Miniproject: Modelling the climate or the weather?

Is past performance an indicator of future weather?

Global Historial Climatology Network

GHCN (Global Historical Climatology Network)-Daily is an integrated database of daily climate summaries from land surface stations across the globe.

THe GHCN has many datasets from weather stations across the globe. A README describing the data form is available here. The stations.txt file and countries.txt contain information about the stations and countries.

Machine Learning Tasks:

1. Can you design a machine learning technique that can predict the climate (defined as the weekly or monthly average) a year in advance? [Later in the term files containing the 2021 data will be made available
2. Can you design a machine learning technique that can predict the weather (temperature, rainfall, snow fall, etc.) any better than assuming that the weather tomorrow will be exactly the same as the weather today

Potential extensions

1. Can you train a machine learning technique to predict 10 or 20 years into the future?
2. Where will the hotest part of the world be in 20 years time?
3. What else can you study with this dataset? Is the sun in Utah a predictor of the rain in Spain?
4. How close do weather stations need to be to provide reliable forecasts at other stations?

Caveats

This is real data from weather stations around the world. This means that there are 'holes' in the data. You must be able to handle these 'holes' in some error tolerant fashion.

```
# import the urllib library
import urllib.request
from datetime import date
import numpy as np
import matplotlib.pyplot as plt

#Class that keeps information about station name and location
class Station():
    def __init__(self,sid,lat,lon,el,state,name,gsn,hcn,wmo,country):
        self.sid=sid
        self.lat=lat
        self.lon=lon
        self.el=el
        self.state=state
        self.name=name
        self.gsn=gsn
        self.hcn=hcn
        self.wmo=wmo
        self.country=country

    def __str__(self):
        return self.sid+" is "+self.name+", "+self.country+" at "+str(self.lat)+",

#Class that hides some ugly reading routines
class GHNCD:

    #Class constructor
    def __init__(self):
        self.station_col_len = [11,4,2,4]
        for i in range(31):
            self.station_col_len.append(5)
            self.station_col_len.append(3)

    # Split up the fixed length text arrays into fields
    def chunkstring(self,string, lengths):
        return (string[pos:pos+length].strip()
                for idx,length in enumerate(lengths)
                for pos in [sum(map(int, lengths[:idx]))])

    # Process a file and extract all the information into a dictionary
    def processFile(self,fileName):
        outDict={} #
        with open(fileName, 'r') as fp: # Open file
            line = fp.readline()  #Read first line
            while line: # Process line
                fields = list(self.chunkstring(line, self.station_col_len)) #Get li

                # For clarity use some variable names
                station=fields[0]
                year=int(fields[1])
                month=int(fields[2])
                field=fields[3]
                vals=fields[4::2]
                flags=fields[5::2]
                # Not clear this is the only check we need, but for now
                def checkInt(x,flag):
                    if flag=='':
                        return -9999
                    return int(x)

                #Convert missing entries to -9999 using this swishy bit of string c
                ivals=[checkInt(x,flag) for (x,flag) in zip(vals,flags)]
                monthDict=dict(year=year,month=month,field=field,vals=ivals,flags=f
                if field in outDict.keys():
                    outDict[field]['monthList'].append(monthDict)
                else:
```

```
                fieldDict=dict(monthList=[monthDict])
                outDict[field]=fieldDict
            line = fp.readline()
        return dict(outDict) #Return a copy

    def readCountriesFile(self,fileName=None):
        self.countryDict={}
        if fileName==None:
            file = urllib.request.urlopen('http://www.hep.ucl.ac.uk/undergrad/0056/
        else:
            file = open(fileName,'r')

        for line in file:
            c=str(line[0:2], 'utf-8')
            d=str(line[3:-2], 'utf-8')
            self.countryDict[c]=d
        print("Read",len(self.countryDict),"countries and codes")


    def readStationsFile(self,fileName=None,justGSN=True):

        #------------------------------
        #Variable   Columns   Type
        #------------------------------
        #ID            1-11   Character
        #LATITUDE     13-20   Real
        #LONGITUDE    22-30   Real
        #ELEVATION    32-37   Real
        #STATE        39-40   Character
        #NAME         42-71   Character
        #GSN FLAG     73-75   Character
        #HCN/CRN FLAG 77-79   Character
        #WMO ID       81-85   Character
        #------------------------------
        self.stationDict={}
        if fileName==None:
            file = urllib.request.urlopen('http://www.hep.ucl.ac.uk/undergrad/0056/
        else:
            file = open(fileName,'r')

        for line in file:
            sid=str(line[0:11], 'utf-8')
            lat=float(str(line[12:20], 'utf-8'))
            lon=float(str(line[21:30], 'utf-8'))
            el=float(str(line[31:37], 'utf-8'))
            state=str(line[38:40], 'utf-8')
            name=str(line[41:71], 'utf-8')
            gsn=str(line[72:75], 'utf-8')
            hcn=str(line[76:79], 'utf-8')
            wmo=str(line[80:85], 'utf-8')


            if justGSN:
                if gsn=='   ':
                    continue
            self.stationDict[sid]=Station(sid,lat,lon,el,state,name.rstrip(),gsn,hc
        print("Read",len(self.stationDict),"stations with justGSN",justGSN)

    # Get all the data for a given variable type
    def getVar(self,statDict,varName='TMAX'):
        #The TMIN, TMAX, PRCP are all quoted in tenths (so need to be multipied by
        cal=0.1
        if varName=='SNOW' or varName=='SNWD':
            cal=1.0
        tempList=[ (date(month['year'],month['month'],ind+1),cal*val)  for month in
        return tempList

    def getTMAX(self,statDict):
        return self.getVar(statDict,'TMAX')

    def printStation(self,sid):
        print(self.stationDict[sid])

    def getStation(self,sid):
        return self.stationDict[sid]

    def getStatKeyNames(self):
        #print(self.stationDict.keys())
        return [*self.stationDict.keys()]
```

```
ghn=GHNCD()
ghn.readCountriesFile()
ghn.readStationsFile()
```

```
    Read 219 countries and codes
    Read 991 stations with justGSN True
```

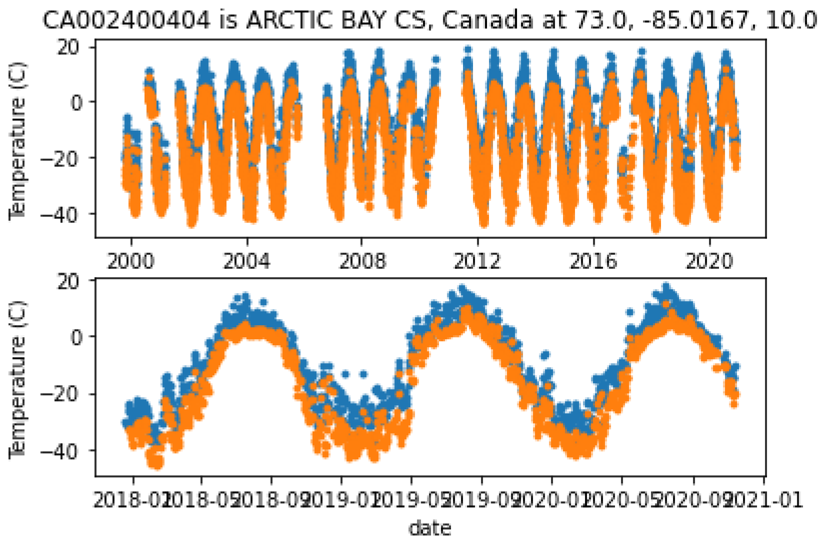
```
# Get list of station names
statNames=ghn.getStatKeyNames()

# Arbitrary number from 0 to 990
whichStat=220
fileName=statNames[whichStat]+'.dly'
urlName='http://www.hep.ucl.ac.uk/undergrad/0056/other/projects/ghcnd/ghcnd_gsn/'+f

# Copy a network object to a local file
urllib.request.urlretrieve(urlName,fileName)
statDict=ghn.processFile(fileName)
print(ghn.getStation(statNames[whichStat]))
```

```
    CA002400404 is ARCTIC BAY CS, Canada at 73.0, -85.0167, 10.0
```

```
tmaxArray=ghn.getVar(statDict,'TMAX')
days, tmax = zip(*tmaxArray)
tminArray=ghn.getVar(statDict,'TMIN')
```

```
days2, tmin = zip(*tminArray)
print(len(days))
fig, ax = plt.subplots(2,1)
ax[0].plot(days,tmax,'.')
ax[0].plot(days2,tmin,'.')
ax[0].set_xlabel("date")
ax[0].set_ylabel("Temperature (C)")
ax[0].set_title(ghn.getStation(statNames[whichStat]))
ax[1].plot(days[-1000:],tmax[-1000:],'.')
ax[1].plot(days2[-1000:],tmin[-1000:],'.')
ax[1].set_xlabel("date")
ax[1].set_ylabel("Temperature (C)")
```

```
5341
Text(0, 0.5, 'Temperature (C)')
```



NB From here, these are student added notes and code

Getting started

1. Identify the requirement (a), analyse the problem (b) and write a short introduction (c)
2. Decompose the problem into manageable sub-problems, giving a short description of what each of the sub problems will do (e.g. bulletted list).
3. Write a short explanation of the reasoning behind the decomposition.

Getting started:

Task 1(a)

The miniproject involves developing machine learning models to predict the climate a year in advance and to predict the weather (temperature, rainfall, snow fall, etc.) and see if this is any better than assuming that the weather tomorrow will be exactly the same as the weather today. There are a list of possible extensions in the brief, but other ones could be considered if interesting.

Task 1(b)

Quite a lot of time will need to be spent analysing the data. The data used in the code above is from a UCL website. What is the structure of the data, what are the best ways to manipulate, analyse and deal with gaps in the data: maybe pandas? Or is it best to stick to the above methodology?

Once this has been resolved models can be designed to fulfil and test the requirements listed in 1(a). Models will be constructed and a training/ test set methodology designed. Models can be adapted until good and consistent results achieved. Probably LSTM models will be used as these seem well suited to making predictions with sequential and periodic data like coursework examples (double pendulum and sunspots).

Extension projects (time allowing) will be decided on based on understanding what data is available and with consideration of interesting areas to investigate.

Task 1(c)

The aim of this miniproject was to see if machine learning techniques could be applied successfully to weather and climate forecasting. Data used was from the Global Historical Climatology Network (GCHN): a series of weather stations around the world. Analysis of the data, best methods of parsing and cleaning it were made. Predictive machine learning models were developed and trained.

As an area of intersting further research and after checking adequate data was available, studies were made into the effect of using data from neighbouring stations to improve weather predictions, as well as exploring the effects of changing other parameters.

Task 2 - Decompose the problem into manageable sub-problems, giving a short description of what wach of the sub problems will do (e.g. bulletted list).

I. Review code provided, investigate extent and quality of UCL data.

II. Determine how to parse, clean and manipulate data, try to use pandas.

III. Determine which station(s) to use for the two main machine learning tasks (climate, weather).

IV. Determine the training/ validation/ test methodology. Probably using sklearn.

V. In deciding models, it is important to review course materials- especially those using RNN models, e.g. LSTM. Week6_pandas.ipynb will be very relevant as uses pandas, sklearn and deals with multi-year periodic data (sunspots). Also the double pendulum exercise is relevant as it used models that input and output several features.

VI. Conduct climate prediction experiments.

VII. Conduct weather prediction experiments.

VIII. Decide on an extention project (hopefully to integrate extra features and data from several stations.

IX. Check the notebook for any opportunities to simplify. Make sure to annotate fully and with supporting text cells.

X. Write report.

XI. Review notebook and reports for any errors and submit.

Task 3 - Write a short explanation of the reasoning behind the decomposition.

The purpose of the decompostion was to break the project down into manageable parts. The ordering is very important: first one needs to understand the code already supplied and the data available. Once a methodology for dealing with the data has been determined, the training methodology and the model can be designed, then run. The extension projects are very dependent on what data is available which was not known at the outset.

Task I: Review code and investigate extent and quality of UCL data.

UCL webpages are text files with UTF-8 encoding. Each line of a text file contains a record from which fields can be extracted as they are each of a fixed column width. For example:

http://www.hep.ucl.ac.uk/undergrad/0056/other/projects/ghcnd/ghcnd-countries.txt

This contains just a country code in the first two columns then a space and then a country name from the fourth column to the end. The file contains 219 rows, which is what has been extracted in the given code They have extracted using these column lengths into a dictionary object called "countryDict".

http://www.hep.ucl.ac.uk/undergrad/0056/other/projects/ghcnd/ghcnd-stations.txt

The above file contains the station details. There are 115074 in the file, but only 991 of these are extracted in the above code. There is a field "gsn" which is either blank or contains 'GSN'. According to documentation, this is a flag which says whether a station is part of GCOS Surface Network (GSN).

According to https://www.ncdc.noaa.gov/gosic/global-climate-observing-system-gcos/gcos-surface-network-gsn-program-overview

"The GCOS Surface Network (GSN) is a baseline network comprising a subset of about 1000 stations chosen mainly to give a fairly uniform spatial coverage from places where there is a good length and quality of data record."

It seems sensible to start using just these 991 stations as they should provide plenty of quality data from stations well spaced across the globe. The key fields are:

ID: unique identifier of station

LATITUDE: is latitude of the station (in decimal degrees)

LONGITUDE: is longitude of the station (in decimal degrees)

ELEVATION: is the elevation of the station (in meters, missing = -999.9)

NAME: is station name

GSN FLAG: blank or 'GSN'

These fields and all others are extracted into the dictionary "stationDict". NB it is easy to relax the constraint to only include GSN stations as demonstrated below:

```
ghn=GHNCD()
ghn.readCountriesFile()
ghn.readStationsFile(justGSN=False)
```

```
Read 219 countries and codes
Read 115074 stations with justGSN False
```

Task I continued

http://www.hep.ucl.ac.uk/undergrad/0056/other/projects/ghcnd/ghcnd_gsn/

contains the index of .dly files which contain the meteorological measurements for each station. Each file is named with the station ID, e.g. AE000041196.dly is the first one. There are 991 stations listed, i.e. corresponding to the GSN stations. For measurements from other stations, access to other data sources would be required.

Each row in a file is a record containing one month of daily data for a particular type of measurement or "element". The variables on each line include the following (and are at fixed column positions):

ID: Station ID

YEAR: e.g. 1944

MONTH: e.g. 03 for March

ELEMENT: There are many elements possible, but the five core ones are:

PRCP = Precipitation (in tenths of mm)

SNOW = Snowfall (mm)

SNWD = Snow depth (mm)

TMAX = Maximum temperature (tenths of degrees C)

TMIN = Minimum temperature (tenths of degrees C)

By inspection of the first .dly file for the first GSN station, "SHARJAH INTER. AIRP" in United Arab Emirates, it is not surprising that there is no mention of "SNOW" or "SNWD" elements. "TAVG" features regularly, but often data is not available. Missing data is recorded as "-9999".

VALUE1: value of this element on the first day of the month

Then follows three flags: MFLAG1, QFLAG1, SFLAG1. These are each single column items.

MFLAG1 - describes measurement methodologies. If left blank, normal measurements were taken otherwise a code is given, e.g.

B = precipitation total formed from two 12-hour totals

None of these look like they would have a dramatic effect on data quality

QFLAG1 - describes quality of measurement, and quality is fine if it left blank. Here the items that appear are more serious and may require exclusion or replacement of data, e.g.

I = failed internal consistency check

SFLAG1 - describes the source of the data, e.g. "U.S. Cooperative Summary of the Day (NCDC DSI-3200)". Unless one has knowledge of the different agencies, this field is less important from a data quality point of view. It is presumed that GSN is only using reputable sources for data. These three flags are repeated for 31 days in the month in question, i.e. VALUE2, MFLAG2, QFLAG2, SFLAG2....VALUE31, MFLAG31, QFLAG31, SFLAG31. For months with less than 31 days, e.g. April, the missing days will be recorded with -9999 in VALUE field and blanks in the others.

Reviewing the supplied code, the data has been extracted using the known column widths.

```
print(statDict)
```

```
    {'TMAX': {'monthList': [{'year': 1999, 'month': 11, 'field': 'TMAX', 'vals': [
```

Task II. Determine how to parse, clean and manipulate data.

The data for each station is extracted as a dictionary *statDict* which has a complicated structure where each ELEMENT is a dictionary entry with values which are a list of months for that ELEMENT. This is itself a list of dictionaries ...

```
#Key library imports and parameters to be used in this notebook
import urllib.request
from datetime import date
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
from google.colab import files
import seaborn as sns
import matplotlib as mpl
mpl.rcParams['figure.figsize'] = [12,10]
from sklearn.model_selection import train_test_split
```

```
import tensorflow as tf
from tensorflow import keras

#Try to construct dataframe from statDict
dly = pd.DataFrame.from_dict(statDict, orient='columns', dtype=None, columns=None)

#display head of dataframe
dly.head()
```

	TMAX	TMIN	PRCP	SNOW	SNWD	TAVG	WDFG	WSFG
monthList	[{'year': 1999, 'month': 11,	[{'year': 1999, 'month': 11,	[{'year': 1999, 'month': 11,	[{'year': 1999, 'month': 11, 'field':	[{'year': 2000, 'month': 8, 'field':	[{'year': 2003, 'month': 6, 'field':	[{'year': 2015, 'month': 4, 'field':	[{'year': 2015, 'month': 4, 'field':

Task II. continued

This information would have been to unpacked. Instead it was decided to test and adapt some code from a certain Dr. Ned Haughton's GitHub pages. This read the underlying data directly into pandas dataframes, see code below with adaptions made to fit the needs of this experiment. The code was available on 20 December 2021, but has subsequently been removed from github. Dr. Ned Haughton works as a risk analyst at a firm called Climate Risk Property Ltd. and obtained a PhD in Climate Science from the University of New South Wales in Australia (according to LinkedIn).

```
#Code is adapted from Dr. Ned Haughton's GitHub Site
#This was accessed on around 20 December 2021
#But code has been removed subsequently
#https://github.com/nedclimaterisk
#Changes made were:
# 1. Added a DataFrame for Countries.
# 2. Changed File/ Filename references to ucl urls.
# 3. Stations DataFrame was adapted like given code to select only GCN (default) or
# 4. Changed a reference of pd.np to np. as numpy installed and to remove a depreca
# 5. Multiplied TMAX, TMIN, TAVG, PRCP values by 0.1 in line with given code
# 6. Removed option to not display FLAGS, as important to show them
# 7. However, added an option to exclude SFLAG (default) - as not important for dat
#    Makes viewing DataFrame easier as reduces columns

#Extract a Dataframe for Countries
country_col_specs = [
    (0,  2),
    (3, 64)]

country_names = [
    "ID",
    "COUNTRY"]

country_dtype = {
    "ID": str,
    "COUNTRY": str}

def read_countries(fileName=None):
  if fileName==None:
    file = urllib.request.urlopen('http://www.hep.ucl.ac.uk/undergrad/0056/other/pr
  else:
    file = open(fileName,'r')
  df = pd.read_fwf(file, country_col_specs, names=country_names,
                     index_col='ID', dtype=country_dtype)

  return df

#Extract a Dataframe for Stations
station_col_specs = [
    (0,  12),
    (12, 21),
    (21, 31),
    (31, 38),
    (38, 41),
    (41, 72),
    (72, 76),
    (76, 80),
    (80, 86)]

station_names = [
    "ID",
    "LATITUDE",
    "LONGITUDE",
    "ELEVATION",
    "STATE",
    "NAME",
    "GSN FLAG",
    "HCN/CRN FLAG",
    "WMO ID"]

station_dtype = {
    "ID": str,
    "STATE": str,
    "NAME": str,
    "GSN FLAG": str,
    "HCN/CRN FLAG": str,
    "WMO ID": str
    }

def read_stations(fileName=None, justGSN=True):
    if fileName==None:
      file = urllib.request.urlopen('http://www.hep.ucl.ac.uk/undergrad/0056/other/
    else:
      file = open(fileName,'r')
    df = pd.read_fwf(file, station_col_specs, names=station_names,
                     index_col='ID', dtype=station_dtype)
    if justGSN: df = df[df['GSN FLAG'] == 'GSN']# selects only rows with GSN FLAG a

    return df
```

```
#Extract a Dataframe for Weather Data from a Station
data_header_names = [
    "ID",
    "YEAR",
    "MONTH",
    "ELEMENT"]

data_header_col_specs = [
    (0,  11),
    (11, 15),
    (15, 17),
    (17, 21)]

data_header_dtypes = {
    "ID": str,
    "YEAR": int,
    "MONTH": int,
    "ELEMENT": str}

data_col_names = [[
    "VALUE" + str(i + 1),
    "MFLAG" + str(i + 1),
    "QFLAG" + str(i + 1),
    "SFLAG" + str(i + 1)]
    for i in range(31)]
# Join sub-lists
data_col_names = sum(data_col_names, [])

data_replacement_col_names = [[
    ("VALUE", i + 1),
    ("MFLAG", i + 1),
    ("QFLAG", i + 1),
    ("SFLAG", i + 1)]
    for i in range(31)]
# Join sub-lists
data_replacement_col_names = sum(data_replacement_col_names, [])
data_replacement_col_names = pd.MultiIndex.from_tuples(
    data_replacement_col_names,
    names=['VAR_TYPE', 'DAY'])

data_col_specs = [[
    (21 + i * 8, 26 + i * 8),
    (26 + i * 8, 27 + i * 8),
    (27 + i * 8, 28 + i * 8),
    (28 + i * 8, 29 + i * 8)]
    for i in range(31)]
data_col_specs = sum(data_col_specs, [])

data_col_dtypes = [{
    "VALUE" + str(i + 1): int,
    "MFLAG" + str(i + 1): str,
    "QFLAG" + str(i + 1): str,
    "SFLAG" + str(i + 1): str}
    for i in range(31)]
```

```
data_header_dtypes.update({k: v for d in data_col_dtypes for k, v in d.items()})

def read_ghcn_data_file(filename='CA002400404.dly',
                        variables=None,
                        dropna='all', include_SFLAG = False):
    """Reads in all data from a GHCN .dly data file

    :param filename: path to file
    :param variables: list of variables to include in output dataframe
        e.g. ['TMAX', 'TMIN', 'PRCP']
    :param include_SFLAG: Whether to include SFLAG in the final output
    :returns: Pandas dataframe
    """
    urlName='http://www.hep.ucl.ac.uk/undergrad/0056/other/projects/ghcnd/ghcnd_gsn
    urllib.request.urlretrieve(urlName,filename)
    df = pd.read_fwf(
        filename,
        colspecs=data_header_col_specs + data_col_specs,
        names=data_header_names + data_col_names,
        index_col=data_header_names,
        dtype=data_header_dtypes
        )

    if variables is not None:
        df = df[df.index.get_level_values('ELEMENT').isin(variables)]

    df.columns = data_replacement_col_names

    df = df.stack(level='DAY').unstack(level='ELEMENT')

    if dropna:
        df.replace(-9999.0, np.nan, inplace=True)
        df.dropna(how=dropna, inplace=True)

    # replace the entire index with the date.
    # This loses the station ID index column!
    # This will usuall fail if dropna=False, since months with <31 days
    # still have day=31 columns
    df.index = pd.to_datetime(
        df.index.get_level_values('YEAR') * 10000 +
        df.index.get_level_values('MONTH') * 100 +
        df.index.get_level_values('DAY'),
        format='%Y%m%d')

    #Multiply temp and precipitation by 0.1 as in example code
    #'If' statements allow for possibility that DataFrame doesn't include
    #these columns. Use of '.loc' methodology adapted from:
    #https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returnin
    if 'PRCP' in df['VALUE']: df.loc[:, ('VALUE', 'PRCP')] = 0.1 * df.loc[:, ('VALU
    if 'TMIN' in df['VALUE']: df.loc[:, ('VALUE', 'TMIN')] = 0.1 * df.loc[:, ('VALU
    if 'TMAX' in df['VALUE']: df.loc[:, ('VALUE', 'TMAX')] = 0.1 * df.loc[:, ('VALU
    if 'TAVG' in df['VALUE']: df.loc[:, ('VALUE', 'TAVG')] = 0.1 * df.loc[:, ('VALU


    #Remove SFLAG column if specified
    if not include_SFLAG:
      df.drop('SFLAG', axis = 1, inplace = True)




    return df
```

Task II. continued

The following code cell extracts the daily data for the example station into a dataframe and outputs it.

```
filename = 'CA002400404.dly'
dly = read_ghcn_data_file(filename=filename)
dly
```

VAR_TYPE	**MFLAG**								**QFLAG**			
ELEMENT	**PRCP**	**SNOW**	**SNWD**	**TAVG**	**TMAX**	**TMIN**	**WDFG**	**WSFG**	**PRCP**	**SNOW**	**SNWD**	**TAVG**
1999-11-01	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
1999-11-02	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
1999-11-03	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
1999-11-04	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
1999-11-05	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
...	...	...	...	...	...	...	...	...	...	...	...	...
2020-11-10	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2020-11-11	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2020-11-												

Task II. continued

There are lots of NaN's. This does not matter in flag columns, in fact that is good, signalling that these is no issue with the data. However NaN in the VALUE columns suggests incomplete data.

```
dly.info()
```

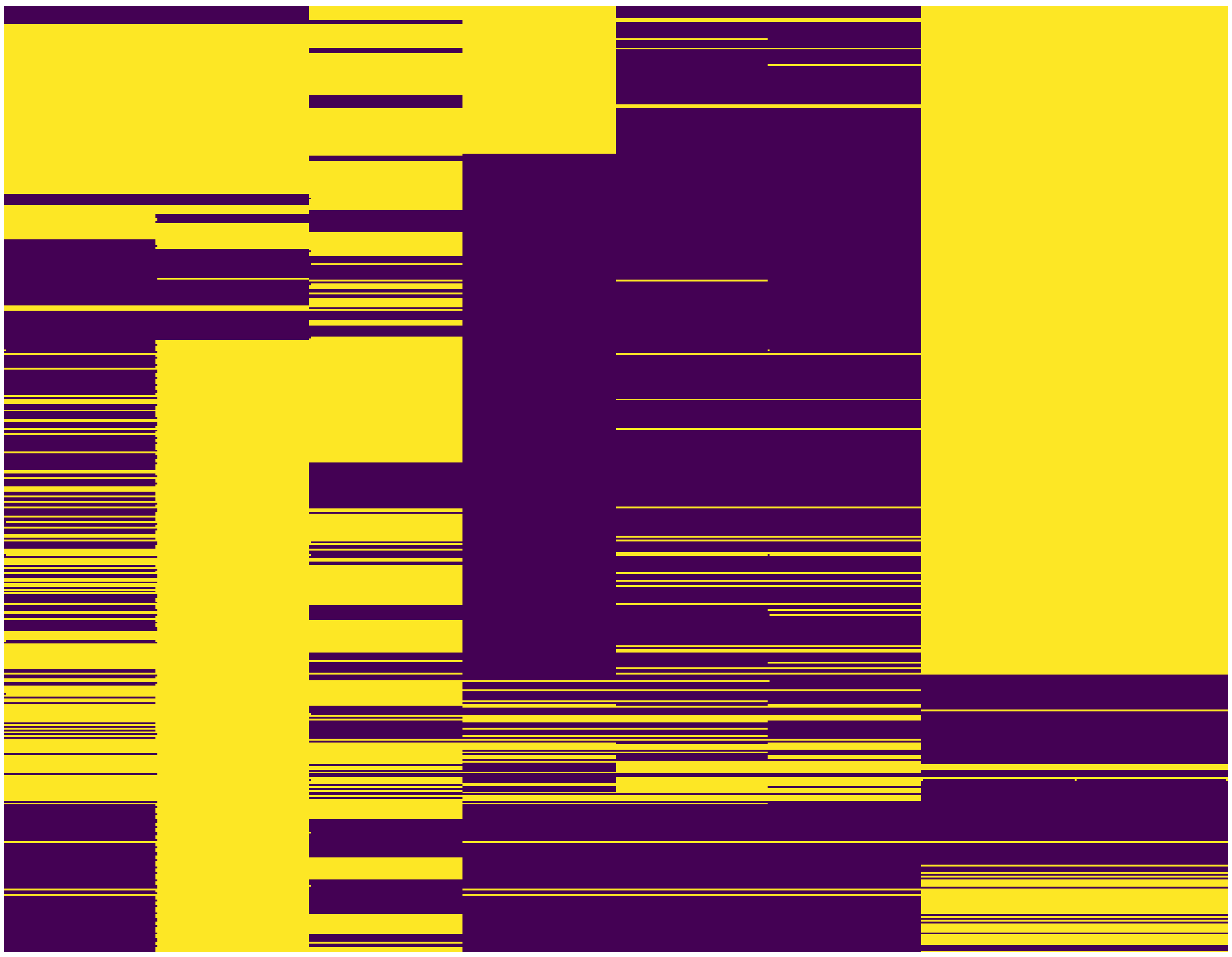
```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 6130 entries, 1999-11-01 to 2020-11-14
Data columns (total 24 columns):
 #   Column          Non-Null Count  Dtype  
---  ------          --------------  -----  
 0   (MFLAG, PRCP)  0 non-null      float64
 1   (MFLAG, SNOW)  0 non-null      float64
 2   (MFLAG, SNWD)  199 non-null    object 
 3   (MFLAG, TAVG)  3309 non-null   object 
 4   (MFLAG, TMAX)  0 non-null      float64
 5   (MFLAG, TMIN)  0 non-null      float64
 6   (MFLAG, WDFG)  0 non-null      float64
 7   (MFLAG, WSFG)  0 non-null      float64
 8   (QFLAG, PRCP)  3 non-null      object 
 9   (QFLAG, SNOW)  1 non-null      object 
 10  (QFLAG, SNWD)  2 non-null      object 
 11  (QFLAG, TAVG)  0 non-null      float64
 12  (QFLAG, TMAX)  0 non-null      float64
 13  (QFLAG, TMIN)  1 non-null      object 
 14  (QFLAG, WDFG)  0 non-null      float64
 15  (QFLAG, WSFG)  0 non-null      float64
 16  (VALUE, PRCP)  3378 non-null   float64
 17  (VALUE, SNOW)  760 non-null    float64
 18  (VALUE, SNWD)  2255 non-null   float64
 19  (VALUE, TAVG)  4790 non-null   float64
 20  (VALUE, TMAX)  5341 non-null   float64
 21  (VALUE, TMIN)  5428 non-null   float64
 22  (VALUE, WDFG)  1357 non-null   float64
 23  (VALUE, WSFG)  1357 non-null   float64
dtypes: float64(18), object(6)
memory usage: 1.2+ MB
```

Task II. continued

As expected, lots of null values in the VALUE columns. How can we visual this? The following code has been adapted from material contained in a lecture series "Data Science & Machine Learning Bootcamp" available on Skillshare by Dr. Junaid Qazi. The lectures were especially useful to learn how to manipulate data with pandas and visualise data (e.g. in the example below using a seaborn heatmap.)

Firstly, for VALUE columns

```
#adapted from "Data Science & Machine Learning Bootcamp"
#"Class 6 of 10 - Linear Regression, Logistic Regression"
#By Dr. Junaid Qazi, available on SkillShare
#NB dates are not shown on y axis for clarity
#yellow areas have null data, purple areas are populated
sns.heatmap(data=dly['VALUE'].isnull(), yticklabels=False, cbar = False, cmap ='vir
```



Task II. continued

Next for MFLAG and QFLAG columns

```
sns.heatmap(data=dly[['MFLAG', 'QFLAG']].isnull(), yticklabels=False, cbar = False,
```

Task II. continued

Overall, this was be a pretty poor data set with many missing data in VALUES columns even for the main 5 elements. It was decided to continue to use the new method of extraction of GHCN data into pandas dataframes.

Task III. Determine which station(s) to use for the two main machine learning tasks (climate, weather).

Rather than manually looking through all 991 stations one by one, it was decided to loop through the different stations and for each open its .dly file. From this, relevant fields could be recorded and then a new DataFrame could be made to include more columns onto to the following stations dataframe (which is shown below)

```
stations = read_stations()
stations
```

	LATITUDE	LONGITUDE	ELEVATION	STATE	NAME	GSN FLAG	HCN/CRN FLAG
ID							
AE000041196	25.3330	55.5170	34.0	NaN	SHARJAH INTER. AIRP	GSN	NaN

Task III continued

It was decided that the new data should contain measures of length of data, completeness of data and quality of data for the five main elements. To this a measure of the broadness of the dataset was made by considering the total number of elements. With this in mind, the following columns were to be added:

start: date where .dly starts. The earlier the better.

end: date where .dly ends. The latter the better.

n_ELEM: number of elements. The more the better as gives a broader dataset.

TMAX_start, TMIN_start, PRCP_start, SNOW_start, SNWD_start: date where these start as often different from 'start'. The earlier the better

TMAX_comp, TMIN_comp, PRCP_comp, SNOW_comp, SNWD_comp: Actual datapoints (i.e. not null) as a proportion from date values start. Best value 1, worst 0.

TMAX_q, TMIN_q, PRCP_q, SNOW_q, SNWD_q: proportion of datapoints without a QFLAG value. Best value 1, worst 0.

```
#Make new_stations DataFrame
#Cell takes a long time to run c40 mins.
#new_stations is converted to a .pkl file and downloaded to local computer.
#This .pkl file can be uploaded if necessary so cell does not need to be re-run
#Apart from adapting an example of dynamic variables within loops, from codegepper.
#this is student written code.

#headings of columns to be added
column_headings = ['start', 'end', 'n_ELEM', 'TMAX_start', 'TMIN_start',
                   'PRCP_start', 'SNOW_start', 'SNWD_start', 'TMAX_comp', 'TMIN_com
                   'PRCP_comp', 'SNOW_comp', 'SNWD_comp', 'TMAX_q', 'TMIN_q',
                   'PRCP_q', 'SNOW_q', 'SNWD_q']

#array to add new data to for each station
extra_data = []#empty list

#loop through all 991 station.
#tested using stations.iloc[0:3].index in place of stations.index
# useful as found first station didn't have SNOW, SNWD data (in UAE!)
for i in stations.index:

  #open and read daily file for station i
  filename = i+'.dly'
  dly = read_ghcn_data_file(filename=filename)

  #calculate the required variables
  start = dly.index.min()
  end = dly.index.max()
  n_ELEM = len(dly['VALUE'].columns)

  #dynamic variable within loop adapted from
  #https://www.codegrepper.com/code-examples/python/dynamically+create+variables+in
  for i in ['TMAX', 'TMIN', 'PRCP', 'SNOW', 'SNWD']:

    if i in dly['VALUE']: #where .dly file contains the relevant data columns
      #start date of each element i
      globals()[f"{i}_start"] = dly[dly['VALUE'][i].notnull() == True].index.min()

      #how complete data is from start date (from 0 to 100%)
      globals()[f"{i}_comp"] = 1- dly.loc[globals()[f"{i}_start"]:end, ('VALUE', i)

      #quality of data from start date: 100% means no quality flags (good), 0% mean
      globals()[f"{i}_q"] = dly.loc[globals()[f"{i}_start"]:end, ('QFLAG', i)].isna

    else: #where dly does not contain data, e.g. SNOW in UAE based station
      globals()[f"{i}_start"] = np.nan
      globals()[f"{i}_comp"] = np.nan
      globals()[f"{i}_q"] = np.nan

  #collect calculated variables in a list
  new_data = [start, end, n_ELEM, TMAX_start, TMIN_start,
              PRCP_start, SNOW_start, SNWD_start, TMAX_comp, TMIN_comp,
              PRCP_comp, SNOW_comp, SNWD_comp, TMAX_q, TMIN_q,
              PRCP_q, SNOW_q, SNWD_q]

  #append to existing data
  extra_data.append(new_data)

#make dataframe from extra_data
new_stations = pd.DataFrame(data=extra_data, index = stations.index, columns = colu

#save it as takes a long time to generate c.40 mins
new_stations.to_pickle("./new_stations.pkl")
files.download("new_stations.pkl")

#display dataset
new_stations
```

	start	end	n_ELEM	TMAX_start	TMIN_start	PRCP_start	SNOW_sta
ID							
AE000041196	1944-03-20	2020-11-13	4	1944-03-20	1944-03-20	1944-03-20	Na
AF000040930	1973-01-13	1992-04-21	5	1973-11-27	1974-02-18	1988-03-24	Na
AG000060390	1940-01-01	2020-11-13	5	1940-01-01	1940-01-01	1940-01-01	Na
AG000060590	1892-01-01	2020-11-13	5	1892-01-01	1892-01-01	1892-01-01	Na
AG000060611	1958-10-01	2020-11-13	5	1958-10-01	1958-10-01	1958-10-01	Na
...	...	...	...	...	...	...	
ZA000067633	1956-01-01	2014-02-12	5	1973-08-05	1973-08-05	1956-01-01	Na
ZA000067743	1950-01-01	2020-11-02	4	1973-07-30	1973-01-16	1950-01-01	Na
ZI000067775	1956-07-01	2020-10-30	5	1956-07-01	1956-07-01	1956-07-01	Na

```
#Run this cell if you need to recover new_stations. Code adapted from:
#https://colab.research.google.com/notebooks/io.ipynb#scrollTo=p2E4EKhCWEC5
uploaded = files.upload()

for fn in uploaded.keys():
  print('User uploaded file "{name}" with length {length} bytes'.format(
      name=fn, length=len(uploaded[fn])))
new_stations = pd.read_pickle("./new_stations.pkl")
```

Choose Files No file chosen Upload widget is only available when the cell has been executed in the current browser session. Please rerun this cell to enable.

```
Saving new_stations.pkl to new_stations.pkl
User uploaded file "new_stations.pkl" with length 157874 bytes
```

```
#create a complete DataFrame concatenating stations and new_stations DataFrames
stations_comp = pd.concat([new_stations, stations], axis =1)
stations_comp
```

	start	end	n_ELEM	TMAX_start	TMIN_start	PRCP_start	SNOW_sta
ID							
AE000041196	1944-03-20	2020-11-13	4	1944-03-20	1944-03-20	1944-03-20	Na
AF000040930	1973-01-13	1992-04-21	5	1973-11-27	1974-02-18	1988-03-24	Na
AG000060390	1940-01-01	2020-11-13	5	1940-01-01	1940-01-01	1940-01-01	Na
AG000060590	1892-01-01	2020-11-13	5	1892-01-01	1892-01-01	1892-01-01	Na
AG000060611	1958-10-01	2020-11-13	5	1958-10-01	1958-10-01	1958-10-01	Na
...	...	...	...	...	...	...	
ZA000067633	1956-01-01	2014-02-12	5	1973-08-05	1973-08-05	1956-01-01	Na
ZA000067743	1950-01-01	2020-11-02	4	1973-07-30	1973-01-16	1950-01-01	Na
ZI000067775	1956-07-01	2020-10-30	5	1956-07-01	1956-07-01	1956-07-01	Na

Task III continued

This larger dataframe could be filtered down using boolean masks to show only those with the best data as shown in the following cell

```
#filter down to only stations with 'best data'
#i.e. longest, most complete, highest quality and broadest

#Filter 1. End date after 30/10/2020
stations_filt = stations_comp[stations_comp['end']>pd.to_datetime('30/10/2020')]

#Filter 2. Exclude those with no SNOW data sets as probably have more varied climat
stations_filt = stations_filt[stations_filt['SNOW_start'].notnull() == True]

#Filter 3. Exclude those with no SNWD data sets as above
stations_filt = stations_filt[stations_filt['SNWD_start'].notnull() == True]

#Filter 4. Exclude those with the least complete temp data, e.g. TMAX_comp <0.995
stations_filt = stations_filt[stations_filt['TMAX_comp'] >= 0.995]

#Filter 5. Exclude those with the lowest quality temp data, e.g. TMAX_q <0.999
stations_filt = stations_filt[stations_filt['TMAX_q'] >= 0.999]

#Filter 6. Exclude those with the least complete SNOW data, e.g. SNOW_comp <0.99
stations_filt = stations_filt[stations_filt['SNOW_comp'] >= 0.99]
```

```
stations_filt
```

```
start   end  n_ELEM  TMAX_start  TMIN_start  PRCP_start  SNOW_sta
```

Task III continued

Selected dataset from 26 station in short list:

USW00023066: GRAND JUNCTION WALKER FLD, CO., USA. It has the longest data (since 1900), with a perfect quality score for all variables, and completeness for each of the five main elements is 0.9998 or above. A continental climate is likely, so high temperature variations and snow is expected. It is also one of the broadest datasets with 60 elements.

Backups, or for extension projects:

USW00026411: FAIRBANKS INTL AP, AK, USA. Long data set (1929). Near perfect quality and completeness scores. Different situation to Colorado, might be interesting comparison

FMW00040308: YAP ISLAND WSO AP, Pacific Ocean. Might be an interesting contrast. Long data set (1951) and good completeness and quality

Investigate selected dataset

Before designing the model, the date needed to be investigated and filled if necessary

```
USW00003945  11-01  11-14   45  1969-11-01  1969-11-01  1969-11-01  1969-11
```

```
filename = 'USW00023066.dly'
dly = read_ghcn_data_file(filename=filename)
sns.heatmap(data=dly['VALUE'].isnull(), yticklabels=False, cbar = False, cmap ='vir
```

Task III. continued

Very good completeness for the five main elements and as we already saw perfect quality scores for all of these.

Some other interesting but shorter elements are available, e.g.:

AWND - Average daily wind speed

WDF2 - Direction of fastest 2-minute wind (degrees)

WDF5 - Direction of fastest 5-second wind (degrees)

WSF2 - Fastest 2-minute wind speed (tenths of meters per second)

WSF5 - Fastest 5-second wind speed (tenths of meters per second)

For the climate experiment, it was decided to use monthly data and therefore long datasets would be better. Thus it was decided to reduce down to the core five elements in a datadrame "dly_5".

There were no quality issues, just the value data was extracted.

```
filename = 'USW00023066.dly'
dly = read_ghcn_data_file(filename=filename)

#drop MFLAG and QFLAG column
dly.drop(('MFLAG'), axis = 1, inplace = True)
dly.drop(('QFLAG'), axis = 1, inplace = True)

#drop VAR_TYPE column hierarchy as no longer needed
dly_5 = dly.droplevel('VAR_TYPE',axis= 1)

#select the desired 5 columns
dly_5 = dly_5[['TMAX', 'TMIN', 'PRCP', 'SNOW', 'SNWD']]

#check on missing data
dly_5.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 44122 entries, 1900-01-01 to 2020-11-14
Data columns (total 5 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
```

```
 0   TMAX    44118 non-null  float64
 1   TMIN    44113 non-null  float64
 2   PRCP    44115 non-null  float64
 3   SNOW    44119 non-null  float64
 4   SNWD    44116 non-null  float64
dtypes: float64(5)
memory usage: 2.0 MB
```

Task III. continued

Very few data points were missing, front fill was used to populate them.

```
#Front fill data
dly_5.fillna(method='ffill', inplace = True)

#Check fill has worked
dly_5.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 44122 entries, 1900-01-01 to 2020-11-14
Data columns (total 5 columns):
 #   Column  Non-Null Count  Dtype  
---  ------  --------------  -----  
 0   TMAX    44122 non-null  float64
 1   TMIN    44122 non-null  float64
 2   PRCP    44122 non-null  float64
 3   SNOW    44122 non-null  float64
 4   SNWD    44122 non-null  float64
dtypes: float64(5)
memory usage: 2.0 MB
```

Task III. continued

That worked as no null values were left.

Now data was checked that it was in the right sort of ranges (no outliers). Max of 'SNOW' is 356mm which seems possible. Max of SNWD is a little above this which also makes sense, if snow builds up over a few days.

```
dly_5.describe()
```

ELEMENT	TMAX	TMIN	PRCP	SNOW	SNWD
count	44122.000000	44122.000000	44122.000000	44122.000000	44122.000000
mean	18.654343	4.589375	0.607568	1.490934	5.607429

```
dly_5.tail()
```

ELEMENT	TMAX	TMIN	PRCP	SNOW	SNWD
2020-11-10	4.4	-3.3	0.0	0.0	0.0
2020-11-11	7.2	-3.9	0.0	0.0	0.0
2020-11-12	7.8	-5.6	0.0	0.0	0.0
2020-11-13	8.9	-7.8	0.0	0.0	0.0
2020-11-14	8.9	-4.4	0.0	0.0	0.0

Task III. continued

Pandas allows resampling over different time intervals. It was decided to use monthly samples and to average each element over the days in the month, using mean() function. The last month was excluded as it only contained 14 days of data.

```
#monthly resample
dly_5_month = dly_5.resample('1M').mean()

#exclude last month as only contains 14 days of data.
dly_5_month = dly_5_month.iloc[:-1,:]

dly_5_month.tail()
```

ELEMENT	TMAX	TMIN	PRCP	SNOW	SNWD
2020-06-30	32.003333	13.630000	0.430000	0.000000	0.000000
2020-07-31	35.448387	18.035484	0.045161	0.000000	0.000000
2020-08-31	36.119355	18.393548	0.058065	0.000000	0.000000
2020-09-30	28.260000	10.536667	0.960000	0.000000	0.000000
2020-10-31	21.151613	3.029032	0.483871	3.354839	3.258065

Task III continued

Now it was decided to normalise all variables and save the adjusment factors for later use in plotting. Normalisation can stabilise LSTM networks which can be subject to gradient explosion.

The following code was designed to be general so it could work with any number of columns in

```
#student written code
def normalise(df):
  '''enter a dataframe to normalise each column
  input: pandas dataframe
  output: the pandadata frame with normalised values
  and a dictionary of normalisation adjustments'''

  #empty dictionary
  adj = {}

  #loop through columns
  for c in df.columns:

    #find maximum of column c
    max_value = df[c].max()

    #normalise column
    df[c] = df[c]/ max_value

    #add relevant dictionary entry
    adj[c] = max_value

  return df, adj
```

```
dly_5_month, adj = normalise(dly_5_month)
```

```
dly_5_month.head()
```

ELEMENT	TMAX	TMIN	PRCP	SNOW	SNWD
1900-01-31	0.159288	-0.232277	0.038835	0.0	0.008336
1900-02-28	0.239224	-0.204955	0.031053	0.0	0.000000
1900-03-31	0.465776	-0.004461	0.035599	0.0	0.000000
1900-04-30	0.454558	0.215984	0.346674	0.0	0.000000
1900-05-31	0.690107	0.508842	0.017260	0.0	0.000000

```
print(adj)
```

```
{'TMAX': 37.89032258064516, 'TMIN': 20.248387096774195, 'PRCP': 2.990322580645
```

Task III. continued

The following code is adapted from Week6_pandas.ipynb. The data needed to be processed into sequences of n_{ts} consecutive values with a target "offset" values later. The code was adapted so that it did not take a series as input but a dataframe with several columns of data. It was designed to be general so would work with later experiments with different data frequencies or a different number of elements (columns).

```
#adapted from Week6_pandas.ipynb

def make_offset_dataframe(df, n_ts, offset):
  '''inputs: df a dataframe
             n_ts an integer, number of consecutive values to calculate
             offset an integer, number of values later for target (column title lab
             '''

  #loop through columns in df
  for c in range(len(df.columns)):

    #create an empty dataframe
    nn_df = pd.DataFrame()

    #loop through from 0 to n_ts
    for i in range(n_ts):
      #for each value of i, c add shifted values
      nn_df[i] = df[df.columns[c]].shift(n_ts-i) #Shift the data by n_ts-i samples

    #for each c, add a column for target values
    nn_df['label'] = df[df.columns[c]].shift(-offset)

    #arrange the column headings
    nn_df.columns = pd.MultiIndex.from_product([nn_df.columns, [df.columns[c]]])

    #if not first iteration of c loop, concatenate existing nn_df_all with nn_df
    if c !=0:
      nn_df_all = pd.concat([nn_df_all, nn_df], axis=1)
    #if first iteration, then nn_df_all is just first instance of nn_df
    elif c==0:
      nn_df_all = nn_df


  return nn_df_all
```

Task III. continued

Using monthly data, the prediction offset was 12 months forward and it was decided to look back 120 months or 10 years of data for training. . As was the case with Week6_pandas.ipynb, rows at the start and end with NaN values needed to be excluded using "dropna". Now Task III was completed.

```
offset=12#predict one year forward
n_ts=120 #10 years of monthly data for training
nn_df=make_offset_dataframe(dly_5_month,n_ts,offset)
nn_df.dropna(axis=0, inplace=True)#lose rows with NaN
```

```
#check
nn_df.info()
```

```
    <class 'pandas.core.frame.DataFrame'>
    DatetimeIndex: 1318 entries, 1910-01-31 to 2019-10-31
    Freq: M
    Columns: 605 entries, (0, 'TMAX') to ('label', 'SNWD')
    dtypes: float64(605)
    memory usage: 6.1 MB
```

Task IV. Determine the training/ validation/ test methodology.

It was decided to separate the dataset into training (60%), validation (20%) and test (20%) sets. These splits could be parameterised, but it was decided not to as we would be consistent.

```
#student written code
def dataset_split(nn_df):
  '''Input a dataframe and extract training (60%), validation (20%) and test data (
  Output are arrays of data shaped for use in model training
  requires numpy, pandas and sklearn'''

  #extract label values (before extraction of test, validation)
  train_label = nn_df.label.values

  #extract training data (before extraction of test, validation)
  train_data=nn_df.drop('label',axis=1, level=0)#lose label column

  #reshape and reorder so fits into model
  #used a roundabout way to extract number of elements int(nn_df.shape[1]/ (n_ts +
  #so that don't need to refer back to prior dataframes, important so function can
  #generally
  A = np.reshape(train_data.values,(len(nn_df),int(nn_df.shape[1]/ (n_ts + 1)),n_ts
  train_data = np.swapaxes(A,1,2)# swaps 2nd and 3rd axis for right order
  #for model fit.

  #choose 60% train, 20% validate, 20% test split
  #determine 20% of length
  t= round(0.2 * len(train_data))

  test_data=train_data[-t:]#take last 20% of data (i.e. most recent data)
  test_label=train_label[-t:]

  train_data=train_data[:-t]#reduce down by last 20% of data
  train_label=train_label[:-t]

  #split into training and validation sets
  #0.25 is used as only 80% of data remains and 0.25*80% = 20% which is validation
  train_data, val_data, train_label, val_label = train_test_split(train_data, train
  #just to check
  print('train_data',train_data.shape)
  print('val_data', val_data.shape)
  print('test_data', test_data.shape)

  return train_data, val_data, test_data, train_label, val_label, test_label
```

```
train_data, val_data, test_data, train_label, val_label, test_label = dataset_split
```

```
    train_data (790, 120, 5)
    val_data (264, 120, 5)
    test_data (264, 120, 5)
```

Task IV. continued

The shapes of train_data, val_data and test_data are correct and so the task is completed.

Task V

Model used for training was adapted from Week6_pandas.ipynb. The only change was to change the input shape into the first LSTM layer and the output layer for the 5 features (elements). This is called model "Alpha".

```
#adapted from Week6_pandas.ipynb
modelAlpha=keras.models.Sequential()
#input shape adapted
#again have calculated no of elements from shape of nn_df and n_ts
#to allow for general use
modelAlpha.add(keras.layers.LSTM(64,input_shape=(n_ts,int(nn_df.shape[1]/ (n_ts + 1
modelAlpha.add(keras.layers.LSTM(32,activation='relu'))
modelAlpha.add(keras.layers.Dense(32,activation='relu'))

#output the 5 elements
modelAlpha.add(keras.layers.Dense(int(nn_df.shape[1]/ (n_ts + 1)),activation="linea
modelAlpha.compile(loss='mean_squared_error',optimizer='adam')
modelAlpha.summary()
```

```
    Model: "sequential_4"
    _________________________________________________________________
     Layer (type)                Output Shape              Param #   
    =================================================================
     lstm_8 (LSTM)               (None, 120, 64)           17920     
                                                                     
     lstm_9 (LSTM)               (None, 32)                12416     
                                                                     
     dense_8 (Dense)             (None, 32)                1056      
                                                                     
     dense_9 (Dense)             (None, 5)                 165       
                                                                     
    =================================================================
    Total params: 31,557
```

```
Trainable params: 31,557
Non-trainable params: 0
________________________________________________________________
```

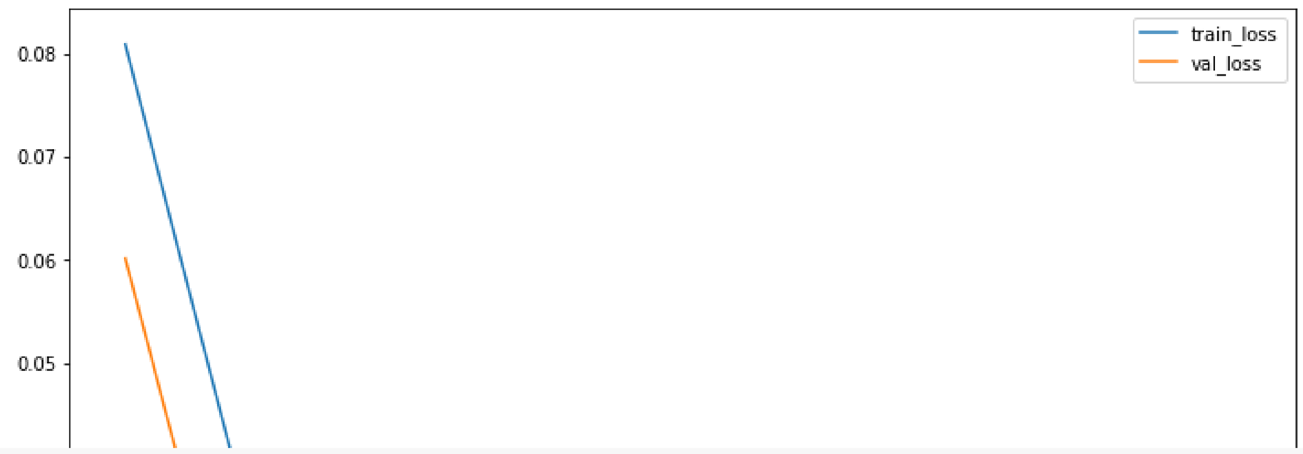
Task VI. Conduct climate prediction experiments.

Now the model could be trained and relevant charts produced (again adapted from Week6_pandas.ipynb).

```
history=modelAlpha.fit(train_data,train_label,epochs=10,batch_size=10,verbose=1,val
```

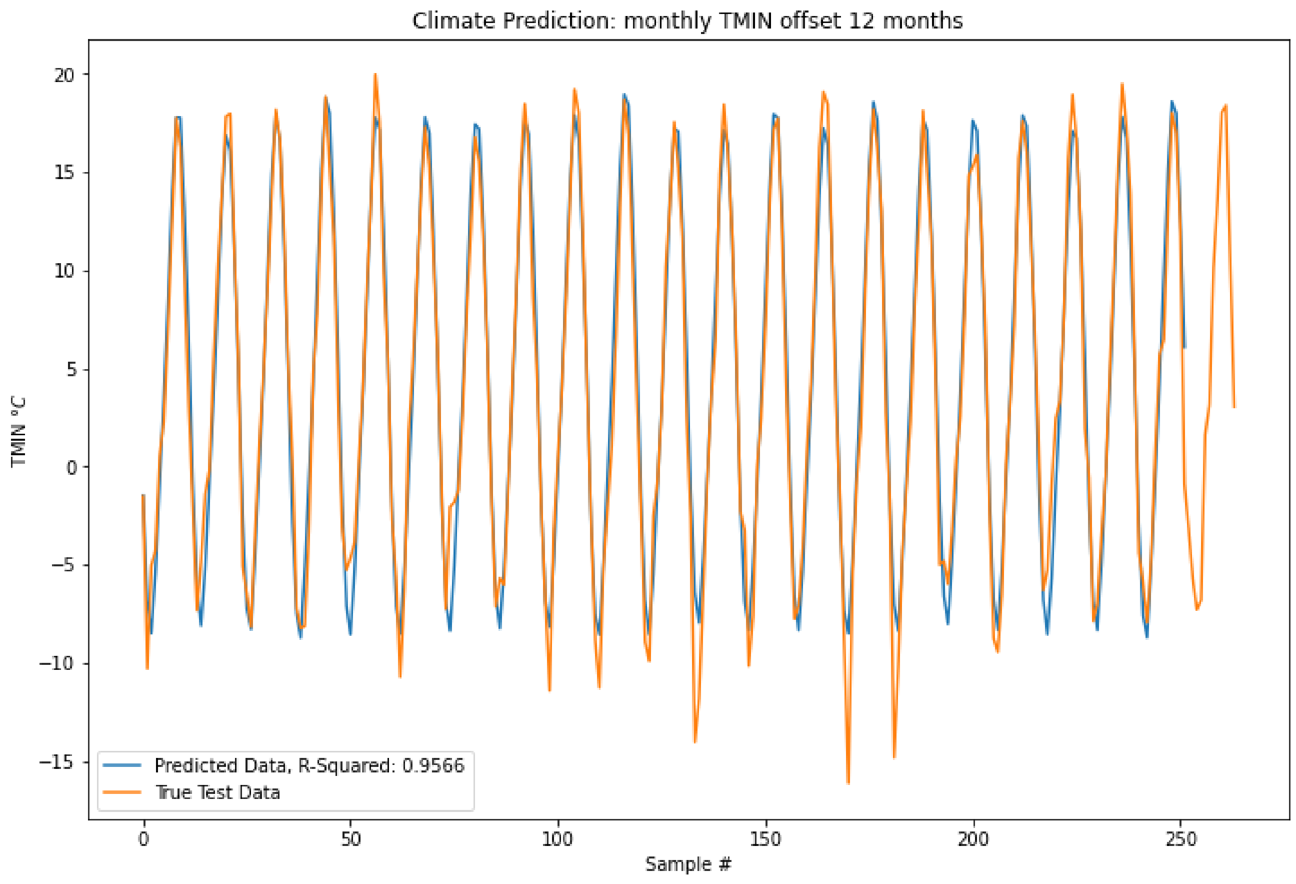
```
Epoch 1/10
79/79 [==============================] - 8s 78ms/step - loss: 0.0670 - val_los
Epoch 2/10
79/79 [==============================] - 6s 70ms/step - loss: 0.0180 - val_los
Epoch 3/10
79/79 [==============================] - 6s 70ms/step - loss: 0.0127 - val_los
Epoch 4/10
79/79 [==============================] - 5s 69ms/step - loss: 0.0128 - val_los
Epoch 5/10
79/79 [==============================] - 6s 70ms/step - loss: 0.0124 - val_los
Epoch 6/10
79/79 [==============================] - 6s 71ms/step - loss: 0.0122 - val_los
Epoch 7/10
79/79 [==============================] - 6s 71ms/step - loss: 0.0120 - val_los
Epoch 8/10
79/79 [==============================] - 6s 70ms/step - loss: 0.0124 - val_los
Epoch 9/10
79/79 [==============================] - 6s 70ms/step - loss: 0.0121 - val_los
Epoch 10/10
79/79 [==============================] - 5s 69ms/step - loss: 0.0120 - val_los
```

```
fig,ax = plt.subplots()
ax.plot(history.history['loss'], label='train_loss')
ax.plot(history.history['val_loss'], label='val_loss')
ax.set_title = 'Loss of the model'
ax.set_xlabel = 'Time (Epochs)'
ax.set_ylabel = 'Loss'
ax.legend();
```

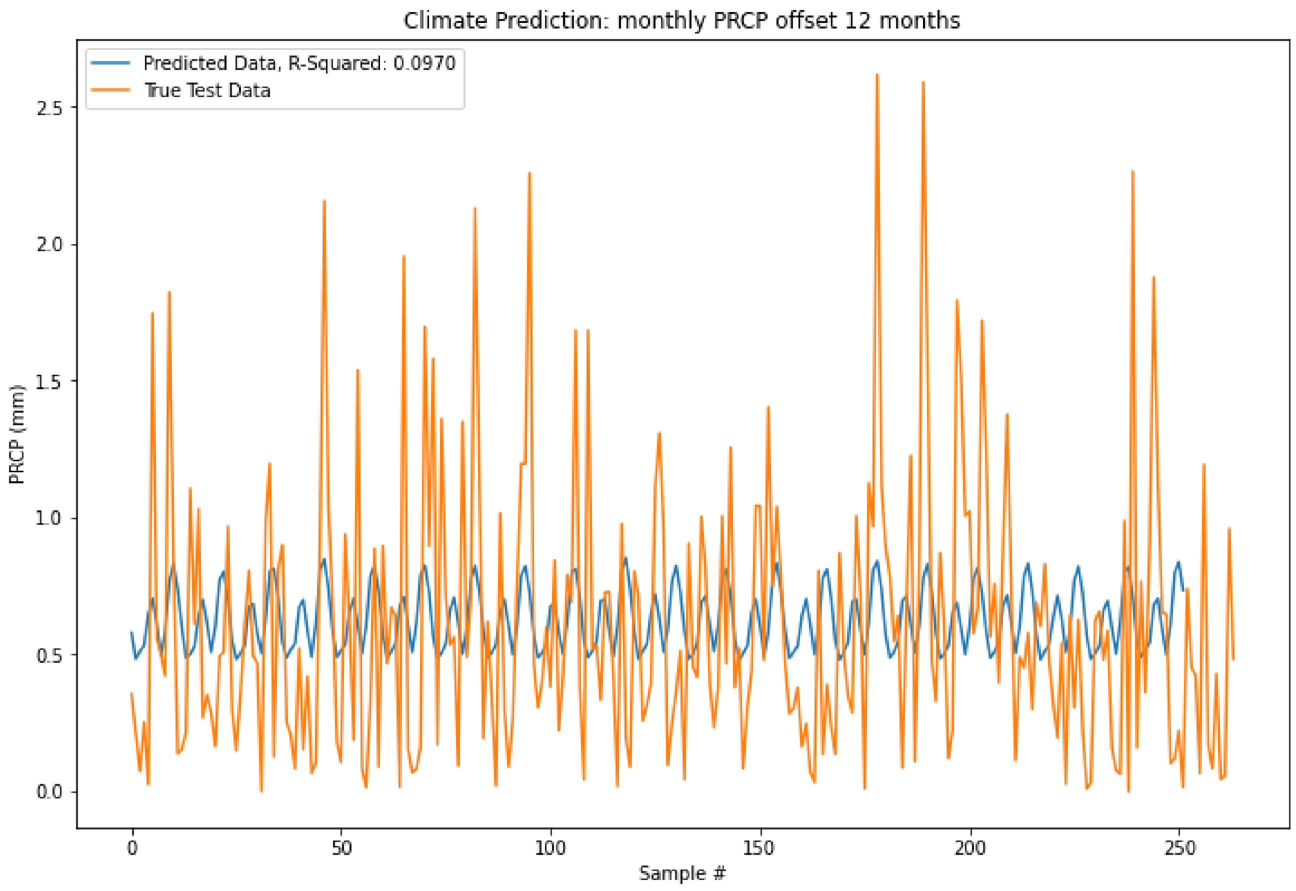


```
#test predictions
test_predict=modelAlpha.predict(test_data)

#For TMAX
#R-squared with true values
Rsqr = np.corrcoef(test_label[:-offset,0], test_predict[offset:,0])[0,1]**2

#plot them
fig,ax=plt.subplots()
ax.plot(test_predict[offset:,0]*adj['TMAX'],label=f"Predicted Data, R-Squared: {Rsq
ax.plot(test_label[:,0]*adj['TMAX'],label="True Test Data")
ax.set_title("Climate Prediction: monthly TMAX offset 12 months")
ax.set_xlabel("Sample #")
ax.set_ylabel("TMAX $\degree C$")
ax.legend();
```

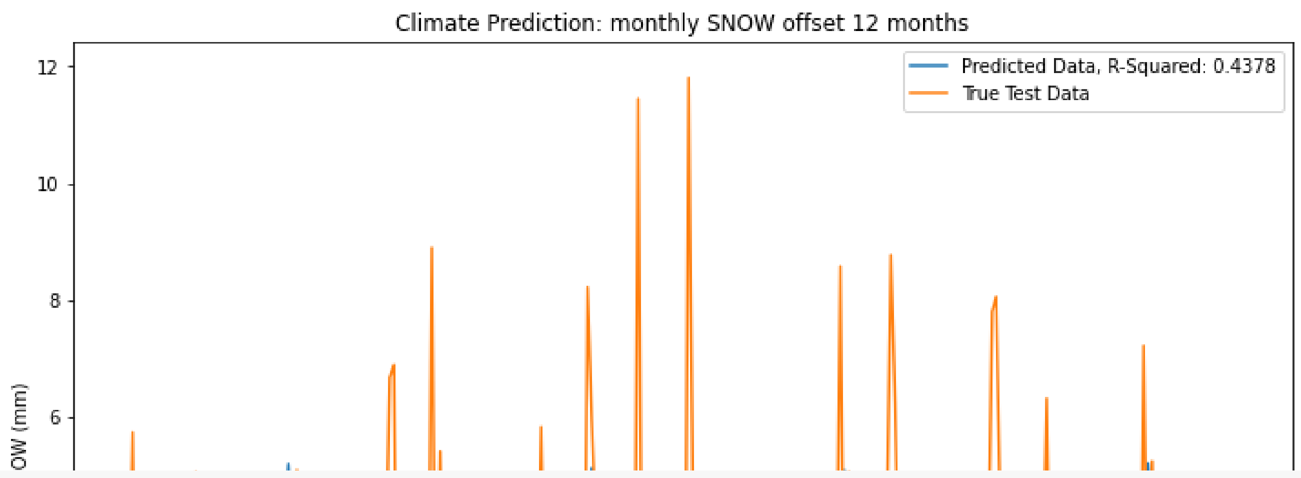
```
#For TMIN
#R-squared with true values
Rsqr = np.corrcoef(test_label[:-offset,1], test_predict[offset:,1])[0,1]**2

#plot them
fig,ax=plt.subplots()
ax.plot(test_predict[offset:,1]*adj['TMIN'],label=f"Predicted Data, R-Squared: {Rsq
ax.plot(test_label[:,1]*adj['TMIN'],label="True Test Data")
ax.set_title("Climate Prediction: monthly TMIN offset 12 months")
ax.set_xlabel("Sample #")
ax.set_ylabel("TMIN $\degree C$")
ax.legend();
```



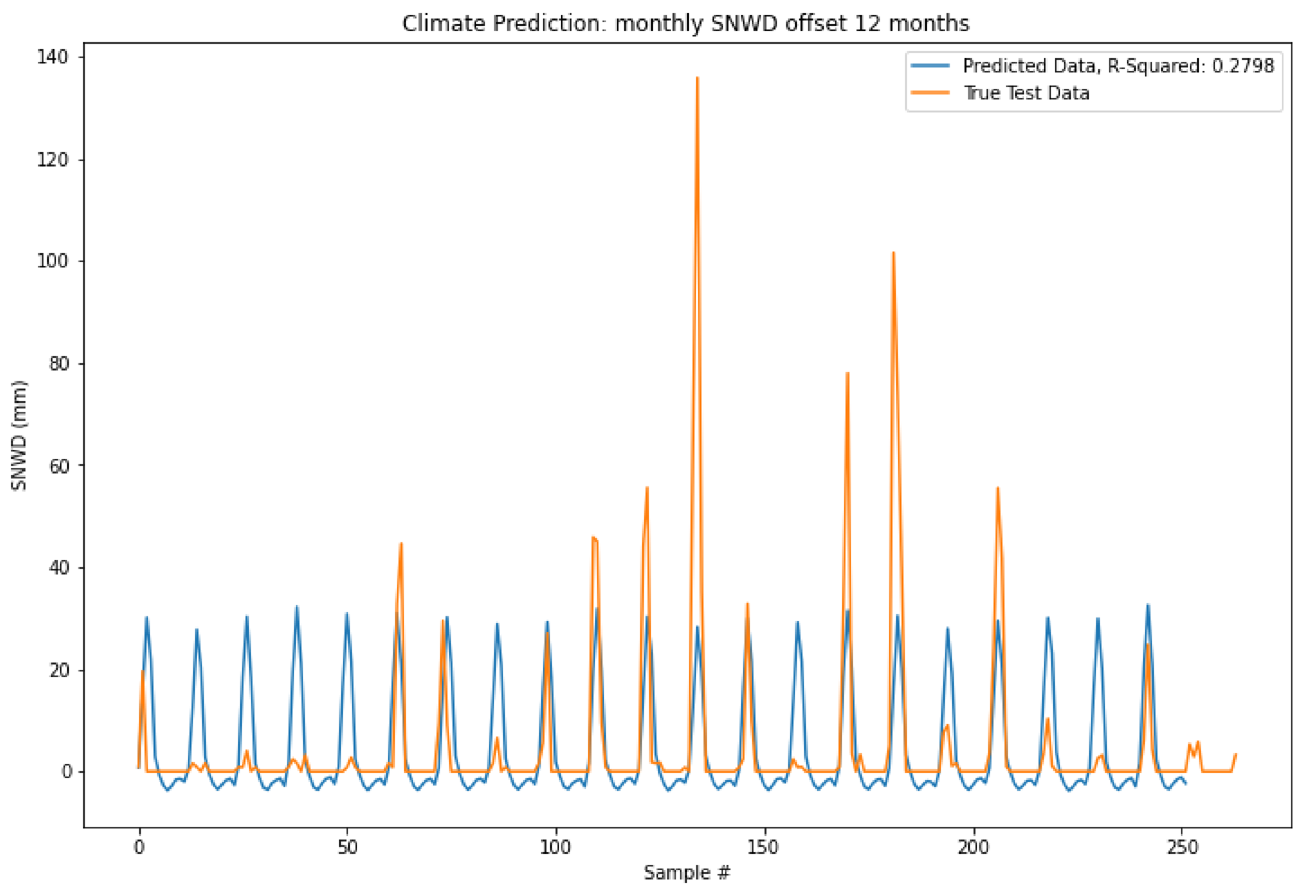
```
#For PRCP
#R-squared with true values
Rsqr = np.corrcoef(test_label[:-offset,2], test_predict[offset:,2])[0,1]**2

#plot them
fig,ax=plt.subplots()
ax.plot(test_predict[offset:,2]*adj['PRCP'],label=f"Predicted Data, R-Squared: {Rsq
ax.plot(test_label[:,2]*adj['PRCP'],label="True Test Data")
ax.set_title("Climate Prediction: monthly PRCP offset 12 months")
ax.set_xlabel("Sample #")
ax.set_ylabel("PRCP (mm)")
ax.legend();
```



```
#For SNOW
#R-squared with true values
Rsqr = np.corrcoef(test_label[:-offset,3], test_predict[offset:,3])[0,1]**2

#plot them
fig,ax=plt.subplots()
ax.plot(test_predict[offset:,3]*adj['SNOW'],label=f"Predicted Data, R-Squared: {Rsq
ax.plot(test_label[:,3]*adj['SNOW'],label="True Test Data")
ax.set_title("Climate Prediction: monthly SNOW offset 12 months")
ax.set_xlabel("Sample #")
ax.set_ylabel("SNOW (mm)")
ax.legend();
```



```
#For SNWD
#R-squared with true values
Rsqr = np.corrcoef(test_label[:-offset,4], test_predict[offset:,4])[0,1]**2

#plot them
fig,ax=plt.subplots()
ax.plot(test_predict[offset:,4]*adj['SNWD'],label=f"Predicted Data, R-Squared: {Rsq
ax.plot(test_label[:,4]*adj['SNWD'],label="True Test Data")
ax.set_title("Climate Prediction: monthly SNWD offset 12 months")
ax.set_xlabel("Sample #")
ax.set_ylabel("SNWD (mm)")
ax.legend();
```



TASK VI. continued

The Model matches the periodicity in the data for all except for PRCP, which seems to be highly variable and hard to model. For the others, often the amplitudes of the extreme values are incorrect as these may vary substantially year by year. TMAX is the closest element modelled with an R-squared of 95%.

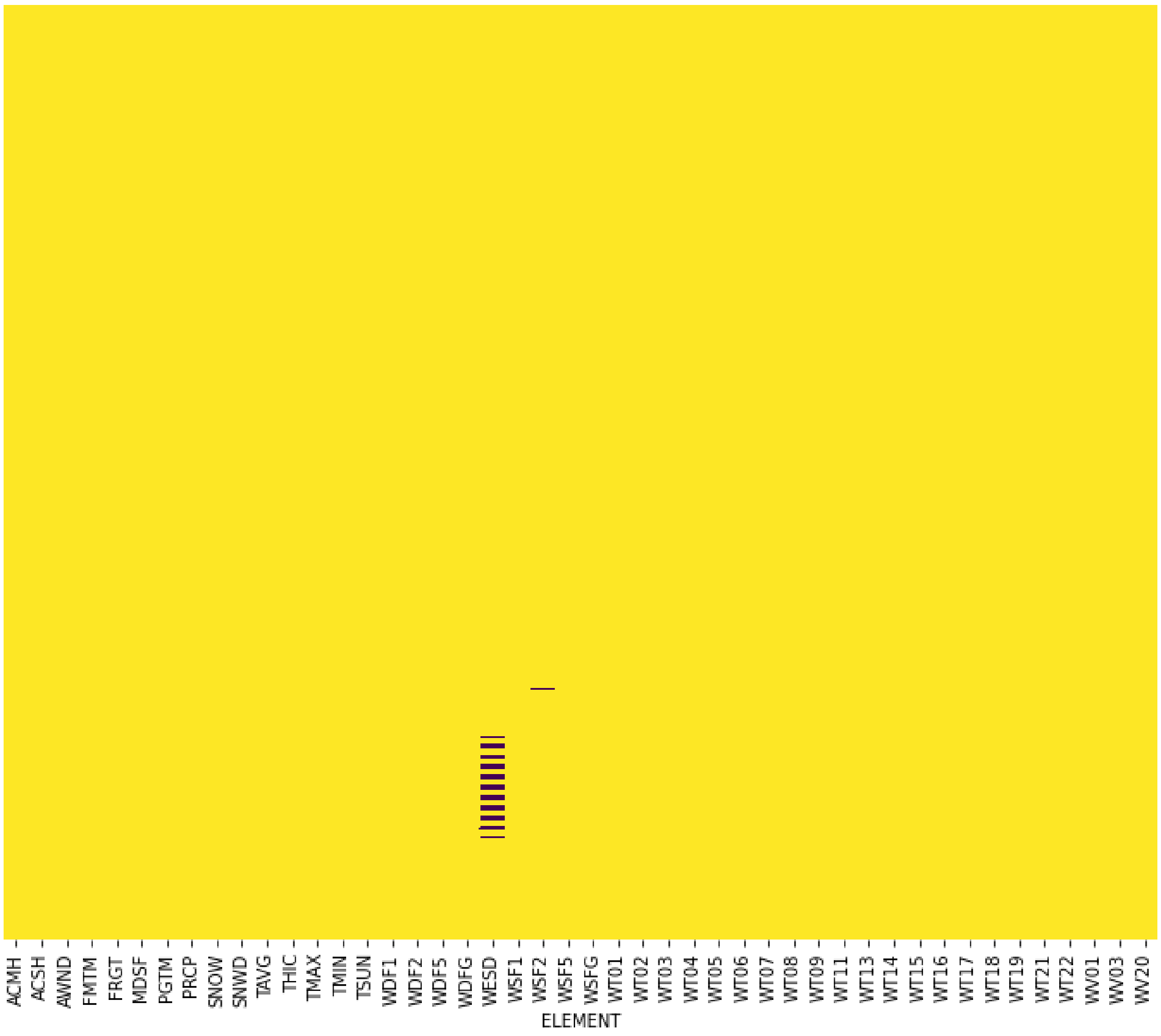
TASK VII. Conduct weather prediction experiments.

For the weather predication, daily data with an offset of zero needed to be used. It was decided to integrate data from the Arkansas station into the model. First this needed to be investigated. Its dataframe was labelled dlyAK to distinguish it; this suffix was continued for other dataframes and elements names used.

```
filename = 'USW00026411.dly'
dlyAK = read_ghcn_data_file(filename=filename)
```

```
#Heatmap for VALUES
sns.heatmap(data=dlyAK['VALUE'].isnull(), yticklabels=False, cbar = False, cmap ='v
```

```
#Heatmap for QFLAG
sns.heatmap(data=dlyAK['QFLAG'].isnull(), yticklabels=False, cbar = False, cmap ='v
```



Task VII. continued

The Arkansas station shows good coverage for the 5 main elements, but also the same five extra wind related elements, albeit again with later starting dates. It does not look like there are any quality issues, but there may be some more significant gaps in two of them. It was decided to investigate whether these should be included into the model.

```
#the following code loops through the 5 main elements and 5 wind elements to determ
print('For AK station, start dates are:')
for i in ['TMAX', 'TMIN', 'PRCP', 'SNOW', 'SNWD', 'AWND', 'WDF2', 'WDF5','WSF2','WS
```

```
    if i in dlyAK['VALUE']: #where .dly file contains the relevant data columns
      #start date of each element i
      print(i, dlyAK[dlyAK['VALUE'][i].notnull() == True].index.min())
```

```
For AK station, start dates are:
TMAX 1929-12-01 00:00:00
TMIN 1929-12-01 00:00:00
PRCP 1929-12-01 00:00:00
SNOW 1929-12-01 00:00:00
SNWD 1929-12-01 00:00:00
AWND 1984-01-01 00:00:00
WDF2 1996-07-01 00:00:00
WDF5 1997-12-01 00:00:00
WSF2 1996-07-01 00:00:00
WSF5 1997-12-01 00:00:00
```

Task VII. continued

Now the same was checked for the Colorado station

```
filename = 'USW00023066.dly'
dly = read_ghcn_data_file(filename=filename)
print('For CO station, start dates are:')
for i in ['TMAX', 'TMIN', 'PRCP', 'SNOW', 'SNWD', 'AWND', 'WDF2', 'WDF5','WSF2','WS

    if i in dly['VALUE']: #where .dly file contains the relevant data columns
      #start date of each element i
      print(i, dly[dly['VALUE'][i].notnull() == True].index.min())
```

```
For CO station, start dates are:
TMAX 1900-01-01 00:00:00
TMIN 1900-01-01 00:00:00
PRCP 1900-01-01 00:00:00
SNOW 1900-01-01 00:00:00
SNWD 1900-01-01 00:00:00
AWND 1984-01-01 00:00:00
WDF2 1996-04-01 00:00:00
WDF5 1996-04-01 00:00:00
WSF2 1996-04-01 00:00:00
WSF5 1996-04-01 00:00:00
```

Task VII. continued

The start date for the data should be 1997-12-01. New dataframe was created for Colorado stations from this date and including the 10 elements

```
filename = 'USW00023066.dly'
dly = read_ghcn_data_file(filename=filename)
#drop MFLAG and QFLAG column
dly.drop(('MFLAG'), axis = 1, inplace = True)
dly.drop(('QFLAG'), axis = 1, inplace = True)
```

```
#drop VAR_TYPE column hierarchy as no longer needed
dly_10 = dly.droplevel('VAR_TYPE',axis= 1)

#select the desired 10 columns
dly_10 = dly_10[['TMAX', 'TMIN', 'PRCP', 'SNOW', 'SNWD', 'AWND', 'WDF2', 'WDF5','WS
dly_10 = dly_10[dly_10.index >= '1997-12-01 00:00:00']

dly_10.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 8385 entries, 1997-12-01 to 2020-11-14
Data columns (total 10 columns):
 #   Column  Non-Null Count  Dtype  
---  ------  --------------  -----  
 0   TMAX    8385 non-null   float64
 1   TMIN    8385 non-null   float64
 2   PRCP    8385 non-null   float64
 3   SNOW    8384 non-null   float64
 4   SNWD    8383 non-null   float64
 5   AWND    8379 non-null   float64
 6   WDF2    8383 non-null   float64
 7   WDF5    8366 non-null   float64
 8   WSF2    8383 non-null   float64
 9   WSF5    8366 non-null   float64
dtypes: float64(10)
memory usage: 720.6 KB
```

Task VII. continued

Only a tiny number of null values, so again front fill was used.

```
dly_10.fillna(method='ffill', inplace = True)
dly_10.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 8385 entries, 1997-12-01 to 2020-11-14
Data columns (total 10 columns):
 #   Column  Non-Null Count  Dtype  
---  ------  --------------  -----  
 0   TMAX    8385 non-null   float64
 1   TMIN    8385 non-null   float64
 2   PRCP    8385 non-null   float64
 3   SNOW    8385 non-null   float64
 4   SNWD    8385 non-null   float64
 5   AWND    8385 non-null   float64
 6   WDF2    8385 non-null   float64
 7   WDF5    8385 non-null   float64
 8   WSF2    8385 non-null   float64
 9   WSF5    8385 non-null   float64
dtypes: float64(10)
memory usage: 720.6 KB
```

Task VII. continued

Procedure was repeated for AK station dataframe.

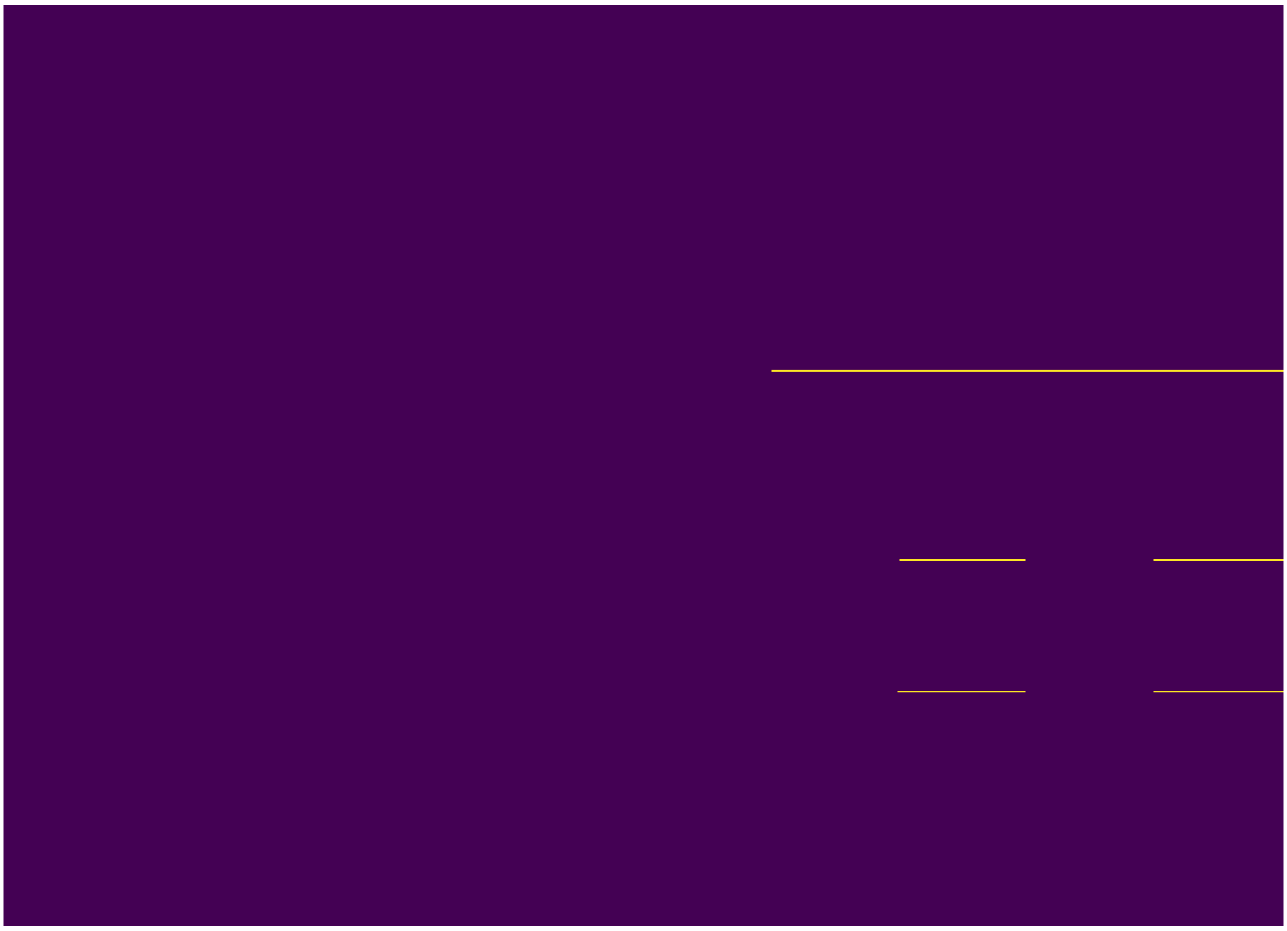
```
filename = 'USW00026411.dly'
dlyAK = read_ghcn_data_file(filename=filename)

#drop MFLAG and QFLAG column
dlyAK.drop(('MFLAG'), axis = 1, inplace = True)
dlyAK.drop(('QFLAG'), axis = 1, inplace = True)

#drop VAR_TYPE column hierarchy as no longer needed
dlyAK_10 = dlyAK.droplevel('VAR_TYPE',axis= 1)

#select the desired 10 columns
dlyAK_10 = dlyAK_10[['TMAX', 'TMIN', 'PRCP', 'SNOW', 'SNWD', 'AWND', 'WDF2', 'WDF5'
dlyAK_10 = dlyAK_10[dlyAK_10.index >= '1997-12-01 00:00:00']

dlyAK_10.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 8385 entries, 1997-12-01 to 2020-11-14
Data columns (total 10 columns):
 #   Column  Non-Null Count  Dtype  
---  ------  --------------  -----  
 0   TMAX    8385 non-null   float64
 1   TMIN    8385 non-null   float64
 2   PRCP    8385 non-null   float64
 3   SNOW    8385 non-null   float64
 4   SNWD    8385 non-null   float64
 5   AWND    8378 non-null   float64
 6   WDF2    8369 non-null   float64
 7   WDF5    8318 non-null   float64
 8   WSF2    8369 non-null   float64
 9   WSF5    8319 non-null   float64
dtypes: float64(10)
memory usage: 720.6 KB
```

Task VII. continued

The were slightly more null values for the wind elements (maximum was 67/8385 for WDF5 or 0.8% of data), so it was decided to run a heatmap to see if this omissions were bunched or spread out.

```
import seaborn as sns
sns.heatmap(data=dlyAK_10.isnull(), yticklabels=False, cbar = False, cmap ='viridis
```



Task VII. continued

The element with the most gaps has the gaps spread out over five or more intervals. It was therefore considered appropriate to use the forward fill method to close the gaps.

```
dlyAK_10.fillna(method='ffill', inplace = True)
dlyAK_10.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 8385 entries, 1997-12-01 to 2020-11-14
Data columns (total 10 columns):
 #   Column  Non-Null Count  Dtype  
---  ------  --------------  -----  
 0   TMAX    8385 non-null   float64
 1   TMIN    8385 non-null   float64
 2   PRCP    8385 non-null   float64
 3   SNOW    8385 non-null   float64
 4   SNWD    8385 non-null   float64
 5   AWND    8385 non-null   float64
 6   WDF2    8385 non-null   float64
 7   WDF5    8385 non-null   float64
 8   WSF2    8385 non-null   float64
 9   WSF5    8385 non-null   float64
dtypes: float64(10)
memory usage: 720.6 KB
```

Task VII. continued

Gaps have been filled in the AK dataframe. It was decided to check on the range of the values for both dataframes. First for Colorado.

```
dly_10.describe()
```

ELEMENT	TMAX	TMIN	PRCP	SNOW	SNWD	AWND
count	8385.000000	8385.000000	8385.000000	8385.000000	8385.000000	8385.000000
mean	19.205176	4.534097	0.609600	1.221705	4.640310	33.073465
std	11.886553	9.770772	2.132795	8.409195	19.436384	13.656783
min	-11.700000	-26.700000	0.000000	0.000000	0.000000	3.000000
25%	8.900000	-2.800000	0.000000	0.000000	0.000000	23.000000
50%	19.400000	4.400000	0.000000	0.000000	0.000000	31.000000
75%	30.000000	13.300000	0.000000	0.000000	0.000000	41.000000
max	41.100000	25.600000	30.700000	183.000000	203.000000	105.000000

Task VII. continued

The wind speeds (WSF2 and WSF5) are measured in tenths of metres per second. The maximum of WSF2 seems too high and needs to be investigated. This was done by counting how many values are greater than 50m/s or 500 tenths of metres per second.

```
count = dly_10['WSF2'][dly_10['WSF2']>500].count()
print('How many WSF2 values > 50 m/s:', count)
```

```
How many WSF2 values > 50 m/s: 1
```

```
#to locate it
dly_10[dly_10['WSF2']>500]
```

ELEMENT	TMAX	TMIN	PRCP	SNOW	SNWD	AWND	WDF2	WDF5	WSF2	WSF5
2003-05-13	25.0	7.8	0.0	0.0	0.0	18.0	90.0	240.0	4095.0	94.0

```
#to find values of WSF2 2 days either side
dly_10[dly_10.index>= '2003-05-11'].head()
```

ELEMENT	TMAX	TMIN	PRCP	SNOW	SNWD	AWND	WDF2	WDF5	WSF2	WSF5
2003-05-11	20.0	3.3	0.0	0.0	0.0	41.0	100.0	330.0	76.0	103.0

```
#average the values two days either side
av = np.mean([76,103,94,98])

#replace 4095.0 with av
#NB is safe to do so as 4095.0 is outside ranges of all other elements
dly_10.replace(4095.0, av, inplace = True)
dly_10.describe()
```

ELEMENT	TMAX	TMIN	PRCP	SNOW	SNWD	AWND
count	8385.000000	8385.000000	8385.000000	8385.000000	8385.000000	8385.000000
mean	19.205176	4.534097	0.609600	1.221705	4.640310	33.073465
std	11.886553	9.770772	2.132795	8.409195	19.436384	13.656783
min	-11.700000	-26.700000	0.000000	0.000000	0.000000	3.000000
25%	8.900000	-2.800000	0.000000	0.000000	0.000000	23.000000
50%	19.400000	4.400000	0.000000	0.000000	0.000000	31.000000
75%	30.000000	13.300000	0.000000	0.000000	0.000000	41.000000
max	41.100000	25.600000	30.700000	183.000000	203.000000	105.000000

Task VII. continued

Anomalous datapoint has been successfully replaced. Now AK station dataframe was investigated.

```
dlyAK_10.describe()
```

ELEMENT	TMAX	TMIN	PRCP	SNOW	SNWD	AWND
count	8385.000000	8385.000000	8385.000000	8385.000000	8385.000000	8385.000000
mean	3.587156	-7.430221	0.848169	4.011568	163.674776	16.447704
std	15.931067	15.732762	2.735986	16.143101	203.174567	12.205077
min	-42.800000	-48.300000	0.000000	0.000000	0.000000	0.000000
25%	-8.800000	-20.600000	0.000000	0.000000	0.000000	7.000000
50%	5.000000	-4.400000	0.000000	0.000000	25.000000	15.000000
75%	17.800000	6.700000	0.300000	0.000000	305.000000	23.000000
max	33.300000	21.100000	57.700000	302.000000	860.000000	100.000000

Task VII. continued

This dateframe seemed fine. To concatenate these two dataframes into one, it was necessary to rename elements (columns) and this was done in the AK station dataframe using "ak" suffix. Then they could be concatenated

```
#rename so we can concatenate dly_10 and dlyAK_10
dlyAK_10.rename(columns={"TMAX": "TMAXak", "TMIN": "TMINak",
                         "PRCP": "PRCPak", "SNOW": "SNOWak",
                         "SNWD": "SNWDak", "AWND": "AWNDak",
                         "WDF2": "WDF2ak", "WDF5": "WDF5ak",
                         "WSF2": "WSF2ak", "WSF5": "WSF5ak"}, inplace=True)
dlyAK_10.head(1)
```

ELEMENT	TMAXak	TMINak	PRCPak	SNOWak	SNWDak	AWNDak	WDF2ak	WDF5ak	WSF2ak
1997-12-01	-12.8	-25.6	1.5	41.0	381.0	4.0	200.0	230.0	27.0

```
dly_10 = pd.concat([dly_10, dlyAK_10], axis =1)
dly_10.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 8385 entries, 1997-12-01 to 2020-11-14
Data columns (total 20 columns):
 #   Column   Non-Null Count  Dtype
---  ------   --------------  -----
 0   TMAX     8385 non-null   float64
 1   TMIN     8385 non-null   float64
 2   PRCP     8385 non-null   float64
 3   SNOW     8385 non-null   float64
 4   SNWD     8385 non-null   float64
 5   AWND     8385 non-null   float64
 6   WDF2     8385 non-null   float64
 7   WDF5     8385 non-null   float64
 8   WSF2     8385 non-null   float64
 9   WSF5     8385 non-null   float64
 10  TMAXak   8385 non-null   float64
 11  TMINak   8385 non-null   float64
 12  PRCPak   8385 non-null   float64
 13  SNOWak   8385 non-null   float64
 14  SNWDak   8385 non-null   float64
 15  AWNDak   8385 non-null   float64
 16  WDF2ak   8385 non-null   float64
 17  WDF5ak   8385 non-null   float64
 18  WSF2ak   8385 non-null   float64
 19  WSF5ak   8385 non-null   float64
dtypes: float64(20)
memory usage: 1.3 MB
```

Task VII. continued

The elements needed to be normalised before training.

```
dly_10, adj = normalise(dly_10)
```

Task VII. continued

It was required to predict the next day's data so the offset was zero. It was decided to use 365 days for n_{ts}.

```
offset=0#predict one day forward
n_ts=365 #1 years of daily data for training
nn_df=make_offset_dataframe(dly_10,n_ts,offset)
nn_df.dropna(axis=0, inplace=True)#lose rows with NaN
#check
nn_df.info()
```

```
    <class 'pandas.core.frame.DataFrame'>
    DatetimeIndex: 8020 entries, 1998-12-01 to 2020-11-14
    Columns: 7320 entries, (0, 'TMAX') to ('label', 'WSF5ak')
    dtypes: float64(7320)
    memory usage: 448.0 MB
```

Task VII. continued

This is a very large dataframe with over 19 million values contained. Now the data needed to be split into training, validation and test datasets as before. The same model was used, but adapted for 20 features and then trained as before.

```
train_data, val_data, test_data, train_label, val_label, test_label = dataset_split
```

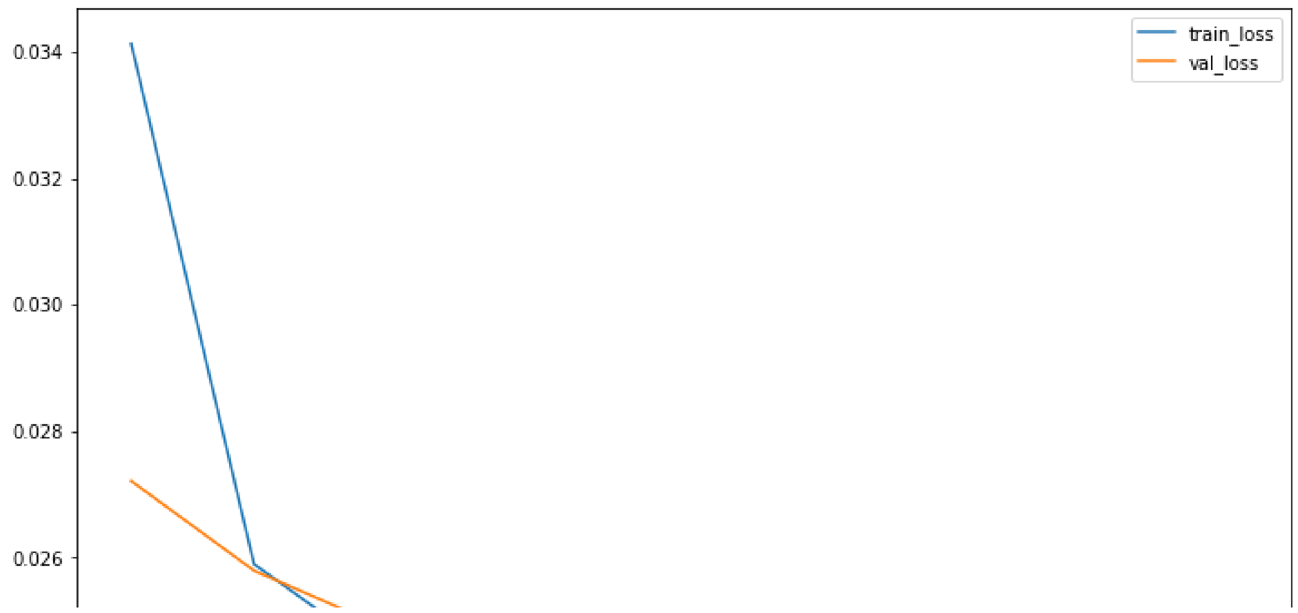
```
    train_data (4812, 365, 20)
    val_data (1604, 365, 20)
    test_data (1604, 365, 20)
```

```
#adapted from Week6_pandas.ipynb
modelAlpha=keras.models.Sequential()
#input shape adapted
#again have calculated no of elements from shape of nn_df and n_ts
#to allow for general use
modelAlpha.add(keras.layers.LSTM(64,input_shape=(n_ts,int(nn_df.shape[1]/ (n_ts + 1
modelAlpha.add(keras.layers.LSTM(32,activation='relu'))
modelAlpha.add(keras.layers.Dense(32,activation='relu'))

#output the 5 elements
modelAlpha.add(keras.layers.Dense(int(nn_df.shape[1]/ (n_ts + 1)),activation="linea
modelAlpha.compile(loss='mean_squared_error',optimizer='adam')
modelAlpha.summary()
```

```
history=modelAlpha.fit(train_data,train_label,epochs=10,batch_size=10,verbose=1,val
```

```
Model: "sequential_5"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 lstm_10 (LSTM)              (None, 365, 64)           21760

 lstm_11 (LSTM)              (None, 32)                12416

 dense_10 (Dense)            (None, 32)                1056

 dense_11 (Dense)            (None, 20)                660

=================================================================
Total params: 35,892
Trainable params: 35,892
Non-trainable params: 0
_________________________________________________________________
Epoch 1/10
482/482 [==============================] - 141s 287ms/step - loss: 0.0373 - va
Epoch 2/10
482/482 [==============================] - 140s 290ms/step - loss: 0.0262 - va
Epoch 3/10
482/482 [==============================] - 143s 297ms/step - loss: 0.0245 - va
Epoch 4/10
482/482 [==============================] - 141s 292ms/step - loss: 0.0239 - va
Epoch 5/10
482/482 [==============================] - 140s 291ms/step - loss: 0.0236 - va
Epoch 6/10
482/482 [==============================] - 140s 291ms/step - loss: 0.0234 - va
Epoch 7/10
482/482 [==============================] - 141s 293ms/step - loss: 0.0231 - va
Epoch 8/10
482/482 [==============================] - 139s 289ms/step - loss: 0.0229 - va
Epoch 9/10
482/482 [==============================] - 139s 289ms/step - loss: 0.0228 - va
Epoch 10/10
482/482 [==============================] - 139s 288ms/step - loss: 0.0226 - va
```

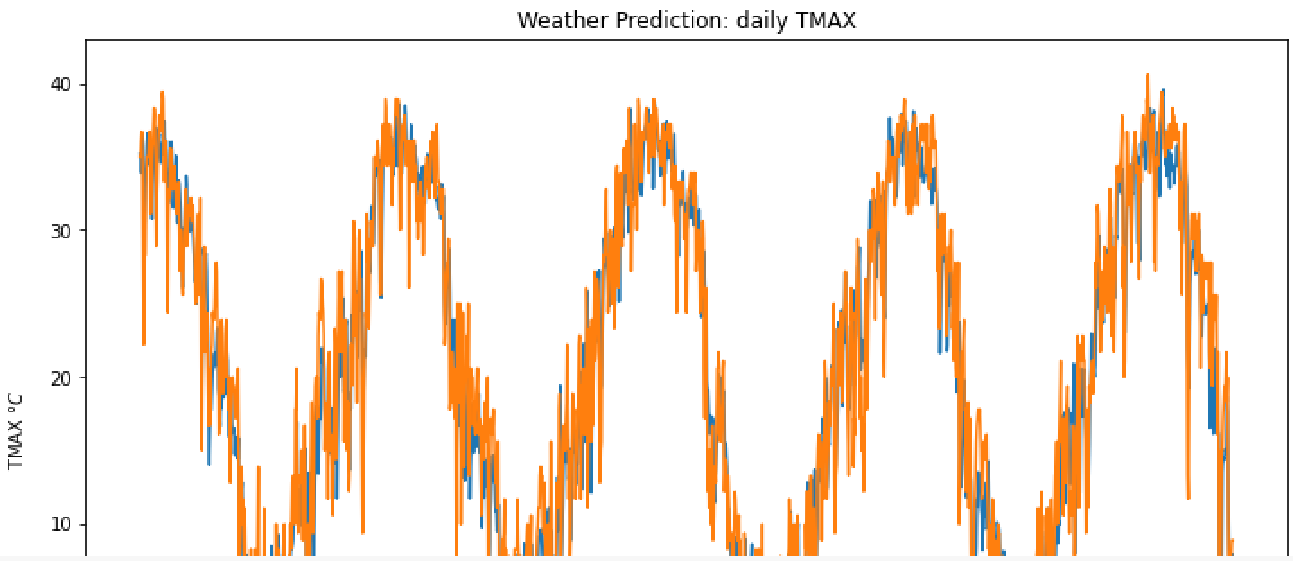
```
fig,ax=plt.subplots()
ax.plot(history.history['loss'], label='train_loss')
ax.plot(history.history['val_loss'], label='val_loss')
ax.set_title = 'Loss of the model'
ax.xlabel = 'Time (Epochs)'
ax.ylabel = 'Loss'
ax.legend();
```



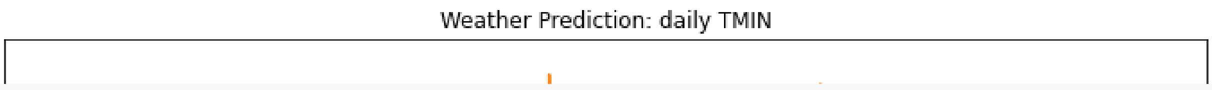
Task VII. continued

Training has completed and loss function converged quickly. It was decided to just consider the main elements for the Colorado station for analysis, rather than all 20 elements used.

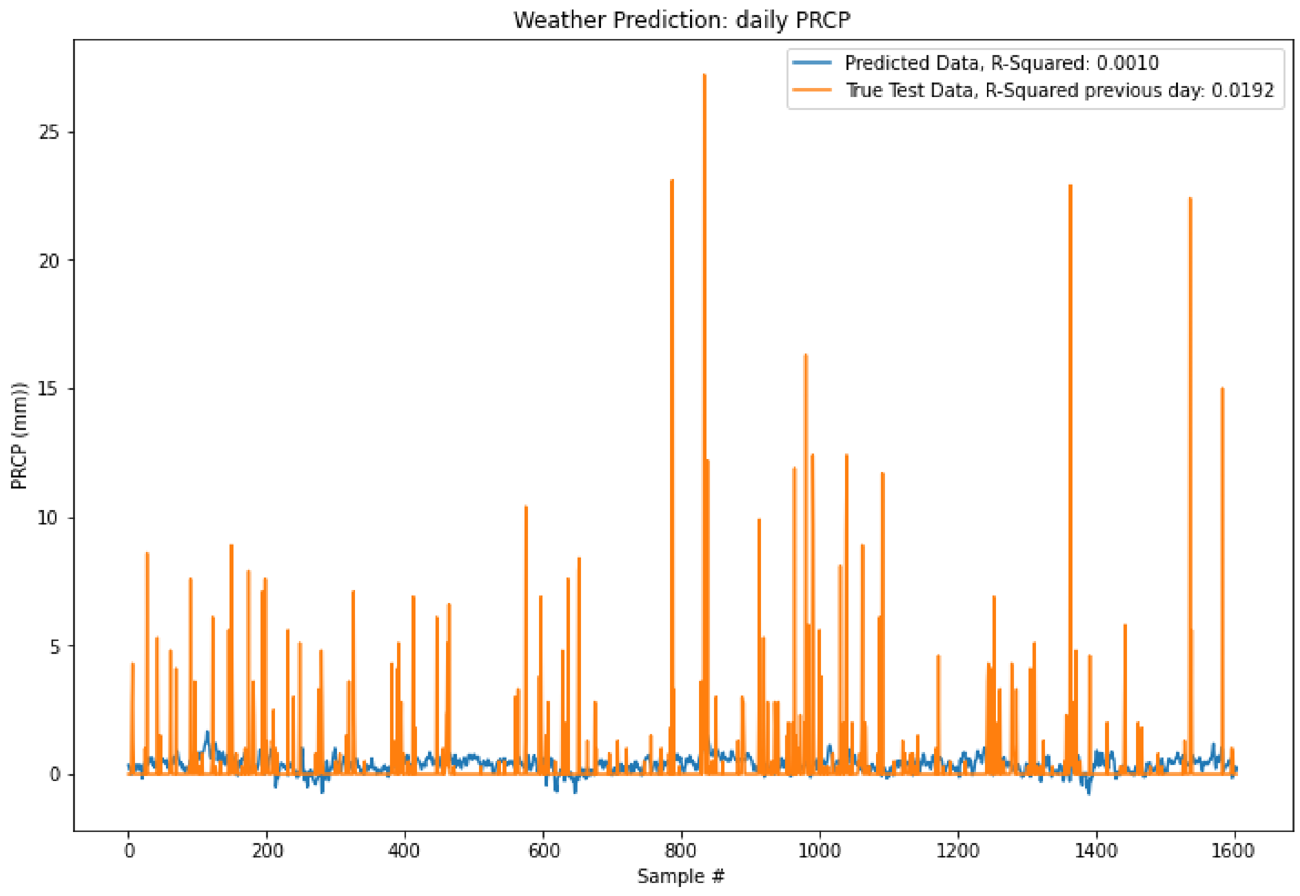
```
#test predictions
test_predict=model.predict(test_data)

#For TMAX
#R-squared with true values
Rsqr = np.corrcoef(test_label[:,0], test_predict[:,0])[0,1]**2

#R-squared with previous day
Rsqr2 = np.corrcoef(test_label[1:,0], test_label[:-1,0])[0,1]**2

#plot them
fig,ax=plt.subplots()
ax.plot(test_predict[offset:,0]*adj['TMAX'],label=f"Predicted Data, R-Squared: {Rsq
ax.plot(test_label[:,0]*adj['TMAX'],label=f"True Test Data, R-Squared previous day:
ax.set_title("Weather Prediction: daily TMAX")
ax.set_xlabel("Sample #")
ax.set_ylabel("TMAX $\degree C$")
ax.legend();
```



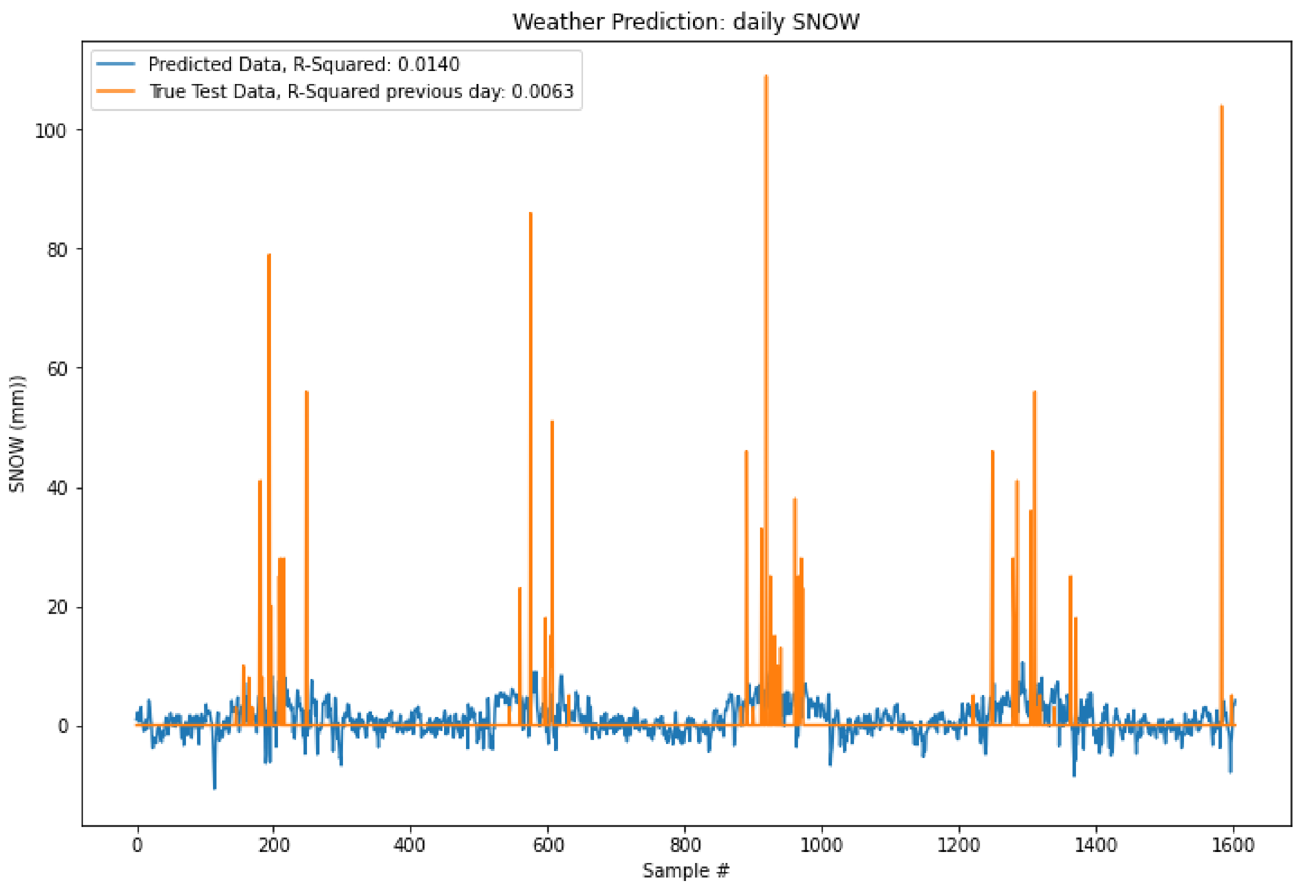
```
#For TMIN
#R-squared with true values
Rsqr = np.corrcoef(test_label[:,1], test_predict[:,1])[0,1]**2

#R-squared with previous day
Rsqr2 = np.corrcoef(test_label[1:,1], test_label[:-1,1])[0,1]**2
#plot them
fig,ax=plt.subplots()
ax.plot(test_predict[offset:,1]*adj['TMIN'],label=f"Predicted Data, R-Squared: {Rsq
ax.plot(test_label[:,1]*adj['TMIN'],label=f"True Test Data, R-Squared previous day:
ax.set_title("Weather Prediction: daily TMIN")
ax.set_xlabel("Sample #")
ax.set_ylabel("TMIN $\degree C$")
ax.legend();
```



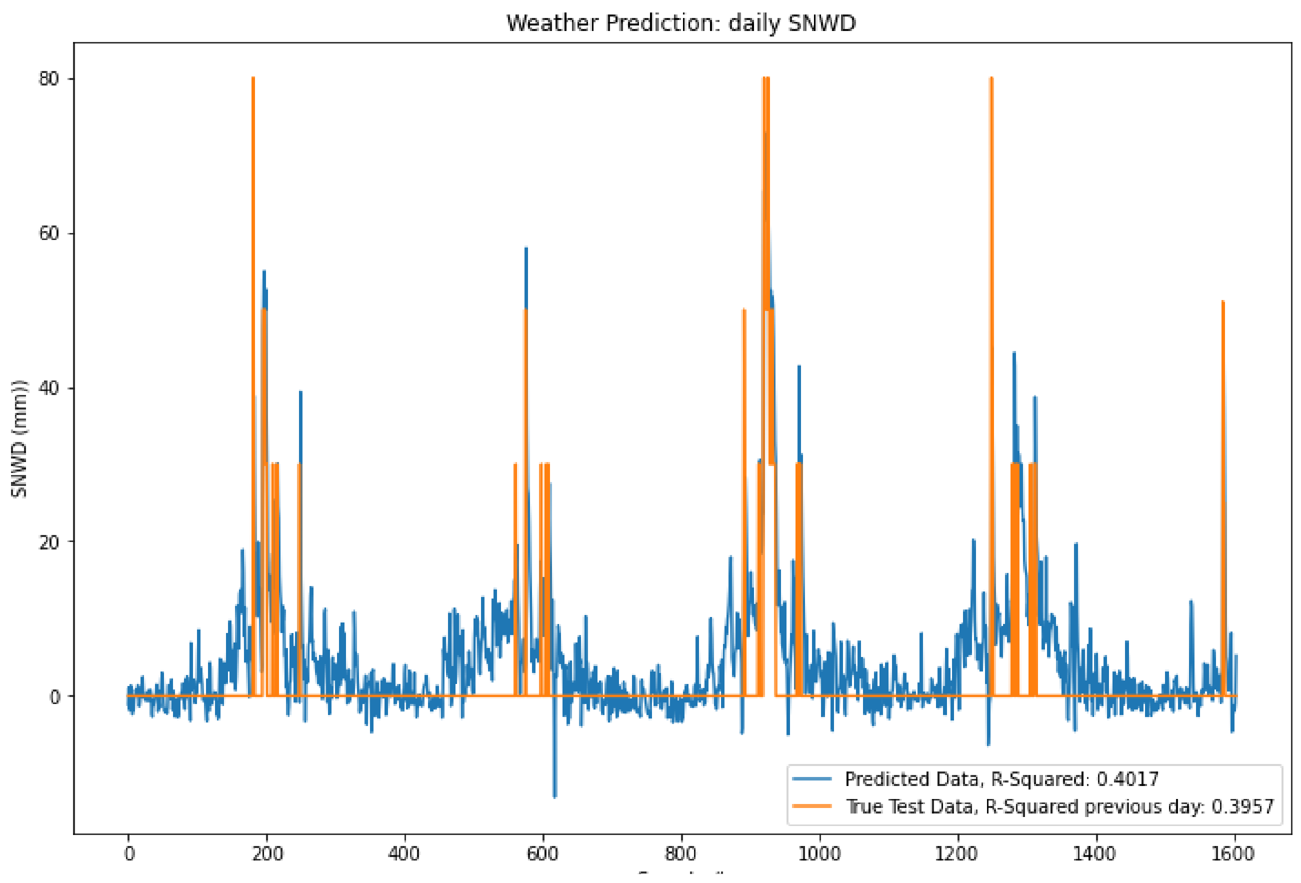
```
#For PRCP
#R-squared with true values
Rsqr = np.corrcoef(test_label[:,2], test_predict[:,2])[0,1]**2

#R-squared with previous day
Rsqr2 = np.corrcoef(test_label[1:,2], test_label[:-1,2])[0,1]**2
#plot them
fig,ax=plt.subplots()
ax.plot(test_predict[offset:,2]*adj['PRCP'],label=f"Predicted Data, R-Squared: {Rsq
ax.plot(test_label[:,2]*adj['PRCP'],label=f"True Test Data, R-Squared previous day:
ax.set_title("Weather Prediction: daily PRCP")
ax.set_xlabel("Sample #")
ax.set_ylabel("PRCP (mm))")
ax.legend();
```



```
#For SNOW
#R-squared with true values
Rsqr = np.corrcoef(test_label[:,3], test_predict[:,3])[0,1]**2

#R-squared with previous day
Rsqr2 = np.corrcoef(test_label[1:,3], test_label[:-1,3])[0,1]**2
#plot them
fig,ax=plt.subplots()
ax.plot(test_predict[offset:,3]*adj['SNOW'],label=f"Predicted Data, R-Squared: {Rsq
ax.plot(test_label[:,3]*adj['SNOW'],label=f"True Test Data, R-Squared previous day:
ax.set_title("Weather Prediction: daily SNOW")
ax.set_xlabel("Sample #")
ax.set_ylabel("SNOW (mm))")
ax.legend();
```



```
#For SNWD
#R-squared with true values
Rsqr = np.corrcoef(test_label[:,4], test_predict[:,4])[0,1]**2

#R-squared with previous day
Rsqr2 = np.corrcoef(test_label[1:,4], test_label[:-1,4])[0,1]**2
#plot them
fig,ax=plt.subplots()
ax.plot(test_predict[offset:,4]*adj['SNWD'],label=f"Predicted Data, R-Squared: {Rsq
ax.plot(test_label[:,4]*adj['SNWD'],label=f"True Test Data, R-Squared previous day:
ax.set_title("Weather Prediction: daily SNWD")
ax.set_xlabel("Sample #")
ax.set_ylabel("SNWD (mm))")
ax.legend();
```



Task VII. continued

The conclusion is that the model has improved the prediction of tomorrow's temperature (as measured by TMAX and TMIN) compared to just assuming it will be the same as today's. The predictive models for the other elements do not provide a good fit as the occurance of precipitation, snow and snow depths are just too variable on a day to day basis.

Task VIII. Decide on an extension project

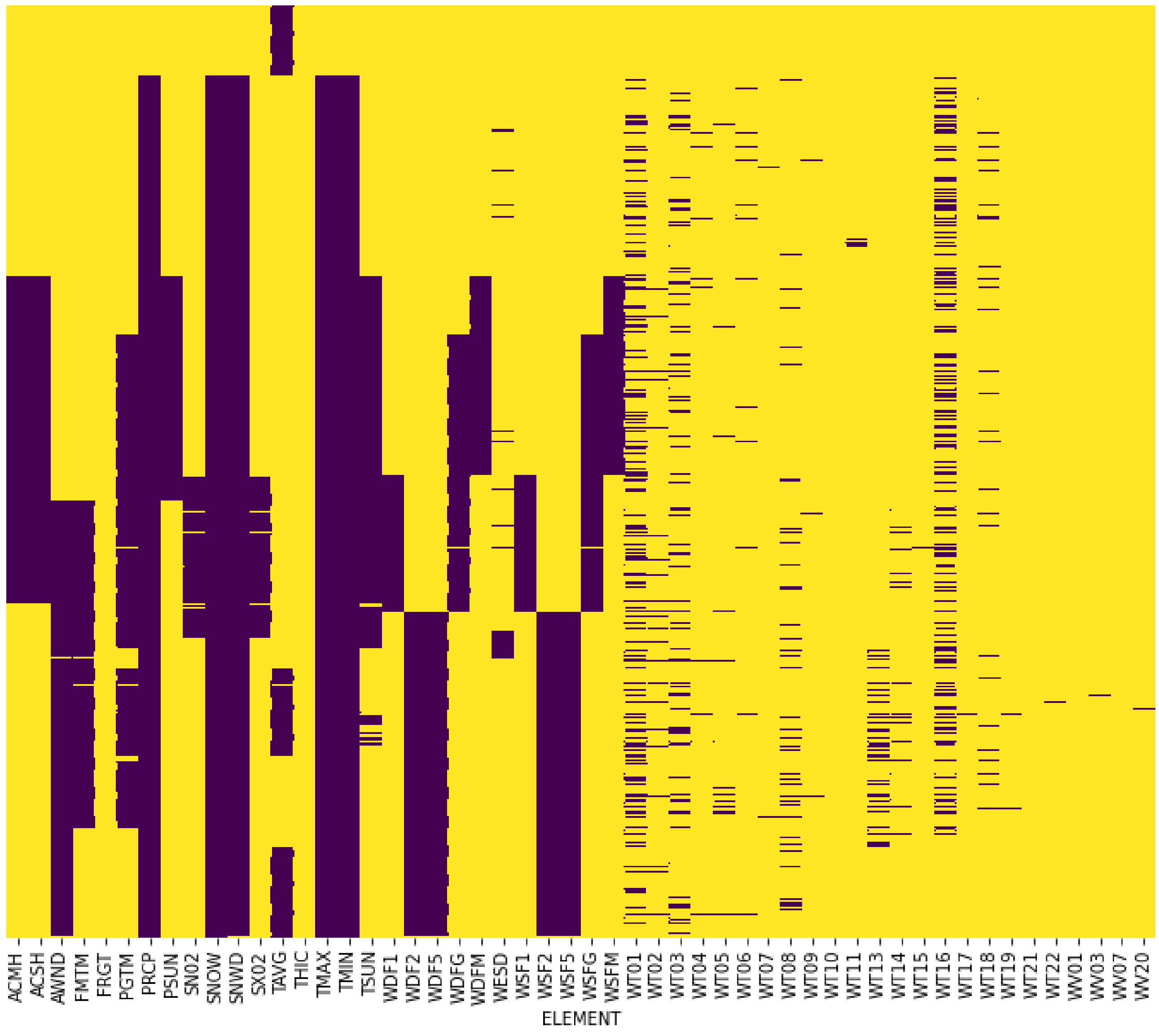
It was decided to see if predictions of tomorrow's temperature (TMAX and TMIN) in Colorado could be improved by including data from closer stations from neigbouring states. Reviewing the 26 filtered stations- i.e. those with the best data, three were selected (no others were in Colorado): Oklahoma City, OK; Albuquerque, NM and North Platte, NE. There was another Nebraska station, Norfolk, but this was further away.

It was decided to also vary some of the parameters to get the best prediction. NB in several cases, the models have been re-trained using the existing code cells after changing a parameter. This was done for the sake of brevity, but the key results are recorded in text cells for use in report.

First, these new datasets needed to be investigated in turn.

```
filename = 'USW00013967.dly'
dlyOK = read_ghcn_data_file(filename=filename)
```

```
#Heatmap for VALUES
sns.heatmap(data=dlyOK['VALUE'].isnull(), yticklabels=False, cbar = False, cmap ='v
```



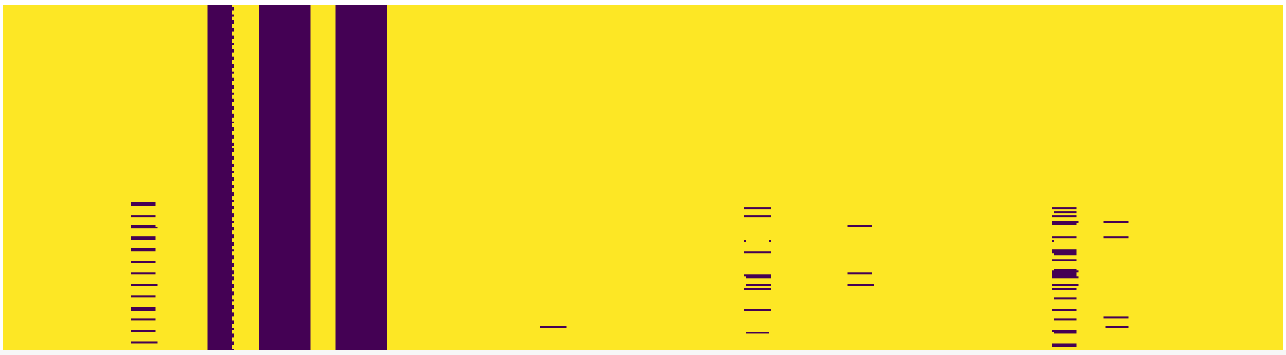
```
#Heatmap for QFLAG
sns.heatmap(data=dlyOK['QFLAG'].isnull(), yticklabels=False, cbar = False, cmap ='v
```

Task VIII. continued

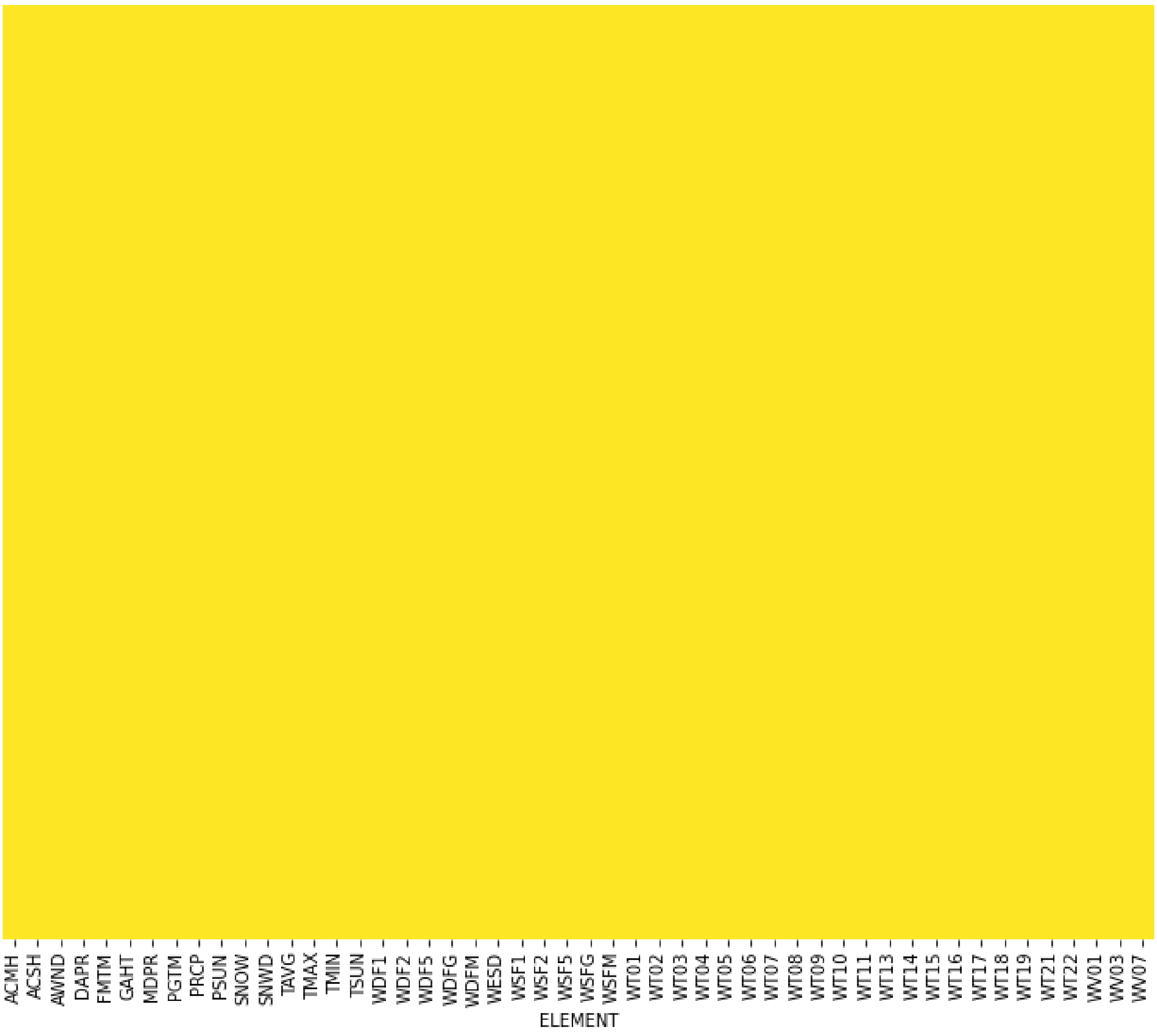
Good coverage of the 10 elements previously used in Task VII, with no quality issues shown. Now for Albuquerque, NM:

```
filename = 'USW00023050.dly'
dlyNM = read_ghcn_data_file(filename=filename)
```

```
#Heatmap for VALUES
sns.heatmap(data=dlyNM['VALUE'].isnull(), yticklabels=False, cbar = False, cmap ='v
```



```
#Heatmap for QFLAG
sns.heatmap(data=dlyNM['QFLAG'].isnull(), yticklabels=False, cbar = False, cmap ='v
```



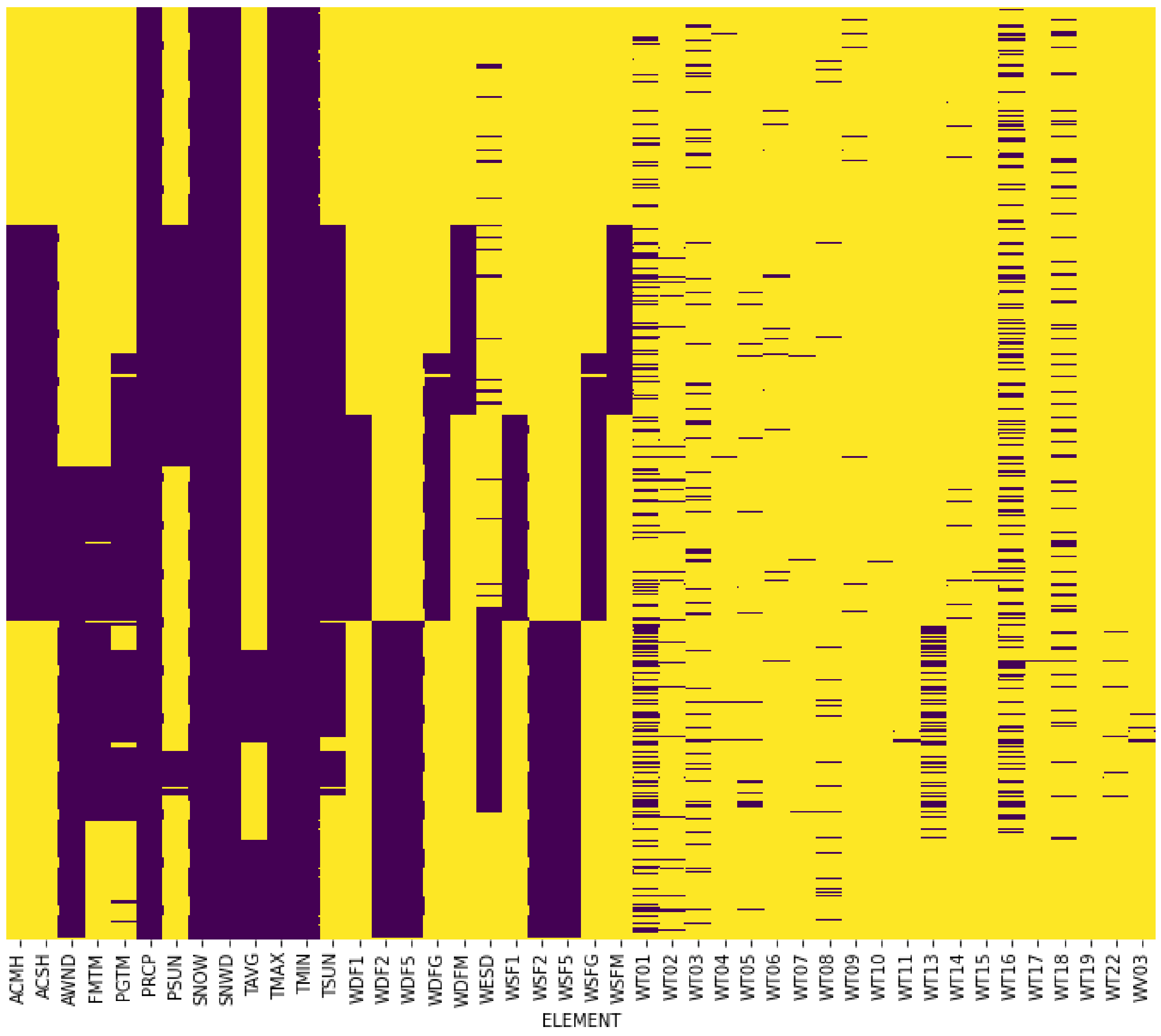
Task VIII. continued

Apart from gap in SNOW and SNWD, good coverage of the 10 elements previously used in Task VII, with no quality issues shown. Now for North Platte, NE:

```
filename = 'USW00024023.dly'
```

```
dlyNE = read_ghcn_data_file(filename=filename)
```

```
#Heatmap for VALUES
sns.heatmap(data=dlyNE['VALUE'].isnull(), yticklabels=False, cbar = False, cmap ='v
```



```
#Heatmap for QFLAG
sns.heatmap(data=dlyNE['QFLAG'].isnull(), yticklabels=False, cbar = False, cmap ='v
```

Task VIII. continued

Good coverage of the 10 elements and no quality issues visible. Now, the start dates of each of the dataframe for the 5 extra elements was determined

```
#the following code loops through the 5 wind elements to determine their start date
cols = ['AWND', 'WDF2', 'WDF5','WSF2','WSF5']
print('OK station')
for i in cols:

    if i in dlyOK['VALUE']: #where .dly file contains the relevant data columns
      #start date of each element i
      print(i, dlyOK[dlyOK['VALUE'][i].notnull() == True].index.min())

print('\nNM station')
for i in cols:

    if i in dlyNM['VALUE']: #where .dly file contains the relevant data columns
      #start date of each element i
      print(i, dlyNM[dlyNM['VALUE'][i].notnull() == True].index.min())

print('\nNE station')
for i in cols:

    if i in dlyNE['VALUE']: #where .dly file contains the relevant data columns
      #start date of each element i
      print(i, dlyNE[dlyNE['VALUE'][i].notnull() == True].index.min())
```

```
OK station
AWND 1984-01-01 00:00:00
```

```
WDF2 1993-06-01 00:00:00
WDF5 1993-06-01 00:00:00
WSF2 1993-06-01 00:00:00
WSF5 1993-06-01 00:00:00

NM station
AWND 1984-01-01 00:00:00
WDF2 1996-03-01 00:00:00
WDF5 1996-03-01 00:00:00
WSF2 1996-03-01 00:00:00
WSF5 1996-03-01 00:00:00

NE station
AWND 1984-01-01 00:00:00
WDF2 1996-02-01 00:00:00
WDF5 1996-02-01 00:00:00
WSF2 1996-02-01 00:00:00
WSF5 1996-02-01 00:00:00
```

Task VIII. continued

Latest start date was from Colorado station 1996-04-01. Now the datasets could be prepared and concatenated.

```
#For Colorado
filename = 'USW00023066.dly'
dly = read_ghcn_data_file(filename=filename)
#drop MFLAG and QFLAG column
dly.drop(('MFLAG'), axis = 1, inplace = True)
dly.drop(('QFLAG'), axis = 1, inplace = True)

#drop VAR_TYPE column hierarchy as no longer needed
dly_10 = dly.droplevel('VAR_TYPE',axis= 1)

#select the desired 10 columns
dly_10 = dly_10[['TMAX', 'TMIN', 'PRCP', 'SNOW', 'SNWD', 'AWND', 'WDF2', 'WDF5','WS
dly_10 = dly_10[dly_10.index >= '1996-04-01 00:00:00']

dly_10.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 8994 entries, 1996-04-01 to 2020-11-14
Data columns (total 10 columns):
 #   Column  Non-Null Count  Dtype  
---  ------  --------------  -----  
 0   TMAX    8994 non-null   float64
 1   TMIN    8994 non-null   float64
 2   PRCP    8994 non-null   float64
 3   SNOW    8993 non-null   float64
 4   SNWD    8992 non-null   float64
 5   AWND    8988 non-null   float64
 6   WDF2    8991 non-null   float64
 7   WDF5    8974 non-null   float64
 8   WSF2    8991 non-null   float64
 9   WSF5    8974 non-null   float64
```

```
dtypes: float64(10)
memory usage: 772.9 KB
```

```
#fill forward and replace extreme value as before
dly_10.fillna(method='ffill', inplace = True)
av = np.mean([76,103,94,98])
#replace 4095.0 with av
#NB is safe to do so as 4095.0 is outside ranges of all other elements
dly_10.replace(4095.0, av, inplace = True)
dly_10.describe()
dly_10.describe()
```

ELEMENT	TMAX	TMIN	PRCP	SNOW	SNWD	AWND
count	8994.000000	8994.000000	8994.000000	8994.000000	8994.000000	8994.000000
mean	19.324194	4.649922	0.627374	1.210140	4.365577	33.157216
std	11.837798	9.713334	2.180278	8.323179	18.854957	13.591177
min	-11.700000	-26.700000	0.000000	0.000000	0.000000	3.000000
25%	9.400000	-2.800000	0.000000	0.000000	0.000000	23.000000
50%	20.000000	4.400000	0.000000	0.000000	0.000000	31.000000
75%	30.000000	13.300000	0.000000	0.000000	0.000000	41.000000
max	41.100000	25.600000	33.300000	183.000000	203.000000	105.000000

```
#For Oklahoma
filename = 'USW00013967.dly'
dlyOK = read_ghcn_data_file(filename=filename)
#drop MFLAG and QFLAG column
dlyOK.drop(('MFLAG'), axis = 1, inplace = True)
dlyOK.drop(('QFLAG'), axis = 1, inplace = True)

#drop VAR_TYPE column hierarchy as no longer needed
dlyOK_10 = dlyOK.droplevel('VAR_TYPE',axis= 1)

#select the desired 10 columns
dlyOK_10 = dlyOK_10[['TMAX', 'TMIN', 'PRCP', 'SNOW', 'SNWD', 'AWND', 'WDF2', 'WDF5'
dlyOK_10 = dlyOK_10[dlyOK_10.index >= '1996-04-01 00:00:00']

dlyOK_10.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 8990 entries, 1996-04-01 to 2020-11-14
Data columns (total 10 columns):
 #   Column  Non-Null Count  Dtype  
---  ------  --------------  -----  
 0   TMAX    8990 non-null   float64
 1   TMIN    8990 non-null   float64
 2   PRCP    8990 non-null   float64
 3   SNOW    8989 non-null   float64
 4   SNWD    8958 non-null   float64
 5   AWND    8981 non-null   float64
 6   WDF2    8986 non-null   float64
 7   WDF5    8977 non-null   float64
 8   WSF2    8986 non-null   float64
 9   WSF5    8977 non-null   float64
dtypes: float64(10)
memory usage: 772.6 KB
```

```
#For New Mexico
filename = 'USW00023050.dly'
dlyNM = read_ghcn_data_file(filename=filename)
#drop MFLAG and QFLAG column
dlyNM.drop(('MFLAG'), axis = 1, inplace = True)
dlyNM.drop(('QFLAG'), axis = 1, inplace = True)

#drop VAR_TYPE column hierarchy as no longer needed
dlyNM_10 = dlyNM.droplevel('VAR_TYPE',axis= 1)

#select the desired 10 columns
dlyNM_10 = dlyNM_10[['TMAX', 'TMIN', 'PRCP', 'SNOW', 'SNWD', 'AWND', 'WDF2', 'WDF5'
dlyNM_10 = dlyNM_10[dlyNM_10.index >= '1996-04-01 00:00:00']

dlyNM_10.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 8990 entries, 1996-04-01 to 2020-11-14
Data columns (total 10 columns):
 #   Column  Non-Null Count  Dtype  
---  ------  --------------  -----  
 0   TMAX    8990 non-null   float64
 1   TMIN    8990 non-null   float64
 2   PRCP    8990 non-null   float64
 3   SNOW    8746 non-null   float64
 4   SNWD    8746 non-null   float64
 5   AWND    8987 non-null   float64
 6   WDF2    8988 non-null   float64
 7   WDF5    8980 non-null   float64
 8   WSF2    8988 non-null   float64
 9   WSF5    8980 non-null   float64
dtypes: float64(10)
memory usage: 772.6 KB
```

```
#For Nebraska
filename = 'USW00024023.dly'
dlyNE = read_ghcn_data_file(filename=filename)
#drop MFLAG and QFLAG column
dlyNE.drop(('MFLAG'), axis = 1, inplace = True)
dlyNE.drop(('QFLAG'), axis = 1, inplace = True)

#drop VAR_TYPE column hierarchy as no longer needed
dlyNE_10 = dlyNE.droplevel('VAR_TYPE',axis= 1)

#select the desired 10 columns
dlyNE_10 = dlyNE_10[['TMAX', 'TMIN', 'PRCP', 'SNOW', 'SNWD', 'AWND', 'WDF2', 'WDF5'
dlyNE_10 = dlyNE_10[dlyNE_10.index >= '1996-04-01 00:00:00']
```

```
dlyNE_10.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 8994 entries, 1996-04-01 to 2020-11-14
Data columns (total 10 columns):
 #   Column  Non-Null Count  Dtype  
---  ------  --------------  -----  
 0   TMAX    8994 non-null   float64
 1   TMIN    8994 non-null   float64
 2   PRCP    8994 non-null   float64
 3   SNOW    8990 non-null   float64
 4   SNWD    8992 non-null   float64
 5   AWND    8986 non-null   float64
 6   WDF2    8993 non-null   float64
 7   WDF5    8989 non-null   float64
 8   WSF2    8993 non-null   float64
 9   WSF5    8989 non-null   float64
dtypes: float64(10)
memory usage: 772.9 KB
```

Task VIII. continued

Strangely, Oklahoma and New Mexico stations had four less entries at 8990 versus 8994 for the other 2.

```
print('Dates not in OK station data')
for i in dly_10.index:
  if i not in dlyOK_10.index:
    print(i)

print('\nDates not in NM station data')
for i in dly_10.index:
  if i not in dlyNM_10.index:
    print(i)
```

```
Dates not in OK station data
2020-10-28 00:00:00
2020-10-29 00:00:00
2020-10-30 00:00:00
2020-10-31 00:00:00

Dates not in NM station data
2020-10-28 00:00:00
2020-10-29 00:00:00
2020-10-30 00:00:00
2020-10-31 00:00:00
```

Task VIII. continued.

These rows need to be added so dataframes all match

```
#adapted from https://www.pythonprogramming.in/how-to-add-row-to-dataframe-with-tim
```

```
for i in ['2020-10-28 00:00:00', '2020-10-29 00:00:00', '2020-10-30 00:00:00', '202
  line = pd.to_datetime(i, format="%Y-%m-%d %H:%M:%S")
  new_row = pd.DataFrame(columns=['TMAX', 'TMIN', 'PRCP', 'SNOW', 'SNWD', 'AWND', '
  dlyOK_10 = pd.concat([dlyOK_10, pd.DataFrame(new_row)], ignore_index=False)
  dlyNM_10 = pd.concat([dlyNM_10, pd.DataFrame(new_row)], ignore_index=False)
```

```
dlyOK_10.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 8994 entries, 1996-04-01 to 2020-10-31
Data columns (total 10 columns):
 #   Column  Non-Null Count  Dtype  
---  ------  --------------  -----  
 0   TMAX    8990 non-null   float64
 1   TMIN    8990 non-null   float64
 2   PRCP    8990 non-null   float64
 3   SNOW    8989 non-null   float64
 4   SNWD    8958 non-null   float64
 5   AWND    8981 non-null   float64
 6   WDF2    8986 non-null   float64
 7   WDF5    8977 non-null   float64
 8   WSF2    8986 non-null   float64
 9   WSF5    8977 non-null   float64
dtypes: float64(10)
memory usage: 772.9 KB
```

```
dlyNM_10.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 8994 entries, 1996-04-01 to 2020-10-31
Data columns (total 10 columns):
 #   Column  Non-Null Count  Dtype  
---  ------  --------------  -----  
 0   TMAX    8990 non-null   float64
 1   TMIN    8990 non-null   float64
 2   PRCP    8990 non-null   float64
 3   SNOW    8746 non-null   float64
 4   SNWD    8746 non-null   float64
 5   AWND    8987 non-null   float64
 6   WDF2    8988 non-null   float64
 7   WDF5    8980 non-null   float64
 8   WSF2    8988 non-null   float64
 9   WSF5    8980 non-null   float64
dtypes: float64(10)
memory usage: 772.9 KB
```

Task VIII. continued

That seemed to have worked and it was decided to continue preparation of datasets in order OK, NM, NE.

For OK station fill forward was used and describe() did not show any extreme values.

```
#fill forward
dlyOK_10.fillna(method='ffill', inplace = True)
dlyOK_10.describe()
```

ELEMENT	TMAX	TMIN	PRCP	SNOW	SNWD	AWND
count	8994.000000	8994.000000	8994.000000	8994.000000	8994.000000	8994.000000
mean	22.657294	10.228664	2.536391	0.464198	0.898488	50.135980
std	10.168416	9.625214	9.202921	6.959854	10.363419	19.302236
min	-9.400000	-20.600000	0.000000	0.000000	0.000000	8.000000
25%	15.600000	2.200000	0.000000	0.000000	0.000000	36.000000
50%	23.900000	11.100000	0.000000	0.000000	0.000000	47.000000
75%	31.100000	19.400000	0.000000	0.000000	0.000000	63.000000
max	45.000000	28.900000	193.500000	343.000000	356.000000	157.000000

```
#rename so we can concatenate
dlyOK_10.rename(columns={"TMAX": "TMAXok", "TMIN": "TMINok",
                         "PRCP": "PRCPok", "SNOW": "SNOWok",
                         "SNWD": "SNWDok", "AWND": "AWNDok",
                         "WDF2": "WDF2ok", "WDF5": "WDF5ok",
                         "WSF2": "WSF2ok", "WSF5": "WSF5ok"}, inplace=True)
dlyOK_10.head(1)
```

ELEMENT	TMAXok	TMINok	PRCPok	SNOWok	SNWDok	AWNDok	WDF2ok	WDF5ok	WSF2ok
1996-04-01	19.4	2.2	0.0	0.0	0.0	41.0	170.0	160.0	72.0

Task VIII. continued

NM station had an issue with completeness of SNOW and SNWD to investigate.

```
dlyNM_10[dlyNM_10['SNOW'].isnull() == True]
```

ELEMENT	TMAX	TMIN	PRCP	SNOW	SNWD	AWND	WDF2	WDF5	WSF2	WSF5
2002-04-01	26.7	7.8	0.0	NaN	NaN	34.0	260.0	270.0	98.0	116.0
2002-04-02	26.7	6.1	0.0	NaN	NaN	67.0	90.0	90.0	192.0	215.0
2002-04-03	21.7	2.8	0.0	NaN	NaN	63.0	90.0	90.0	165.0	192.0
2002-04-04	24.4	7.2	0.0	NaN	NaN	41.0	220.0	220.0	170.0	192.0

```
dlyNM_10[dlyNM_10.index == '2002-03-31']
```

ELEMENT	TMAX	TMIN	PRCP	SNOW	SNWD	AWND	WDF2	WDF5	WSF2	WSF5
2002-03-31	22.8	6.7	0.0	0.0	0.0	27.0	180.0	210.0	54.0	67.0
2020-10-29	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN

Task VIII. continued

It was assumed that SNOW and SNWD for these mostly spring, summer and autumn months are zero so can use forward fill from 2002-03-31 when there was no snow or snwd.

```
#fill forward
dlyNM_10.fillna(method='ffill', inplace = True)
dlyNM_10.describe()
```

ELEMENT	TMAX	TMIN	PRCP	SNOW	SNWD	AWND
count	8994.000000	8994.000000	8994.000000	8994.000000	8994.000000	8994.000000
mean	21.615944	7.894307	0.608495	0.516567	0.451634	36.384034
std	9.639201	8.680149	2.595973	5.920355	6.739745	16.556658
min	-12.800000	-21.700000	0.000000	0.000000	0.000000	5.000000
25%	13.300000	0.600000	0.000000	0.000000	0.000000	25.000000
50%	22.800000	7.800000	0.000000	0.000000	0.000000	33.000000
75%	30.000000	16.100000	0.000000	0.000000	0.000000	44.000000
max	40.600000	25.600000	48.800000	287.000000	254.000000	139.000000

```
#rename so we can concatenate
dlyNM_10.rename(columns={"TMAX": "TMAXnm", "TMIN": "TMINnm",
                          "PRCP": "PRCPnm", "SNOW": "SNOWnm",
                          "SNWD": "SNWDnm", "AWND": "AWNDnm",
                          "WDF2": "WDF2nm", "WDF5": "WDF5nm",
                          "WSF2": "WSF2nm", "WSF5": "WSF5nm"}, inplace=True)
dlyNM_10.head(1)
```

ELEMENT	TMAXnm	TMINnm	PRCPnm	SNOWnm	SNWDnm	AWNDnm	WDF2nm	WDF5nm	WSF2nm

```
#fill forward
dlyNE_10.fillna(method='ffill', inplace = True)
dlyNE_10.describe()
```

ELEMENT	TMAX	TMIN	PRCP	SNOW	SNWD	AWND
count	8994.000000	8994.000000	8994.000000	8994.000000	8994.000000	8994.000000
mean	17.919024	1.904937	1.481877	2.040138	6.231488	39.323660
std	11.710348	10.902464	5.307846	13.370988	25.444174	17.131418
min	-16.700000	-31.600000	0.000000	0.000000	0.000000	0.000000
25%	9.400000	-6.700000	0.000000	0.000000	0.000000	27.000000
50%	18.900000	1.100000	0.000000	0.000000	0.000000	36.000000
75%	27.800000	11.700000	0.000000	0.000000	0.000000	47.000000
max	42.200000	24.400000	74.900000	300.000000	305.000000	147.000000

```
#rename so we can concatenate
dlyNE_10.rename(columns={"TMAX": "TMAXne", "TMIN": "TMINne",
                         "PRCP": "PRCPne", "SNOW": "SNOWne",
                         "SNWD": "SNWDne", "AWND": "AWNDne",
                         "WDF2": "WDF2ne", "WDF5": "WDF5ne",
                         "WSF2": "WSF2ne", "WSF5": "WSF5ne"}, inplace=True)
dlyNE_10.head(1)
```

ELEMENT	TMAXne	TMINne	PRCPne	SNOWne	SNWDne	AWNDne	WDF2ne	WDF5ne	WSF2ne
1996-04-01	20.6	0.6	0.0	0.0	0.0	65.0	170.0	170.0	112.0

```
dly_10 = pd.concat([dly_10, dlyOK_10], axis =1)
```

```
dly_10 = pd.concat([dly_10, dlyNM_10], axis =1)
```

```
dly_10 = pd.concat([dly_10, dlyNE_10], axis =1)
```

```
dly_10.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 8994 entries, 1996-04-01 to 2020-11-14
Freq: D
Data columns (total 40 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   TMAX    8994 non-null   float64
 1   TMIN    8994 non-null   float64
 2   PRCP    8994 non-null   float64
 3   SNOW    8994 non-null   float64
 4   SNWD    8994 non-null   float64
 5   AWND    8994 non-null   float64
 6   WDF2    8994 non-null   float64
 7   WDF5    8994 non-null   float64
 8   WSF2    8994 non-null   float64
 9   WSF5    8994 non-null   float64
 10  TMAXok  8994 non-null   float64
 11  TMINok  8994 non-null   float64
 12  PRCPok  8994 non-null   float64
 13  SNOWok  8994 non-null   float64
 14  SNWDok  8994 non-null   float64
 15  AWNDok  8994 non-null   float64
 16  WDF2ok  8994 non-null   float64
 17  WDF5ok  8994 non-null   float64
 18  WSF2ok  8994 non-null   float64
 19  WSF5ok  8994 non-null   float64
 20  TMAXnm  8994 non-null   float64
 21  TMINnm  8994 non-null   float64
 22  PRCPnm  8994 non-null   float64
 23  SNOWnm  8994 non-null   float64
 24  SNWDnm  8994 non-null   float64
 25  AWNDnm  8994 non-null   float64
 26  WDF2nm  8994 non-null   float64
 27  WDF5nm  8994 non-null   float64
 28  WSF2nm  8994 non-null   float64
 29  WSF5nm  8994 non-null   float64
 30  TMAXne  8994 non-null   float64
 31  TMINne  8994 non-null   float64
 32  PRCPne  8994 non-null   float64
 33  SNOWne  8994 non-null   float64
 34  SNWDne  8994 non-null   float64
 35  AWNDne  8994 non-null   float64
 36  WDF2ne  8994 non-null   float64
 37  WDF5ne  8994 non-null   float64
 38  WSF2ne  8994 non-null   float64
 39  WSF5ne  8994 non-null   float64
dtypes: float64(40)
memory usage: 2.8 MB
```

```
dly_10, adj = normalise(dly_10)
```

```
offset=0#predict one day forward
n_ts=30 #1 month of daily data for training
nn_df=make_offset_dataframe(dly_10,n_ts,offset)
nn_df.dropna(axis=0, inplace=True)#lose rows with NaN
#check
nn_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 8964 entries, 1996-05-01 to 2020-11-14
Freq: D
Columns: 1240 entries, (0, 'TMAX') to ('label', 'WSF5ne')
dtypes: float64(1240)
memory usage: 84.9 MB
```

Task VIII. continued

This is a very large dataframe. Now the data needed to be split into training, validation and test datasets as before. The alpha model was used first, then beta (shown here). It is the same as alpha except the 2 LTSM and 1 Dense hidden layers are twice as wide (number of neurons).

```
train_data, val_data, test_data, train_label, val_label, test_label = dataset_split

#Beta model
model=keras.models.Sequential()
model.add(keras.layers.LSTM(128,input_shape=(n_ts,dly_10.shape[1]),return_sequences
model.add(keras.layers.LSTM(64,activation='relu'))
model.add(keras.layers.Dense(64,activation='relu'))
model.add(keras.layers.Dense(dly_10.shape[1],activation="linear"))
model.compile(loss='mean_squared_error',optimizer='adam')
model.summary()

history=model.fit(train_data,train_label,epochs=10,batch_size=10,verbose=1,validati
```

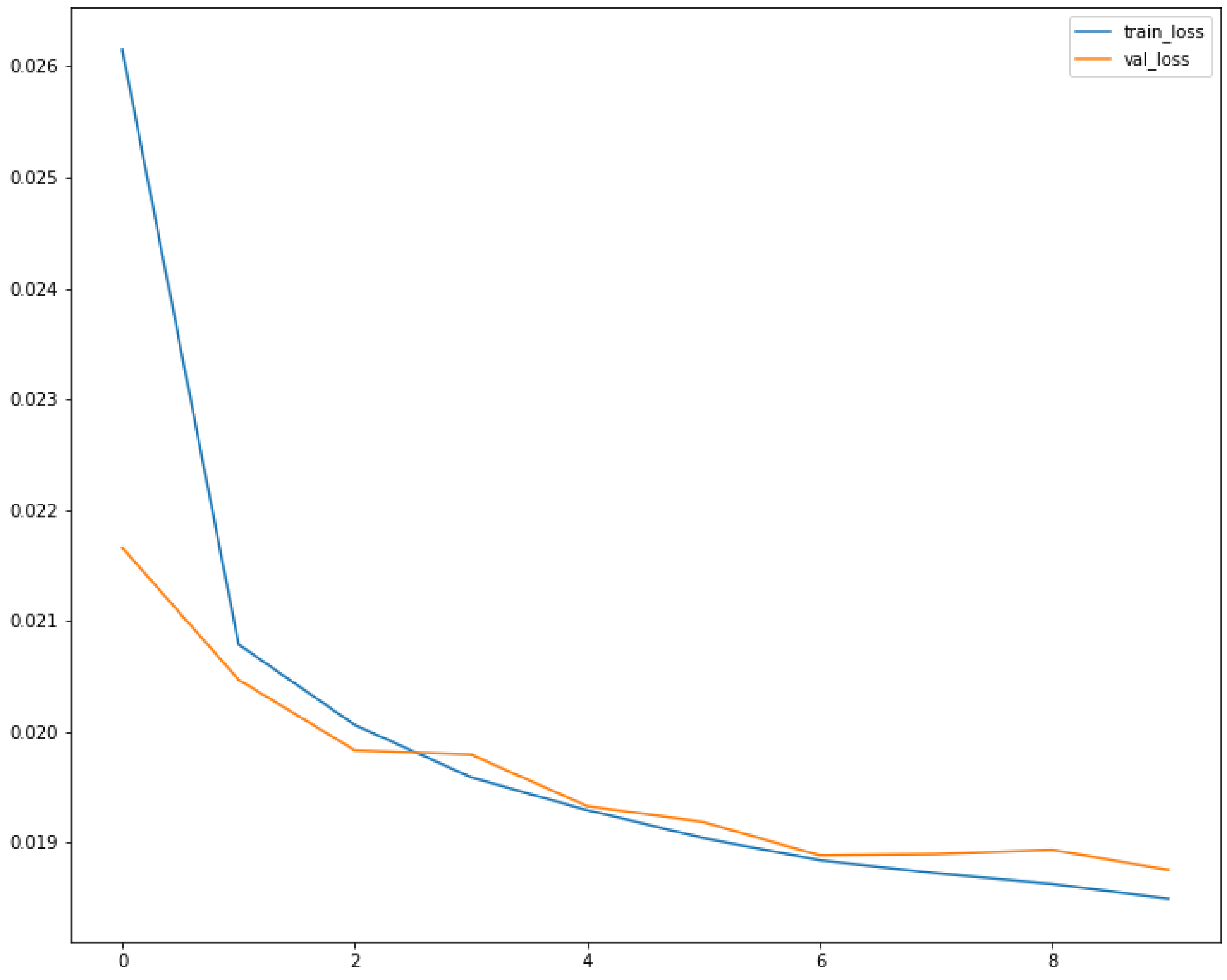
```
train_data (5378, 30, 40)
val_data (1793, 30, 40)
test_data (1793, 30, 40)
Model: "sequential_6"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 lstm_12 (LSTM)              (None, 30, 128)           86528

 lstm_13 (LSTM)              (None, 64)                49408

 dense_12 (Dense)            (None, 64)                4160

 dense_13 (Dense)            (None, 40)                2600

=================================================================
Total params: 142,696
Trainable params: 142,696
Non-trainable params: 0
_________________________________________________________________
Epoch 1/10
538/538 [==============================] - 25s 42ms/step - loss: 0.0259 - val_
Epoch 2/10
538/538 [==============================] - 22s 40ms/step - loss: 0.0209 - val_
Epoch 3/10
538/538 [==============================] - 22s 40ms/step - loss: 0.0202 - val_
Epoch 4/10
538/538 [==============================] - 21s 40ms/step - loss: 0.0197 - val_
Epoch 5/10
538/538 [==============================] - 22s 40ms/step - loss: 0.0194 - val_
Epoch 6/10
538/538 [==============================] - 21s 40ms/step - loss: 0.0191 - val_
Epoch 7/10
538/538 [==============================] - 21s 40ms/step - loss: 0.0190 - val_
Epoch 8/10
538/538 [==============================] - 22s 40ms/step - loss: 0.0189 - val_
Epoch 9/10
```

```
538/538 [==============================] - 22s 40ms/step - loss: 0.0188 - val_
Epoch 10/10
538/538 [==============================] - 21s 40ms/step - loss: 0.0186 - val_
```

Task VIII. continued

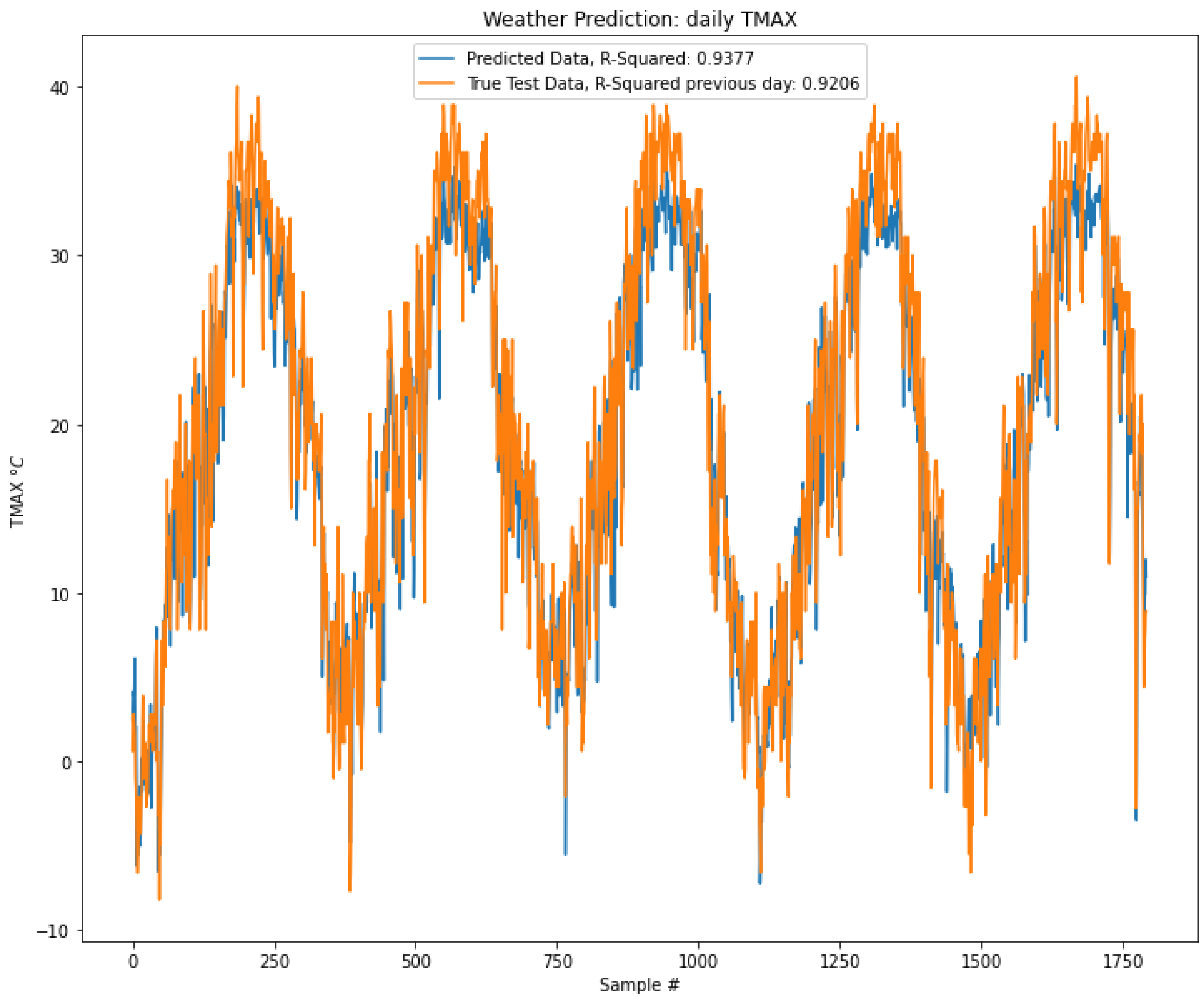
Training has completed and loss function converged quickly. It was decided to just consider the main elements for the Colorado station for analysis, rather than all 20 elements used.

```
fig,ax=plt.subplots()
ax.plot(history.history['loss'], label='train_loss')
ax.plot(history.history['val_loss'], label='val_loss')
ax.set_title = 'Loss of the model'
ax.xlabel = 'Time (Epochs)'
ax.ylabel = 'Loss'
ax.legend();
```



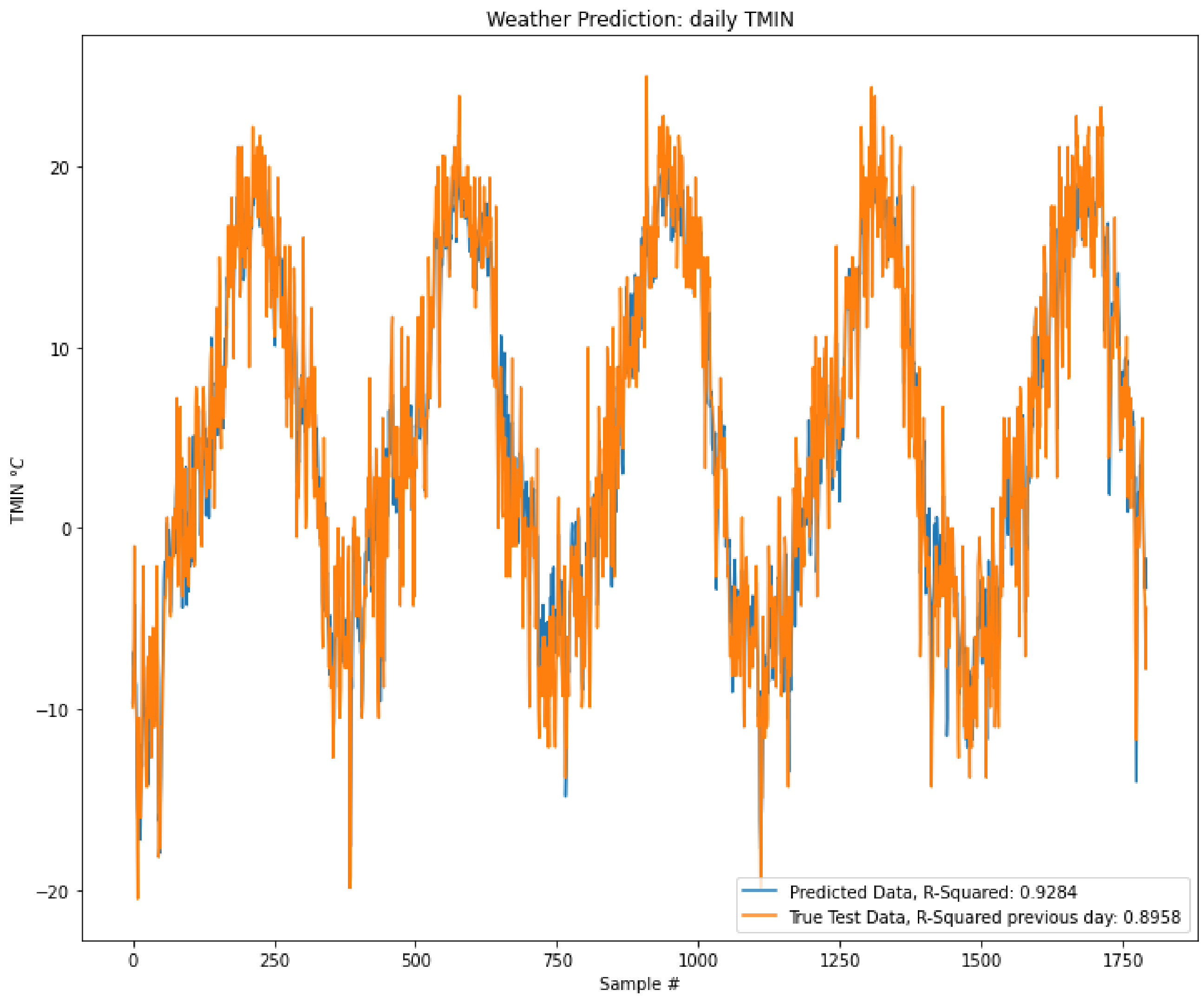
```
#test predictions
test_predict=model.predict(test_data)
```

```
#For TMAX
#R-squared with true values
Rsqr = np.corrcoef(test_label[:,0], test_predict[:,0])[0,1]**2

#R-squared with previous day
Rsqr2 = np.corrcoef(test_label[1:,0], test_label[:-1,0])[0,1]**2

#plot them
fig,ax=plt.subplots()
ax.plot(test_predict[offset:,0]*adj['TMAX'],label=f"Predicted Data, R-Squared: {Rsq
ax.plot(test_label[:,0]*adj['TMAX'],label=f"True Test Data, R-Squared previous day:
ax.set_title("Weather Prediction: daily TMAX")
ax.set_xlabel("Sample #")
ax.set_ylabel("TMAX $\degree C$")
ax.legend();
```

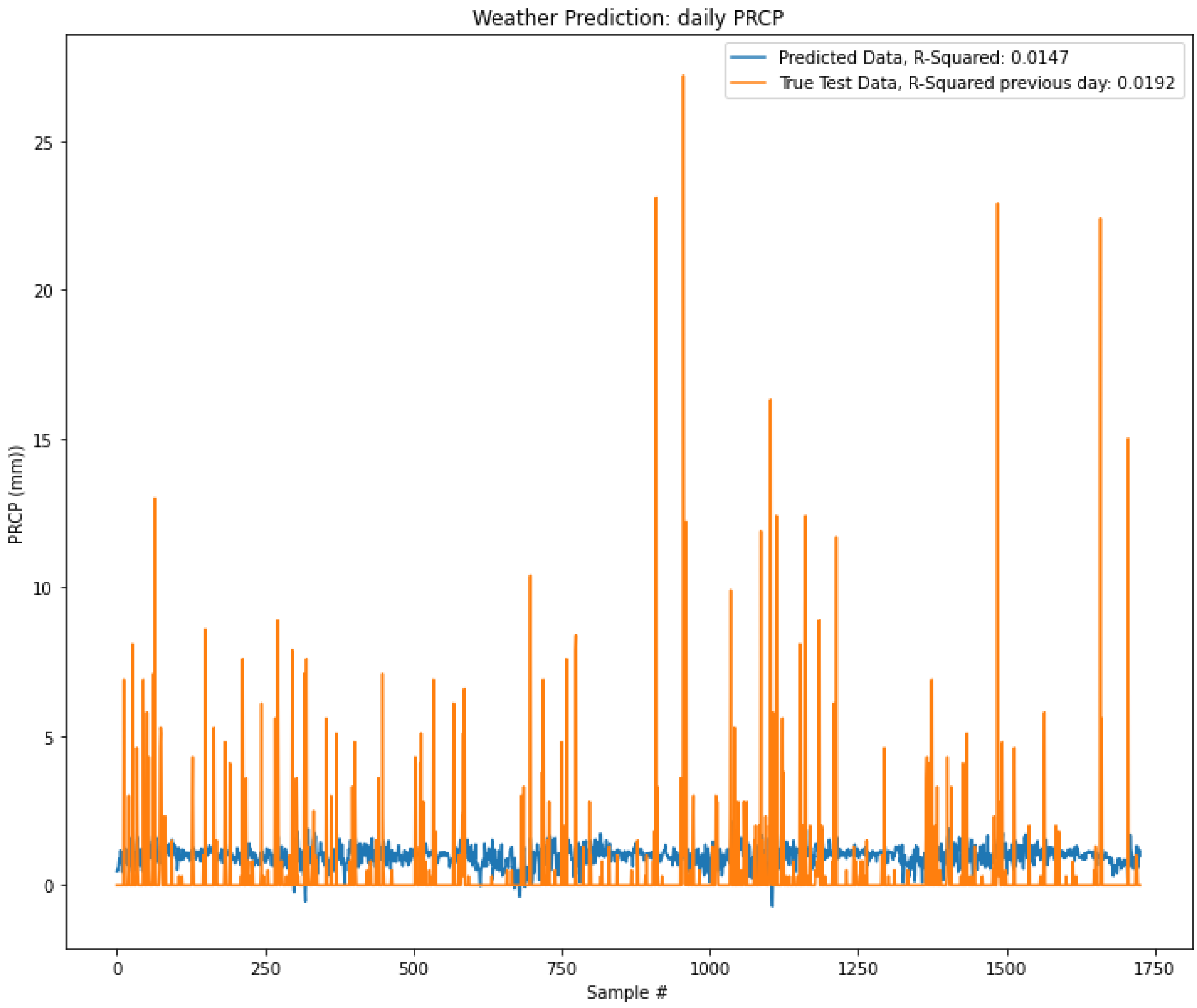


```
#For TMIN
#R-squared with true values
Rsqr = np.corrcoef(test_label[:,1], test_predict[:,1])[0,1]**2

#R-squared with previous day
```

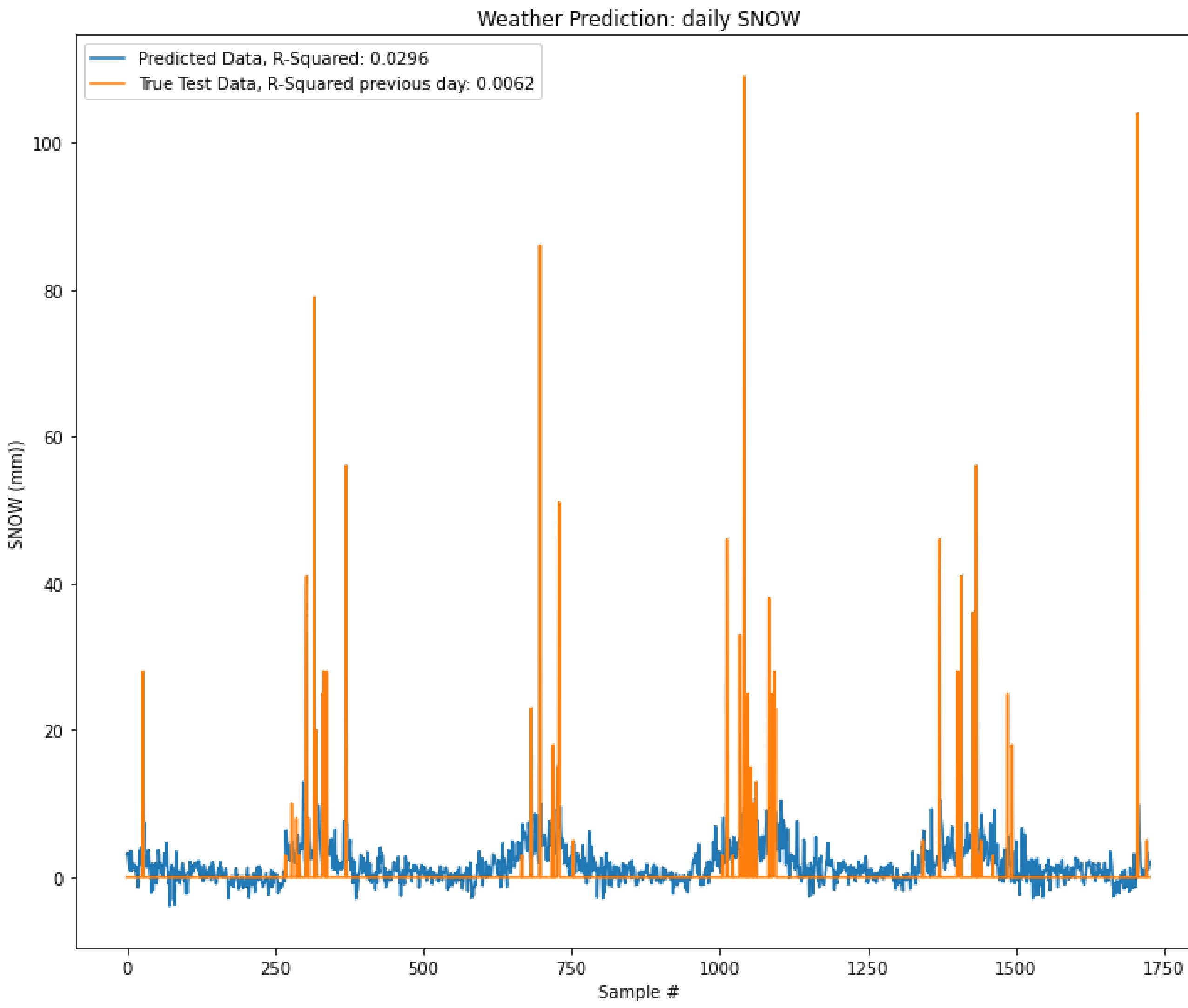
```
Rsqr2 = np.corrcoef(test_label[1:,1], test_label[:-1,1])[0,1]**2
#plot them
fig,ax=plt.subplots()
ax.plot(test_predict[offset:,1]*adj['TMIN'],label=f"Predicted Data, R-Squared: {Rsq
ax.plot(test_label[:,1]*adj['TMIN'],label=f"True Test Data, R-Squared previous day:
ax.set_title("Weather Prediction: daily TMIN")
ax.set_xlabel("Sample #")
ax.set_ylabel("TMIN $\degree C$")
ax.legend();
```



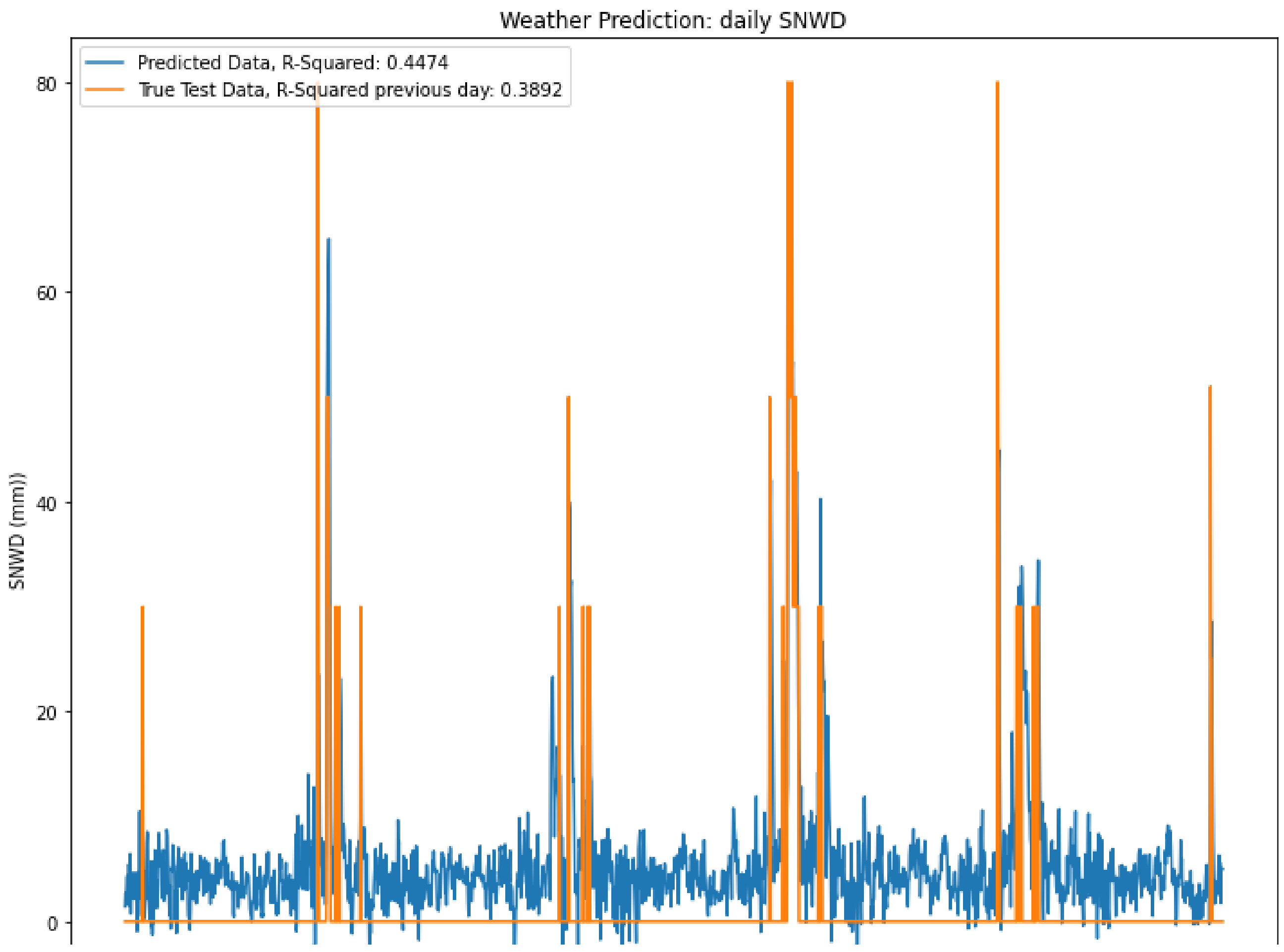
```
#For PRCP
#R-squared with true values
Rsqr = np.corrcoef(test_label[:,2], test_predict[:,2])[0,1]**2

#R-squared with previous day
Rsqr2 = np.corrcoef(test_label[1:,2], test_label[:-1,2])[0,1]**2
#plot them
fig,ax=plt.subplots()
ax.plot(test_predict[offset:,2]*adj['PRCP'],label=f"Predicted Data, R-Squared: {Rsq
ax.plot(test_label[:,2]*adj['PRCP'],label=f"True Test Data, R-Squared previous day:
ax.set_title("Weather Prediction: daily PRCP")
ax.set_xlabel("Sample #")
ax.set_ylabel("PRCP (mm))")
ax.legend();
```



```
#For SNOW
#R-squared with true values
Rsqr = np.corrcoef(test_label[:,3], test_predict[:,3])[0,1]**2

#R-squared with previous day
Rsqr2 = np.corrcoef(test_label[1:,3], test_label[:-1,3])[0,1]**2
#plot them
fig,ax=plt.subplots()
ax.plot(test_predict[offset:,3]*adj['SNOW'],label=f"Predicted Data, R-Squared: {Rsq
ax.plot(test_label[:,3]*adj['SNOW'],label=f"True Test Data, R-Squared previous day:
ax.set_title("Weather Prediction: daily SNOW")
ax.set_xlabel("Sample #")
ax.set_ylabel("SNOW (mm))")
ax.legend();
```



```
#For SNWD
#R-squared with true values
Rsqr = np.corrcoef(test_label[:,4], test_predict[:,4])[0,1]**2

#R-squared with previous day
Rsqr2 = np.corrcoef(test_label[1:,4], test_label[:-1,4])[0,1]**2
#plot them
fig,ax=plt.subplots()
ax.plot(test_predict[offset:,4]*adj['SNWD'],label=f"Predicted Data, R-Squared: {Rsq
ax.plot(test_label[:,4]*adj['SNWD'],label=f"True Test Data, R-Squared previous day:
ax.set_title("Weather Prediction: daily SNWD")
ax.set_xlabel("Sample #")
ax.set_ylabel("SNWD (mm))")
ax.legend();
```



Task VIII. continued

The key results of different runs were recorded in Excel, but are shown at the end of this notebook.

```
#gamma model
model=keras.models.Sequential()
model.add(keras.layers.LSTM(256,input_shape=(n_ts,dly_10.shape[1]),return_sequences
model.add(keras.layers.Conv1D(32, (10), activation='relu', input_shape=(None, 365,
model.add(keras.layers.LSTM(256,activation='relu'))
model.add(keras.layers.Dropout(0.20))
model.add(keras.layers.Dense(64,activation='relu'))
model.add(keras.layers.Dropout(0.20))
model.add(keras.layers.Dense(dly_10.shape[1],activation="linear"))
model.compile(loss='mean_squared_error',optimizer='adam')
model.summary()
```

```
Model: "sequential_7"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 lstm_14 (LSTM)              (None, 30, 256)           304128

 conv1d (Conv1D)             (None, 21, 32)            81952

 lstm_15 (LSTM)              (None, 256)               295936

 dense_14 (Dense)            (None, 64)                16448
 dense_15 (Dense)            (None, 40)                2600

=================================================================
Total params: 701,064
Trainable params: 701,064
Non-trainable params: 0
_________________________________________________________________
```

```
#delta model
model=keras.models.Sequential()
model.add(keras.layers.LSTM(256,input_shape=(n_ts,dly_10.shape[1]),return_sequences
#model.add(keras.layers.Conv1D(32, (10), activation='relu', input_shape=(None, 365,
model.add(keras.layers.LSTM(256,activation='relu'))
model.add(keras.layers.Dropout(0.20))
model.add(keras.layers.Dense(64,activation='relu'))
model.add(keras.layers.Dropout(0.20))
model.add(keras.layers.Dense(dly_10.shape[1],activation="linear"))
model.compile(loss='mean_squared_error',optimizer='adam')
model.summary()
```

```
Model: "sequential_8"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 lstm_16 (LSTM)              (None, 30, 256)           304128

 lstm_17 (LSTM)              (None, 256)               525312

 dropout (Dropout)           (None, 256)               0

 dense_16 (Dense)            (None, 64)                16448

 dropout_1 (Dropout)         (None, 64)                0

 dense_17 (Dense)            (None, 40)                2600

=================================================================
Total params: 848,488
Trainable params: 848,488
Non-trainable params: 0
_________________________________________________________________
```

```
#epsilon model
model=keras.models.Sequential()
model.add(keras.layers.LSTM(256,input_shape=(n_ts,dly_10.shape[1]),return_sequences
model.add(keras.layers.Conv1D(32, (10), activation='relu', input_shape=(None, 365,
model.add(keras.layers.LSTM(256,activation='relu'))
#model.add(keras.layers.Dropout(0.20))
model.add(keras.layers.Dense(64,activation='relu'))
#model.add(keras.layers.Dropout(0.20))
model.add(keras.layers.Dense(dly_10.shape[1],activation="linear"))
model.compile(loss='mean_squared_error',optimizer='adam')
model.summary()
```

```
Model: "sequential_9"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 lstm_18 (LSTM)              (None, 30, 256)           304128

 conv1d_1 (Conv1D)           (None, 21, 32)            81952

 lstm_19 (LSTM)              (None, 256)               295936

 dense_18 (Dense)            (None, 64)                16448

 dense_19 (Dense)            (None, 40)                2600

=================================================================
Total params: 701,064
Trainable params: 701,064
Non-trainable params: 0
_________________________________________________________________
```

Task VIII. continued

Now it was decided to see if the results would change by just using the single station. That had not been tried before and was done for completeness and using the same date range as for four stations. Much of the following code is very similar to that already used.

```
#For Colorado- replicating earlier cells so can run separately instead of re-runnin
filename = 'USW00023066.dly'
dly = read_ghcn_data_file(filename=filename)
#drop MFLAG and QFLAG column
dly.drop(('MFLAG'), axis = 1, inplace = True)
dly.drop(('QFLAG'), axis = 1, inplace = True)

#drop VAR_TYPE column hierarchy as no longer needed
dly_10 = dly.droplevel('VAR_TYPE',axis= 1)

#select the desired 10 columns
dly_10 = dly_10[['TMAX', 'TMIN', 'PRCP', 'SNOW', 'SNWD', 'AWND', 'WDF2', 'WDF5','WS
dly_10 = dly_10[dly_10.index >= '1996-04-01 00:00:00']

dly_10.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 8994 entries, 1996-04-01 to 2020-11-14
Data columns (total 10 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   TMAX    8994 non-null   float64
 1   TMIN    8994 non-null   float64
 2   PRCP    8994 non-null   float64
 3   SNOW    8993 non-null   float64
 4   SNWD    8992 non-null   float64
 5   AWND    8988 non-null   float64
 6   WDF2    8991 non-null   float64
 7   WDF5    8974 non-null   float64
 8   WSF2    8991 non-null   float64
 9   WSF5    8974 non-null   float64
dtypes: float64(10)
memory usage: 772.9 KB
```

```
#fill forward and replace extreme value as before
dly_10.fillna(method='ffill', inplace = True)
av = np.mean([76,103,94,98])
#replace 4095.0 with av
#NB is safe to do so as 4095.0 is outside ranges of all other elements
dly_10.replace(4095.0, av, inplace = True)
dly_10.describe()
```

ELEMENT	TMAX	TMIN	PRCP	SNOW	SNWD	AWND
count	8994.000000	8994.000000	8994.000000	8994.000000	8994.000000	8994.000000
mean	19.324194	4.649922	0.627374	1.210140	4.365577	33.157216
std	11.837798	9.713334	2.180278	8.323179	18.854957	13.591177
min	-11.700000	-26.700000	0.000000	0.000000	0.000000	3.000000
25%	9.400000	-2.800000	0.000000	0.000000	0.000000	23.000000
50%	20.000000	4.400000	0.000000	0.000000	0.000000	31.000000
75%	30.000000	13.300000	0.000000	0.000000	0.000000	41.000000
max	41.100000	25.600000	33.300000	183.000000	203.000000	105.000000

```
dly_10, adj = normalise(dly_10)
```

```
offset=0#predict one day forward
n_ts=365 #1 years of daily data for training
nn_df=make_offset_dataframe(dly_10,n_ts,offset)
nn_df.dropna(axis=0, inplace=True)#lose rows with NaN
#check
nn_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 8629 entries, 1997-04-01 to 2020-11-14
Columns: 3660 entries, (0, 'TMAX') to ('label', 'WSF5')
dtypes: float64(3660)
memory usage: 241.0 MB
```

```
nn_df.describe()
```

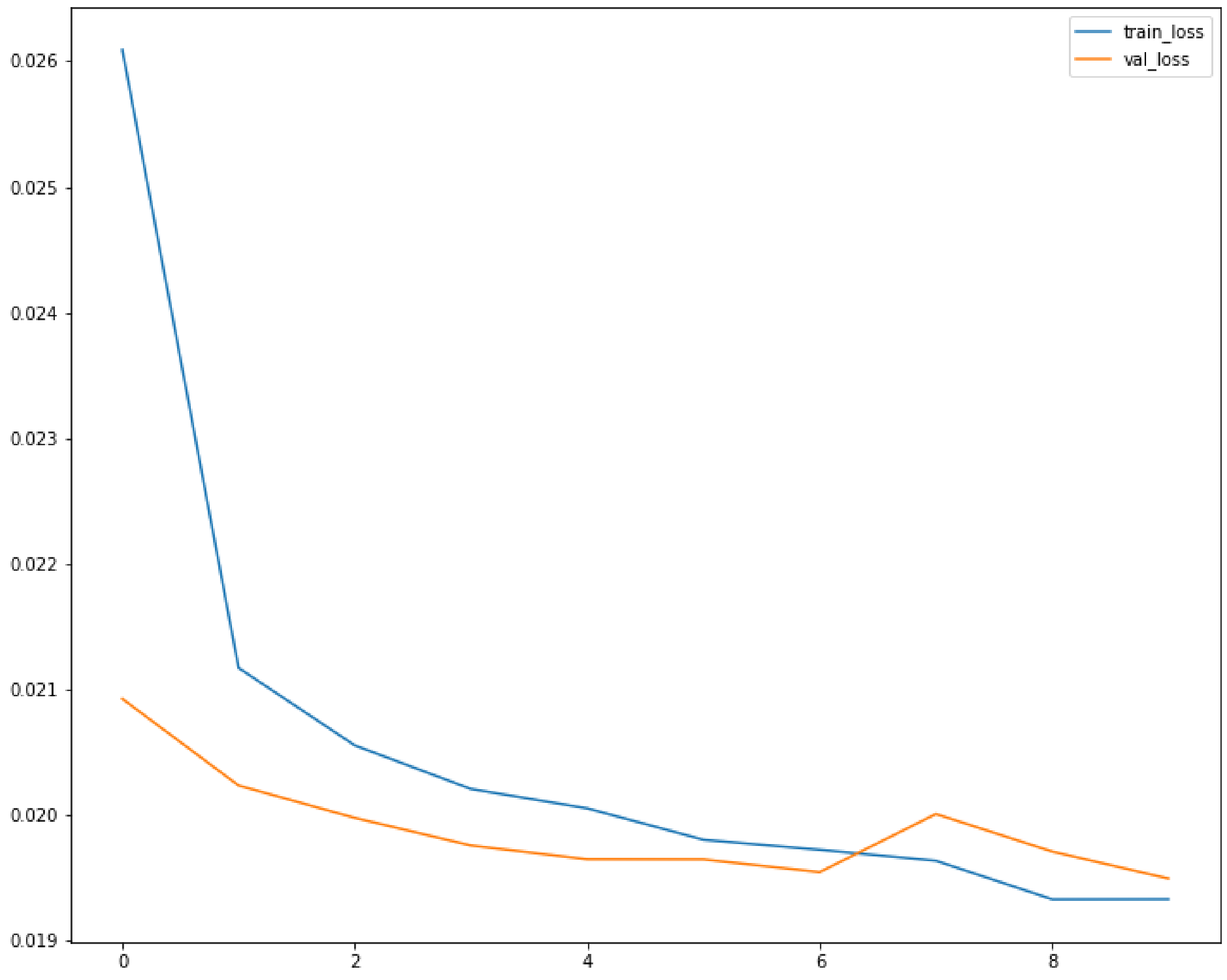
	0	1	2	3	4	5	6
	TMAX	TMAX	TMAX	TMAX	TMAX	TMAX	TM
count	8629.000000	8629.000000	8629.000000	8629.000000	8629.000000	8629.000000	86
mean	0.469437	0.469410	0.469390	0.469383	0.469380	0.469369	
std	0.287337	0.287335	0.287337	0.287339	0.287340	0.287344	
min	-0.284672	-0.284672	-0.284672	-0.284672	-0.284672	-0.284672	
25%	0.228710	0.228710	0.228710	0.228710	0.228710	0.228710	
50%	0.472019	0.472019	0.472019	0.472019	0.472019	0.472019	
75%	0.729927	0.729927	0.729927	0.729927	0.729927	0.729927	
max	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	

```
#alpha model
model=keras.models.Sequential()
model.add(keras.layers.LSTM(64,input_shape=(n_ts,dly_10.shape[1]),return_sequences=
model.add(keras.layers.LSTM(32,activation='relu'))
model.add(keras.layers.Dense(32,activation='relu'))
model.add(keras.layers.Dense(dly_10.shape[1],activation="linear"))
model.compile(loss='mean_squared_error',optimizer='adam')
model.summary()

history=model.fit(train_data,train_label,epochs=10,batch_size=10,verbose=1,validati
```

```
train_data (5177, 365, 10)
val_data (1726, 365, 10)
test_data (1726, 365, 10)
Model: "sequential_1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 lstm_2 (LSTM)               (None, 365, 64)           19200

 lstm_3 (LSTM)               (None, 32)                12416

 dense_2 (Dense)             (None, 32)                1056

 dense_3 (Dense)             (None, 10)                330

=================================================================
Total params: 33,002
Trainable params: 33,002
Non-trainable params: 0
_________________________________________________________________
Epoch 1/10
518/518 [==============================] - 149s 282ms/step - loss: 0.0261 - va
Epoch 2/10
518/518 [==============================] - 146s 282ms/step - loss: 0.0212 - va
Epoch 3/10
518/518 [==============================] - 145s 280ms/step - loss: 0.0206 - va
Epoch 4/10
518/518 [==============================] - 144s 278ms/step - loss: 0.0202 - va
```

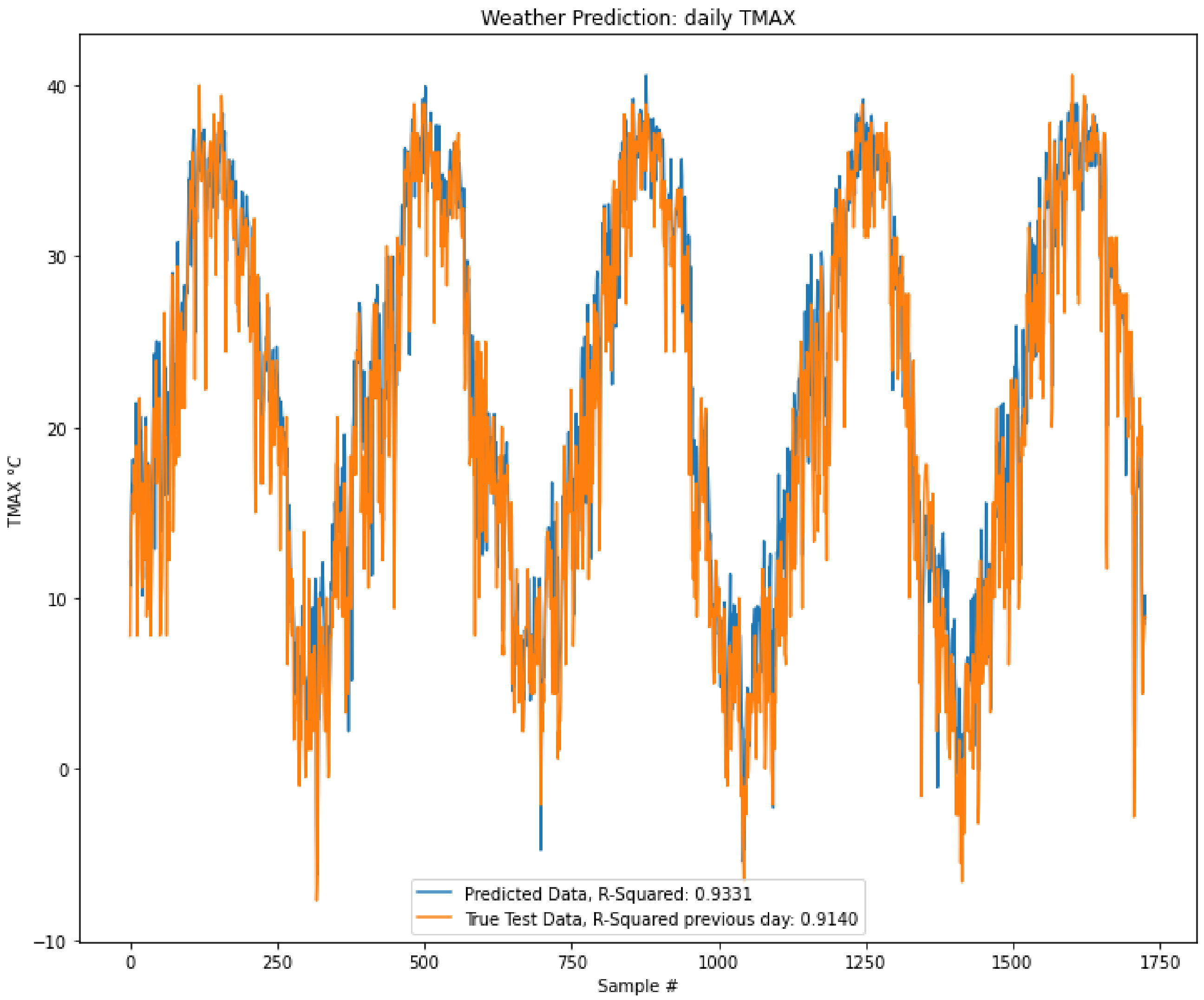
```
Epoch 5/10
518/518 [==============================] - 145s 279ms/step - loss: 0.0201 - va
Epoch 6/10
518/518 [==============================] - 144s 278ms/step - loss: 0.0198 - va
Epoch 7/10
518/518 [==============================] - 147s 284ms/step - loss: 0.0197 - va
Epoch 8/10
518/518 [==============================] - 148s 286ms/step - loss: 0.0196 - va
Epoch 9/10
518/518 [==============================] - 148s 285ms/step - loss: 0.0193 - va
Epoch 10/10
518/518 [==============================] - 147s 284ms/step - loss: 0.0193 - va
```

```
fig,ax=plt.subplots()
ax.plot(history.history['loss'], label='train_loss')
ax.plot(history.history['val_loss'], label='val_loss')
ax.set_title = 'Loss of the model'
ax.xlabel = 'Time (Epochs)'
ax.ylabel = 'Loss'
ax.legend();
```



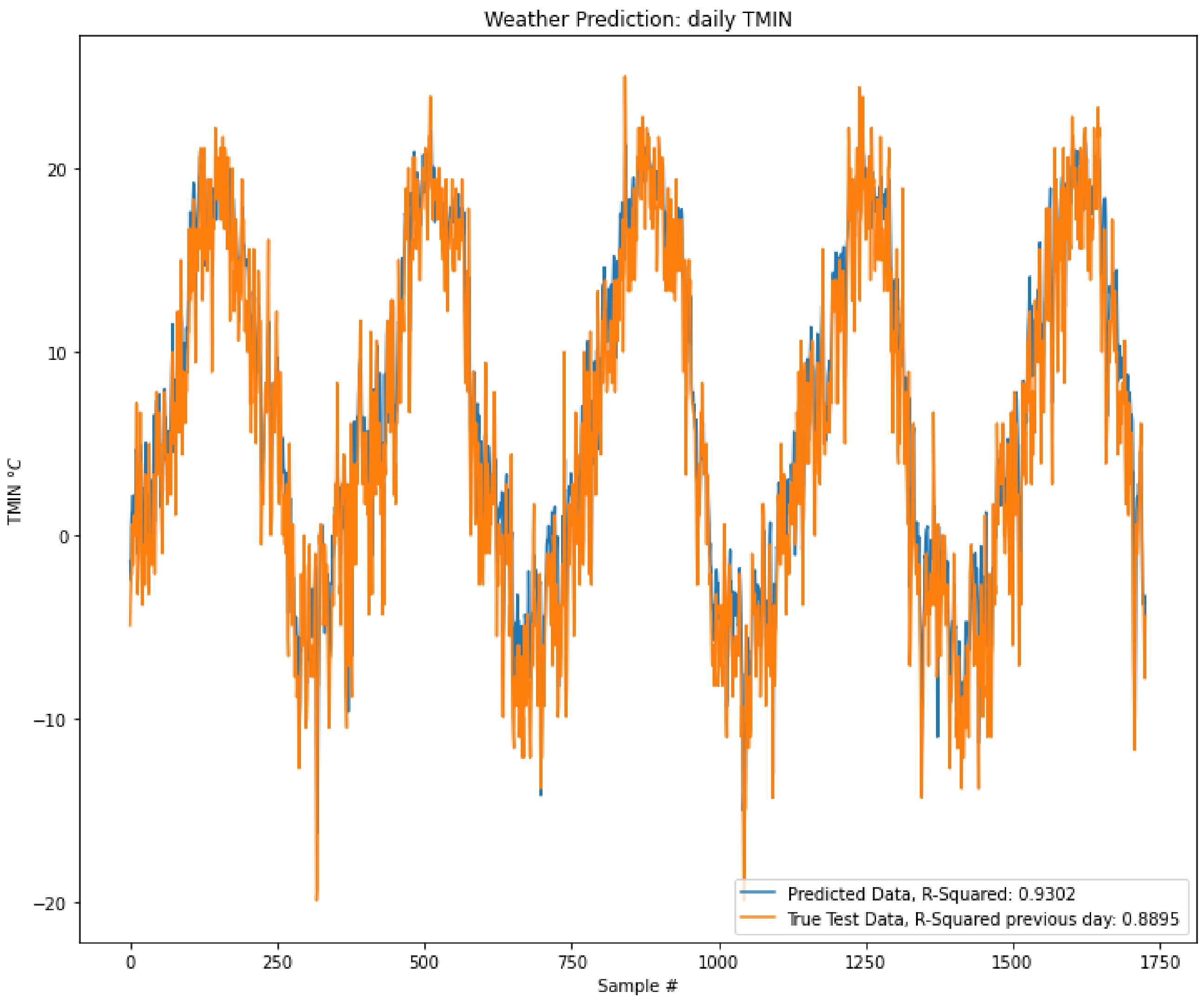
```
#test predictions
test_predict=model.predict(test_data)
```

```
#For TMAX
#R-squared with true values
Rsqr = np.corrcoef(test_label[:,0], test_predict[:,0])[0,1]**2

#R-squared with previous day
Rsqr2 = np.corrcoef(test_label[1:,0], test_label[:-1,0])[0,1]**2

#plot them
fig,ax=plt.subplots()
ax.plot(test_predict[offset:,0]*adj['TMAX'],label=f"Predicted Data, R-Squared: {Rsq
ax.plot(test_label[:,0]*adj['TMAX'],label=f"True Test Data, R-Squared previous day:
ax.set_title("Weather Prediction: daily TMAX")
ax.set_xlabel("Sample #")
ax.set_ylabel("TMAX $\degree C$")
ax.legend();
```



```
#For TMIN
#R-squared with true values
Rsqr = np.corrcoef(test_label[:,1], test_predict[:,1])[0,1]**2

#R-squared with previous day
```

```
Rsqr2 = np.corrcoef(test_label[1:,1], test_label[:-1,1])[0,1]**2
#plot them
fig,ax=plt.subplots()
ax.plot(test_predict[offset:,1]*adj['TMIN'],label=f"Predicted Data, R-Squared: {Rsq
ax.plot(test_label[:,1]*adj['TMIN'],label=f"True Test Data, R-Squared previous day:
ax.set_title("Weather Prediction: daily TMIN")
ax.set_xlabel("Sample #")
ax.set_ylabel("TMIN $\degree C$")
ax.legend();
```



Task VIII.

Now this was repeated only using just the two temperature elements.

```
#For Colorado- replicating earlier cells so can run separately instead of re-runnin
filename = 'USW00023066.dly'
dly = read_ghcn_data_file(filename=filename)
#drop MFLAG and QFLAG column
dly.drop(('MFLAG'), axis = 1, inplace = True)
dly.drop(('QFLAG'), axis = 1, inplace = True)

#drop VAR_TYPE column hierarchy as no longer needed
dly_10 = dly.droplevel('VAR_TYPE',axis= 1)

#select the desired 10 columns
dly_10 = dly_10[['TMAX', 'TMIN']]
dly_10 = dly_10[dly_10.index >= '1996-04-01 00:00:00']

dly_10.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 8994 entries, 1996-04-01 to 2020-11-14
Data columns (total 2 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   TMAX    8994 non-null   float64
 1   TMIN    8994 non-null   float64
dtypes: float64(2)
memory usage: 210.8 KB
```

```
dly_10.describe()
```

ELEMENT	TMAX	TMIN
count	8994.000000	8994.000000
mean	19.324194	4.649922
std	11.837798	9.713334
min	-11.700000	-26.700000
25%	9.400000	-2.800000
50%	20.000000	4.400000
75%	30.000000	13.300000
max	41.100000	25.600000

```
dly_10, adj = normalise(dly_10)
```

```
offset=0#predict one day forward
n_ts=365 #1 years of daily data for training
nn_df=make_offset_dataframe(dly_10,n_ts,offset)
nn_df.dropna(axis=0, inplace=True)#lose rows with NaN
#check
nn_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 8629 entries, 1997-04-01 to 2020-11-14
Columns: 732 entries, (0, 'TMAX') to ('label', 'TMIN')
dtypes: float64(732)
memory usage: 48.3 MB
```

```
nn_df.describe()
```

	0	1	2	3	4	5	6
	TMAX	TMAX	TMAX	TMAX	TMAX	TMAX	TM
count	8629.000000	8629.000000	8629.000000	8629.000000	8629.000000	8629.000000	86
mean	0.469437	0.469410	0.469390	0.469383	0.469380	0.469369	
std	0.287337	0.287335	0.287337	0.287339	0.287340	0.287344	
min	-0.284672	-0.284672	-0.284672	-0.284672	-0.284672	-0.284672	
25%	0.228710	0.228710	0.228710	0.228710	0.228710	0.228710	
50%	0.472019	0.472019	0.472019	0.472019	0.472019	0.472019	
75%	0.729927	0.729927	0.729927	0.729927	0.729927	0.729927	
max	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	

8 rows × 732 columns

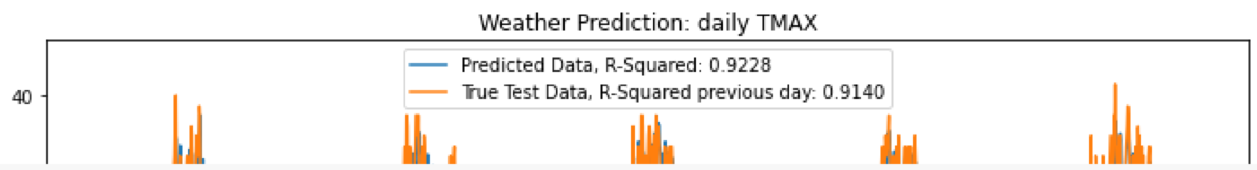
```
train_data, val_data, test_data, train_label, val_label, test_label = dataset_split

#alpha model
model=keras.models.Sequential()
model.add(keras.layers.LSTM(64,input_shape=(n_ts,dly_10.shape[1]),return_sequences=
model.add(keras.layers.LSTM(32,activation='relu'))
model.add(keras.layers.Dense(32,activation='relu'))
model.add(keras.layers.Dense(dly_10.shape[1],activation="linear"))
model.compile(loss='mean_squared_error',optimizer='adam')
model.summary()

history=model.fit(train_data,train_label,epochs=10,batch_size=10,verbose=1,validati
```

```
train_data (5177, 365, 2)
val_data (1726, 365, 2)
test_data (1726, 365, 2)
Model: "sequential_2"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 lstm_4 (LSTM)               (None, 365, 64)           17152

 lstm_5 (LSTM)               (None, 32)                12416

 dense_4 (Dense)             (None, 32)                1056

 dense_5 (Dense)             (None, 2)                 66

=================================================================
Total params: 30,690
```

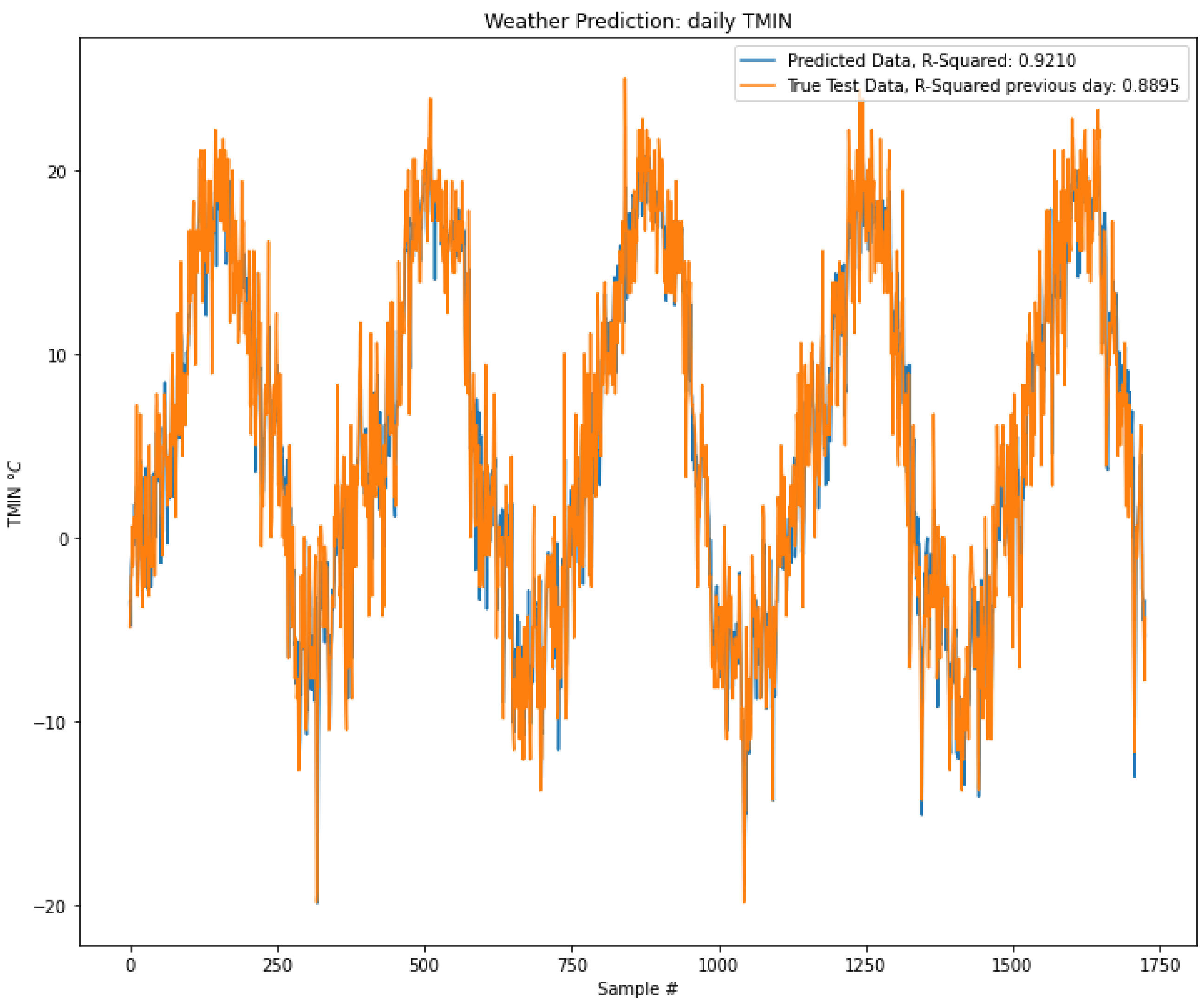
```
Trainable params: 30,690
Non-trainable params: 0
_________________________________________________________________
Epoch 1/10
518/518 [==============================] - 149s 282ms/step - loss: 0.0209 - va
Epoch 2/10
518/518 [==============================] - 145s 279ms/step - loss: 0.0121 - va
Epoch 3/10
518/518 [==============================] - 144s 279ms/step - loss: 0.0097 - va
Epoch 4/10
518/518 [==============================] - 143s 276ms/step - loss: 0.0091 - va
Epoch 5/10
518/518 [==============================] - 145s 280ms/step - loss: 0.0089 - va
Epoch 6/10
518/518 [==============================] - 144s 279ms/step - loss: 0.0087 - va
Epoch 7/10
518/518 [==============================] - 143s 277ms/step - loss: 0.0086 - va
Epoch 8/10
518/518 [==============================] - 143s 275ms/step - loss: 0.0086 - va
Epoch 9/10
518/518 [==============================] - 144s 278ms/step - loss: 0.0084 - va
Epoch 10/10
518/518 [==============================] - 144s 278ms/step - loss: 0.0084 - va
```

```
fig,ax=plt.subplots()
ax.plot(history.history['loss'], label='train_loss')
ax.plot(history.history['val_loss'], label='val_loss')
ax.set_title = 'Loss of the model'
ax.xlabel = 'Time (Epochs)'
ax.ylabel = 'Loss'
ax.legend();
```

```
#test predictions
test_predict=model.predict(test_data)

#For TMAX
#R-squared with true values
Rsqr = np.corrcoef(test_label[:,0], test_predict[:,0])[0,1]**2

#R-squared with previous day
Rsqr2 = np.corrcoef(test_label[1:,0], test_label[:-1,0])[0,1]**2

#plot them
fig,ax=plt.subplots()
ax.plot(test_predict[offset:,0]*adj['TMAX'],label=f"Predicted Data, R-Squared: {Rsq
ax.plot(test_label[:,0]*adj['TMAX'],label=f"True Test Data, R-Squared previous day:
ax.set_title("Weather Prediction: daily TMAX")
ax.set_xlabel("Sample #")
ax.set_ylabel("TMAX $\degree C$")
ax.legend();
```



```
#For TMIN
#R-squared with true values
Rsqr = np.corrcoef(test_label[:,1], test_predict[:,1])[0,1]**2

#R-squared with previous day
Rsqr2 = np.corrcoef(test_label[1:,1], test_label[:-1,1])[0,1]**2
#plot them
fig,ax=plt.subplots()
ax.plot(test_predict[offset:,1]*adj['TMIN'],label=f"Predicted Data, R-Squared: {Rsq
ax.plot(test_label[:,1]*adj['TMIN'],label=f"True Test Data, R-Squared previous day:
ax.set_title("Weather Prediction: daily TMIN")
ax.set_xlabel("Sample #")
ax.set_ylabel("TMIN $\degree C$")
ax.legend();
```



Task VIII. continued.

As final test, it was decided to run four stations, 2 features and 30 days.

Four stations, 2 feaures, 30 days.

```
#For Colorado- replicating earlier cells so can run separately instead of re-runnin
filename = 'USW00023066.dly'
dly = read_ghcn_data_file(filename=filename)
#drop MFLAG and QFLAG column
dly.drop(('MFLAG'), axis = 1, inplace = True)
dly.drop(('QFLAG'), axis = 1, inplace = True)

#drop VAR_TYPE column hierarchy as no longer needed
dly_10 = dly.droplevel('VAR_TYPE',axis= 1)

#select the desired 10 columns
dly_10 = dly_10[['TMAX', 'TMIN']]
dly_10 = dly_10[dly_10.index >= '1996-04-01 00:00:00']

dly_10.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 8994 entries, 1996-04-01 to 2020-11-14
Data columns (total 2 columns):
 #   Column  Non-Null Count  Dtype  
---  ------  --------------  -----  
 0   TMAX    8994 non-null   float64
 1   TMIN    8994 non-null   float64
dtypes: float64(2)
memory usage: 210.8 KB
```

```
#For Oklahoma
filename = 'USW00013967.dly'
dlyOK = read_ghcn_data_file(filename=filename)
#drop MFLAG and QFLAG column
dlyOK.drop(('MFLAG'), axis = 1, inplace = True)
dlyOK.drop(('QFLAG'), axis = 1, inplace = True)

#drop VAR_TYPE column hierarchy as no longer needed
dlyOK_10 = dlyOK.droplevel('VAR_TYPE',axis= 1)

#select the desired 10 columns
dlyOK_10 = dlyOK_10[['TMAX', 'TMIN']]
dlyOK_10 = dlyOK_10[dlyOK_10.index >= '1996-04-01 00:00:00']

dlyOK_10.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 8990 entries, 1996-04-01 to 2020-11-14
Data columns (total 2 columns):
 #   Column  Non-Null Count  Dtype  
---  ------  --------------  -----  
```

```
 0   TMAX    8990 non-null   float64
 1   TMIN    8990 non-null   float64
dtypes: float64(2)
memory usage: 210.7 KB
```

```
#For New Mexico
filename = 'USW00023050.dly'
dlyNM = read_ghcn_data_file(filename=filename)
#drop MFLAG and QFLAG column
dlyNM.drop(('MFLAG'), axis = 1, inplace = True)
dlyNM.drop(('QFLAG'), axis = 1, inplace = True)

#drop VAR_TYPE column hierarchy as no longer needed
dlyNM_10 = dlyNM.droplevel('VAR_TYPE',axis= 1)

#select the desired 10 columns
dlyNM_10 = dlyNM_10[['TMAX', 'TMIN']]
dlyNM_10 = dlyNM_10[dlyNM_10.index >= '1996-04-01 00:00:00']

dlyNM_10.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 8990 entries, 1996-04-01 to 2020-11-14
Data columns (total 2 columns):
 #   Column  Non-Null Count  Dtype  
---  ------  --------------  -----  
 0   TMAX    8990 non-null   float64
 1   TMIN    8990 non-null   float64
dtypes: float64(2)
memory usage: 210.7 KB
```

```
#For Nebraska
filename = 'USW00024023.dly'
dlyNE = read_ghcn_data_file(filename=filename)
#drop MFLAG and QFLAG column
dlyNE.drop(('MFLAG'), axis = 1, inplace = True)
dlyNE.drop(('QFLAG'), axis = 1, inplace = True)

#drop VAR_TYPE column hierarchy as no longer needed
dlyNE_10 = dlyNE.droplevel('VAR_TYPE',axis= 1)

#select the desired 10 columns
dlyNE_10 = dlyNE_10[['TMAX', 'TMIN']]
dlyNE_10 = dlyNE_10[dlyNE_10.index >= '1996-04-01 00:00:00']

dlyNE_10.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 8994 entries, 1996-04-01 to 2020-11-14
Data columns (total 2 columns):
 #   Column  Non-Null Count  Dtype  
---  ------  --------------  -----  
 0   TMAX    8994 non-null   float64
 1   TMIN    8994 non-null   float64
```

```
dtypes: float64(2)
memory usage: 210.8 KB
```

```
#adapted from https://www.pythonprogramming.in/how-to-add-row-to-dataframe-with-tim

for i in ['2020-10-28 00:00:00', '2020-10-29 00:00:00', '2020-10-30 00:00:00', '202
  line = pd.to_datetime(i, format="%Y-%m-%d %H:%M:%S")
  new_row = pd.DataFrame(columns=['TMAX', 'TMIN'], index=[line])
  dlyOK_10 = pd.concat([dlyOK_10, pd.DataFrame(new_row)], ignore_index=False)
  dlyNM_10 = pd.concat([dlyNM_10, pd.DataFrame(new_row)], ignore_index=False)
```

```
dlyOK_10.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 8994 entries, 1996-04-01 to 2020-10-31
Data columns (total 2 columns):
 #   Column  Non-Null Count  Dtype  
---  ------  --------------  -----  
 0   TMAX    8990 non-null   float64
 1   TMIN    8990 non-null   float64
dtypes: float64(2)
memory usage: 210.8 KB
```

```
dlyNM_10.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 8994 entries, 1996-04-01 to 2020-10-31
Data columns (total 2 columns):
 #   Column  Non-Null Count  Dtype  
---  ------  --------------  -----  
 0   TMAX    8990 non-null   float64
 1   TMIN    8990 non-null   float64
dtypes: float64(2)
memory usage: 210.8 KB
```

```
#fill forward
dlyOK_10.fillna(method='ffill', inplace = True)
dlyOK_10.describe()
```

ELEMENT	TMAX	TMIN
count	8994.000000	8994.000000
mean	22.657294	10.228664
std	10.168416	9.625214
min	-9.400000	-20.600000
25%	15.600000	2.200000
50%	23.900000	11.100000
75%	31.100000	19.400000
max	45.000000	28.900000

```
#rename so we can concatenate
dlyOK_10.rename(columns={"TMAX": "TMAXok", "TMIN": "TMINok"}, inplace=True)
dlyOK_10.head(1)
```

ELEMENT	TMAXok	TMINok
1996-04-01	19.4	2.2

```
#fill forward
dlyNM_10.fillna(method='ffill', inplace = True)
dlyNM_10.describe()
```

ELEMENT	TMAX	TMIN
count	8994.000000	8994.000000
mean	21.615944	7.894307
std	9.639201	8.680149
min	-12.800000	-21.700000
25%	13.300000	0.600000
50%	22.800000	7.800000
75%	30.000000	16.100000
max	40.600000	25.600000

```
#rename so we can concatenate
dlyNM_10.rename(columns={"TMAX": "TMAXnm", "TMIN": "TMINnm"}, inplace=True)
dlyNM_10.head(1)
```

ELEMENT	TMAXnm	TMINnm
1996-04-01	23.9	5.0

```
#fill forward
dlyNE_10.fillna(method='ffill', inplace = True)
dlyNE_10.describe()
```

ELEMENT	TMAX	TMIN
count	8994.000000	8994.000000

```
#rename so we can concatenate
dlyNE_10.rename(columns={"TMAX": "TMAXne", "TMIN": "TMINne"}, inplace=True)
dlyNE_10.head(1)
```

ELEMENT	TMAXne	TMINne
1996-04-01	20.6	0.6

75%	27.800000	11.700000

```
dly_10 = pd.concat([dly_10, dlyOK_10], axis =1)
```

```
dly_10 = pd.concat([dly_10, dlyNM_10], axis =1)
```

```
dly_10 = pd.concat([dly_10, dlyNE_10], axis =1)
```

```
dly_10.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 8994 entries, 1996-04-01 to 2020-11-14
Freq: D
Data columns (total 8 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   TMAX    8994 non-null   float64
 1   TMIN    8994 non-null   float64
 2   TMAXok  8994 non-null   float64
 3   TMINok  8994 non-null   float64
 4   TMAXnm  8994 non-null   float64
 5   TMINnm  8994 non-null   float64
 6   TMAXne  8994 non-null   float64
 7   TMINne  8994 non-null   float64
dtypes: float64(8)
memory usage: 632.4 KB
```

```
dly_10.describe()
```

ELEMENT	TMAX	TMIN	TMAXok	TMINok	TMAXnm	TMINnm
count	8994.000000	8994.000000	8994.000000	8994.000000	8994.000000	8994.000000

```
dly_10, adj = normalise(dly_10)
```

```
offset=0#predict one day forward
n_ts=30 #1 years of daily data for training
nn_df=make_offset_dataframe(dly_10,n_ts,offset)
nn_df.dropna(axis=0, inplace=True)#lose rows with NaN
#check
nn_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 8964 entries, 1996-05-01 to 2020-11-14
Freq: D
Columns: 248 entries, (0, 'TMAX') to ('label', 'TMINne')
dtypes: float64(248)
memory usage: 17.0 MB
```

```
nn_df.describe()
```

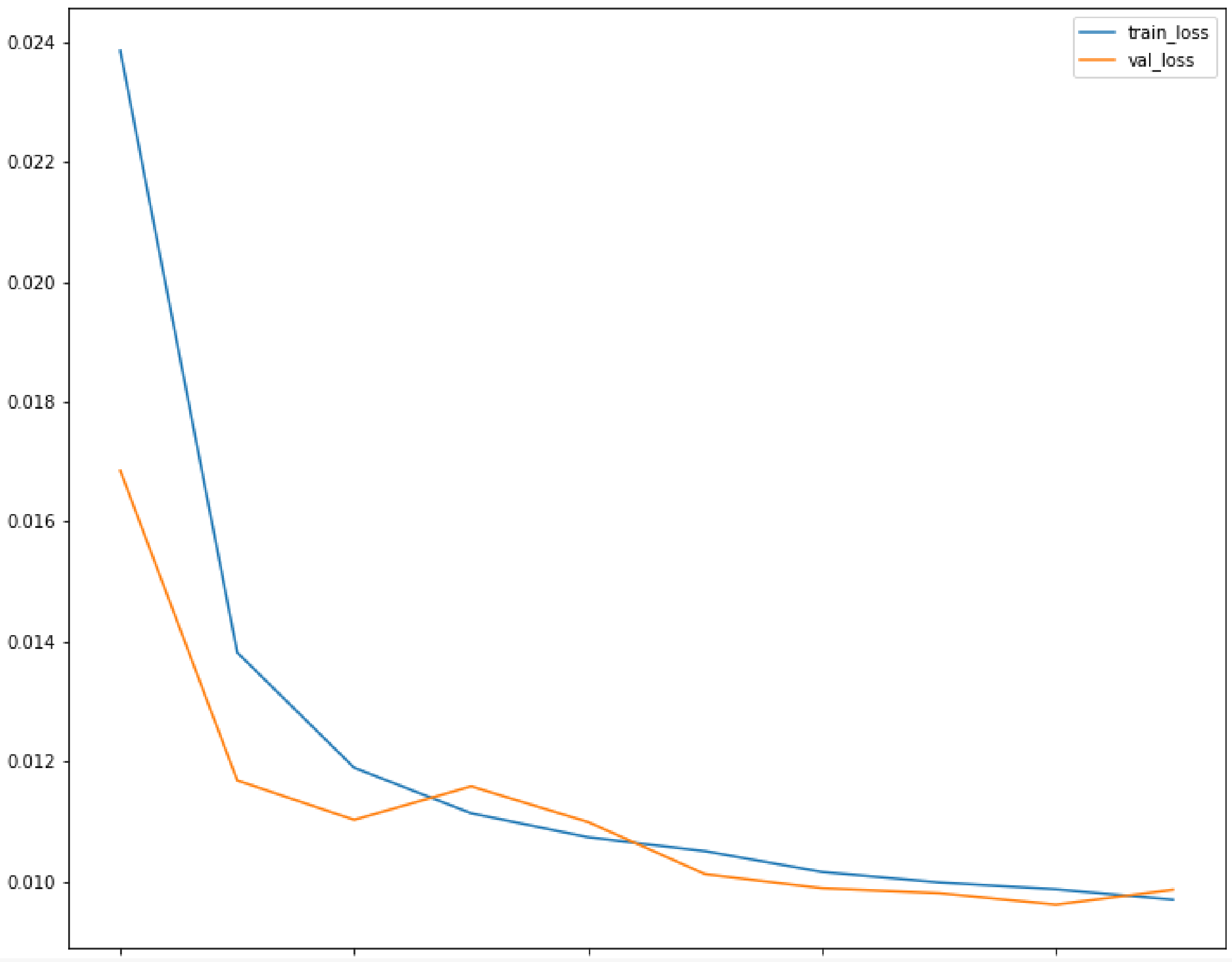
	0	1	2	3	4	5	6
	TMAX	TMAX	TMAX	TMAX	TMAX	TMAX	TM
count	8964.000000	8964.000000	8964.000000	8964.000000	8964.000000	8964.000000	89
mean	0.470499	0.470483	0.470486	0.470511	0.470529	0.470548	
std	0.288253	0.288249	0.288250	0.288254	0.288256	0.288257	
min	-0.284672	-0.284672	-0.284672	-0.284672	-0.284672	-0.284672	
25%	0.228710	0.228710	0.228710	0.228710	0.228710	0.228710	
50%	0.486618	0.486618	0.486618	0.486618	0.486618	0.486618	
75%	0.729927	0.729927	0.729927	0.729927	0.729927	0.729927	
max	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	

8 rows × 248 columns

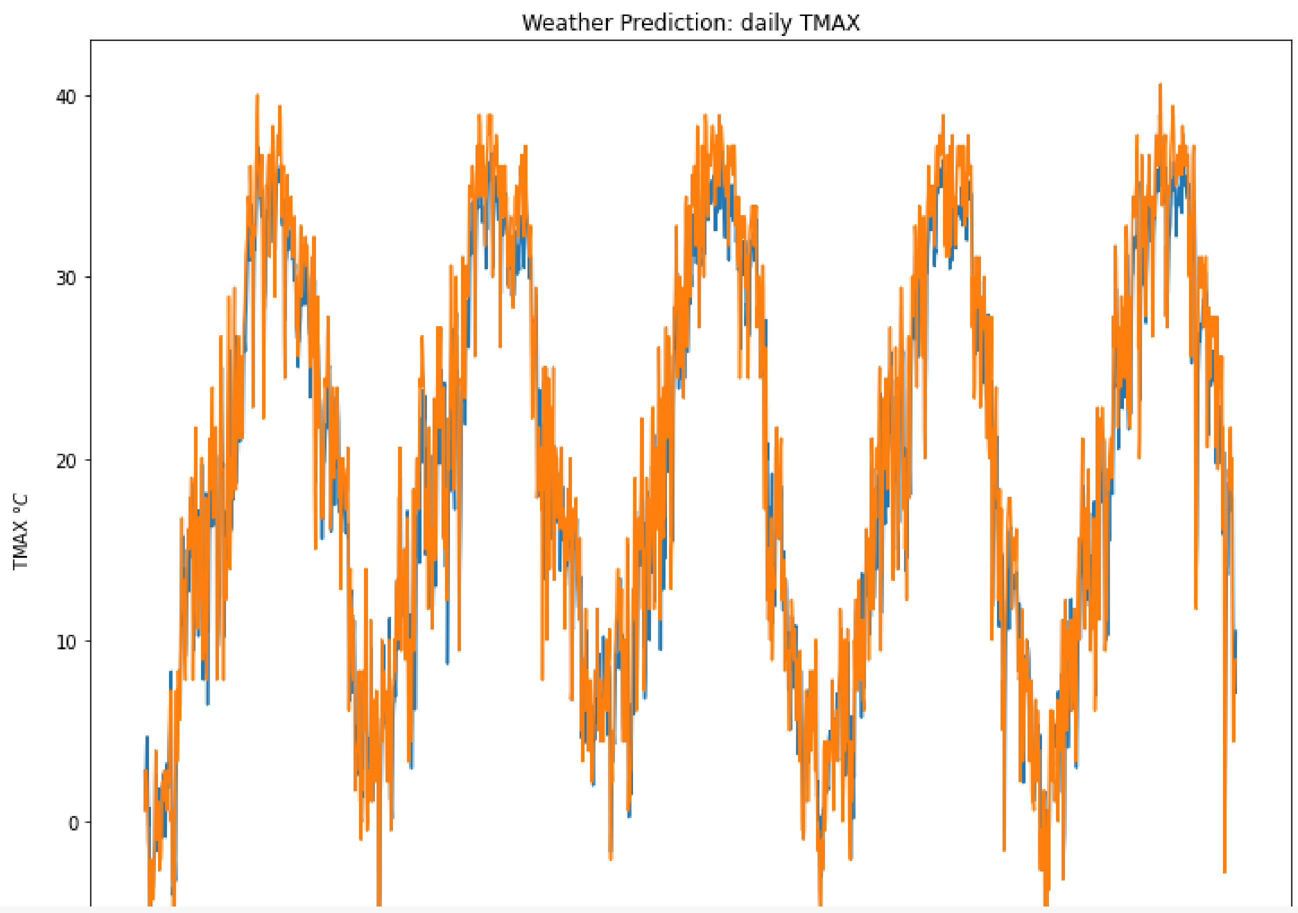
```
train_data, val_data, test_data, train_label, val_label, test_label = dataset_split

#alpha model
model=keras.models.Sequential()
model.add(keras.layers.LSTM(64,input_shape=(n_ts,dly_10.shape[1]),return_sequences=
model.add(keras.layers.LSTM(32,activation='relu'))
model.add(keras.layers.Dense(32,activation='relu'))
model.add(keras.layers.Dense(dly_10.shape[1],activation="linear"))
model.compile(loss='mean_squared_error',optimizer='adam')
model.summary()

history=model.fit(train_data,train_label,epochs=10,batch_size=10,verbose=1,validati
```

```
train_data (5378, 30, 8)
val_data (1793, 30, 8)
test_data (1793, 30, 8)
Model: "sequential_5"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 lstm_10 (LSTM)              (None, 30, 64)            18688

 lstm_11 (LSTM)              (None, 32)                12416

 dense_10 (Dense)            (None, 32)                1056

 dense_11 (Dense)            (None, 8)                 264

=================================================================
Total params: 32,424
Trainable params: 32,424
Non-trainable params: 0
_________________________________________________________________
Epoch 1/10
538/538 [==============================] - 18s 29ms/step - loss: 0.0239 - val_
Epoch 2/10
538/538 [==============================] - 15s 28ms/step - loss: 0.0138 - val_
Epoch 3/10
538/538 [==============================] - 15s 28ms/step - loss: 0.0119 - val_
Epoch 4/10
538/538 [==============================] - 15s 27ms/step - loss: 0.0111 - val_
Epoch 5/10
538/538 [==============================] - 15s 28ms/step - loss: 0.0107 - val_
Epoch 6/10
538/538 [==============================] - 15s 28ms/step - loss: 0.0105 - val_
Epoch 7/10
538/538 [==============================] - 15s 28ms/step - loss: 0.0102 - val_
Epoch 8/10
538/538 [==============================] - 15s 27ms/step - loss: 0.0100 - val_
Epoch 9/10
538/538 [==============================] - 15s 28ms/step - loss: 0.0099 - val_
Epoch 10/10
538/538 [==============================] - 15s 28ms/step - loss: 0.0097 - val_
```

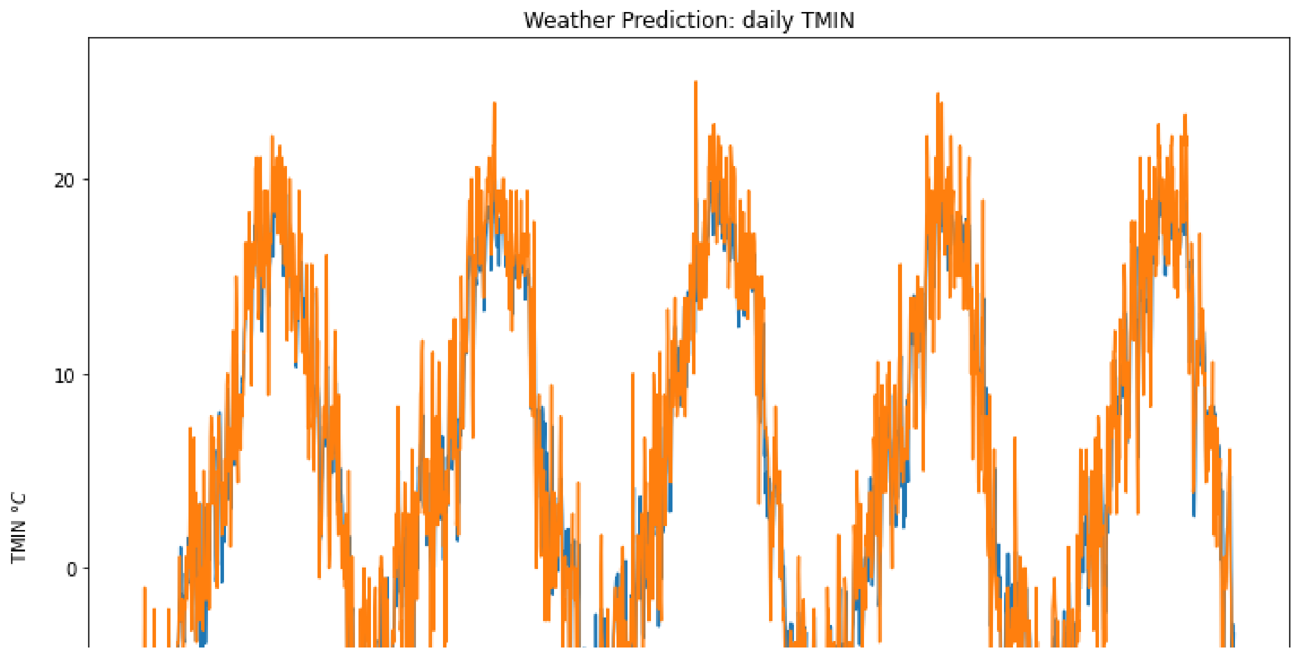
```
fig,ax=plt.subplots()
ax.plot(history.history['loss'], label='train_loss')
ax.plot(history.history['val_loss'], label='val_loss')
ax.set_title = 'Loss of the model'
ax.xlabel = 'Time (Epochs)'
ax.ylabel = 'Loss'
ax.legend();
```



```
#test predictions
test_predict=model.predict(test_data)

#For TMAX
#R-squared with true values
Rsqr = np.corrcoef(test_label[:,0], test_predict[:,0])[0,1]**2

#R-squared with previous day
Rsqr2 = np.corrcoef(test_label[1:,0], test_label[:-1,0])[0,1]**2

#plot them
fig,ax=plt.subplots()
ax.plot(test_predict[offset:,0]*adj['TMAX'],label=f"Predicted Data, R-Squared: {Rsq
ax.plot(test_label[:,0]*adj['TMAX'],label=f"True Test Data, R-Squared previous day:
ax.set_title("Weather Prediction: daily TMAX")
ax.set_xlabel("Sample #")
ax.set_ylabel("TMAX $\degree C$")
ax.legend();
```



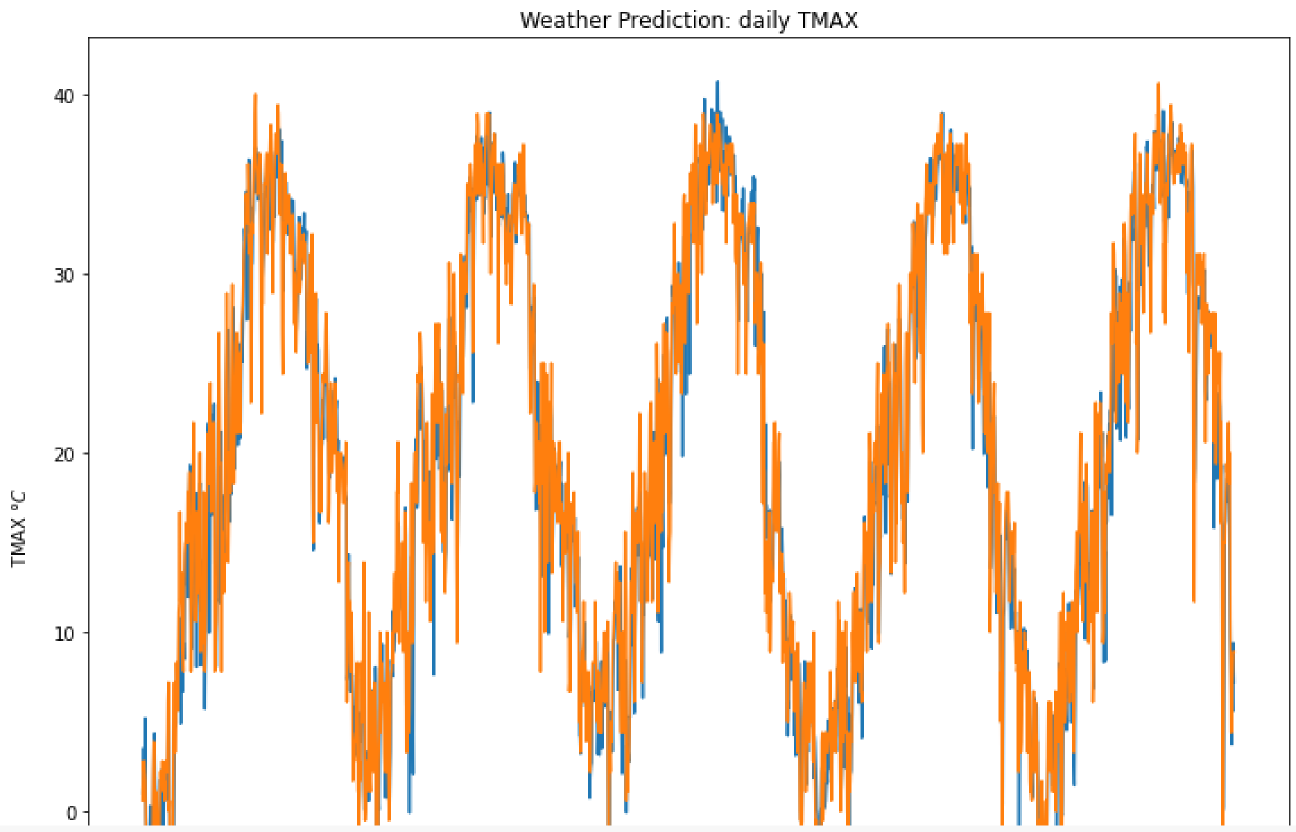
```
#For TMIN
#R-squared with true values
Rsqr = np.corrcoef(test_label[:,1], test_predict[:,1])[0,1]**2

#R-squared with previous day
Rsqr2 = np.corrcoef(test_label[1:,1], test_label[:-1,1])[0,1]**2
#plot them
fig,ax=plt.subplots()
ax.plot(test_predict[offset:,1]*adj['TMIN'],label=f"Predicted Data, R-Squared: {Rsq
ax.plot(test_label[:,1]*adj['TMIN'],label=f"True Test Data, R-Squared previous day:
ax.set_title("Weather Prediction: daily TMIN")
ax.set_xlabel("Sample #")
ax.set_ylabel("TMIN $\degree C$")
ax.legend();
```



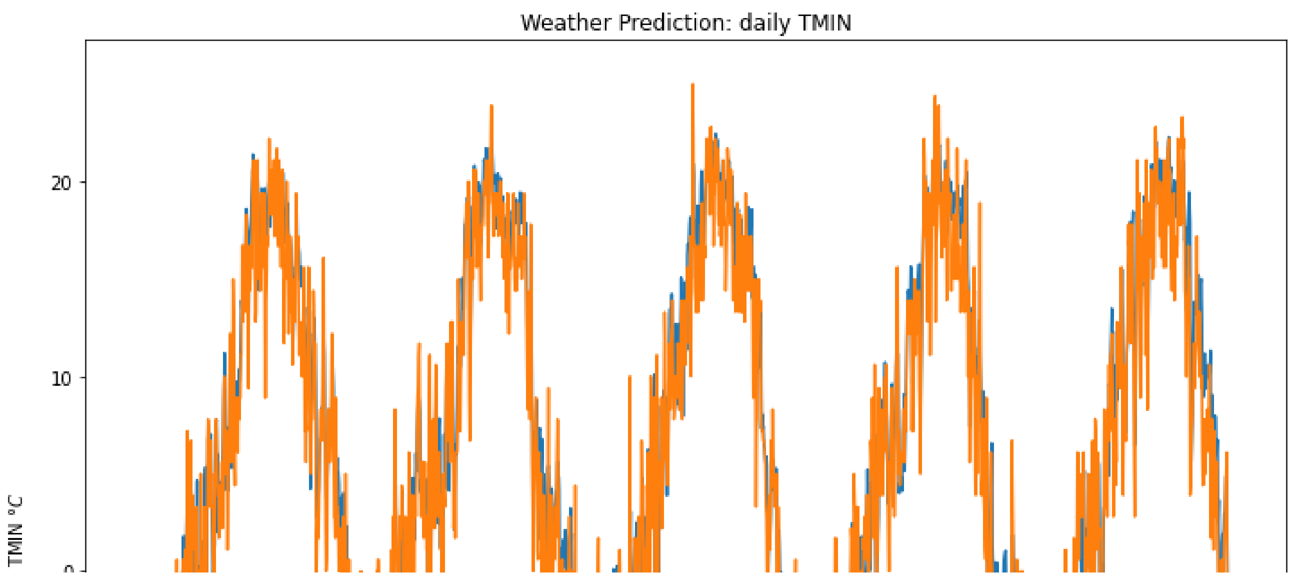
Task VIII. continued

Showing results for best combination: 1 station, 10 elements, 30 time steps, beta model. Don't run code cells as intervening steps have been deleted for brevity.

```
#test predictions
test_predict=model.predict(test_data)

#For TMAX
#R-squared with true values
Rsqr = np.corrcoef(test_label[:,0], test_predict[:,0])[0,1]**2

#R-squared with previous day
Rsqr2 = np.corrcoef(test_label[1:,0], test_label[:-1,0])[0,1]**2

#plot them
fig,ax=plt.subplots()
ax.plot(test_predict[offset:,0]*adj['TMAX'],label=f"Predicted Data, R-Squared: {Rsq
ax.plot(test_label[:,0]*adj['TMAX'],label=f"True Test Data, R-Squared previous day:
ax.set_title("Weather Prediction: daily TMAX")
ax.set_xlabel("Sample #")
ax.set_ylabel("TMAX $\degree C$")
ax.legend();
```



```
#For TMIN
#R-squared with true values
Rsqr = np.corrcoef(test_label[:,1], test_predict[:,1])[0,1]**2

#R-squared with previous day
Rsqr2 = np.corrcoef(test_label[1:,1], test_label[:-1,1])[0,1]**2
#plot them
fig,ax=plt.subplots()
ax.plot(test_predict[offset:,1]*adj['TMIN'],label=f"Predicted Data, R-Squared: {Rsq
ax.plot(test_label[:,1]*adj['TMIN'],label=f"True Test Data, R-Squared previous day:
ax.set_title("Weather Prediction: daily TMIN")
ax.set_xlabel("Sample #")
ax.set_ylabel("TMIN $\degree C$")
ax.legend();
```



Task VIII. continued.

Results were recorded in excel and are shown below for completeness

```
results_order = ['stations', 'elements', 'timesteps', 'model', 'TMAX_RSqr', 'TMIN_R

results = [[4,2,30, 'alpha', 0.9286, 0.9288],
           [4,10,30, 'alpha', 0.9389, 0.9258],
           [4,10,365, 'alpha', 0.9322, 0.9204],
           [4,10,30,'beta', 0.9377, 0.9284],
           [4,10,30, 'gamma', 0.9158, 0.9105],
           [4,10,30, 'delta', 0.9302, 0.9195],
           [4,10,30, 'epsilon', 0.9364, 0.9210],
           [1,2,7,'alpha',0.9281,0.9248],
           [1,2,30,'alpha', 0.9291,0.9247],
           [1,2,365,'alpha', 0.9228,0.9210],
           [1,10,30, 'alpha', 0.9418,0.9330],
           [1,10,365, 'alpha', 0.9331,0.9302],
           [1,10,30, 'beta', 0.9443,0.9329]]
```

Task VIII. Conclusions

All models improved on today predicting tomorrow's temperature.

30 days seemed to be the best of number of time steps tested.

Increasing number of elements from just temperature to include,

precipitation, snow and wind data brought the largest improvement.

Increasing to include data from 3 neighbouring stations worsened the model.

Increasing he width of layers in networks increased performance slightly.

Beta was the best model tested, but did not improve much over the original and simpler alpha model.

Adding in CNN and Dropout layers was unsuccessful and worsened performance.

Task IX. Check the notebook for any opportunities to simplify. Make sure to annotate fully and with supporting text cells.

This has been checked and code streamlined by adding in functions, for example, normalise, dataset_split.