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 [19]:
```
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 [20]:
```
df = pd.read_csv("M2_A4_ClimateData20092012.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 [21]:
```
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 [22]:
```
df.head()
```

Out[22]:

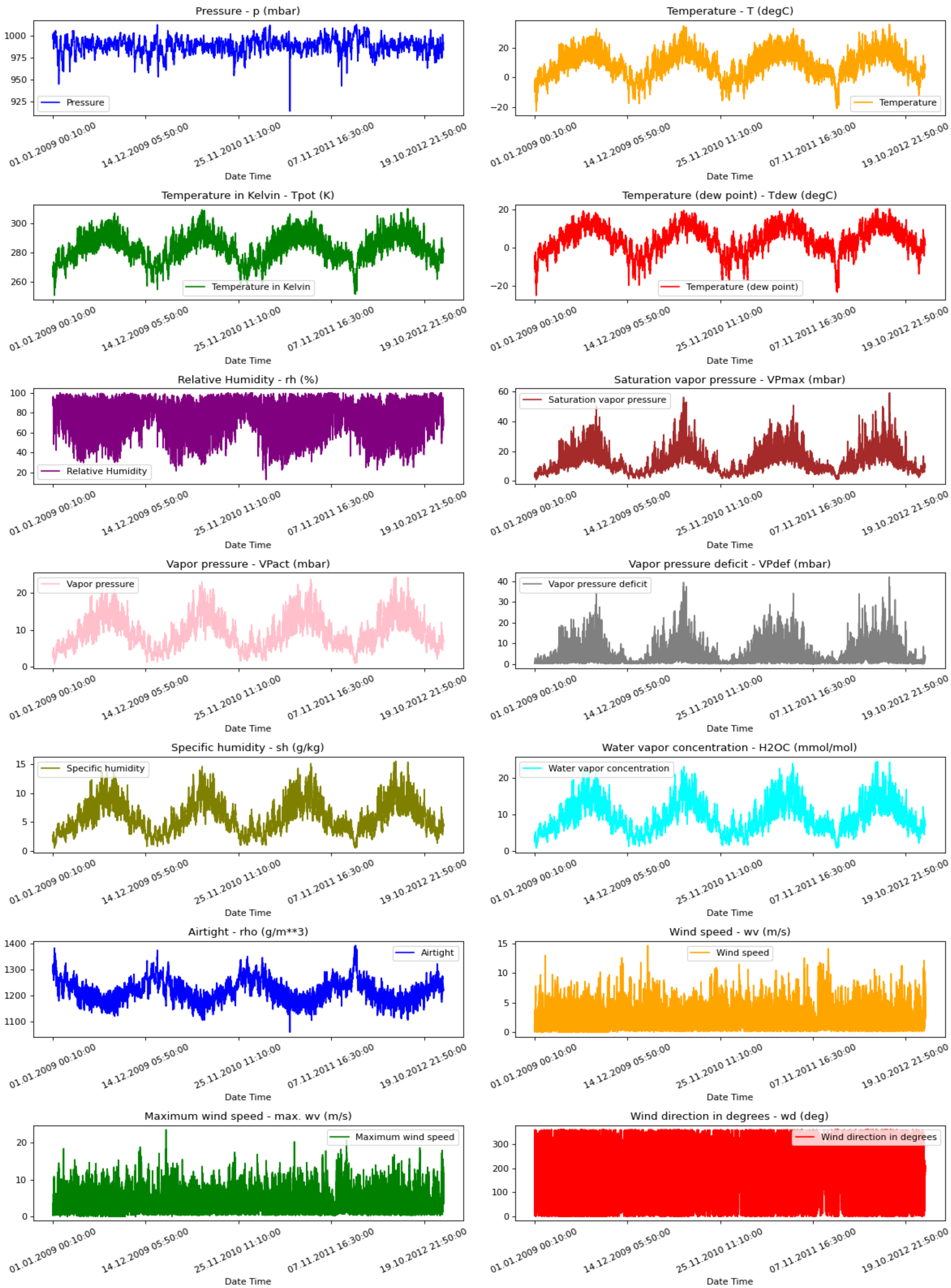
	Date Time	p (mbar)	T (degC)	Tpot (K)	Tdew (degC)	rh (%)	VPmax (mbar)	VPact (mbar)	VPdef (mbar)	sh (g/kg)	(r
0	01.01.2009 00:10:00	996.52	-8.02	265.40	-8.90	93.3	3.33	3.11	0.22	1.94	
1	01.01.2009 00:20:00	996.57	-8.41	265.01	-9.28	93.4	3.23	3.02	0.21	1.89	
2	01.01.2009 00:30:00	996.53	-8.51	264.91	-9.31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

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

In [23]:
```
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 [24]:
```
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 [25]:
```
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()
```

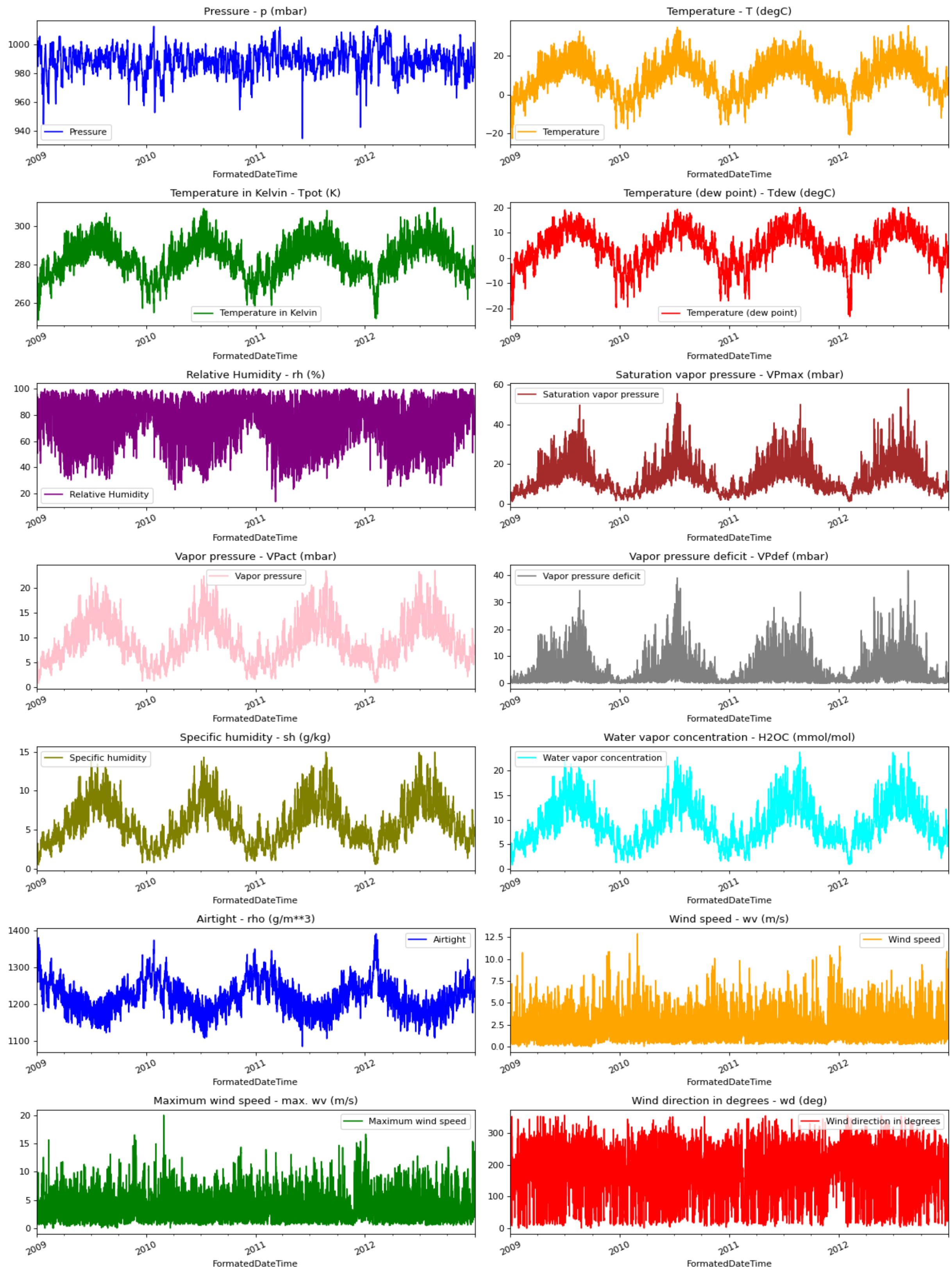
```
<ipython-input-25-e61db8939877>:3: FutureWarning: 'H' is deprecated and will
be removed in a future version, please use 'h' instead.
  df_resampled = df[feature_keys].resample('H').mean()
```

Out[25]:

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

Let's look at our fields again

In [26]:
```
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.
- The temperature after 12 hours observation will be used as a label.

In [27]:
```
# 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 [28]:
```
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 pressur
e, 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 [29]:
```
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 [30]:
```
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 [31]:
```
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 [32]:
```
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, 120, 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)

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

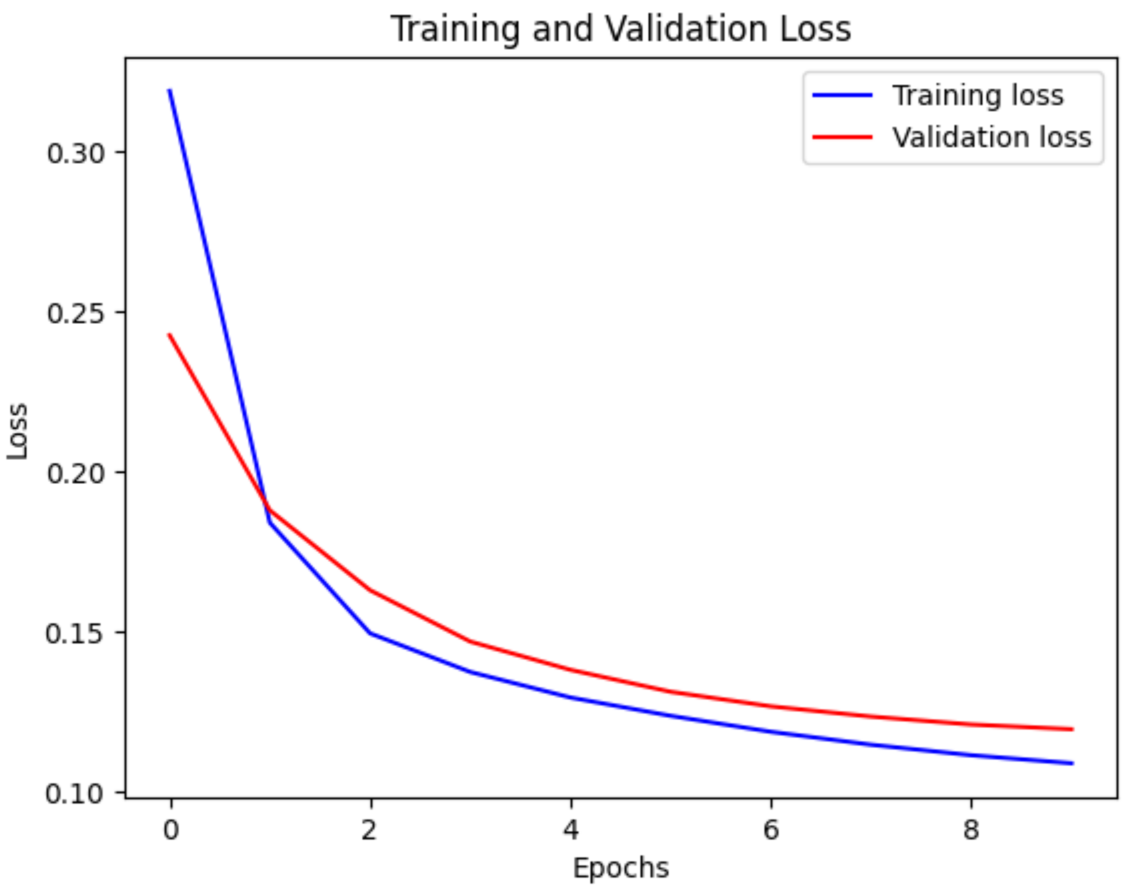
In [33]:
```
path_checkpoint = "model_checkpoint.weights.h5"
es_callback = keras.callbacks.EarlyStopping(monitor="val_loss", min_delta=0,

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 66ms/step - loss: 0.5326
Epoch 1: val_loss improved from inf to 0.24251, saving model to model_checkp
oint.weights.h5
96/96 ━━━━━━━━━━━━━━━━━━━━ 10s 85ms/step - loss: 0.5304 - val_loss: 0.2425
Epoch 2/10
96/96 ━━━━━━━━━━━━━━━━━━━━ 0s 78ms/step - loss: 0.2013
Epoch 2: val_loss improved from 0.24251 to 0.18793, saving model to model_ch
eckpoint.weights.h5
96/96 ━━━━━━━━━━━━━━━━━━━━ 10s 101ms/step - loss: 0.2011 - val_loss: 0.1879
Epoch 3/10
95/96 ━━━━━━━━━━━━━━━━━━━━ 0s 85ms/step - loss: 0.1578
Epoch 3: val_loss improved from 0.18793 to 0.16303, saving model to model_ch
eckpoint.weights.h5
96/96 ━━━━━━━━━━━━━━━━━━━━ 10s 101ms/step - loss: 0.1576 - val_loss: 0.1630
Epoch 4/10
96/96 ━━━━━━━━━━━━━━━━━━━━ 0s 71ms/step - loss: 0.1426
Epoch 4: val_loss improved from 0.16303 to 0.14701, saving model to model_ch
eckpoint.weights.h5
96/96 ━━━━━━━━━━━━━━━━━━━━ 9s 94ms/step - loss: 0.1425 - val_loss: 0.1470
Epoch 5/10
95/96 ━━━━━━━━━━━━━━━━━━━━ 0s 68ms/step - loss: 0.1333
Epoch 5: val_loss improved from 0.14701 to 0.13819, saving model to model_ch
eckpoint.weights.h5
96/96 ━━━━━━━━━━━━━━━━━━━━ 8s 85ms/step - loss: 0.1332 - val_loss: 0.1382
Epoch 6/10
96/96 ━━━━━━━━━━━━━━━━━━━━ 0s 97ms/step - loss: 0.1273
Epoch 6: val_loss improved from 0.13819 to 0.13134, saving model to model_ch
eckpoint.weights.h5
96/96 ━━━━━━━━━━━━━━━━━━━━ 11s 115ms/step - loss: 0.1273 - val_loss: 0.1313
Epoch 7/10
95/96 ━━━━━━━━━━━━━━━━━━━━ 0s 78ms/step - loss: 0.1217
Epoch 7: val_loss improved from 0.13134 to 0.12680, saving model to model_ch
eckpoint.weights.h5
96/96 ━━━━━━━━━━━━━━━━━━━━ 9s 94ms/step - loss: 0.1216 - val_loss: 0.1268
Epoch 8/10
96/96 ━━━━━━━━━━━━━━━━━━━━ 0s 66ms/step - loss: 0.1174
Epoch 8: val_loss improved from 0.12680 to 0.12362, saving model to model_ch
eckpoint.weights.h5
96/96 ━━━━━━━━━━━━━━━━━━━━ 8s 84ms/step - loss: 0.1173 - val_loss: 0.1236
Epoch 9/10
95/96 ━━━━━━━━━━━━━━━━━━━━ 0s 77ms/step - loss: 0.1141
Epoch 9: val_loss improved from 0.12362 to 0.12114, saving model to model_ch
eckpoint.weights.h5
96/96 ━━━━━━━━━━━━━━━━━━━━ 10s 98ms/step - loss: 0.1141 - val_loss: 0.1211
Epoch 10/10
95/96 ━━━━━━━━━━━━━━━━━━━━ 0s 80ms/step - loss: 0.1117
Epoch 10: val_loss improved from 0.12114 to 0.11968, saving model to model_c
heckpoint.weights.h5
96/96 ━━━━━━━━━━━━━━━━━━━━ 9s 95ms/step - loss: 0.1116 - val_loss: 0.1197
```

Plot the results of your training:

In [34]:
```
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")
```

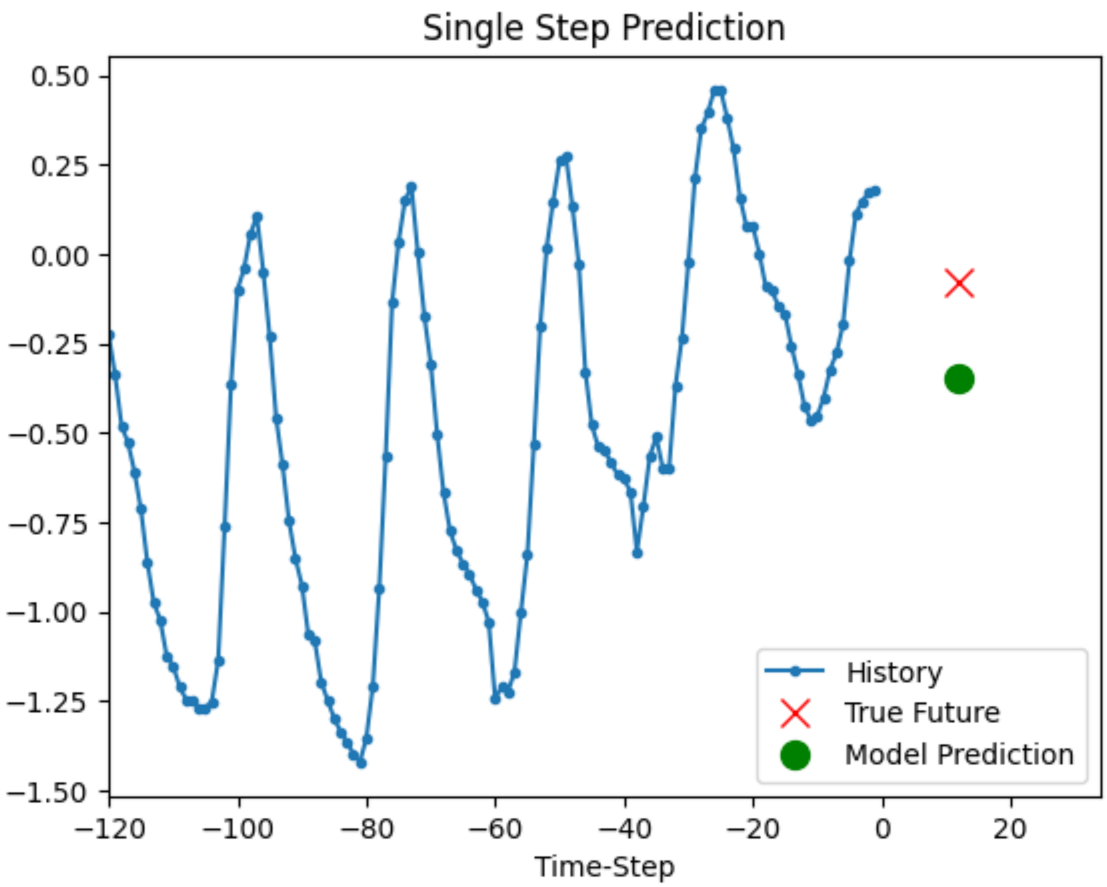


Make 5 predictions and display the predicted value

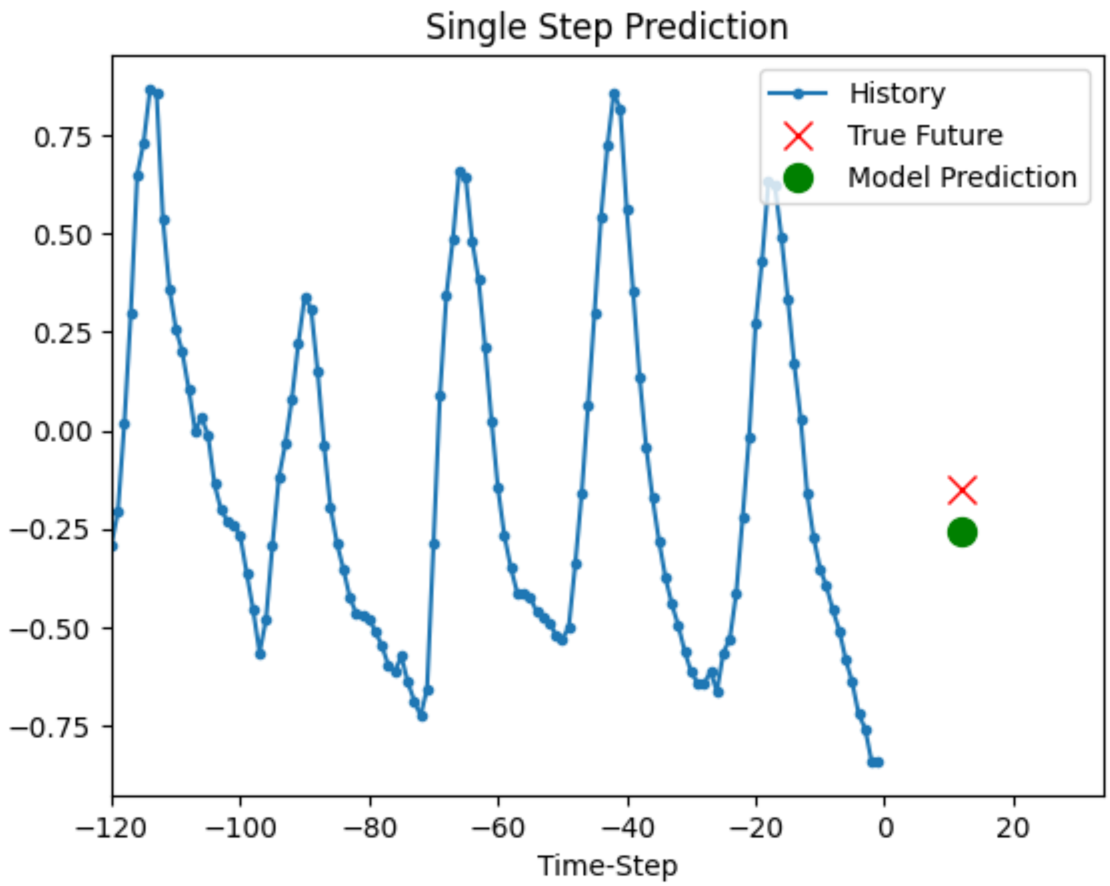
In [35]:
```
def show_plot(plot_data, delta, title):
    labels = ["History", "True Future", "Model Prediction"]
    marker = [".-", "rx", "go"]
    time_steps = list(range(-(plot_data[0].shape[0]), 0))
    if delta:
        future = delta
    else:
        future = 0

    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",
    )
```

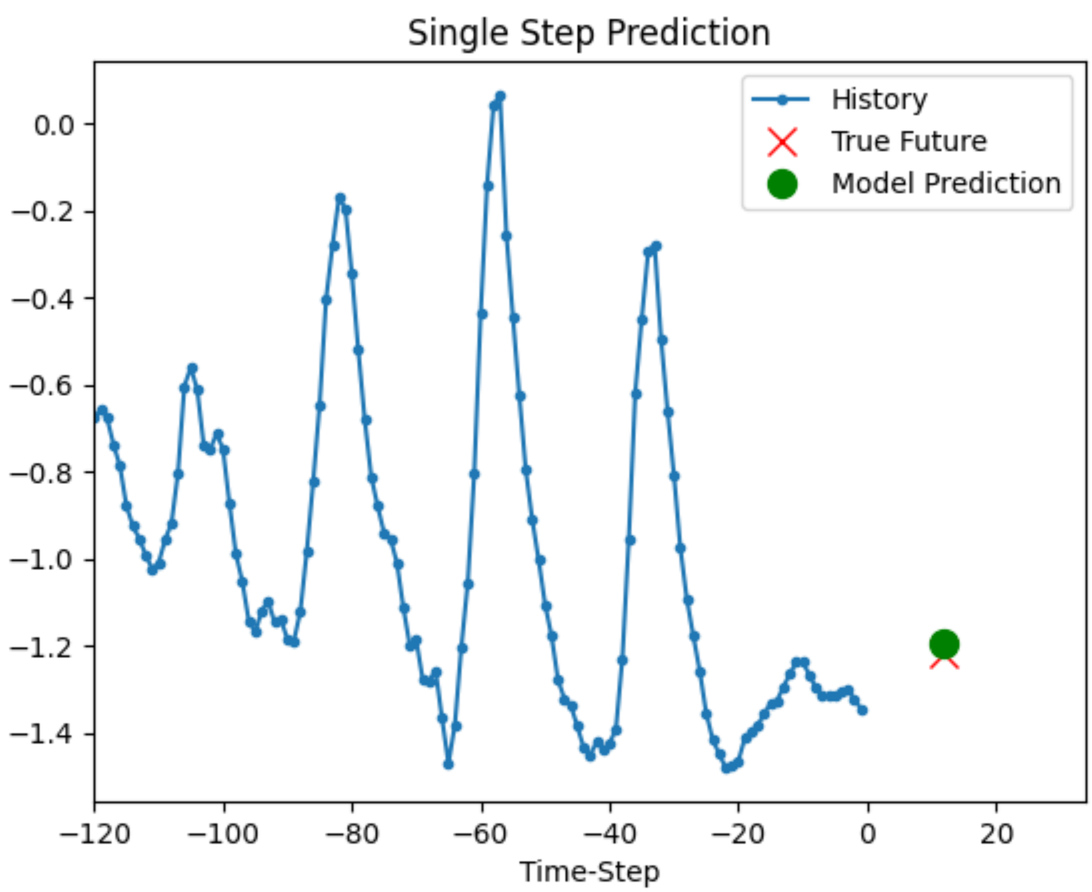
```
8/8 ━━━━━━━━━━━━━━━━━━━━ 0s 7ms/step
```



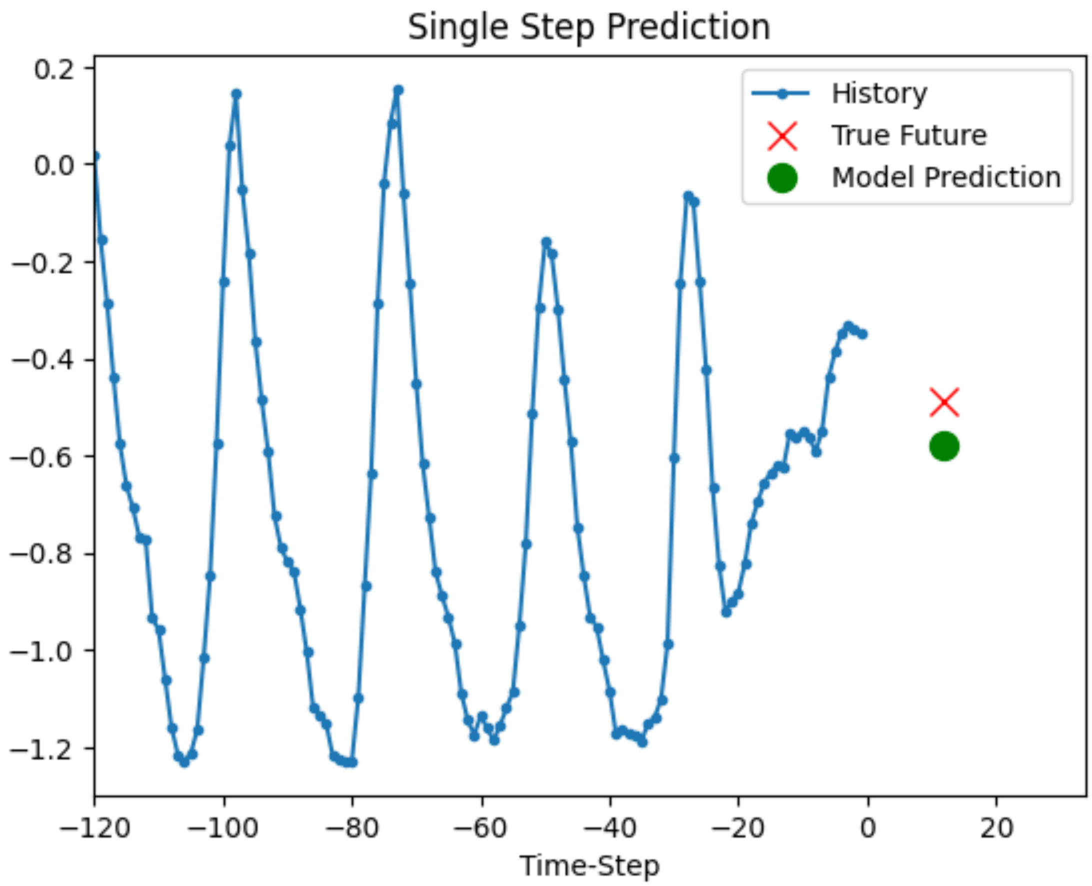

```
8/8 ━━━━━━━━━━━━━━━━━━━━ 0s 8ms/step
```



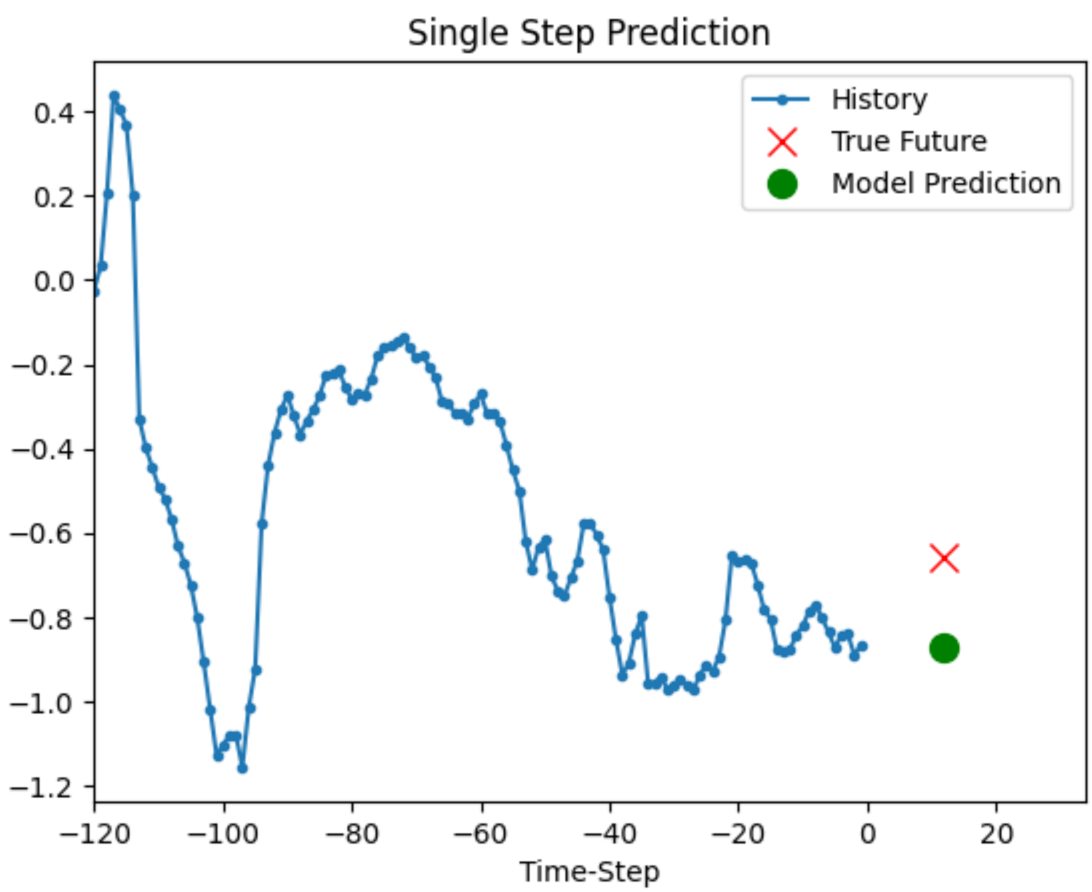

```
8/8 ━━━━━━━━━━━━━━━━━━━━ 0s 8ms/step
```




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




```
8/8 ━━━━━━━━━━━━━━━━━━━━ 0s 7ms/step
```



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

In [36]:
```
# 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 = 72
# Number of samples in the future to predict (the value in the 72nd hour is
future = 3
# 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
```

In [37]:
```
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 pressur
e, 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 [44]:

```python
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

dataset_train = keras.preprocessing.timeseries_dataset_from_array(
    x_train,
    y_train,
    sequence_length=sequence_length,
    sampling_rate=step,
    batch_size=batch_size,
)

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 [41]:
```
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_2"

Layer (type)	Output Shape
input_layer_2 (InputLayer)	(None, 72, 7)
lstm_2 (LSTM)	(None, 32)
dense_2 (Dense)	(None, 1)

Total params: 5,153 (20.13 KB)

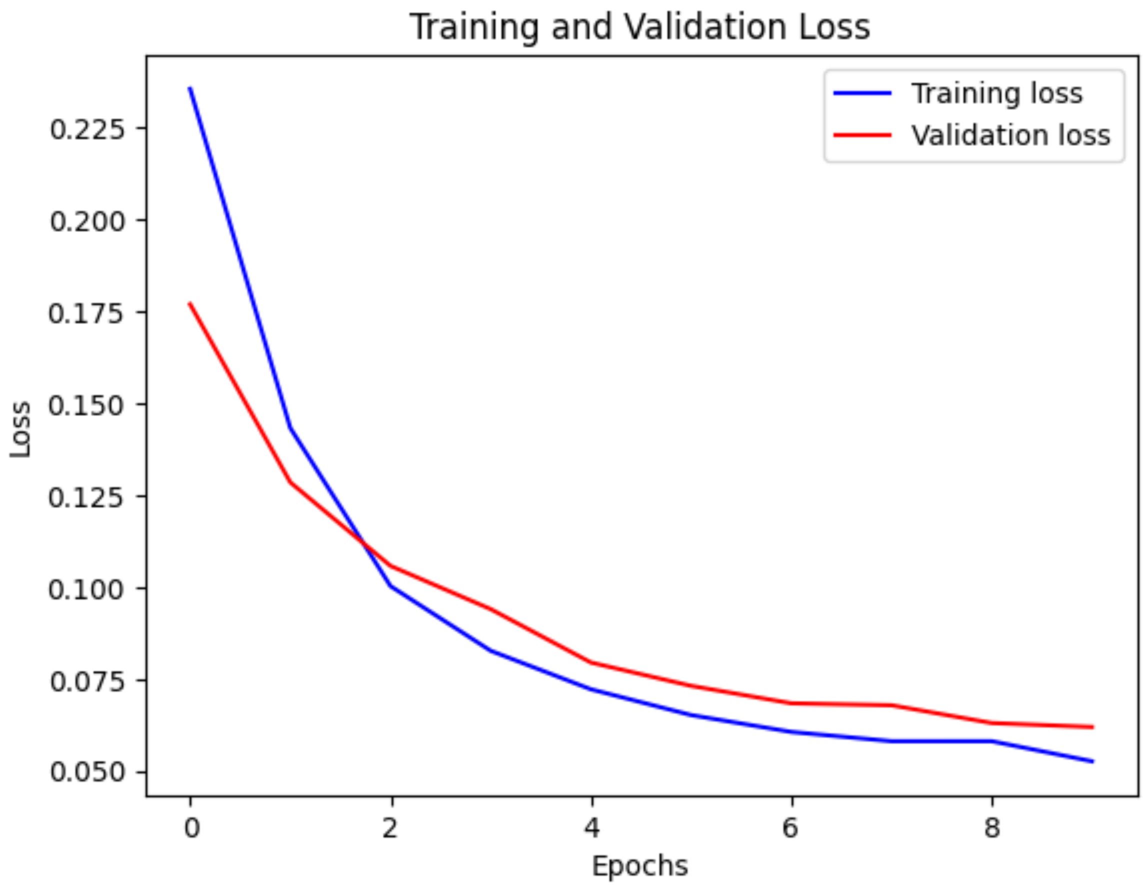
Trainable params: 5,153 (20.13 KB)

Non-trainable params: 0 (0.00 B)

In [42]:
```
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],
)

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)
```

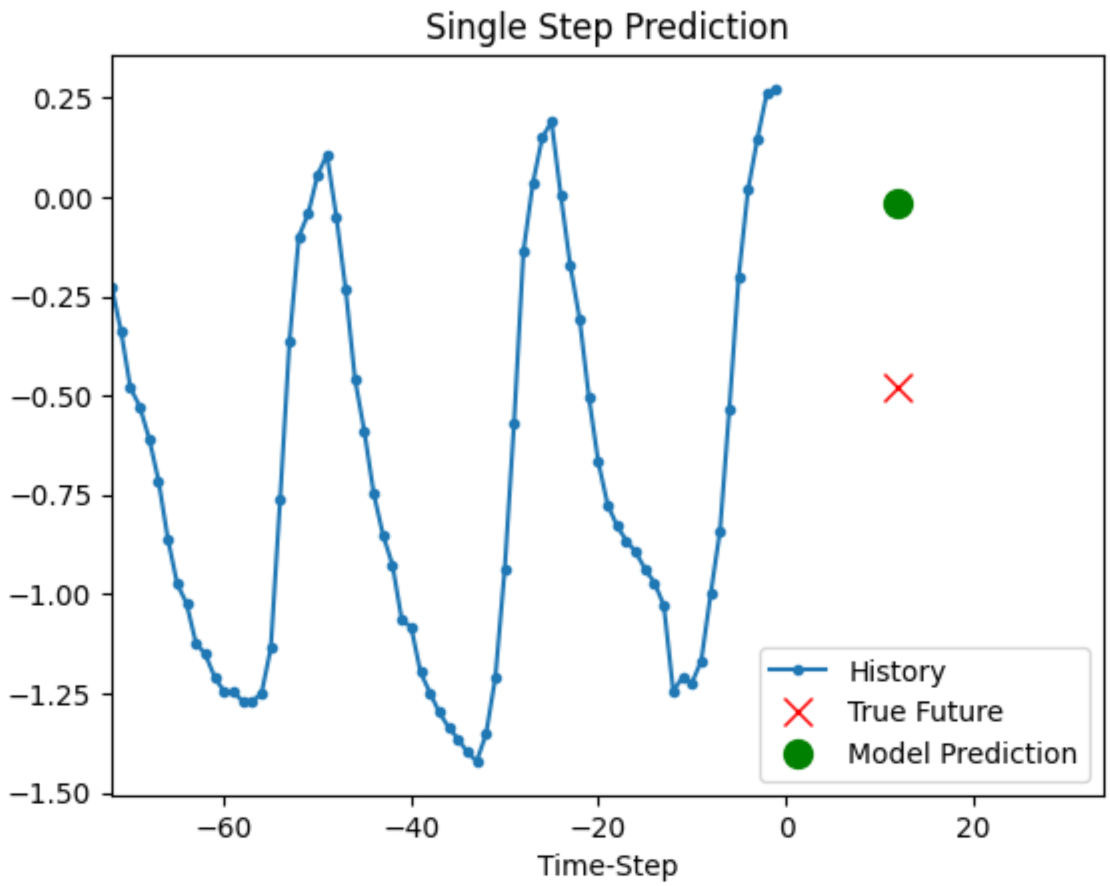
```
    plt.xlabel("Epochs")
    plt.ylabel("Loss")
    plt.legend()
    plt.show()


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

```
Epoch 1/10
95/96 ━━━━━━━━━━━━━━━━━━━━ 0s 61ms/step - loss: 0.3139
Epoch 1: val_loss improved from inf to 0.17688, saving model to model_checkp
oint.weights.h5
96/96 ━━━━━━━━━━━━━━━━━━━━ 9s 76ms/step - loss: 0.3122 - val_loss: 0.1769
Epoch 2/10
95/96 ━━━━━━━━━━━━━━━━━━━━ 0s 52ms/step - loss: 0.1477
Epoch 2: val_loss improved from 0.17688 to 0.12845, saving model to model_ch
eckpoint.weights.h5
96/96 ━━━━━━━━━━━━━━━━━━━━ 6s 65ms/step - loss: 0.1476 - val_loss: 0.1285
Epoch 3/10
94/96 ━━━━━━━━━━━━━━━━━━━━ 0s 63ms/step - loss: 0.1070
Epoch 3: val_loss improved from 0.12845 to 0.10574, saving model to model_ch
eckpoint.weights.h5
96/96 ━━━━━━━━━━━━━━━━━━━━ 8s 81ms/step - loss: 0.1068 - val_loss: 0.1057
Epoch 4/10
95/96 ━━━━━━━━━━━━━━━━━━━━ 0s 58ms/step - loss: 0.0898
Epoch 4: val_loss improved from 0.10574 to 0.09398, saving model to model_ch
eckpoint.weights.h5
96/96 ━━━━━━━━━━━━━━━━━━━━ 10s 76ms/step - loss: 0.0896 - val_loss: 0.0940
Epoch 5/10
95/96 ━━━━━━━━━━━━━━━━━━━━ 0s 55ms/step - loss: 0.0800
Epoch 5: val_loss improved from 0.09398 to 0.07946, saving model to model_ch
eckpoint.weights.h5
96/96 ━━━━━━━━━━━━━━━━━━━━ 10s 69ms/step - loss: 0.0798 - val_loss: 0.0795
Epoch 6/10
94/96 ━━━━━━━━━━━━━━━━━━━━ 0s 61ms/step - loss: 0.0704
Epoch 6: val_loss improved from 0.07946 to 0.07312, saving model to model_ch
eckpoint.weights.h5
96/96 ━━━━━━━━━━━━━━━━━━━━ 7s 75ms/step - loss: 0.0703 - val_loss: 0.0731
Epoch 7/10
96/96 ━━━━━━━━━━━━━━━━━━━━ 0s 55ms/step - loss: 0.0652
Epoch 7: val_loss improved from 0.07312 to 0.06838, saving model to model_ch
eckpoint.weights.h5
96/96 ━━━━━━━━━━━━━━━━━━━━ 9s 89ms/step - loss: 0.0652 - val_loss: 0.0684
Epoch 8/10
96/96 ━━━━━━━━━━━━━━━━━━━━ 0s 53ms/step - loss: 0.0614
Epoch 8: val_loss improved from 0.06838 to 0.06785, saving model to model_ch
eckpoint.weights.h5
96/96 ━━━━━━━━━━━━━━━━━━━━ 8s 68ms/step - loss: 0.0614 - val_loss: 0.0679
Epoch 9/10
94/96 ━━━━━━━━━━━━━━━━━━━━ 0s 62ms/step - loss: 0.0631
Epoch 9: val_loss improved from 0.06785 to 0.06302, saving model to model_ch
eckpoint.weights.h5
96/96 ━━━━━━━━━━━━━━━━━━━━ 7s 75ms/step - loss: 0.0630 - val_loss: 0.0630
Epoch 10/10
94/96 ━━━━━━━━━━━━━━━━━━━━ 0s 54ms/step - loss: 0.0560
Epoch 10: val_loss improved from 0.06302 to 0.06194, saving model to model_c
heckpoint.weights.h5
96/96 ━━━━━━━━━━━━━━━━━━━━ 6s 67ms/step - loss: 0.0559 - val_loss: 0.0619
```

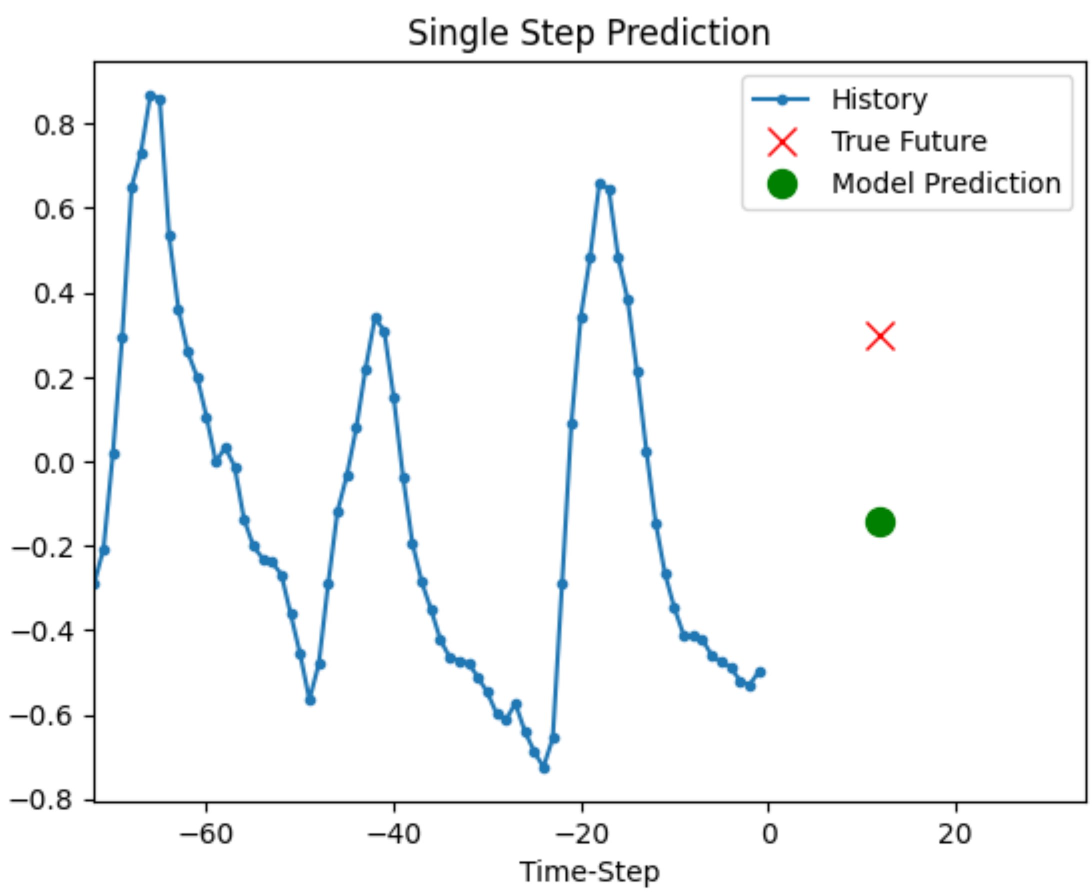


In [43]:
```
for x, y in dataset_val.take(5):
    show_plot(
        [x[0][:, 1].numpy(), y[0].numpy(), model.predict(x)[0]],
        12,
        "Single Step Prediction",
    )
```

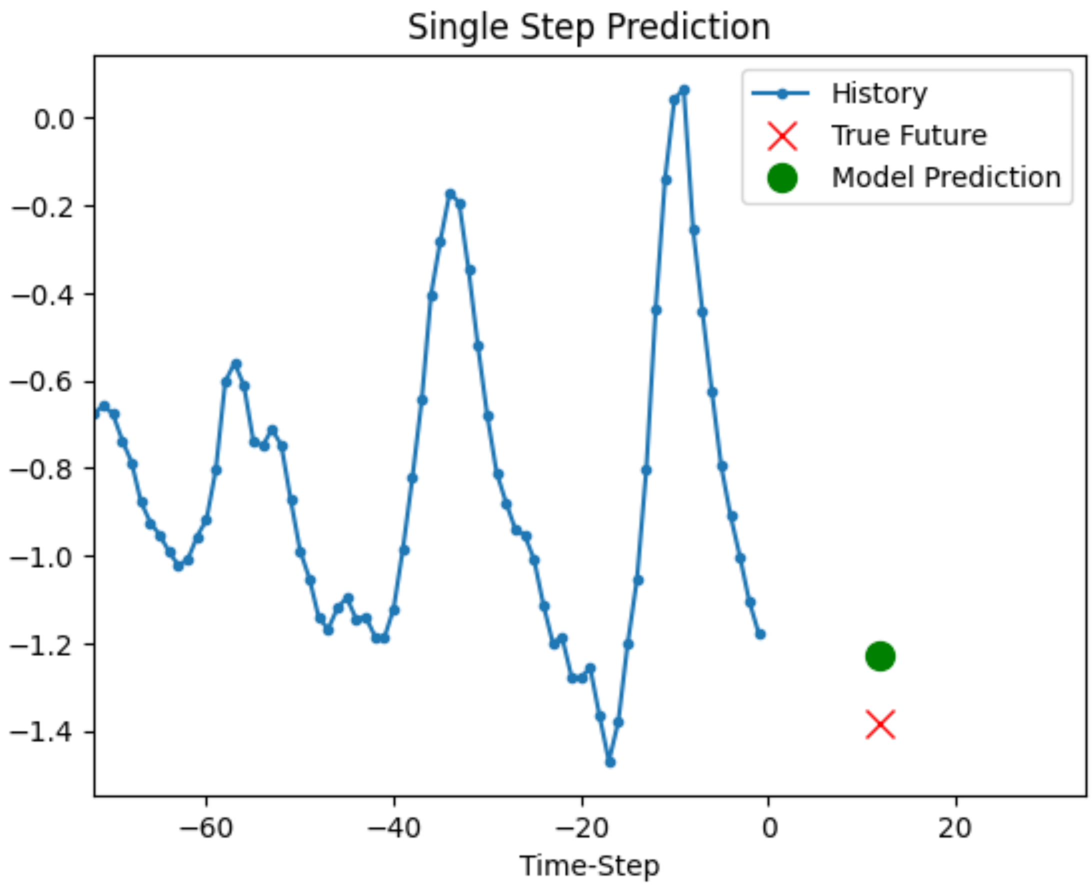
```
8/8 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step
```



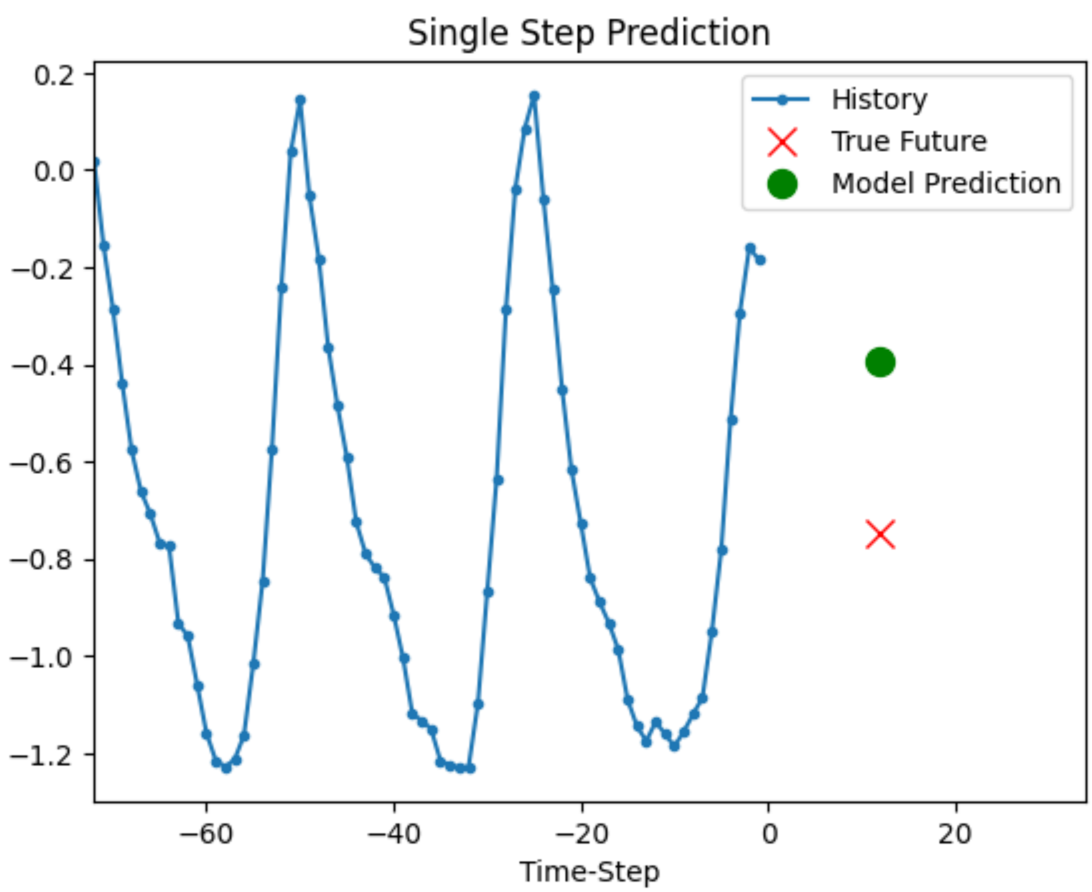

```
8/8 ━━━━━━━━━━━━━━━━━━━━ 0s 7ms/step
```



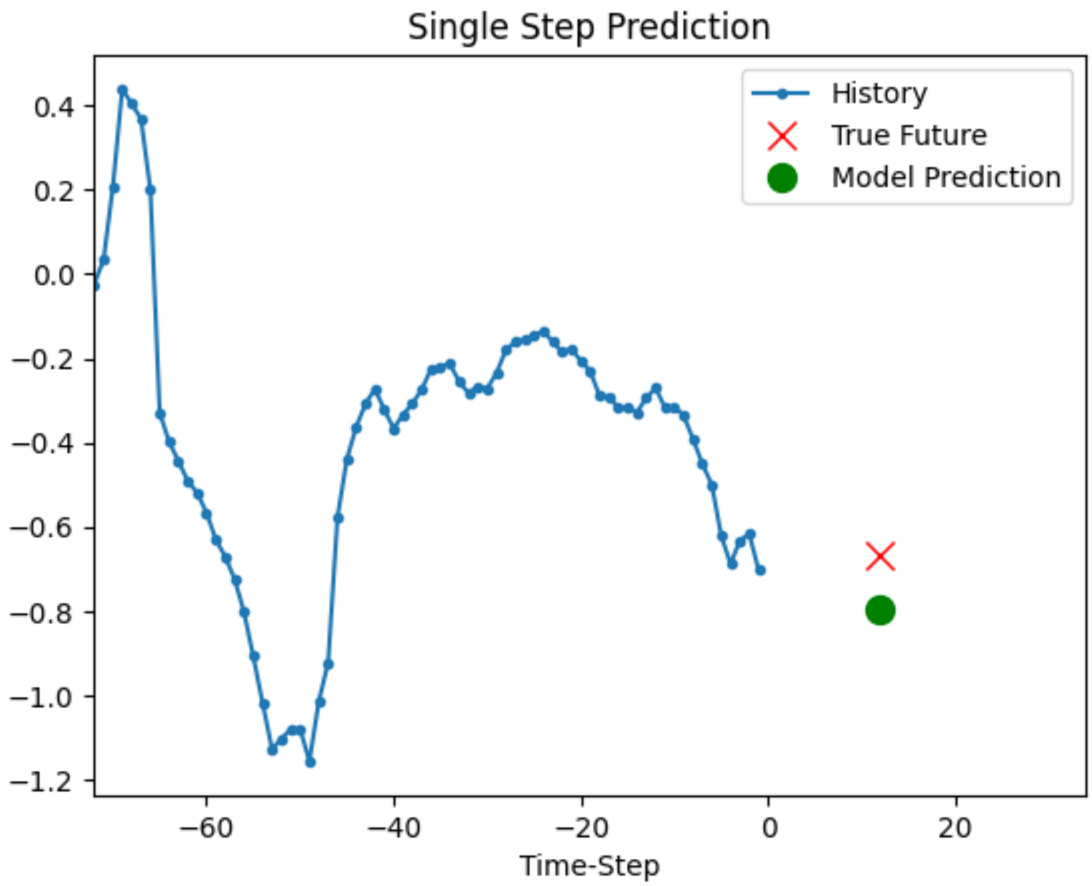

```
8/8 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step
```




```
8/8 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step
```




```
8/8 ━━━━━━━━━━━━━━━━━━━━ 0s 7ms/step
```



Comparison

```
The initial predictive algorithm demonstrates a validation
loss of 0.1201 when forecasting meteorological conditions for
the upcoming half-day period.
In contrast, the subsequent predictive algorithm exhibits a
notably lower validation loss of 0.0640 when projecting
weather patterns for the next quarter-day timeframe.
```

Upon examination of these validation loss metrics, it becomes evident that the latter algorithm outperforms its predecessor in terms of predictive accuracy. This superior performance can be attributed to the shorter time horizon it aims to forecast. Specifically, the second model focuses on near-term predictions, which inherently present less of a challenge compared to long-range forecasts. This discrepancy in difficulty arises from the fundamental nature of weather systems, which are characterized by increasing unpredictability and chaotic behavior as the prediction window extends further into the future. Consequently, the model tasked with the more immediate forecast benefits from reduced atmospheric variability and thus achieves a higher degree of precision in its projections. Claude can make mistakes. Please double-check responses.