06:40
16:40
22:13:20
time



1.2 Box Plots

[6]:
```
k.plot(
    kind="box",
    y="temperature_site1",
    figsize=(15, 10),
    title="Temperature Box Plot",
    ylabel="Temperature",
)
k.plot(
    kind="box",
    y="humidity_site1",
    figsize=(15, 10),
    title="Humidity Box Plot",
    ylabel="Humidity",
)
plt.show()
```

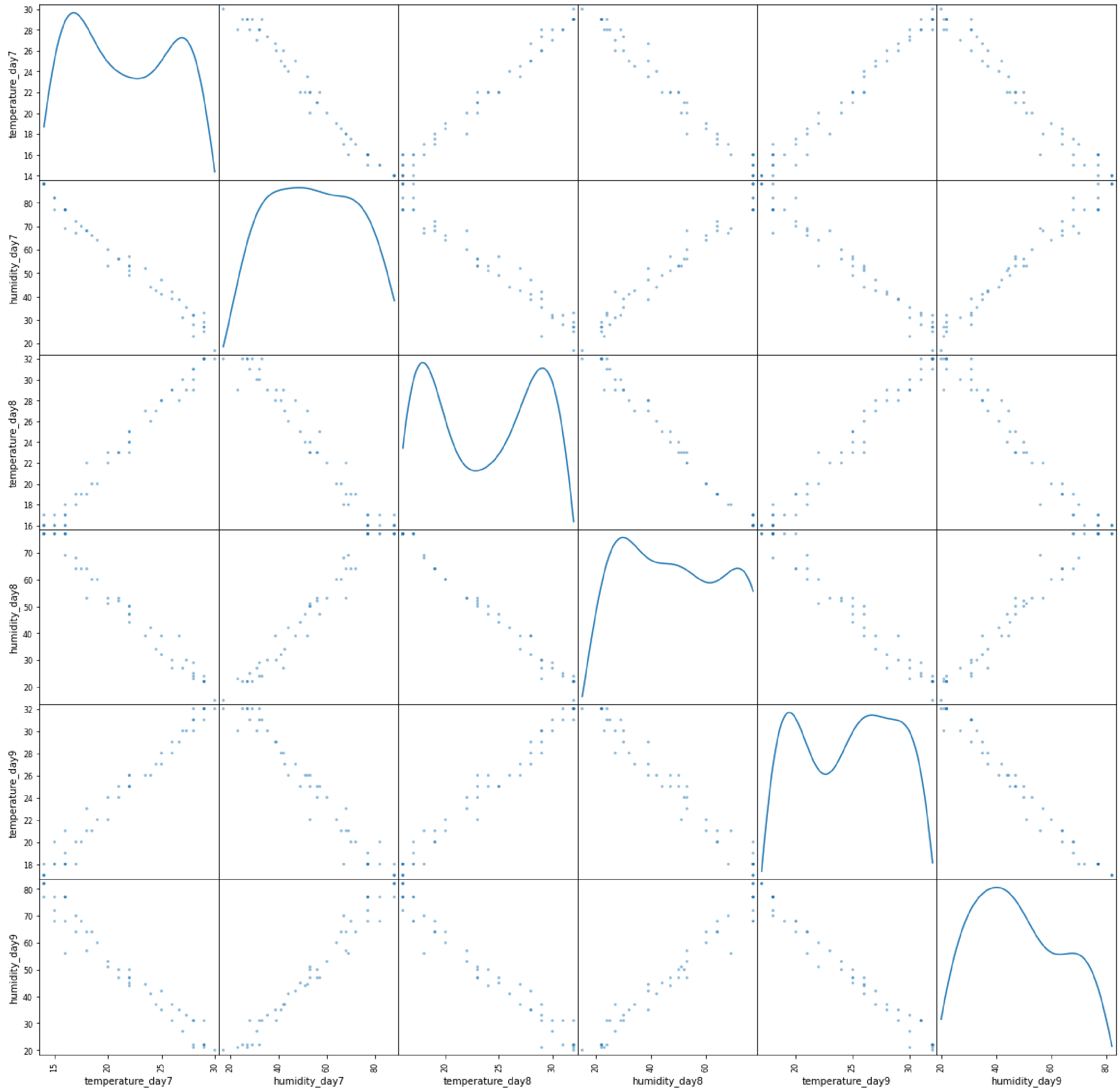




1.3 Scatter Matrix

[7]:
```
start_date = "2018-03-07 00:00:00"
end_date = "2018-03-10 00:00:00"
df_tmp = df[(df["timestamp"] >= start_date) & (df["timestamp"] < end_date)]

k = pd.DataFrame()
for day in df_tmp["day"].unique():
```

```
    k[f"temperature_day{day}"] = df_tmp[df_tmp["day"] == day][
        "temperature_site1"
    ].values
    k[f"humidity_day{day}"] = df_tmp[df_tmp["day"] == day]["humidity_site1"].values
pd.plotting.scatter_matrix(k, figsize=[20, 20], diagonal="kde")
plt.show()
```



[ ]:

2 Component # 2: Analysis

2.0.1 Loading and pre-processing the data

[8]:
```
Syn_weather = pd.read_csv(
    "weather_data_2sites-1.csv",
    parse_dates=["timestamp"],
    infer_datetime_format="%yyyy-%m-%dd %H:%M:%S",
    skiprows=[1],
).drop(columns=["temperature_site2", "humidity_site2", "Unnamed: 0"])

Syn_weather["day-minutes"] = (
    Syn_weather["timestamp"].dt.hour * 60 + Syn_weather["timestamp"].dt.minute
)
Syn_weather["day-of-the-week"] = Syn_weather["timestamp"].dt.dayofweek
Syn_weather["previous-temperature"] = Syn_weather["temperature_site1"].shift()

Syn_weather.drop(columns="timestamp", inplace=True)
```

```
Syn_weather.rename(
    columns={"temperature_site1": "temperature", "humidity_site1": "humidity"},
    inplace=True,
)
Syn_weather.index = Syn_weather.index + 1

Syn_weather.loc[1, "previous-temperature"] = Syn_weather.loc[
    1, "temperature"
]  # setting the first previous-temperature value to the temperature in its row otherwise,
# it would take 'NaN' value, which will raise an error during the model training.

Syn_weather
```

[8]:

```
      temperature  humidity  day-minutes  day-of-the-week  \
1            21.0      68.0           30                3
2            20.0      73.0           60                3
3            20.0      73.0           90                3
4            20.0      73.0          120                3
5            20.0      70.0          150                3
...           ...       ...          ...              ...
5775         28.0      84.0           60                4
5776         28.0      84.0           90                4
5777         28.0      84.0          120                4
5778         28.0      84.0          150                4
5779         28.0      84.0          180                4

      previous-temperature
1                     21.0
2                     21.0
3                     20.0
4                     20.0
5                     20.0
...                    ...
5775                  28.0
5776                  28.0
5777                  28.0
5778                  28.0
5779                  28.0

[5779 rows x 5 columns]
```

2.1 Regression

[9]:

```
import pandas as pd  # data structure and the operations
import numpy as np  # arrays and the operations

import sklearn.linear_model as skl_lm  # for regression
from sklearn.model_selection import (
    train_test_split,
)  # splitting data into test,train sets

from sklearn.metrics import mean_squared_error  # for metrics

import matplotlib.pyplot as plt  # plotting library

import seaborn as sns  # another plotting library
```

[10]:

```
X = Syn_weather[
    ["humidity", "day-minutes", "day-of-the-week", "previous-temperature"]
]  # Preparing the Dependent and Independent Variables
y = Syn_weather.temperature
```

2.2 Linear regression

Making test, train sets of the data and, fitting the model

[11]:

```
M1 = skl_lm.LinearRegression()  # defining a Regression model
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=1 / 3, random_state=5
)  # test, train sets are split from the original data

M1.fit(X_train, y_train)  # Fitting the model to the train sets

print("Intercept :", M1.intercept_)
print("Coefficients :", M1.coef_)
```

```
Intercept : 1.9119579822386612
Coefficients : [-1.52052587e-02 -4.70626721e-04 -7.08096125e-03  9.69701851e-01]
```

[12]:
```python
m1_pred = M1.predict(X_test)
rmse = mean_squared_error(
    y_test, m1_pred, squared=False
)  # if squared is 'True' it gives MSE or else it gives RMSE
print("RMSE (M1) : %.3f" % rmse)
```

```
RMSE (M1) : 0.924
```

2.3 Cross Validation

[13]:
```python
from sklearn.model_selection import (
    KFold,
)  # Splitting the data into K folds used for cv (Cross Validation)
from sklearn.model_selection import cross_val_score  # For calculating the RMSE
from sklearn.model_selection import cross_val_predict  # For predictions using cv
```

[14]:
```python
X = Syn_weather[
    ["humidity", "day-minutes", "day-of-the-week", "previous-temperature"]
]  # Independent Variables
y = Syn_weather.temperature  # Dependent Variable

kfold = KFold(
    n_splits=10, random_state=5, shuffle=True
)  # 10 fold splitting of the input data

M2 = skl_lm.LinearRegression()

results = cross_val_score(
    M2, X, y, cv=kfold, scoring="neg_mean_squared_error"
)  # Calculating the RMSE of Cross Validation method
rmse = np.mean(np.sqrt(np.abs(results)))  # Converting MSE to RMSE
print("RMSE (M2) : %.3f" % rmse)
```

```
RMSE (M2) : 0.938
```

2.4 Step-Wise Regression

[15]:
```python
import statsmodels.api as sm
```

[16]:
```python
x_columns = [
    "humidity",
    "day-minutes",
    "day-of-the-week",
    "previous-temperature",
]  # getting the regression variables
y = Syn_weather.temperature


def stepwise_reg():
    x = Syn_weather[x_columns]
    results = sm.OLS(y, x).fit()  # Fitting a OLS model on y,x
    aic = []
    if len(x_columns) != 2:  # condition, so we only get top 2 regressors
        re = results.pvalues  # Finding the p values of independent variables
        aic.append(results.aic)
        k = re[
            re == re.max()
        ].index.array  # removing the least favorable regressor ie., max p value.
        x_columns.remove(k[0])
        #          print(results.pvalues,results.aic,x_columns)
        stepwise_reg()  # looping through the regression once again.
    else:
        print(f"The top 2 regressors are : {x_columns[0]}, {x_columns[1]}")


stepwise_reg()
```

```
The top 2 regressors are : day-minutes, previous-temperature
```

- Even though the Humidity has highest correlation with temperature, we see that it has less significance compared to day-minutes or previous-temperature

2.5 Corr coeff

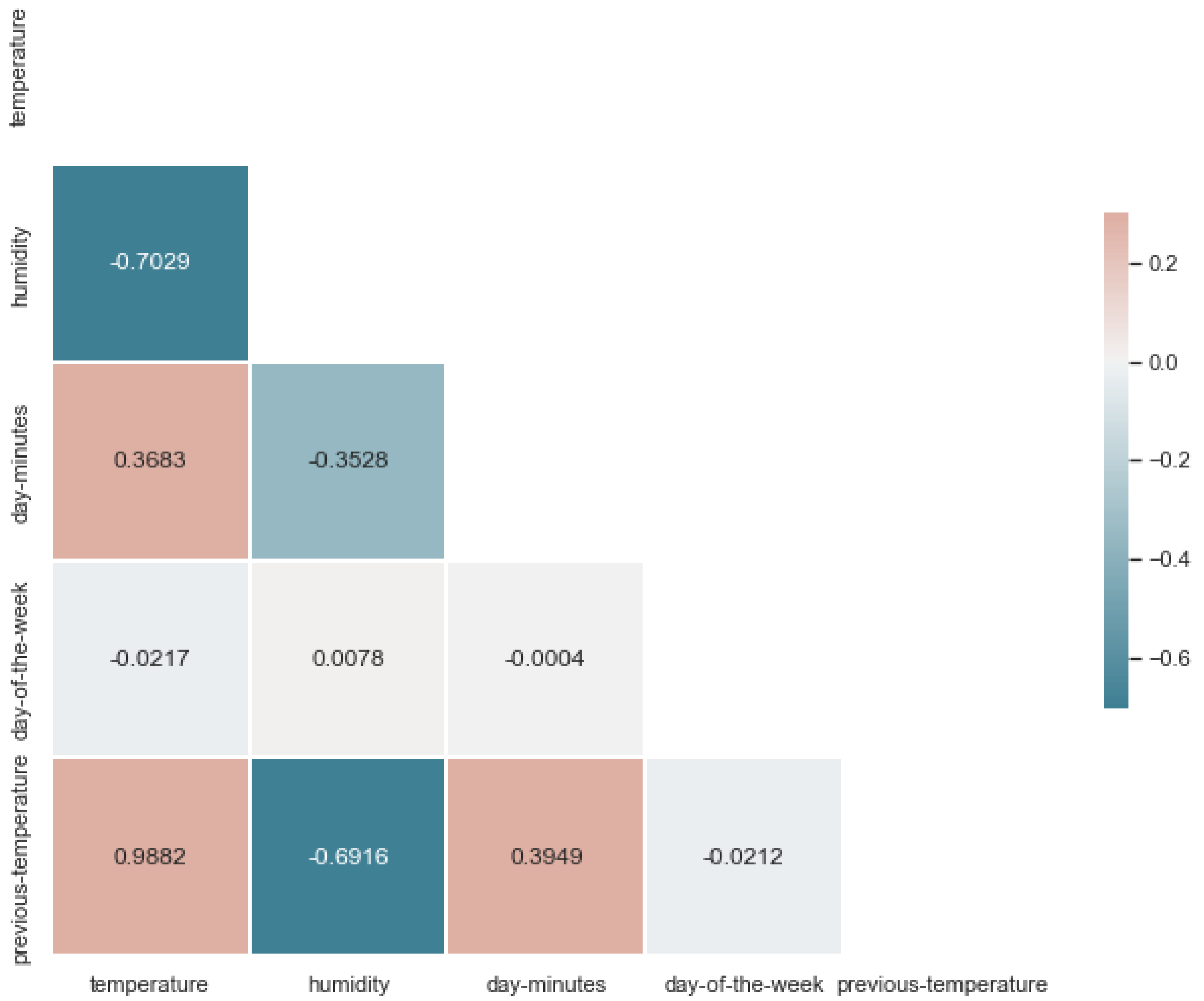
[17]:
```
corr = Syn_weather.corr()
corr
```

[17]:

	temperature	humidity	day-minutes	day-of-the-week	previous-temperature
temperature	1.000000	-0.702853	0.368295	-0.021720	0.988245
humidity	-0.702853	1.000000	-0.352824	0.007783	-0.691608
day-minutes	0.368295	-0.352824	1.000000	-0.000376	0.394892
day-of-the-week	-0.021720	0.007783	-0.000376	1.000000	-0.021230
previous-temperature	0.988245	-0.691608	0.394892	-0.021230	1.000000

2.5.1 Correlation Matrix

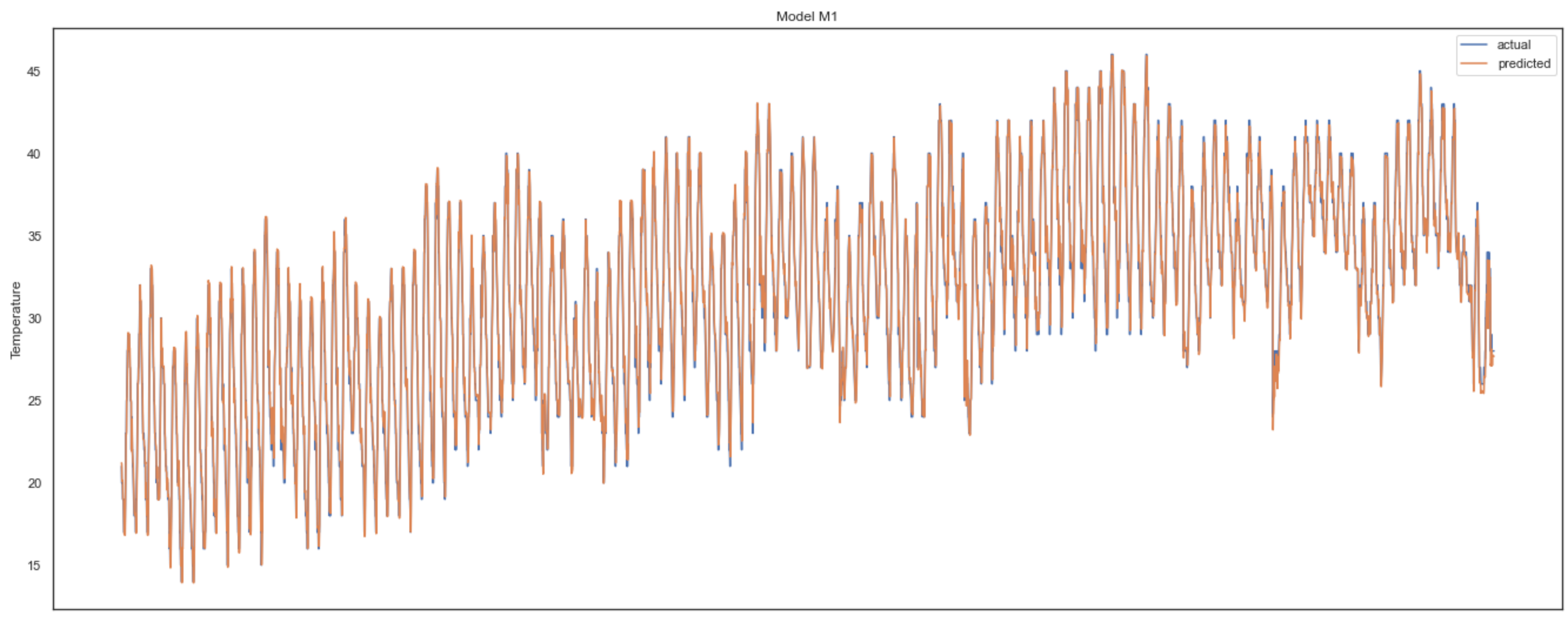
[18]:
```
mask = np.triu(np.ones_like(corr, dtype=bool))
sns.set_theme(style="white")
fig, ax = plt.subplots(figsize=(11, 9))
cmap = sns.diverging_palette(220, 20, n=200, as_cmap=True)
sns.heatmap(
    corr,
    mask=mask,
    vmax=0.3,
    center=0,
    square=True,
    fmt=".4f",
    annot=True,
    cmap=cmap,
    linewidths=2,
    cbar_kws={"shrink": 0.5},
)
plt.show()
```

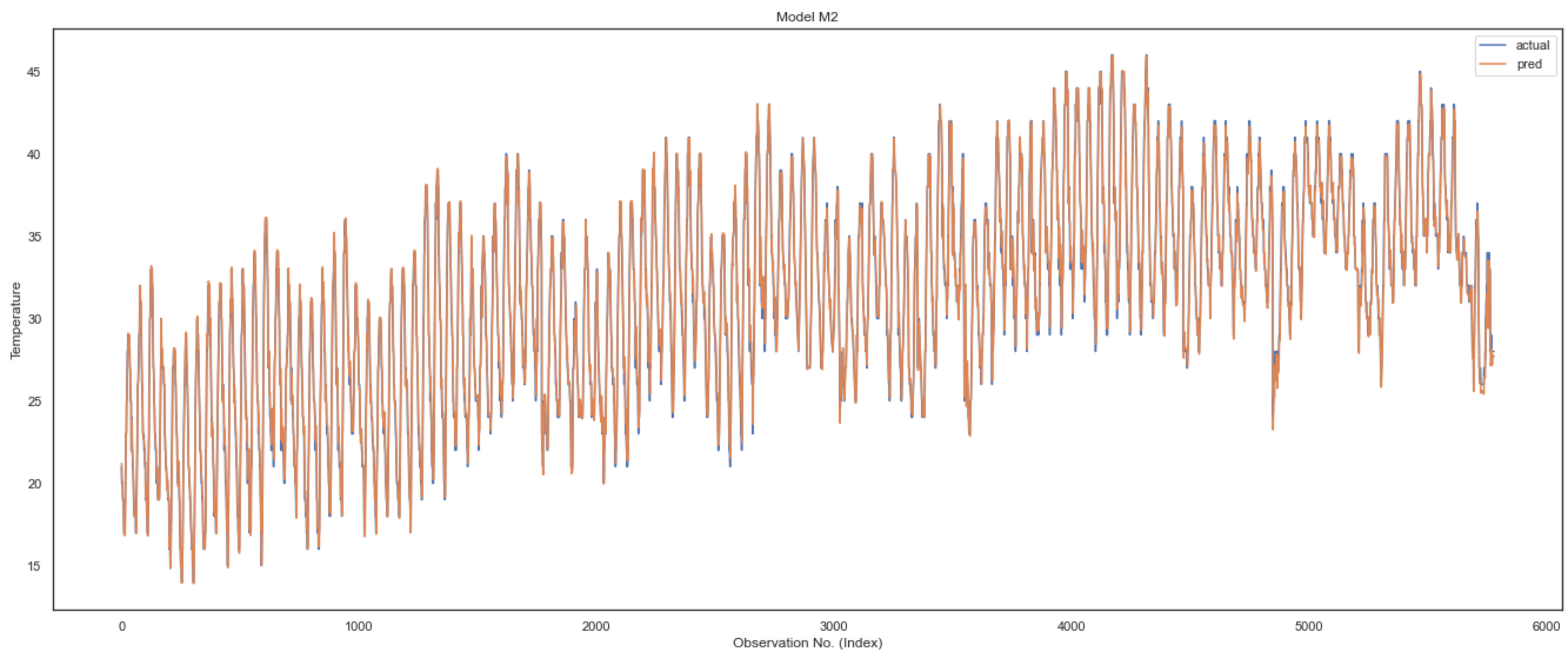


- The Correlation between temperature and Humidity is very -ve. This tells that as humidity increases the temperature decreases, which is accurate.
- The 'day-minutes' (basically tells us what time of the day) is +ve correlated to temperature. This is also accurate to the real world.
- From the correlation plot/ matrix, it's very clear that 'day-of-the-week' has very little effect on temperature and humidity.
- Previous temperature has a considerate effect on humidity.

2.6 Plotting

[19]:
```
m1_pred = M1.predict(X)
pred_M1 = pd.DataFrame({"actual": y, "predicted": m1_pred})

m2_pred = cross_val_predict(
    M2, X, y, cv=kfold
)  # Predicting using Crosss Validation method
pred_M2 = pd.DataFrame({"actual": y, "pred": m2_pred})

fig, axes = plt.subplots(2, 1, figsize=(23, 20))

pred_M1.plot(
    ax=axes[0], subplots=False, ylabel="Temperature", sharex=True, title="Model M1"
)

pred_M2.plot(
    ax=axes[1],
    subplots=False,
    ylabel="Temperature",
    xlabel="Observation No. (Index)",
    title="Model M2",
)
plt.show()
```





- Since, both M1 and M2 have an RMSE of <1, we expect a good fit of values
- Considering the RMSE values of M! and M2 only differ by ~0.01, we expect both the models to be very similar in performance
- Both M1 and M2 models are very accurate and precise and this can be seen by the plots.
- The plots shows that, in this case the Cross Validation method has very minimal improvements over regular Linear regression with test, train split.

[ ]: