# Import libraries

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

from sklearn.preprocessing import MinMaxScaler, StandardScaler

import warnings
warnings.filterwarnings('ignore')

from scipy import stats
%matplotlib inline

import tensorflow as tf
from tensorflow import keras
from tensorflow.keras import Sequential, layers, callbacks
from tensorflow.keras.layers import Dense, LSTM, Dropout, GRU, Bidirectional
```

In [2]:
```
# Set random seed to get the same result after each time running the code
tf.random.set_seed(1234)
```

# Import dataset

In [3]:
```
file = 'Data.csv'
df = pd.read_csv(file, parse_dates = ['Date'], index_col = 'Date')
df
```

Out[3]:

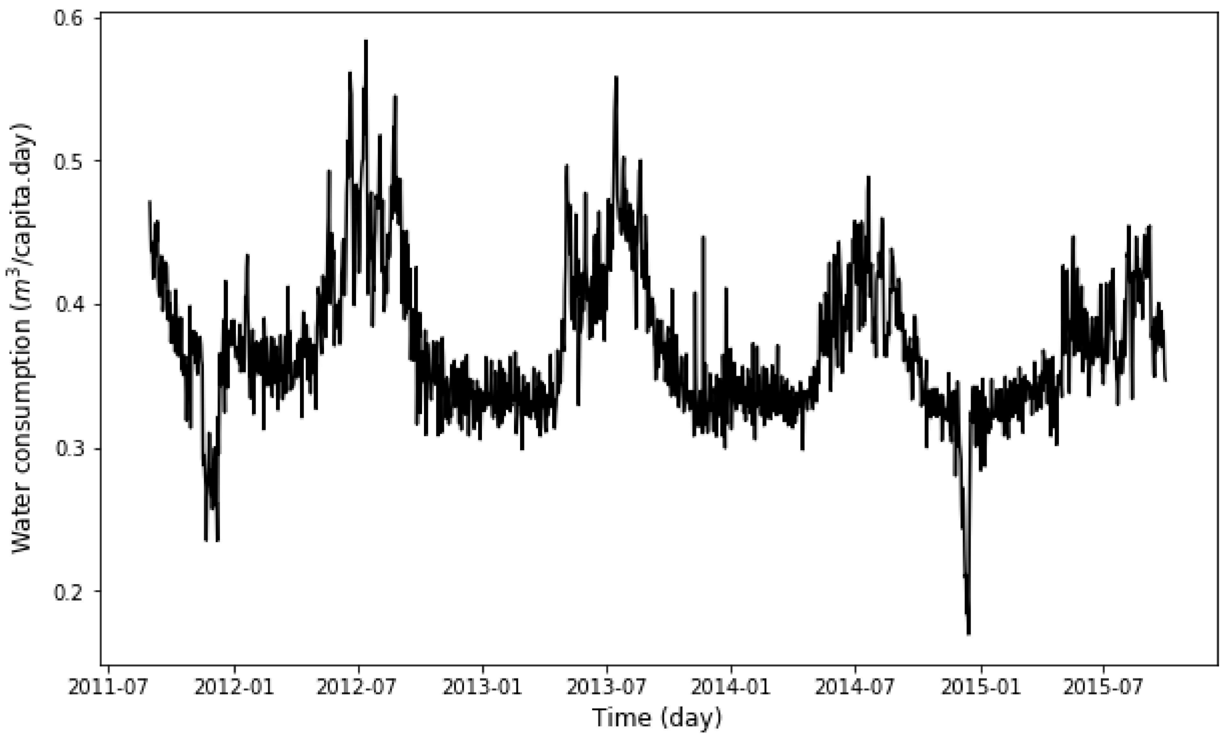
| | Max Temp (C) | Min Temp (C) | Total Precip (mm) | WC (m3/capita.day) |
|---|---|---|---|---|
| **Date** | | | | |
| 2011-09-01 | 25.8 | 14.1 | 0.0 | 0.471092 |
| 2011-09-02 | 26.9 | 19.7 | 0.0 | 0.455604 |
| 2011-09-03 | 29.5 | 21.1 | 0.0 | 0.436626 |
| 2011-09-04 | 27.8 | 19.2 | 15.0 | 0.442867 |
| 2011-09-05 | 21.5 | 14.6 | 11.0 | 0.437708 |
| ... | ... | ... | ... | ... |
| 2015-09-26 | 18.0 | 5.6 | 0.0 | 0.377468 |
| 2015-09-27 | 23.1 | 5.2 | 0.0 | 0.380783 |
| 2015-09-28 | 21.4 | 13.0 | 0.6 | 0.361291 |
| 2015-09-29 | 24.9 | 13.3 | 29.3 | 0.349194 |
| 2015-09-30 | 13.4 | 6.2 | 3.7 | 0.346802 |

1491 rows × 4 columns

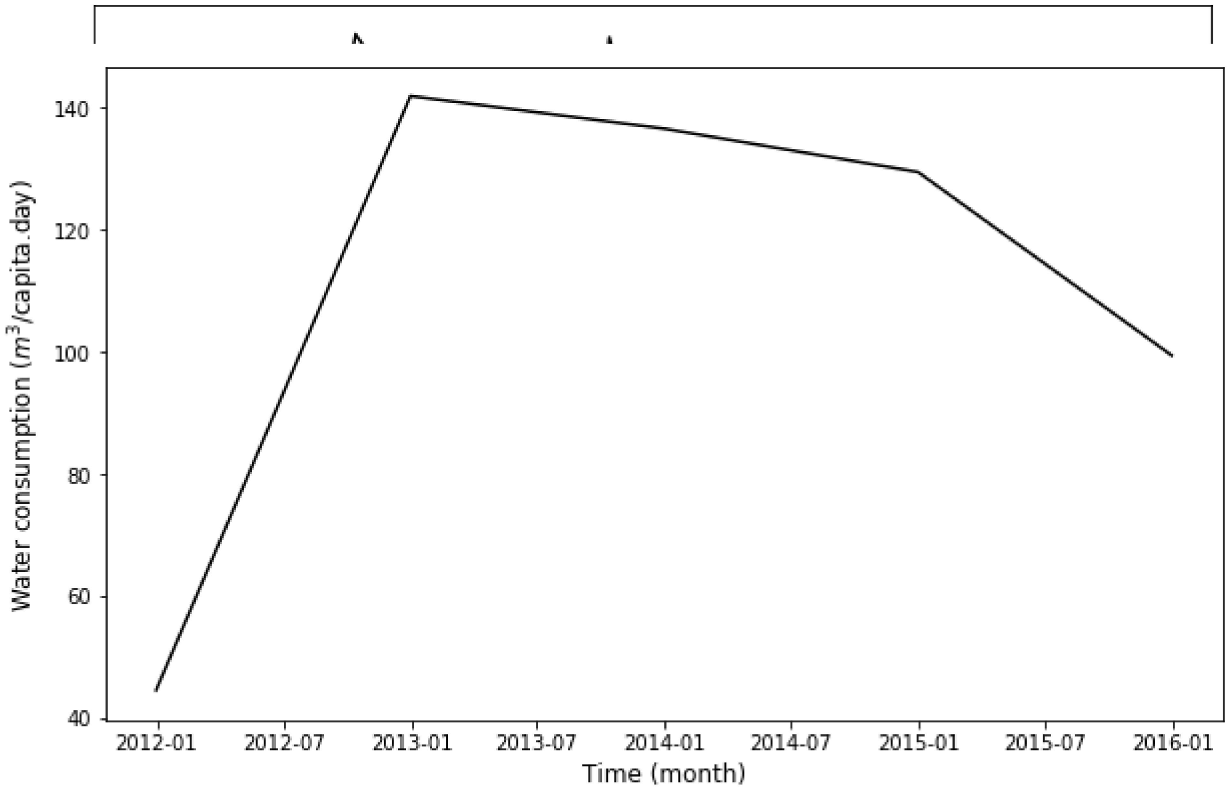
# Data preprocessing

In [4]:

```
# Select the target
df = df.rename(columns = {'WC (m3/capita.day)':'WC'})

# Define a function to draw time_series plot
def timeseries (x_axis, y_axis, x_label):
    plt.figure(figsize = (10, 6))
    plt.plot(x_axis, y_axis, color ='black')
    plt.xlabel(x_label, {'fontsize': 12})
    plt.ylabel('Water consumption ($m^3$/capita.day)', {'fontsize': 12})


dataset = df.copy()
timeseries(df.index, dataset['WC'], 'Time (day)')

dataset['month'] = dataset.index.month
dataset_by_month = dataset.resample('M').sum()
timeseries(dataset_by_month.index, dataset_by_month['WC'], 'Time (month)')

dataset['year'] = dataset.index.year
dataset_by_year = dataset.resample('Y').sum()
timeseries(dataset_by_year.index, dataset_by_year['WC'], 'Time (month)')
```



0.6
0.5
0.4
0.3
0.2
Water consumption ($m^3$/capita.day)
2011-07
2012-01
2012-07
2013-01
2013-07
2014-01
2014-07
2015-01
2015-07
Time (day)


140
120
100
80
60
40
Water consumption ($m^3$/capita.day)
2012-01
2012-07
2013-01
2013-07
2014-01
2014-07
2015-01
2015-07
2016-01
Time (month)

In [5]:
```
# Check for missing values
df = df.loc[:,['Date','WC']]

print('Total num of missing values:')
print(df.WC.isna().sum())
print('')

# Locate the missing value
df_missing_date = df.loc[df.WC.isna() == True]
print('The date of missing value:')
print(df_missing_date.loc[:,['Date']])

# Replcase missing value with interpolation
df.WC.interpolate(inplace = True)

df = df.drop('Date', axis = 1)
```

```
Total num of missing values:
1

The date of missing value:
            Date
Date
2012-12-31   NaN
```

In [6]:
```
# Split train data and test data
train_size = int(len(df)*0.8)

# train_data = df.WC.loc[:train_size] -----> it gives a series
# Do not forget use iloc to select a number of rows
train_data = df.iloc[:train_size]
test_data = df.iloc[train_size:]
```

In [7]:
```
# Scale data
# The input to scaler.fit -> array-like, sparse matrix, dataframe of shape (n_samples, n_features)
scaler = MinMaxScaler().fit(train_data)

train_scaled = scaler.transform(train_data)
test_scaled = scaler.transform(test_data)
```

In [8]:
```
# Create input dataset
# Th input shape should be [samples, time steps, features]
def create_dataset (X, look_back = 1):
    Xs, ys = [], []

    for i in range(len(X)-look_back):
        v = X[i:i+look_back]
        Xs.append(v)
        ys.append(X[i+look_back])

    return np.array(Xs), np.array(ys)

X_train, y_train = create_dataset(train_scaled,30)
X_test, y_test = create_dataset(test_scaled,30)

print('X_train.shape: ', X_train.shape)
print('y_train.shape: ', y_train.shape)
print('X_test.shape: ', X_test.shape)
print('y_test.shape: ', y_test.shape)
```

```
X_train.shape:  (1162, 30, 1)
y_train.shape:  (1162, 1)
X_test.shape:  (269, 30, 1)
y_test.shape:  (269, 1)
```

In [9]:
```
X_test[:33].shape
```

Out[9]:
```
(33, 30, 1)
```

# Create models

In [10]:
```python
# Create GRU model
def create_gru(units):
    model = Sequential()
    # Input layer
    model.add(GRU (units = units, return_sequences = True,
                   input_shape = [X_train.shape[1], X_train.shape[2]]))
    model.add(Dropout(0.2))
    # Hidden layer
    model.add(GRU(units = units))
    model.add(Dropout(0.2))
    model.add(Dense(units = 1))
    #Compile model
    model.compile(optimizer='adam',loss='mse')

    return model
model_gru = create_gru(64)

# Create BiLSTM model
def create_bilstm(units):
    model = Sequential()
    # Input layer
    model.add(Bidirectional(LSTM(units = units, return_sequences=True),
                            input_shape=(X_train.shape[1], X_train.shape[2])))
    # Hidden layer
    model.add(Bidirectional(LSTM(units = units)))
    model.add(Dense(1))
    #Compile model
    model.compile(optimizer='adam',loss='mse')
    return model

model_bilstm = create_bilstm(64)

def fit_model(model):
    early_stop = keras.callbacks.EarlyStopping(monitor = 'val_loss',
                                               patience = 10)
    history = model.fit(X_train, y_train, epochs = 100, validation_split = 0.2,
                    batch_size = 16, shuffle = False, callbacks = [early_stop])
    return history

history_gru = fit_model(model_gru)
history_bilstm = fit_model(model_bilstm)
```

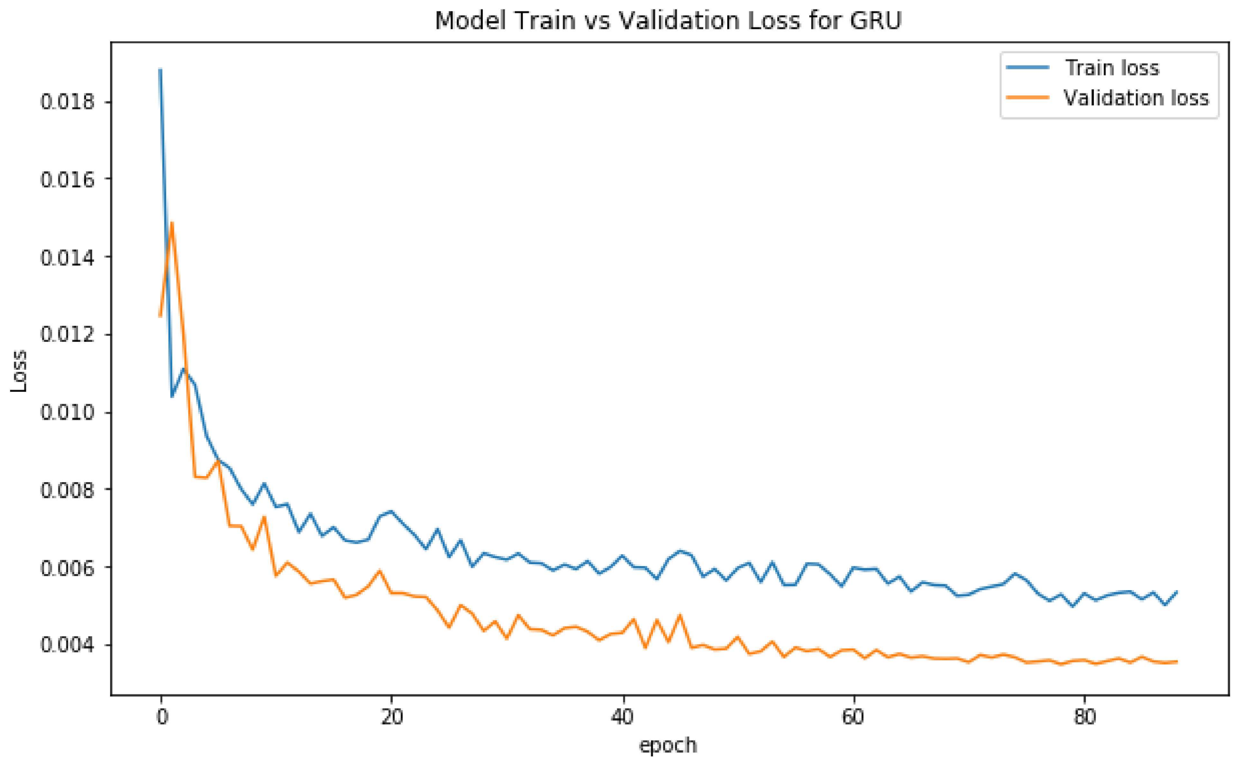
```
Train on 929 samples, validate on 233 samples
Epoch 1/100
929/929 [==============================] - 11s 12ms/sample - loss: 0.0188 - val_loss: 0.0125
Epoch 2/100
929/929 [==============================] - 4s 4ms/sample - loss: 0.0104 - val_loss: 0.0149
Epoch 3/100
929/929 [==============================] - 4s 4ms/sample - loss: 0.0111 - val_loss: 0.0120
Epoch 4/100
929/929 [==============================] - 4s 4ms/sample - loss: 0.0107 - val_loss: 0.0083
Epoch 5/100
929/929 [==============================] - 4s 4ms/sample - loss: 0.0094 - val_loss: 0.0083 ETA: 0s
Epoch 6/100
929/929 [==============================] - 4s 4ms/sample - loss: 0.0087 - val_loss: 0.0087
Epoch 7/100
929/929 [==============================] - 4s 4ms/sample - loss: 0.0085 - val_loss: 0.0070
Epoch 8/100
929/929 [==============================] - 4s 4ms/sample - loss: 0.0080 - val_loss: 0.0070
Epoch 9/100
929/929 [==============================] - 4s 4ms/sample - loss: 0.0076 - val_loss: 0.0064
```

# Model performance

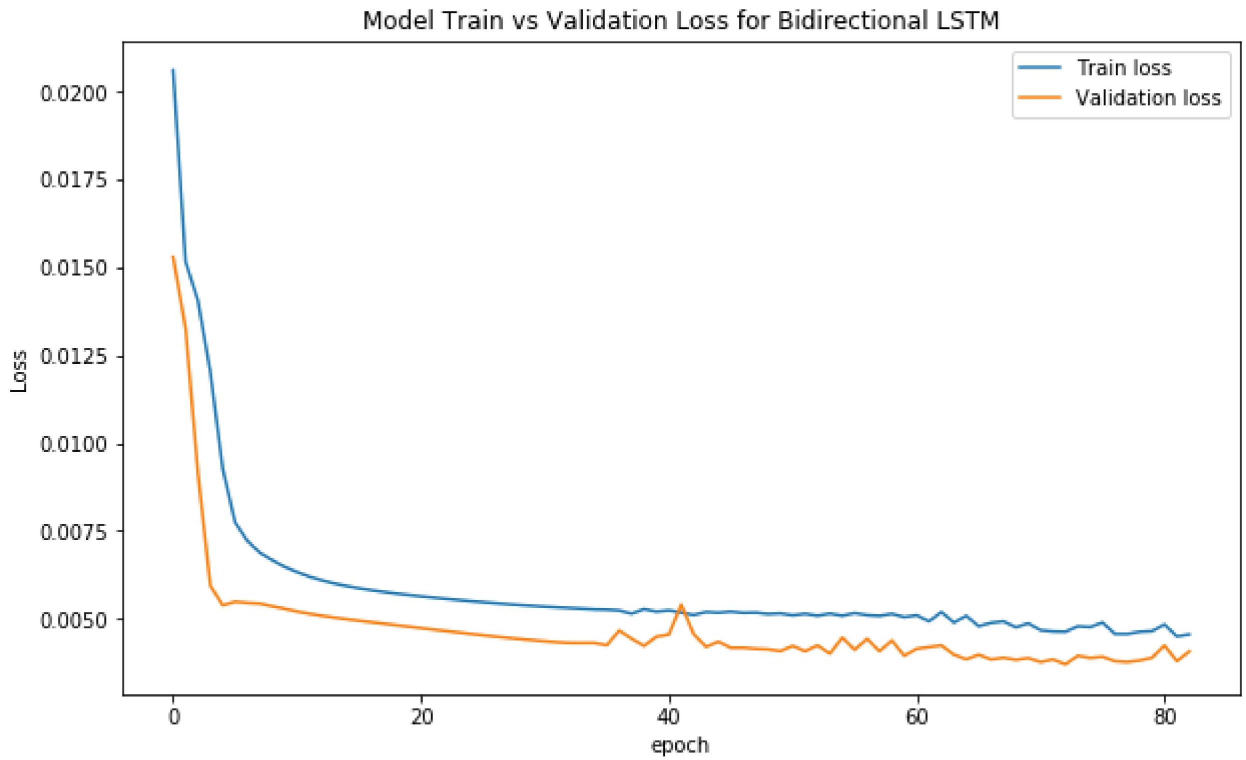
In [11]:
```
# Plot train loss and validation loss
def plot_loss (history, model_name):
    plt.figure(figsize = (10, 6))
    plt.plot(history.history['loss'])
    plt.plot(history.history['val_loss'])
    plt.title('Model Train vs Validation Loss for ' + model_name)
    plt.ylabel('Loss')
    plt.xlabel('epoch')
    plt.legend(['Train loss', 'Validation loss'], loc='upper right')
    plt.savefig('C:/Users/nious/Documents/Medium/Time series/loss_'+model_name+'.jpg', format='jpg', dpi=1000)

plot_loss (history_gru, 'GRU')
plot_loss (history_bilstm, 'Bidirectional LSTM')

# Transform data back to original data space
y_test = scaler.inverse_transform(y_test)
y_train = scaler.inverse_transform(y_train)

# Make prediction
def prediction(model):
    prediction = model.predict(X_test)
    prediction = scaler.inverse_transform(prediction)
    return prediction

prediction_gru = prediction(model_gru)
prediction_bilstm = prediction(model_bilstm)

# Plot test data vs prediction
def plot_future(prediction, model_name, y_test):

    plt.figure(figsize=(10, 6))

    range_future = len(prediction)

    plt.plot(np.arange(range_future), np.array(y_test), label='Test data')
    plt.plot(np.arange(range_future), np.array(prediction),label='Prediction')

    plt.title('Test data vs prediction for ' + model_name)
    plt.legend(loc='upper left')
    plt.xlabel('Time (day)')
    plt.ylabel('Daily water consumption ($m^3$/capita.day)')
```

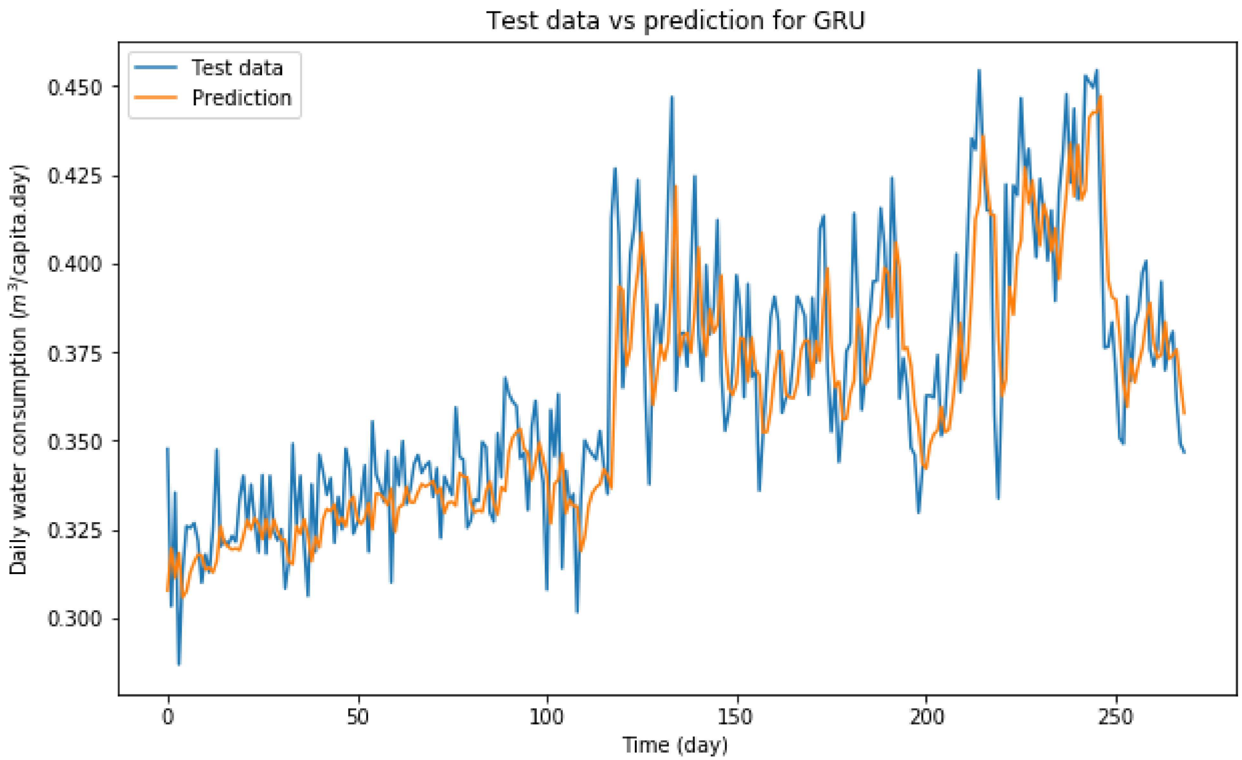
```python
plot_future(prediction_gru, 'GRU', y_test)
plot_future(prediction_bilstm, 'Bidirectional LSTM', y_test)

# Calculate MAE and RMSE
def evaluate_prediction(predictions, actual, model_name):
    errors = predictions - actual
    mse = np.square(errors).mean()
    rmse = np.sqrt(mse)
    mae = np.abs(errors).mean()

    print(model_name + ':')
    print('Mean Absolute Error: {:.4f}'.format(mae))
    print('Root Mean Square Error: {:.4f}'.format(rmse))
    print('')

evaluate_prediction(prediction_gru, y_test, 'GRU')
evaluate_prediction(prediction_bilstm, y_test, 'Bidirectiona LSTM')
```

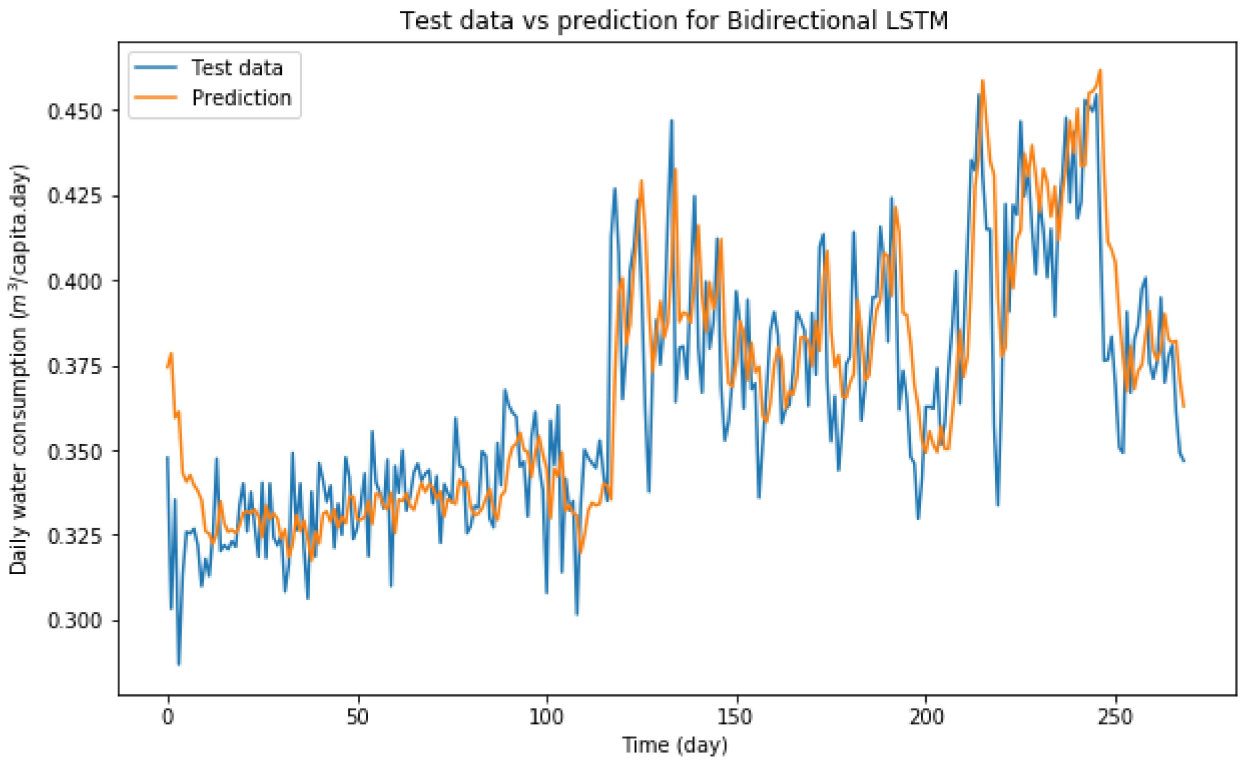
```
GRU:
Mean Absolute Error: 0.0159
Root Mean Square Error: 0.0203

Bidirectiona LSTM:
Mean Absolute Error: 0.0170
Root Mean Square Error: 0.0223
```



Model Train vs Validation Loss for GRU
Train loss
Validation loss
Loss
0.018
0.016
0.014
0.012
0.010
0.008
0.006
0.004
0
20
40
60
80
epoch


Model Train vs Validation Loss for Bidirectional LSTM
Train loss
Validation loss
Loss
epoch
0.0200
0.0175
0.0150
0.0125
0.0100
0.0075
0.0050
0
20
40
60
80


Test data vs prediction for GRU
Test data
Prediction
Daily water consumption ($m^3$/capita.day)
0.450
0.425
0.400
0.375
0.350
0.325
0.300
0
50
100
150
200
250
Time (day)

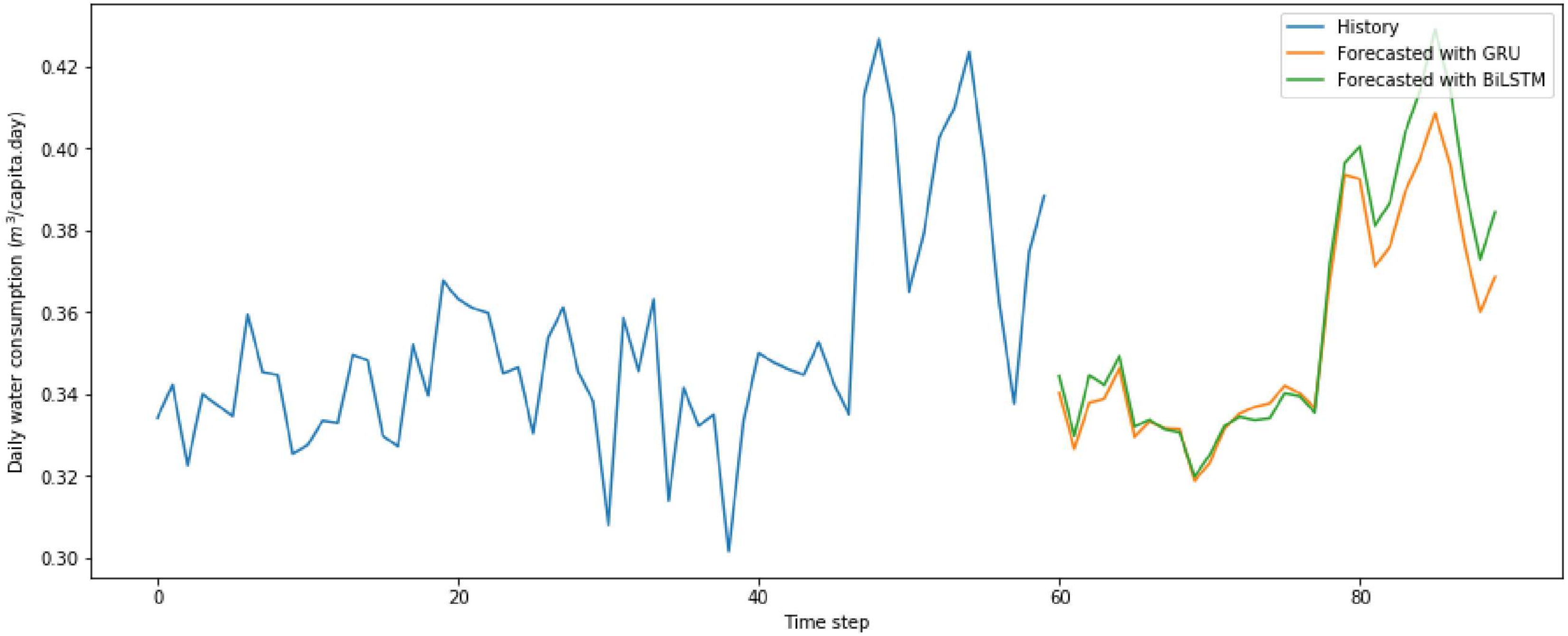



## Multi-step forecasting

In [12]:
```
# Select 60 days of data from test data
new_data = test_data.iloc[100:160]
# Scale the input
scaled_data = scaler.transform(new_data)
# Reshape the input
def create_dataset (X, look_back = 1):
    Xs = []
    for i in range(len(X)-look_back):
        v = X[i:i+look_back]
        Xs.append(v)

    return np.array(Xs)

X_30= create_dataset(scaled_data,30)
print('X_30.shape: ', X_30.shape)
```

```
X_30.shape:  (30, 30, 1)
```

In [13]:
```
# Make prediction for new data
def prediction(model):
    prediction = model.predict(X_30)
    prediction = scaler.inverse_transform(prediction)
    return prediction

prediction_gru = prediction(model_gru)
prediction_bilstm = prediction(model_bilstm)

# Plot history and future
def plot_multi_step(history, prediction1, prediction2):

    plt.figure(figsize=(15, 6))

    range_history = len(history)
    range_future = list(range(range_history, range_history + len(prediction1)))

    plt.plot(np.arange(range_history), np.array(history), label='History')
    plt.plot(range_future, np.array(prediction1),label='Forecasted with GRU')
    plt.plot(range_future, np.array(prediction2),label='Forecasted with BiLSTM')

    plt.legend(loc='upper right')
    plt.xlabel('Time step')
    plt.ylabel('Daily water consumption ($m^3$/capita.day)')


plot_multi_step(new_data, prediction_gru, prediction_bilstm)
```


History
Forecasted with GRU
Forecasted with BiLSTM
Daily water consumption ($m^3$/capita.day)
0.42
0.40
0.38
0.36
0.34
0.32
0.30
0
20
40
60
80
Time step

In [ ]: