Climate Data Time-Series

You are again moving to another role, not at *The Weather Channel*, where you are ask to create a Weather Forecasting Model.

For that, you will be using *Jena Climate* dataset recorded by the *Max Planck Institute for Biogeochemistry*.

The dataset consists of 14 features such as temperature, pressure, humidity etc, recorded **once per 10 minutes**.

Location: Weather Station, Max Planck Institute for Biogeochemistry in Jena, Germany

Time-frame Considered: **Jan 10, 2009 - December 31, 2012**

Library Imports

In [1]:
```
import pandas as pd
import matplotlib.pyplot as plt
import keras
```

1) Load your data

Your data can be found on the Deep Learning Module under a file named: climate_data_2009_2012.csv

In [2]:
```

df = pd.read_csv("/content/climate_data_2009_2012.csv")
```

2) Data engineering

You are given 3 lists:

- titles: Display names of your columns
- feature_keys: Names of the columns used as features
- colors: The color to use when ploting that column's value

In [3]:
```
titles = [
    "Pressure",
    "Temperature",
    "Temperature in Kelvin",
    "Temperature (dew point)",
    "Relative Humidity",
    "Saturation vapor pressure",
    "Vapor pressure",
    "Vapor pressure deficit",
    "Specific humidity",
    "Water vapor concentration",
    "Airtight",
    "Wind speed",
    "Maximum wind speed",
    "Wind direction in degrees",
]

feature_keys = [
    "p (mbar)",
    "T (degC)",
    "Tpot (K)",
    "Tdew (degC)",
    "rh (%)",
    "VPmax (mbar)",
    "VPact (mbar)",
    "VPdef (mbar)",
    "sh (g/kg)",
    "H2OC (mmol/mol)",
    "rho (g/m**3)",
    "wv (m/s)",
    "max. wv (m/s)",
    "wd (deg)",
]

colors = [
    "blue",
    "orange",
    "green",
    "red",
    "purple",
    "brown",
    "pink",
    "gray",
    "olive",
    "cyan",
]
```

Let's look at the climate data:

In [4]:
```
df.head()
```

Out[4]:

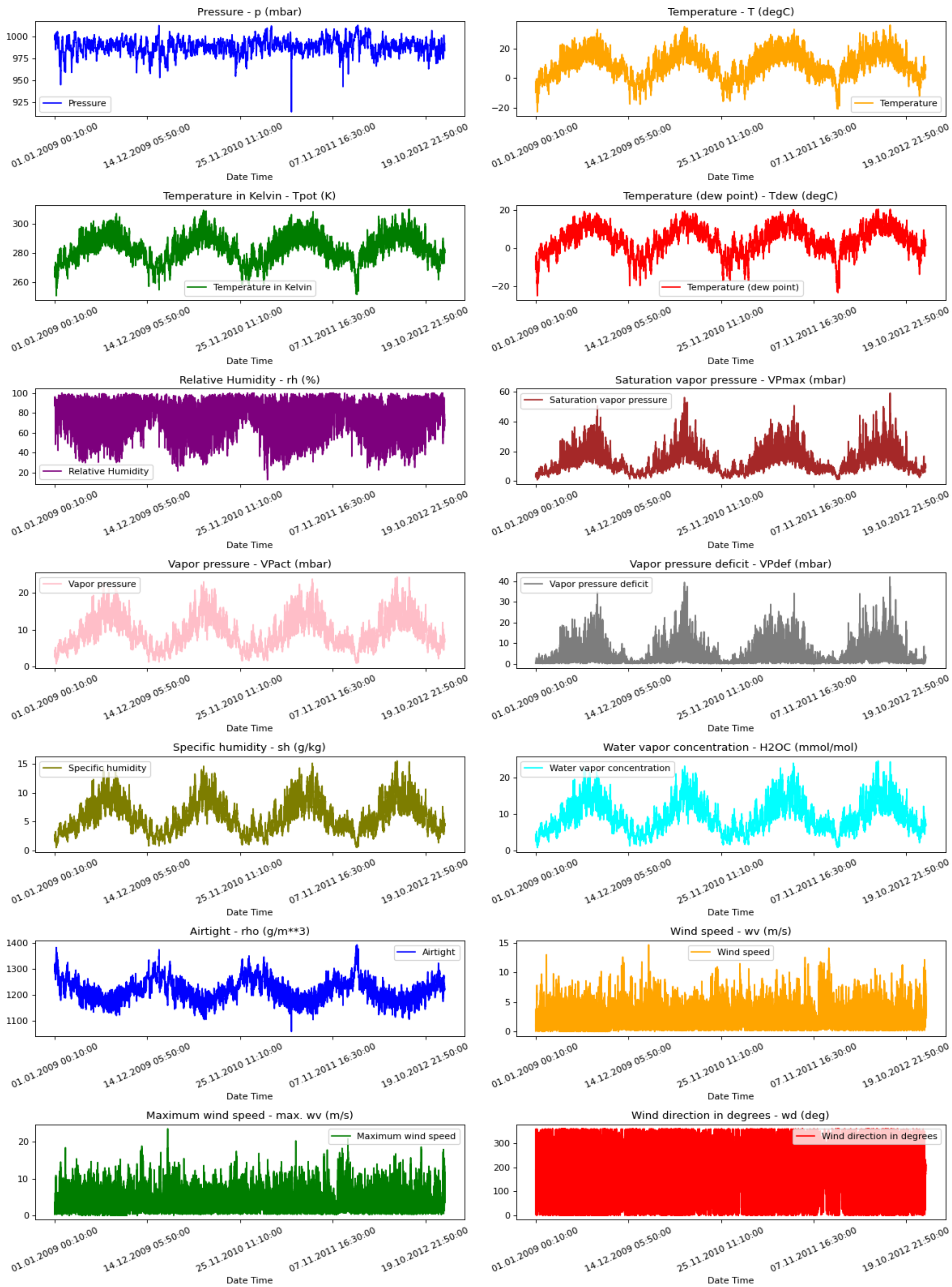
	Date Time	p (mbar)	T (degC)	Tpot (K)	Tdew (degC)	rh (%)	VPmax (mbar)	VPact (mbar)	VPdef (mbar)	sh (g/kg)	H2O (mmol/mo
0	01.01.2009 00:10:00	996.52	-8.02	265.40	-8.90	93.3	3.33	3.11	0.22	1.94	3.1
1	01.01.2009 00:20:00	996.57	-8.41	265.01	-9.28	93.4	3.23	3.02	0.21	1.89	3.C
2	01.01.2009 00:30:00	996.53	-8.51	264.91	-9.31	93.9	3.21	3.01	0.20	1.88	3.C
3	01.01.2009 00:40:00	996.51	-8.31	265.12	-9.07	94.2	3.26	3.07	0.19	1.92	3.C
4	01.01.2009 00:50:00	996.51	-8.27	265.15	-9.04	94.1	3.27	3.08	0.19	1.92	3.C

Define a function to show a plot of each column (using the respective color)

In [5]:
```
def show_raw_visualization(data, date_time_key):
    time_data = data[date_time_key]
    fig, axes = plt.subplots(
        nrows=7, ncols=2, figsize=(15, 20), dpi=80, facecolor="w", edgecolor
    )
    for i in range(len(feature_keys)):
        key = feature_keys[i]
        c = colors[i % (len(colors))]
        t_data = data[key]
        t_data.index = time_data
        t_data.head()
        ax = t_data.plot(
            ax=axes[i // 2, i % 2],
            color=c,
            title="{} - {}".format(titles[i], key),
            rot=25,
        )
        ax.legend([titles[i]])
    plt.tight_layout()
```

Display each column in a plot using above funciton:

In [6]:
```python
show_raw_visualization(df, "Date Time")
```



As you can see we have lots of data, this can be a challenge when we train our model, to resolve that we will reduce the resolution of our data, instead of having a climate signal each 10 minutes, we will have it each hour

- Add a new column to your dataframe with the Date Time information
- Name that column FormatedDateTime

- Convert that column into date time data type
- Set that column as the dataframe index
- Regroup data to be each 1 hour instead of each 10 minutes
- Save the grouped data into a dataframe called df_resampled
- Remove the FormatedDateTime as the index.
- Show the top 5 rows of df_resampled

In [7]:
```
df['FormatedDateTime'] = pd.to_datetime(df['Date Time'], format='%d.%m.%Y %H
df = df.set_index('FormatedDateTime')
df_resampled = df[feature_keys].resample('H').mean()
df_resampled = df_resampled.reset_index()

df_resampled.head()
```

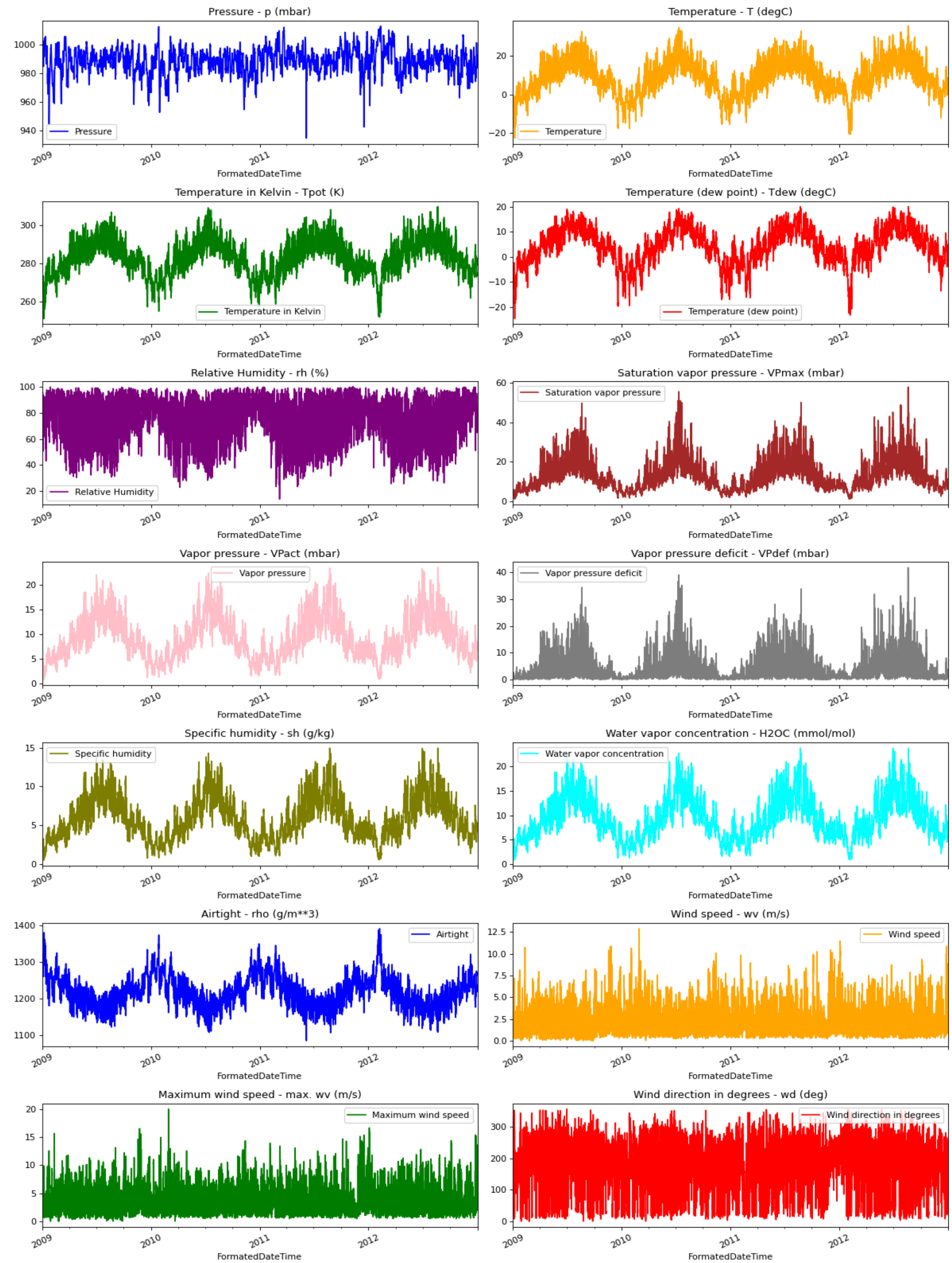
```
<ipython-input-7-e61db8939877>:3: FutureWarning: 'H' is deprecated and wil
l be removed in a future version, please use 'h' instead.
  df_resampled = df[feature_keys].resample('H').mean()
```

Out[7]:

	FormatedDateTime	p (mbar)	T (degC)	Tpot (K)	Tdew (degC)	rh (%)	VPmax (mbar)	(
0	2009-01-01 00:00:00	996.528000	-8.304000	265.118000	-9.120000	93.780000	3.260000	3.0
1	2009-01-01 01:00:00	996.525000	-8.065000	265.361667	-8.861667	93.933333	3.323333	3.1
2	2009-01-01 02:00:00	996.745000	-8.763333	264.645000	-9.610000	93.533333	3.145000	2.9
3	2009-01-01 03:00:00	996.986667	-8.896667	264.491667	-9.786667	93.200000	3.111667	2.8
4	2009-01-01 04:00:00	997.158333	-9.348333	264.026667	-10.345000	92.383333	3.001667	2.7

Let's look at our fields again

In [8]:
```
show_raw_visualization(df_resampled, "FormatedDateTime")
```



3) Data Split: Train and Evaluation datasets.

- We are tracking data from past 120 timestamps (120 hours = 5 days).
- This data will be used to predict the temperature after 12 timestamps (12 hours).

- Since every feature has values with varying ranges, we do normalization to confine feature values to a range of [0, 1] before training a neural network.
- We do this by subtracting the mean and dividing by the standard deviation of each feature in the *normalize* function
- The model is shown data for first 5 days i.e. 120 observations, that are sampled every hour.

In [9]:
```
# 70% of the data will be used for training, the rest for testing
split_fraction = 0.7
# The number of samples is the number of rows in the data
number_of_samples = df_resampled.shape[0]
# The size in rows of the split dataset
train_split = int(split_fraction * int(number_of_samples))

# Number of samples in the past used to predict the future
past = 120
# Number of samples in the future to predict (the value in the 72nd hour is
future = 12
# Learning rate parameter for the Adam optimizer
learning_rate = 0.001
# Batch size for the model training
batch_size = 256
# Number of epochs for the model training
epochs = 10

# Another way to normalize the data (all columns in the same range)
def normalize(data, train_split):
    data_mean = data[:train_split].mean(axis=0)
    data_std = data[:train_split].std(axis=0)
    return (data - data_mean) / data_std
```

- Let's select the following parameters as our features:
  - Pressure, Temperature, Saturation vapor pressure, Vapor pressure deficit, Specific humidity, Airtight, Wind speed
- Set the column FormatedDateTime as the index of our dataframe.
  - This is important since now, FormatedDateTime is used as our datetime field and not as a Feature field
- Normalize all fields
- Generate two datasets:
  - train_data: Train dataset with our normalized fields
  - val_data: Validation dataset

In [10]:
```
print(
    "The selected parameters are:",
    ", ".join([titles[i] for i in [0, 1, 5, 7, 8, 10, 11]]),
)
selected_features = [feature_keys[i] for i in [0, 1, 5, 7, 8, 10, 11]]
features = df_resampled[selected_features]
features.index = df_resampled["FormatedDateTime"]
print(features.head())

features = normalize(features.values, train_split)
features = pd.DataFrame(features)
print(features.head())

train_data = features.loc[0 : train_split - 1]
val_data = features.loc[train_split:]
```

```
The selected parameters are: Pressure, Temperature, Saturation vapor press
ure, Vapor pressure deficit, Specific humidity, Airtight, Wind speed
                       p (mbar)  T (degC)  VPmax (mbar)  VPdef (mbar)  \
FormatedDateTime
2009-01-01 00:00:00  996.528000 -8.304000      3.260000      0.202000
2009-01-01 01:00:00  996.525000 -8.065000      3.323333      0.201667
2009-01-01 02:00:00  996.745000 -8.763333      3.145000      0.201667
2009-01-01 03:00:00  996.986667 -8.896667      3.111667      0.210000
2009-01-01 04:00:00  997.158333 -9.348333      3.001667      0.231667

                     sh (g/kg)  rho (g/m**3)  wv (m/s)
FormatedDateTime
2009-01-01 00:00:00   1.910000   1309.196000  0.520000
2009-01-01 01:00:00   1.951667   1307.981667  0.316667
2009-01-01 02:00:00   1.836667   1311.816667  0.248333
2009-01-01 03:00:00   1.811667   1312.813333  0.176667
2009-01-01 04:00:00   1.733333   1315.355000  0.290000
          0         1         2         3         4         5         6
0  0.988366 -1.936957 -1.314750 -0.797292 -1.472751  2.198783 -1.116409
1  0.988002 -1.909978 -1.306369 -0.797363 -1.457136  2.169559 -1.256715
2  1.014643 -1.988807 -1.329968 -0.797363 -1.500234  2.261854 -1.303867
3  1.043907 -2.003858 -1.334379 -0.795594 -1.509604  2.285840 -1.353320
4  1.064694 -2.054843 -1.348935 -0.790994 -1.538961  2.347009 -1.275116
```

Now, here we need to set our Label Dataset.

- We want to use the last 5 days of data, to predict the next 12 hours
- This means that our label starts at the 12th hour after the history data.
  - [......................... .]
  - -----Start----->
- And it will end at the end of our train dataset size.
  - <-------- Train ---------> <--- Test --->
  - [..|...........]
  - ----------End---------->

In [11]:
```
start = past + future
end = start + train_split

x_train = train_data[[i for i in range(7)]].values
y_train = features.iloc[start:end][[1]]

step = 1
sequence_length = past
```

The *timeseries_dataset_from_array* function takes in a sequence of data-points gathered at equal intervals, along with time series parameters such as length of the sequences/windows, spacing between two sequence/windows, etc., to produce batches of sub-timeseries inputs and targets sampled from the main timeseries.

- Input data (hour features) = x_train
- The **corresponding** value of the temperature 12 hours into the future = y_train
- Since we want to use 5 days of data to predict the future temperature then: sequence_length = 120
- Since we want to sample every hour then: sampling_rate = 1
- Let's use a common batch size of 256 (variable above)

In [12]:
```
dataset_train = keras.preprocessing.timeseries_dataset_from_array(
    x_train,
    y_train,
    sequence_length=sequence_length,
    sampling_rate=step,
    batch_size=batch_size,
)
```

Now let's prepare our validation dataset:

- The validation dataset must not contain the last 120+12 rows as we won't have label data for those records, hence these rows must be subtracted from the end of the data.
- The validation label dataset must start from 120+12 after train_split, hence we must add past + future to label_start.

In [13]:
```
x_end = len(val_data) - past - future

label_start = train_split + past + future

x_val = val_data.iloc[:x_end][[i for i in range(7)]].values
y_val = features.iloc[label_start:][[1]]

dataset_val = keras.preprocessing.timeseries_dataset_from_array(
    x_val,
    y_val,
    sequence_length=sequence_length,
    sampling_rate=step,
    batch_size=batch_size,
)


for batch in dataset_train.take(1):
    inputs, targets = batch

print("Input shape:", inputs.numpy().shape)
print("Target shape:", targets.numpy().shape)
```

```
Input shape: (256, 120, 7)
Target shape: (256, 1)
```

4) Define and Compile your model:

- An input layer
- A Long Short-Term Memory Hidden Layer with 32 units. LSTM is a type of recurrent neural network layer that is well-suited for time series data.
- An output Dense Layer (Linear Activation function)

In [14]:
```
inputs = keras.layers.Input(shape=(inputs.shape[1], inputs.shape[2]))
lstm_out = keras.layers.LSTM(32)(inputs)
outputs = keras.layers.Dense(1)(lstm_out)

model = keras.Model(inputs=inputs, outputs=outputs)
model.compile(optimizer=keras.optimizers.Adam(learning_rate=learning_rate),
model.summary()
```

Model: "functional"

Layer (type)	Output Shape
input_layer (InputLayer)	(None, 120, 7)
lstm (LSTM)	(None, 32)
dense (Dense)	(None, 1)

Total params: 5,153 (20.13 KB)

Trainable params: 5,153 (20.13 KB)

Non-trainable params: 0 (0.00 B)

5) Train your model:

Specify the file path where the model's weights will be saved with: `path_checkpoint = "model_checkpoint.weights.h5"`

We want to add a callback to stop training when a monitored metric stops improving: `es_callback = keras.callbacks.EarlyStopping(monitor="val_loss", min_delta=0, patience=5)`

Train the model using Fit

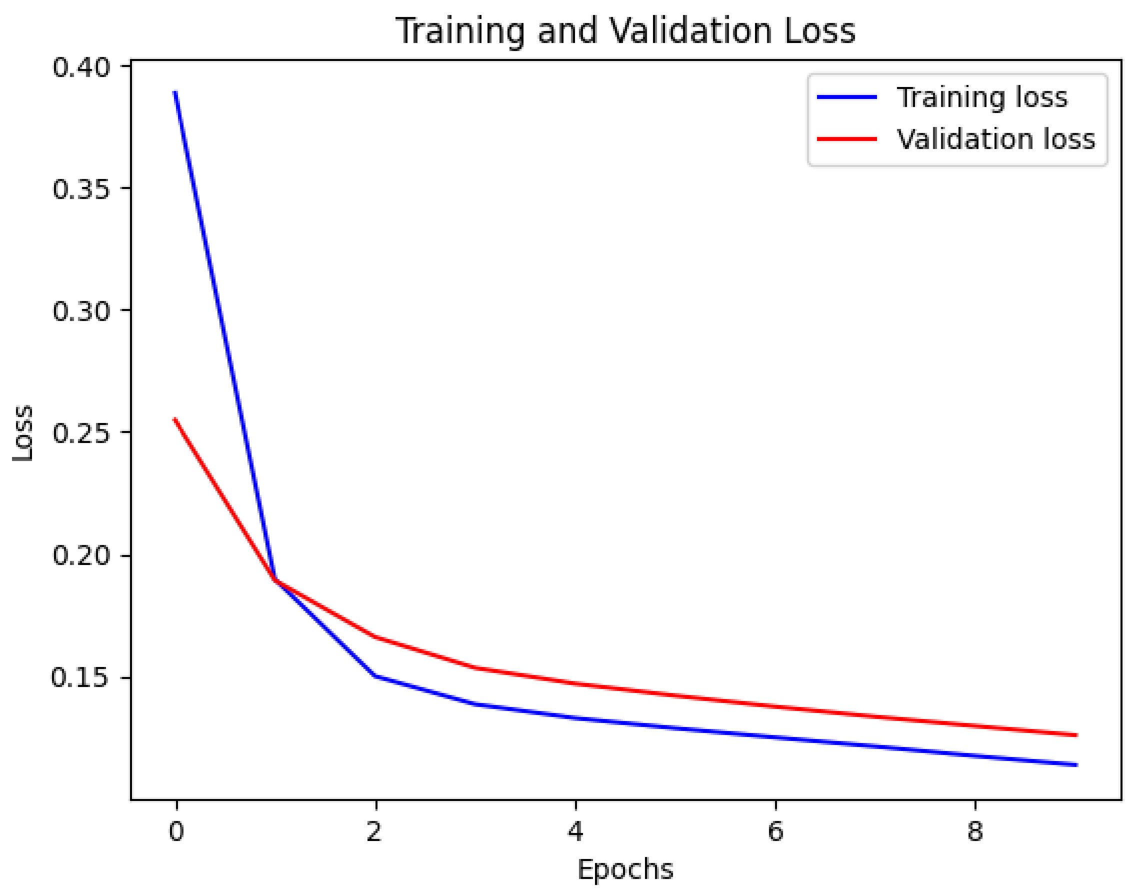
In [17]:
```
path_checkpoint = "model_checkpoint.weights.h5"
es_callback = keras.callbacks.EarlyStopping(monitor="val_loss", min_delta=0,

modelckpt_callback = keras.callbacks.ModelCheckpoint(
    monitor="val_loss",
    filepath=path_checkpoint,
    verbose=1,
    save_weights_only=True,
    save_best_only=True,
)

history = model.fit(
    dataset_train,
    epochs=epochs,
    validation_data=dataset_val,
    callbacks=[es_callback, modelckpt_callback],
)
```

```
Epoch 1/10
96/96 ━━━━━━━━━━━━━━━━━━━━ 0s 162ms/step - loss: 0.6943
Epoch 1: val_loss improved from inf to 0.25485, saving model to model_chec
kpoint.weights.h5
96/96 ━━━━━━━━━━━━━━━━━━━━ 22s 202ms/step - loss: 0.6912 - val_loss: 0.254
8
Epoch 2/10
96/96 ━━━━━━━━━━━━━━━━━━━━ 0s 107ms/step - loss: 0.2089
Epoch 2: val_loss improved from 0.25485 to 0.18929, saving model to model_
checkpoint.weights.h5
96/96 ━━━━━━━━━━━━━━━━━━━━ 14s 144ms/step - loss: 0.2087 - val_loss: 0.189
3
Epoch 3/10
96/96 ━━━━━━━━━━━━━━━━━━━━ 0s 106ms/step - loss: 0.1585
Epoch 3: val_loss improved from 0.18929 to 0.16612, saving model to model_
checkpoint.weights.h5
96/96 ━━━━━━━━━━━━━━━━━━━━ 14s 145ms/step - loss: 0.1584 - val_loss: 0.166
1
Epoch 4/10
96/96 ━━━━━━━━━━━━━━━━━━━━ 0s 103ms/step - loss: 0.1426
Epoch 4: val_loss improved from 0.16612 to 0.15350, saving model to model_
checkpoint.weights.h5
96/96 ━━━━━━━━━━━━━━━━━━━━ 14s 142ms/step - loss: 0.1426 - val_loss: 0.153
5
Epoch 5/10
95/96 ━━━━━━━━━━━━━━━━━━━━ 0s 122ms/step - loss: 0.1358
Epoch 5: val_loss improved from 0.15350 to 0.14706, saving model to model_
checkpoint.weights.h5
96/96 ━━━━━━━━━━━━━━━━━━━━ 21s 149ms/step - loss: 0.1358 - val_loss: 0.147
1
Epoch 6/10
96/96 ━━━━━━━━━━━━━━━━━━━━ 0s 135ms/step - loss: 0.1319
Epoch 6: val_loss improved from 0.14706 to 0.14216, saving model to model_
checkpoint.weights.h5
96/96 ━━━━━━━━━━━━━━━━━━━━ 16s 168ms/step - loss: 0.1319 - val_loss: 0.142
2
Epoch 7/10
96/96 ━━━━━━━━━━━━━━━━━━━━ 0s 121ms/step - loss: 0.1286
Epoch 7: val_loss improved from 0.14216 to 0.13765, saving model to model_
checkpoint.weights.h5
96/96 ━━━━━━━━━━━━━━━━━━━━ 14s 145ms/step - loss: 0.1285 - val_loss: 0.137
7
Epoch 8/10
95/96 ━━━━━━━━━━━━━━━━━━━━ 0s 124ms/step - loss: 0.1253
Epoch 8: val_loss improved from 0.13765 to 0.13354, saving model to model_
checkpoint.weights.h5
96/96 ━━━━━━━━━━━━━━━━━━━━ 14s 149ms/step - loss: 0.1252 - val_loss: 0.133
5
Epoch 9/10
96/96 ━━━━━━━━━━━━━━━━━━━━ 0s 129ms/step - loss: 0.1217
Epoch 9: val_loss improved from 0.13354 to 0.12975, saving model to model_
checkpoint.weights.h5
96/96 ━━━━━━━━━━━━━━━━━━━━ 16s 165ms/step - loss: 0.1216 - val_loss: 0.129
8
Epoch 10/10
96/96 ━━━━━━━━━━━━━━━━━━━━ 0s 118ms/step - loss: 0.1177
Epoch 10: val_loss improved from 0.12975 to 0.12601, saving model to model
```

```
_checkpoint.weights.h5
96/96 ━━━━━━━━━━━━━━━━━━━━ 14s 146ms/step - loss: 0.1176 - val_loss: 0.126
0
```

Plot the results of your training:

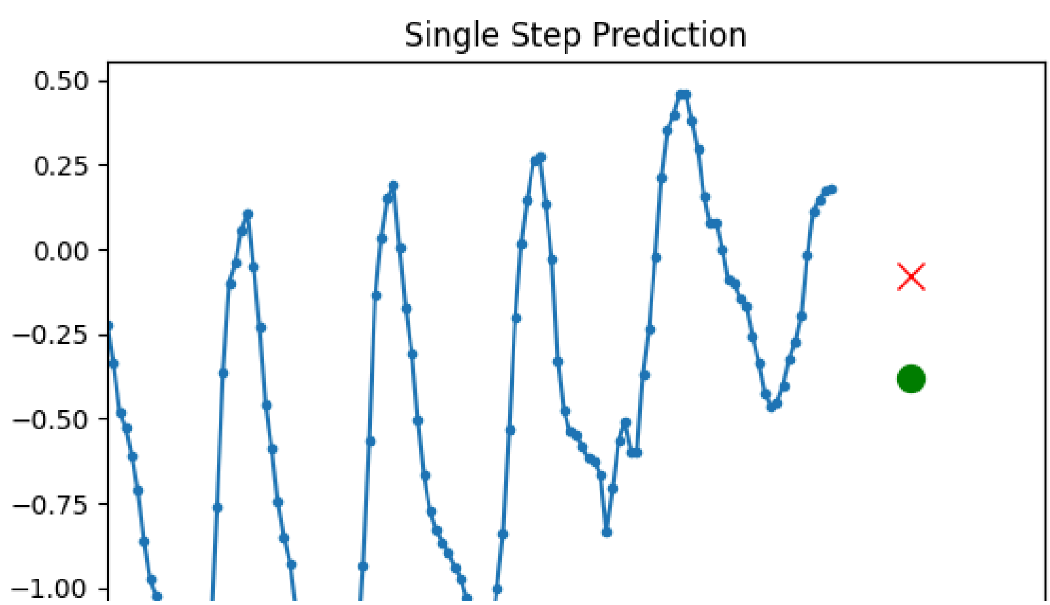
In [18]:
```
def visualize_loss(history, title):
    loss = history.history["loss"]
    val_loss = history.history["val_loss"]
    epochs = range(len(loss))
    plt.figure()
    plt.plot(epochs, loss, "b", label="Training loss")
    plt.plot(epochs, val_loss, "r", label="Validation loss")
    plt.title(title)
    plt.xlabel("Epochs")
    plt.ylabel("Loss")
    plt.legend()
    plt.show()


visualize_loss(history, "Training and Validation Loss")
```



Make 5 predictions and display the predicted value

In [19]:
```
def show_plot(plot_data, delta, title):
    labels = ["History", "True Future", "Model Prediction"]
    marker = [".-", "rx", "go"]
    time_steps = list(range(-(plot_data[0].shape[0]), 0))
    if delta:
        future = delta
    else:
        future = 0

    plt.title(title)
    for i, val in enumerate(plot_data):
        if i:
            plt.plot(future, plot_data[i], marker[i], markersize=10, label=l
        else:
            plt.plot(time_steps, plot_data[i].flatten(), marker[i], label=la
    plt.legend()
    plt.xlim([time_steps[0], (future + 5) * 2])
    plt.xlabel("Time-Step")
    plt.show()
    return


for x, y in dataset_val.take(5):
    show_plot(
        [x[0][:, 1].numpy(), y[0].numpy(), model.predict(x)[0]],
        12,
        "Single Step Prediction",
    )
```

```
8/8 ━━━━━━━━━━━━━━━━━━━━ 0s 14ms/step
```



Now make a Time Series Forecasting where using the last 3 days you will predict the weather in the next 3 hours.

In [20]:
```
# Number of samples in the past used to predict the future
past = 72
# Number of samples in the future to predict (the value in the 72nd hour is
future = 3
```

In [21]:
```
print(
    "The selected parameters are:",
    ", ".join([titles[i] for i in [0, 1, 5, 7, 8, 10, 11]]),
)
selected_features = [feature_keys[i] for i in [0, 1, 5, 7, 8, 10, 11]]
features = df_resampled[selected_features]
features.index = df_resampled["FormatedDateTime"]
print(features.head())

features = normalize(features.values, train_split)
features = pd.DataFrame(features)
print(features.head())

train_data = features.loc[0 : train_split - 1]
val_data = features.loc[train_split:]
```

```
The selected parameters are: Pressure, Temperature, Saturation vapor press
ure, Vapor pressure deficit, Specific humidity, Airtight, Wind speed
                       p (mbar)  T (degC)  VPmax (mbar)  VPdef (mbar)  \
FormatedDateTime
2009-01-01 00:00:00  996.528000 -8.304000      3.260000      0.202000
2009-01-01 01:00:00  996.525000 -8.065000      3.323333      0.201667
2009-01-01 02:00:00  996.745000 -8.763333      3.145000      0.201667
2009-01-01 03:00:00  996.986667 -8.896667      3.111667      0.210000
2009-01-01 04:00:00  997.158333 -9.348333      3.001667      0.231667

                     sh (g/kg)  rho (g/m**3)  wv (m/s)
FormatedDateTime
2009-01-01 00:00:00   1.910000   1309.196000  0.520000
2009-01-01 01:00:00   1.951667   1307.981667  0.316667
2009-01-01 02:00:00   1.836667   1311.816667  0.248333
2009-01-01 03:00:00   1.811667   1312.813333  0.176667
2009-01-01 04:00:00   1.733333   1315.355000  0.290000
          0         1         2         3         4         5         6
0  0.988366 -1.936957 -1.314750 -0.797292 -1.472751  2.198783 -1.116409
1  0.988002 -1.909978 -1.306369 -0.797363 -1.457136  2.169559 -1.256715
2  1.014643 -1.988807 -1.329968 -0.797363 -1.500234  2.261854 -1.303867
3  1.043907 -2.003858 -1.334379 -0.795594 -1.509604  2.285840 -1.353320
4  1.064694 -2.054843 -1.348935 -0.790994 -1.538961  2.347009 -1.275116
```

In [22]:
```
start = past + future
end = start + train_split

x_train = train_data[[i for i in range(7)]].values
y_train = features.iloc[start:end][[1]]

step = 1
sequence_length = past
```

In [23]:
```
dataset_train = keras.preprocessing.timeseries_dataset_from_array(
    x_train,
    y_train,
    sequence_length=sequence_length,
    sampling_rate=step,
    batch_size=batch_size,
)
```

In [24]:
```
x_end = len(val_data) - past - future

label_start = train_split + past + future

x_val = val_data.iloc[:x_end][[i for i in range(7)]].values
y_val = features.iloc[label_start:][[1]]

dataset_val = keras.preprocessing.timeseries_dataset_from_array(
    x_val,
    y_val,
    sequence_length=sequence_length,
    sampling_rate=step,
    batch_size=batch_size,
)


for batch in dataset_train.take(1):
    inputs, targets = batch

print("Input shape:", inputs.numpy().shape)
print("Target shape:", targets.numpy().shape)
```

```
Input shape: (256, 72, 7)
Target shape: (256, 1)
```

In [25]:
```
inputs = keras.layers.Input(shape=(inputs.shape[1], inputs.shape[2]))
lstm_out = keras.layers.LSTM(32)(inputs)
outputs = keras.layers.Dense(1)(lstm_out)

model = keras.Model(inputs=inputs, outputs=outputs)
model.compile(optimizer=keras.optimizers.Adam(learning_rate=learning_rate),
model.summary()
```

Model: "functional_1"

Layer (type)	**Output Shape**	
input_layer_1 (InputLayer)	(None, 72, 7)	
lstm_1 (LSTM)	(None, 32)	
dense_1 (Dense)	(None, 1)	

Total params: 5,153 (20.13 KB)

Trainable params: 5,153 (20.13 KB)

Non-trainable params: 0 (0.00 B)

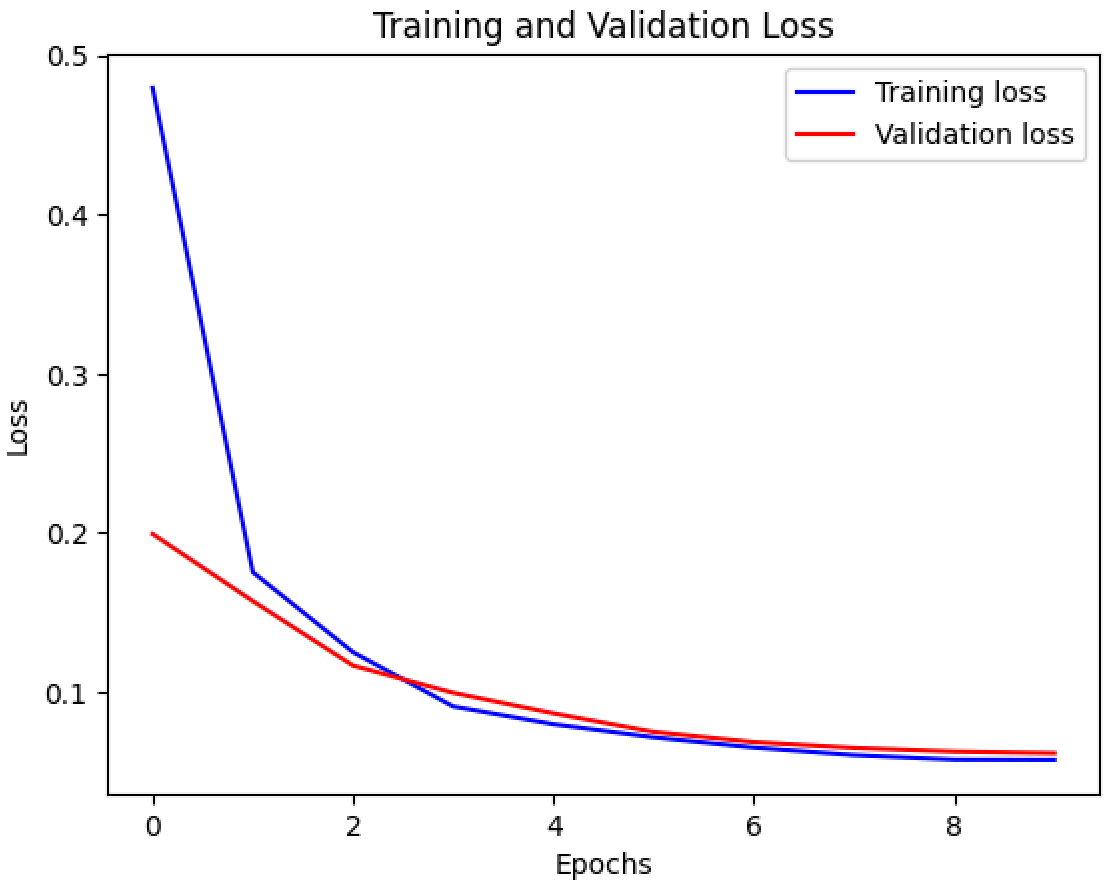
In [26]:
```
path_checkpoint = "model_checkpoint.weights.h5"
es_callback = keras.callbacks.EarlyStopping(monitor="val_loss", min_delta=0,

modelckpt_callback = keras.callbacks.ModelCheckpoint(
    monitor="val_loss",
    filepath=path_checkpoint,
    verbose=1,
    save_weights_only=True,
    save_best_only=True,
)

history = model.fit(
    dataset_train,
    epochs=epochs,
    validation_data=dataset_val,
    callbacks=[es_callback, modelckpt_callback],
)
```

```
Epoch 1/10
95/96 ━━━━━━━━━━━━━━━━━━━━ 0s 94ms/step - loss: 0.9126
Epoch 1: val_loss improved from inf to 0.19934, saving model to model_chec
kpoint.weights.h5
96/96 ━━━━━━━━━━━━━━━━━━━━ 14s 117ms/step - loss: 0.9037 - val_loss: 0.199
3
Epoch 2/10
96/96 ━━━━━━━━━━━━━━━━━━━━ 0s 101ms/step - loss: 0.1918
Epoch 2: val_loss improved from 0.19934 to 0.15718, saving model to model_
checkpoint.weights.h5
96/96 ━━━━━━━━━━━━━━━━━━━━ 13s 132ms/step - loss: 0.1916 - val_loss: 0.157
2
Epoch 3/10
96/96 ━━━━━━━━━━━━━━━━━━━━ 0s 86ms/step - loss: 0.1365
Epoch 3: val_loss improved from 0.15718 to 0.11663, saving model to model_
checkpoint.weights.h5
96/96 ━━━━━━━━━━━━━━━━━━━━ 11s 112ms/step - loss: 0.1364 - val_loss: 0.116
6
Epoch 4/10
96/96 ━━━━━━━━━━━━━━━━━━━━ 0s 76ms/step - loss: 0.0987
Epoch 4: val_loss improved from 0.11663 to 0.09954, saving model to model_
checkpoint.weights.h5
96/96 ━━━━━━━━━━━━━━━━━━━━ 9s 98ms/step - loss: 0.0986 - val_loss: 0.0995
Epoch 5/10
95/96 ━━━━━━━━━━━━━━━━━━━━ 0s 86ms/step - loss: 0.0892
Epoch 5: val_loss improved from 0.09954 to 0.08664, saving model to model_
checkpoint.weights.h5
96/96 ━━━━━━━━━━━━━━━━━━━━ 11s 105ms/step - loss: 0.0890 - val_loss: 0.086
6
Epoch 6/10
95/96 ━━━━━━━━━━━━━━━━━━━━ 0s 96ms/step - loss: 0.0787
Epoch 6: val_loss improved from 0.08664 to 0.07497, saving model to model_
checkpoint.weights.h5
96/96 ━━━━━━━━━━━━━━━━━━━━ 11s 117ms/step - loss: 0.0785 - val_loss: 0.075
0
Epoch 7/10
96/96 ━━━━━━━━━━━━━━━━━━━━ 0s 74ms/step - loss: 0.0706
Epoch 7: val_loss improved from 0.07497 to 0.06859, saving model to model_
checkpoint.weights.h5
96/96 ━━━━━━━━━━━━━━━━━━━━ 19s 99ms/step - loss: 0.0705 - val_loss: 0.0686
Epoch 8/10
96/96 ━━━━━━━━━━━━━━━━━━━━ 0s 79ms/step - loss: 0.0651
Epoch 8: val_loss improved from 0.06859 to 0.06495, saving model to model_
checkpoint.weights.h5
96/96 ━━━━━━━━━━━━━━━━━━━━ 10s 98ms/step - loss: 0.0650 - val_loss: 0.0649
Epoch 9/10
95/96 ━━━━━━━━━━━━━━━━━━━━ 0s 93ms/step - loss: 0.0615
Epoch 9: val_loss improved from 0.06495 to 0.06265, saving model to model_
checkpoint.weights.h5
96/96 ━━━━━━━━━━━━━━━━━━━━ 11s 113ms/step - loss: 0.0614 - val_loss: 0.062
6
Epoch 10/10
95/96 ━━━━━━━━━━━━━━━━━━━━ 0s 94ms/step - loss: 0.0609
Epoch 10: val_loss improved from 0.06265 to 0.06167, saving model to model
_checkpoint.weights.h5
```

```
96/96 ━━━━━━━━━━━━━━━━━━━━ 11s 113ms/step - loss: 0.0609 - val_loss: 0.061
7
```

In [27]:

```
visualize_loss(history, "Training and Validation Loss")
```



In [30]:
```
def show_plot(plot_data, delta, title):
    labels = ["History", "True Future", "Model Prediction"]
    marker = [".-", "rx", "go"]
    time_steps = list(range(-(plot_data[0].shape[0]), 0))
    if delta:
        future = delta
    else:
        future = 0

    plt.title(title)
    for i, val in enumerate(plot_data):
        if i:
            plt.plot(future, plot_data[i], marker[i], markersize=10, label=l
        else:
            plt.plot(time_steps, plot_data[i].flatten(), marker[i], label=la
    plt.legend()
    plt.xlim([time_steps[0], (future + 3) * 2])
    plt.xlabel("Time-Step")
    plt.show()
    return

for x, y in dataset_val.take(5):
    show_plot(
        [x[0][:, 1].numpy(), y[0].numpy(), model.predict(x)[0]],
        3,
        "Single Step Prediction",
    )
```

```
8/8 ━━━━━━━━━━━━━━━━━━━━ 0s 8ms/step
```