MACHINE LEARNING

(PREDICTION ALGORITHM)

TOPIC CHOSEN: Time Series Analysis

DATASET LINK: https://www.kaggle.com/code/andreshg/timeseries-analysis-a-complete-guide/notebook

DATASET NAME: Aquier_Petrignano.csv

SOURCE: Kaggle

DATASET DETAILS:

In this project I want to deep dive into TimeSeries analysis to show how to review the data, how to preview it and how to engineering.

I also want to explore some of the typical TimeSeries topics such as:

ACF/PACF
ARIMA
Auto-ARIMA
Prophet
Augmented Dickey-Fuller (ADF)

DATA VISUALIZATION:

FEATURES:

Rainfall indicates the quantity of rain falling (mm)
Temperature indicates the temperature (°C)

TARGET:

- **Depth to Groundwater** indicates the groundwater level (m from the ground floor)

```
import pandas as pd
import numpy as np
import datetime as dt
```

```
df = pd.read_csv("Aquifer_Petrignano.csv")
df.head()
```

	Date	Rainfall_Bastia_Umbra	Depth_to_Groundwater_P24	Depth_to_Groundwater_P25	Temperature_Bastia_Umbra	Temperat
0	14/03/2006	NaN	-22.48	-22.18	NaN	
1	15/03/2006	NaN	-22.38	-22.14	NaN	
2	16/03/2006	NaN	-22.25	-22.04	NaN	
3	17/03/2006	NaN	-22.38	-22.04	NaN	
4	18/03/2006	NaN	-22.60	-22.04	NaN	

```
# Remove old rows
df = df[df.Rainfall_Bastia_Umbra.notna()].reset_index(drop=True)
# Remove not usefull columns
df = df.drop(['Depth_to_Groundwater_P24', 'Temperature_Petrignano'], axis=1)


# Simplify column names
df.columns = ['date', 'rainfall', 'depth_to_groundwater', 'temperature', 'drainage_volume',
'river_hydrometry']

targets = ['depth_to_groundwater']
features = [feature for feature in df.columns if feature not in targets]
df.head()
```

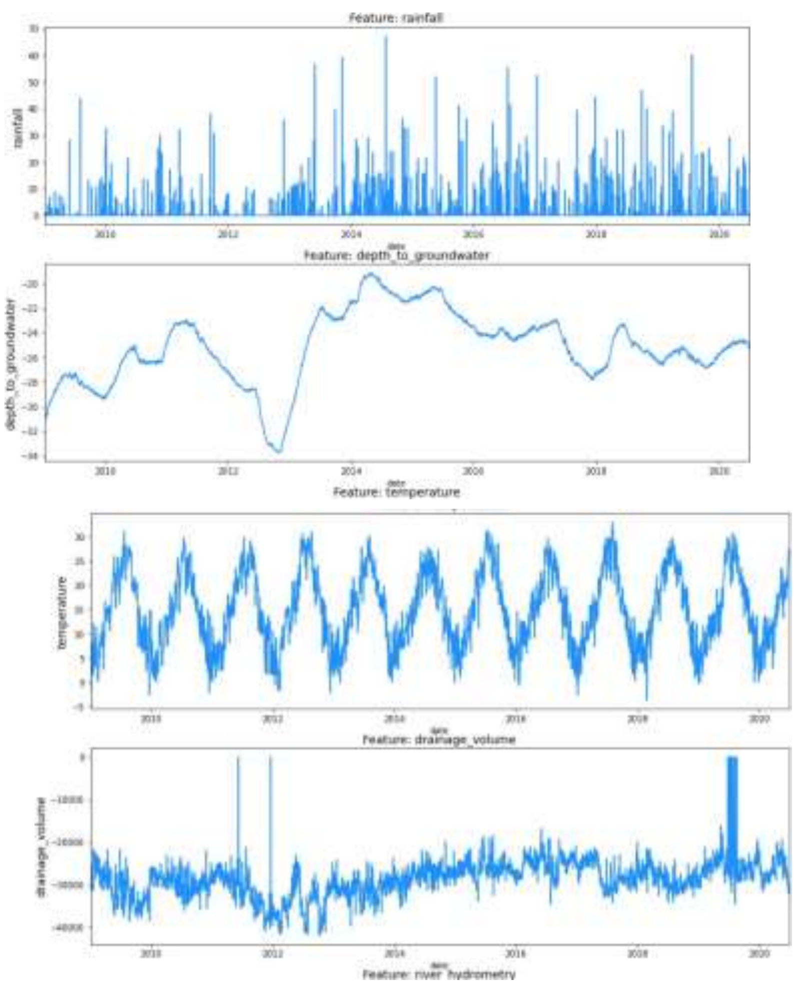
	date	rainfall	depth_to_groundwater	temperature	drainage_volume	river_hydrometry
0	01/01/2009	0.0	-31.14	5.2	-24530.688	2.4
1	02/01/2009	0.0	-31.11	2.3	-28785.888	2.5
2	03/01/2009	0.0	-31.07	4.4	-25766.208	2.4
3	04/01/2009	0.0	-31.05	0.8	-27919.296	2.4
4	05/01/2009	0.0	-31.01	-1.9	-29854.656	2.3

from datetime import datetime, date

```
from datetime import datetime, date

df['date'] = pd.to_datetime(df['date'], format = '%d/%m/%Y')
df.head().style.set_properties(subset=['date'], **{'background-color': 'dodgerblue'})
```

	date	rainfall	depth_to_groundwater	temperature	drainage_volume	river_hydrometry
0	2009-01-01 00:00:00	0.000000	-31.140000	5.200000	-24530.688000	2.400000
1	2009-01-02 00:00:00	0.000000	-31.110000	2.300000	-28785.888000	2.500000
2	2009-01-03 00:00:00	0.000000	-31.070000	4.400000	-25766.208000	2.400000
3	2009-01-04 00:00:00	0.000000	-31.050000	0.800000	-27919.296000	2.400000
4	2009-01-05 00:00:00	0.000000	-31.010000	-1.900000	-29854.656000	2.300000

```
import matplotlib.pyplot as plt
import seaborn as sns
f,ax = plt.subplots(nrows=5, ncols=1, figsize=(15, 25))

for i, column in enumerate(df.drop('date', axis=1).columns):
    sns.lineplot(x=df['date'], y=df[column].fillna(method='ffill'), ax=ax[i], color='dodgerblue')
    ax[i].set_title('Feature: {}'.format(column), fontsize=14)
    ax[i].set_ylabel(ylabel=column, fontsize=14)

    ax[i].set_xlim([date(2009, 1, 1), date(2020, 6, 30)])
```



DATA PREPROCESSING:

df = df.sort_values(by='date')

Check time intervals
df['delta'] = df['date'] - df['date'].shift(1)

df[['date', 'delta']].head()

	date	delta
0	2009-01-01	NaT
1	2009-01-02	1 days
2	2009-01-03	1 days
3	2009-01-04	1 days
4	2009-01-05	1 days

df['delta'].sum(), df['delta'].count()

```
(Timedelta('4198 days 00:00:00'), 4198)
```

HANDLE MISSING DATA:

df = df.drop('delta', axis=1)
df.isna().sum()

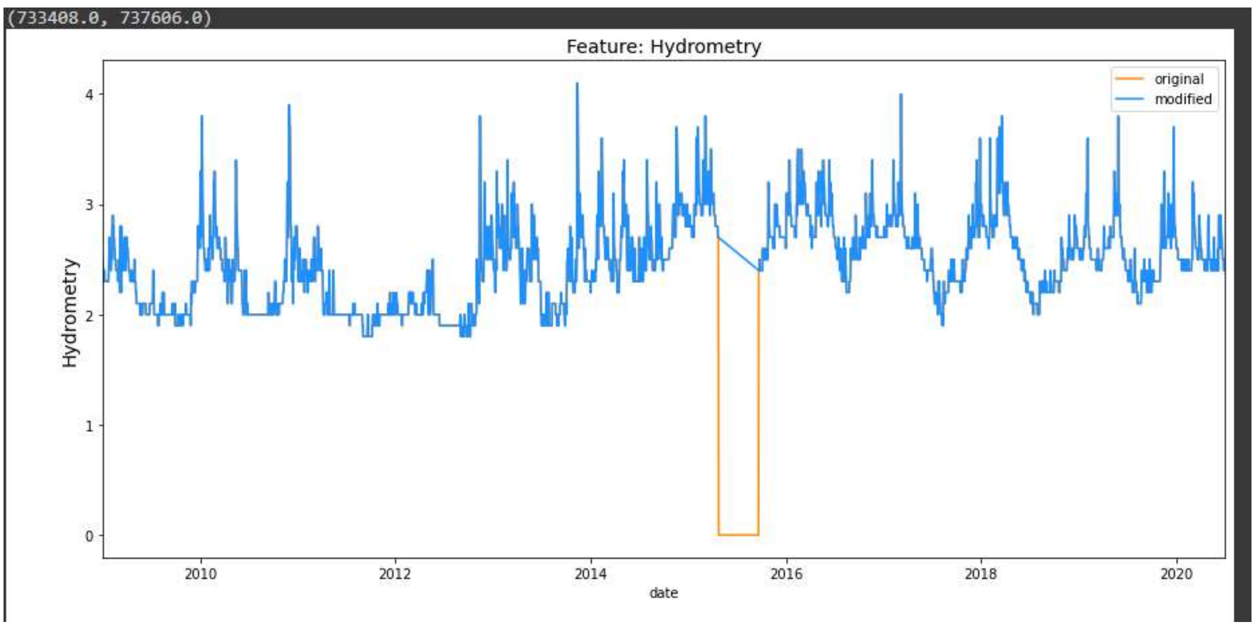
```
date                   0
rainfall               0
depth_to_groundwater  27
temperature            0
drainage_volume        1
river_hydrometry       0
dtype: int64
```

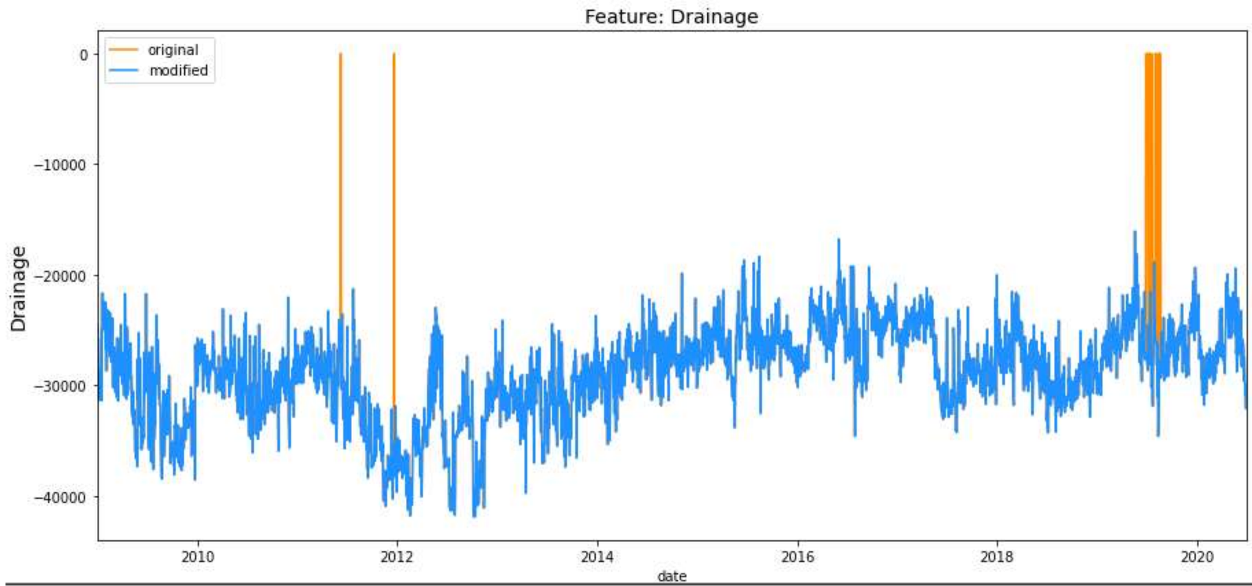
f, ax = plt.subplots(nrows=2, ncols=1, figsize=(15, 15))

old_hydrometry = df['river_hydrometry'].copy()
df['river_hydrometry'] = df['river_hydrometry'].replace(0, np.nan)

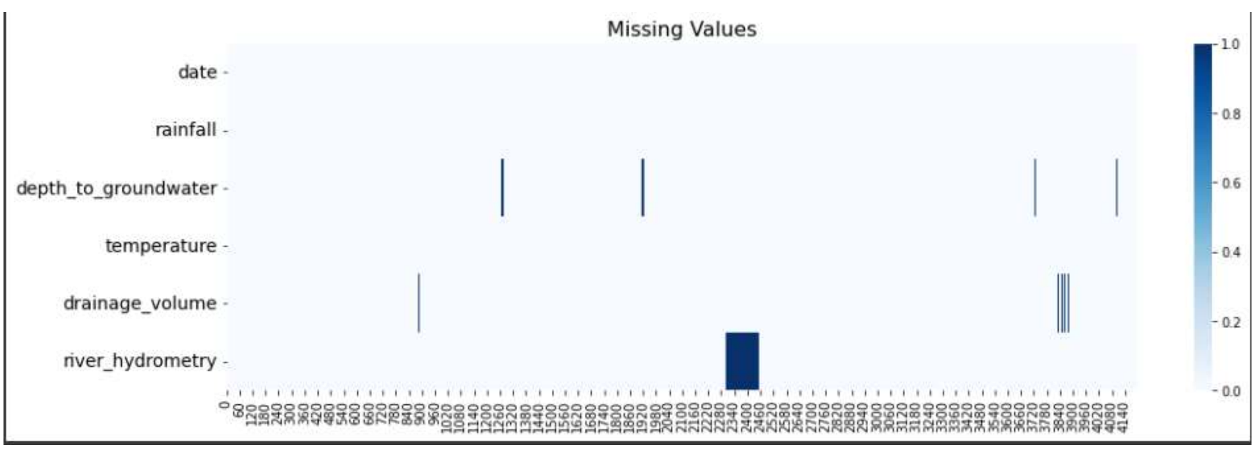
sns.lineplot(x=df['date'], y=old_hydrometry, ax=ax[0], color='darkorange', label='original')
sns.lineplot(x=df['date'], y=df['river_hydrometry'].fillna(np.inf), ax=ax[0], color='dodgerblue', label='modified')
ax[0].set_title('Feature: Hydrometry', fontsize=14)

```
ax[0].set_ylabel(ylabel='Hydrometry', fontsize=14)
ax[0].set_xlim([date(2009, 1, 1), date(2020, 6, 30)])

old_drainage = df['drainage_volume'].copy()
df['drainage_volume'] = df['drainage_volume'].replace(0, np.nan)

sns.lineplot(x=df['date'], y=old_drainage, ax=ax[1], color='darkorange', label='original')
sns.lineplot(x=df['date'], y=df['drainage_volume'].fillna(np.inf), ax=ax[1], color='dodgerblue',
label='modified')
ax[1].set_title('Feature: Drainage', fontsize=14)
ax[1].set_ylabel(ylabel='Drainage', fontsize=14)
ax[1].set_xlim([date(2009, 1, 1), date(2020, 6, 30)])
```

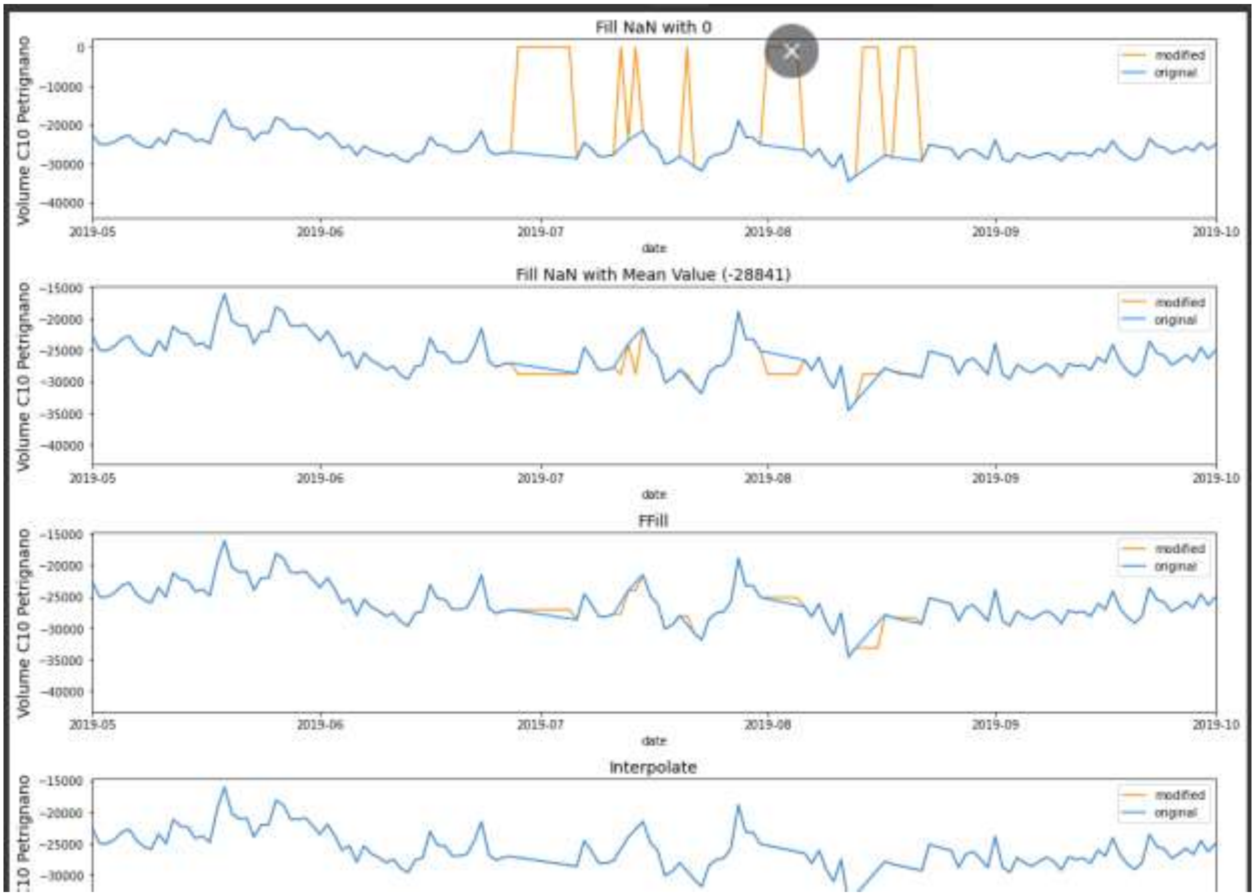





```
f, ax = plt.subplots(nrows=1, ncols=1, figsize=(16,5))

sns.heatmap(df.T.isna(), cmap='Blues')
ax.set_title('Missing Values', fontsize=16)

for tick in ax.yaxis.get_major_ticks():
    tick.label.set_fontsize(14)
plt.show()
```



```
f, ax = plt.subplots(nrows=4, ncols=1, figsize=(15, 12))

sns.lineplot(x=df['date'], y=df['drainage_volume'].fillna(0), ax=ax[0], color='darkorange', label = 'modified')
sns.lineplot(x=df['date'], y=df['drainage_volume'].fillna(np.inf), ax=ax[0], color='dodgerblue', label = 'original')
ax[0].set_title('Fill NaN with 0', fontsize=14)
ax[0].set_ylabel(ylabel='Volume C10 Petrignano', fontsize=14)

mean_drainage = df['drainage_volume'].mean()
sns.lineplot(x=df['date'], y=df['drainage_volume'].fillna(mean_drainage), ax=ax[1], color='darkorange', label = 'modified')
sns.lineplot(x=df['date'], y=df['drainage_volume'].fillna(np.inf), ax=ax[1], color='dodgerblue', label = 'original')
ax[1].set_title(f'Fill NaN with Mean Value ({mean_drainage:.0f})', fontsize=14)
ax[1].set_ylabel(ylabel='Volume C10 Petrignano', fontsize=14)

sns.lineplot(x=df['date'], y=df['drainage_volume'].ffill(), ax=ax[2], color='darkorange', label = 'modified')
sns.lineplot(x=df['date'], y=df['drainage_volume'].fillna(np.inf), ax=ax[2], color='dodgerblue', label = 'original')
ax[2].set_title(f'FFill', fontsize=14)
ax[2].set_ylabel(ylabel='Volume C10 Petrignano', fontsize=14)

sns.lineplot(x=df['date'], y=df['drainage_volume'].interpolate(), ax=ax[3], color='darkorange', label = 'modified')
sns.lineplot(x=df['date'], y=df['drainage_volume'].fillna(np.inf), ax=ax[3], color='dodgerblue', label = 'original')
ax[3].set_title(f'Interpolate', fontsize=14)
ax[3].set_ylabel(ylabel='Volume C10 Petrignano', fontsize=14)

for i in range(4):
    ax[i].set_xlim([date(2019, 5, 1), date(2019, 10, 1)])

plt.tight_layout()
plt.show()
```



df['drainage_volume'] = df['drainage_volume'].interpolate()
df['river_hydrometry'] = df['river_hydrometry'].interpolate()
df['depth_to_groundwater'] = df['depth_to_groundwater'].interpolate()

Smoothing data:

Resampling can provide additional information on the data. There are two types of resampling:

- **Upsampling** is when the frequency of samples is increased (e.g. days to hours)
- **Downsampling** is when the frequency of samples is decreased (e.g. days to weeks)

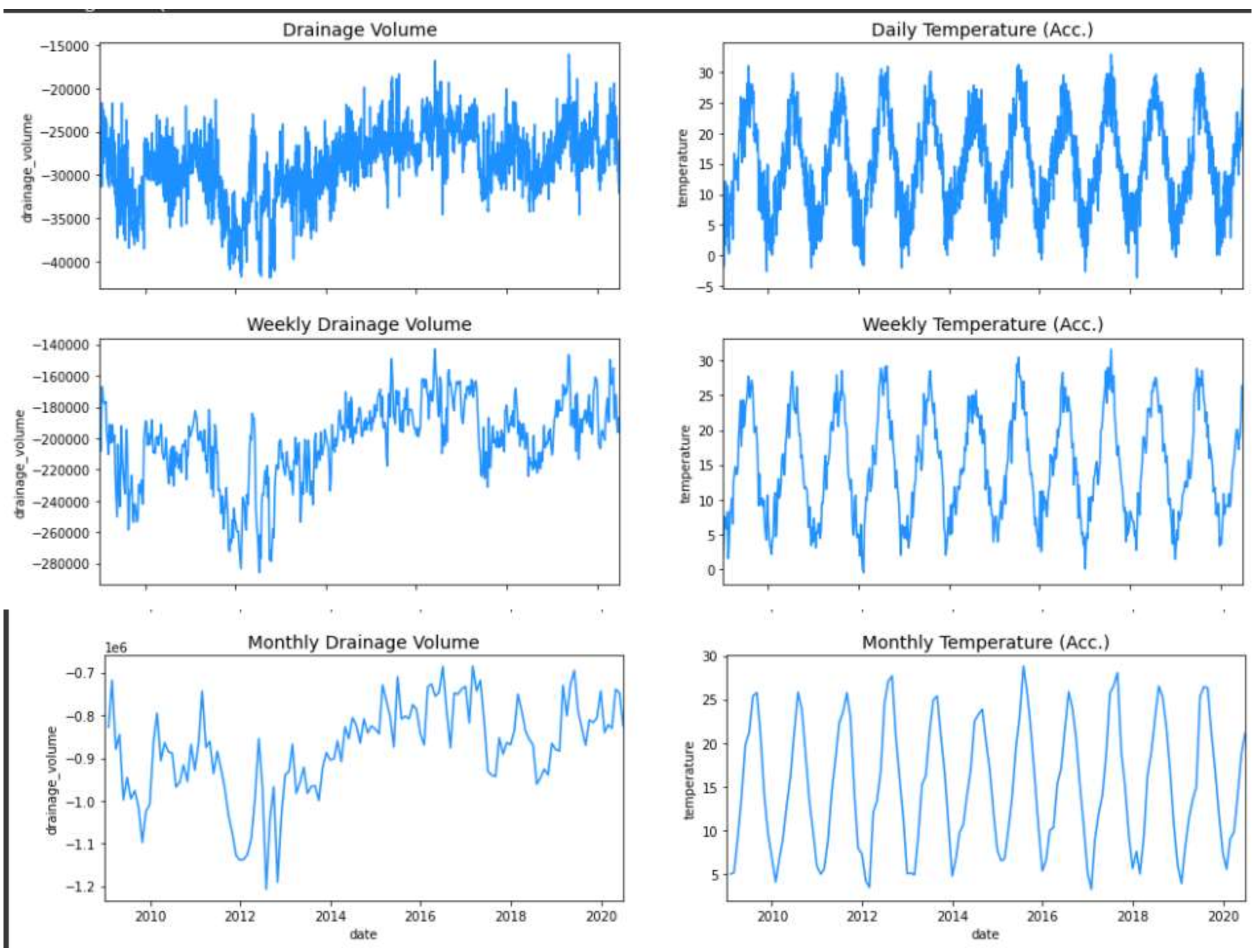
fig, ax = plt.subplots(ncols=2, nrows=3, sharex=True, figsize=(16,12))

sns.lineplot(df['date'], df['drainage_volume'], color='dodgerblue', ax=ax[0, 0])
ax[0, 0].set_title('Drainage Volume', fontsize=14)

resampled_df = df[['date','drainage_volume']].resample('7D', on='date').sum().reset_index(drop=False)
sns.lineplot(resampled_df['date'], resampled_df['drainage_volume'], color='dodgerblue', ax=ax[1, 0])
ax[1, 0].set_title('Weekly Drainage Volume', fontsize=14)

resampled_df = df[['date','drainage_volume']].resample('M', on='date').sum().reset_index(drop=False)

```
sns.lineplot(resampled_df['date'], resampled_df['drainage_volume'], color='dodgerblue', ax=ax[2, 0])
ax[2, 0].set_title('Monthly Drainage Volume', fontsize=14)

for i in range(3):
   ax[i, 0].set_xlim([date(2009, 1, 1), date(2020, 6, 30)])

sns.lineplot(df['date'], df['temperature'], color='dodgerblue', ax=ax[0, 1])
ax[0, 1].set_title('Daily Temperature (Acc.)', fontsize=14)

resampled_df = df[['date','temperature']].resample('7D', on='date').mean().reset_index(drop=False)
sns.lineplot(resampled_df['date'], resampled_df['temperature'], color='dodgerblue', ax=ax[1, 1])
ax[1, 1].set_title('Weekly Temperature (Acc.)', fontsize=14)

resampled_df = df[['date','temperature']].resample('M', on='date').mean().reset_index(drop=False)
sns.lineplot(resampled_df['date'], resampled_df['temperature'], color='dodgerblue', ax=ax[2, 1])
ax[2, 1].set_title('Monthly Temperature (Acc.)', fontsize=14)

for i in range(3):
   ax[i, 1].set_xlim([date(2009, 1, 1), date(2020, 6, 30)])
plt.show()
```



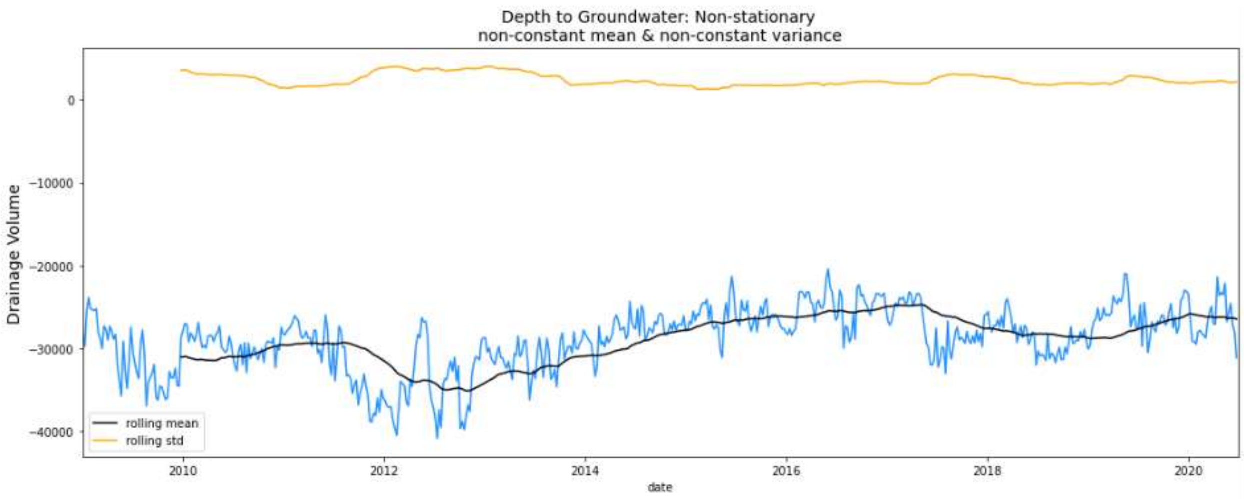
```
downsample = df[['date',
                 'depth_to_groundwater',
                 'temperature',
                 'drainage_volume',
                 'river_hydrometry',
                 'rainfall'
                ]].resample('7D', on='date').mean().reset_index(drop=False)

df = downsample.copy()
```

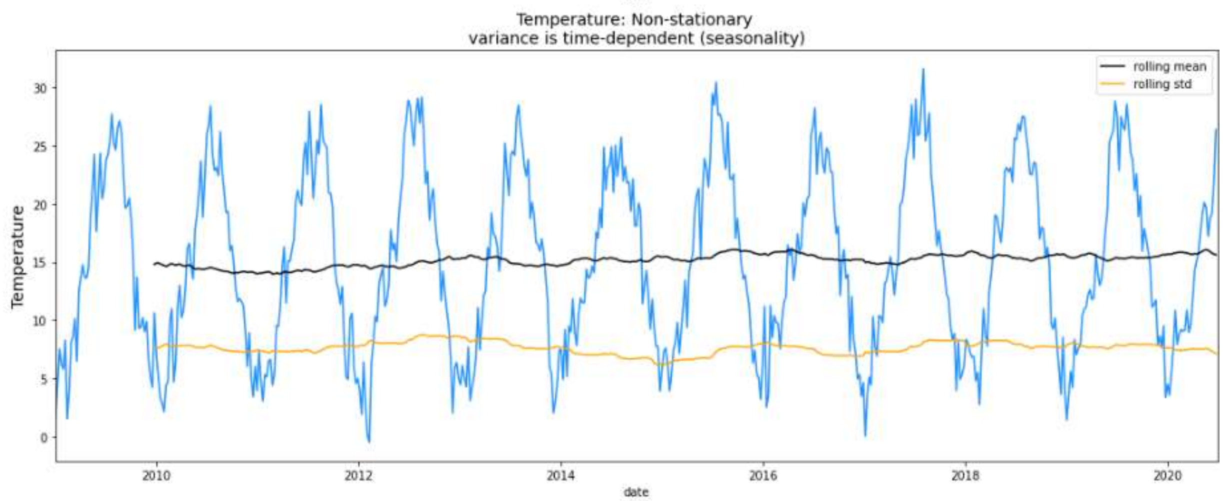
STATIONARITY:

Some time-series models, such as such as ARIMA, assume that the underlying data is stationary. Stationarity describes that the time-series has

- constant mean and mean is not time-dependent
- constant variance and variance is not time-dependent
- constant covariance and covariance is not time-dependent

```
rolling_window = 52
f, ax = plt.subplots(nrows=2, ncols=1, figsize=(15, 12))

sns.lineplot(x=df['date'], y=df['drainage_volume'], ax=ax[0], color='dodgerblue')
sns.lineplot(x=df['date'], y=df['drainage_volume'].rolling(rolling_window).mean(), ax=ax[0],
color='black', label='rolling mean')
sns.lineplot(x=df['date'], y=df['drainage_volume'].rolling(rolling_window).std(), ax=ax[0], color='orange',
label='rolling std')
ax[0].set_title('Depth to Groundwater: Non-stationary \nnon-constant mean & non-constant variance',
fontsize=14)
ax[0].set_ylabel(ylabel='Drainage Volume', fontsize=14)
ax[0].set_xlim([date(2009, 1, 1), date(2020, 6, 30)])

sns.lineplot(x=df['date'], y=df['temperature'], ax=ax[1], color='dodgerblue')
sns.lineplot(x=df['date'], y=df['temperature'].rolling(rolling_window).mean(), ax=ax[1], color='black',
label='rolling mean')
sns.lineplot(x=df['date'], y=df['temperature'].rolling(rolling_window).std(), ax=ax[1], color='orange',
label='rolling std')
ax[1].set_title('Temperature: Non-stationary \nvariance is time-dependent (seasonality)', fontsize=14)
ax[1].set_ylabel(ylabel='Temperature', fontsize=14)
ax[1].set_xlim([date(2009, 1, 1), date(2020, 6, 30)])

plt.tight_layout()
plt.show()
```



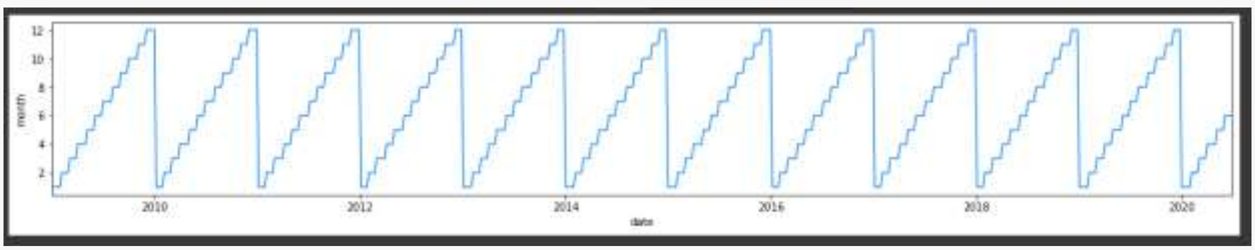


Feature engineering:

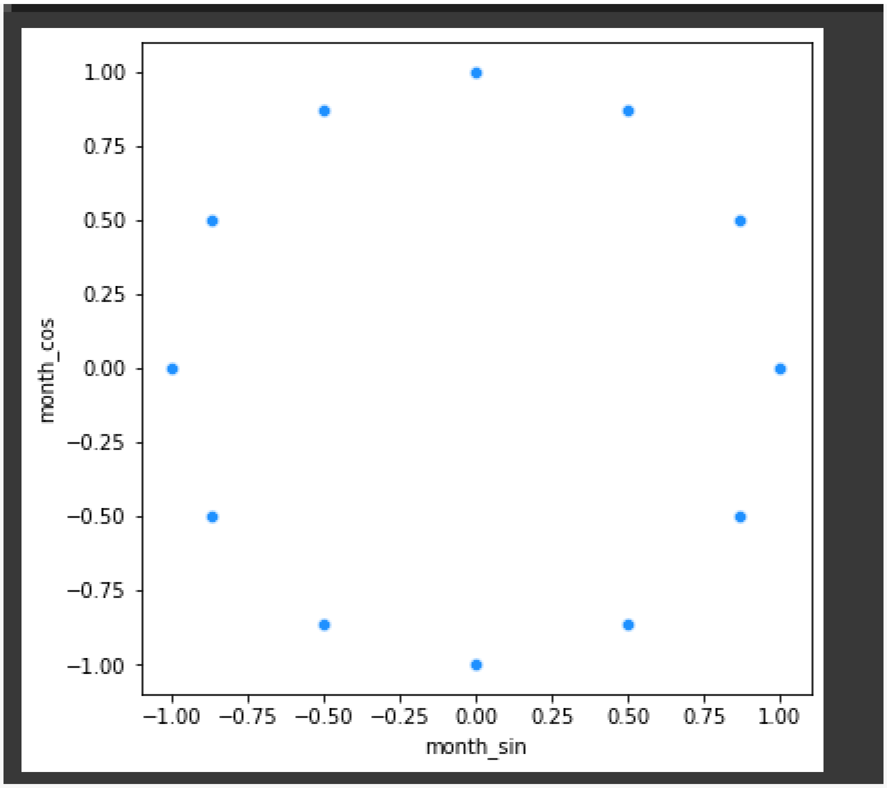
```
df['year'] = pd.DatetimeIndex(df['date']).year
df['month'] = pd.DatetimeIndex(df['date']).month
df['day'] = pd.DatetimeIndex(df['date']).day
df['day_of_year'] = pd.DatetimeIndex(df['date']).dayofyear
df['week_of_year'] = pd.DatetimeIndex(df['date']).weekofyear
df['quarter'] = pd.DatetimeIndex(df['date']).quarter
df['season'] = df['month'] % 12 // 3 + 1

df[['date', 'year', 'month', 'day', 'day_of_year', 'week_of_year', 'quarter', 'se
ason']].head()
```

	date	year	month	day	day_of_year	week_of_year	quarter	season
0	2009-01-01	2009	1	1	1	1	1	1
1	2009-01-08	2009	1	8	8	2	1	1
2	2009-01-15	2009	1	15	15	3	1	1
3	2009-01-22	2009	1	22	22	4	1	1
4	2009-01-29	2009	1	29	29	5	1	1

```
f, ax = plt.subplots(nrows=1, ncols=1, figsize=(20, 3))

sns.lineplot(x=df['date'], y=df['month'], color='dodgerblue')
ax.set_xlim([date(2009, 1, 1), date(2020, 6, 30)])
plt.show()
```




```
month_in_year = 12
df['month_sin'] = np.sin(2*np.pi*df['month']/month_in_year)
df['month_cos'] = np.cos(2*np.pi*df['month']/month_in_year)

f, ax = plt.subplots(nrows=1, ncols=1, figsize=(6, 6))

sns.scatterplot(x=df.month_sin, y=df.month_cos, color='dodgerblue')
plt.show()
```



TIME SERIES DECOMPOSISTION:

Time series decomposition involves thinking of a series as a combination of level, trend, seasonality, and noise components.

These components are defined as follows:

- **Level**: The average value in the series.
- **Trend**: The increasing or decreasing value in the series.
- **Seasonality**: The repeating short-term cycle in the series.
- **Noise**: The random variation in the series.

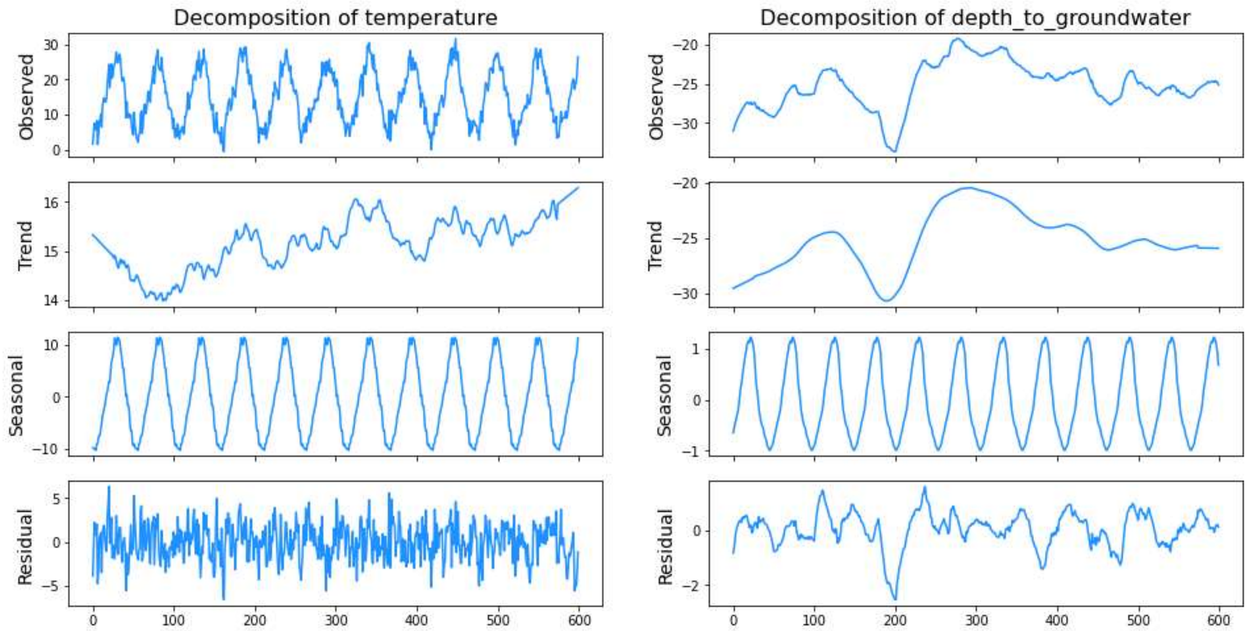
It is helpful to think of the components as combining either additively or multiplicatively:

- **Additive**: $y(t)=Level+Trend+Seasonality+Noise$y(t)=Level+Trend+Seasonality+Noise
- **Multiplicative**: $y(t)=Level*Trend*Seasonality*Noise$

```
from statsmodels.tsa.seasonal import seasonal_decompose
```

```python
core_columns =  [
    'rainfall', 'temperature', 'drainage_volume',
    'river_hydrometry', 'depth_to_groundwater'
]

for column in core_columns:
    decomp = seasonal_decompose(df[column], period=52, model='additive', extrapol
ate_trend='freq')
    df[f"{column}_trend"] = decomp.trend
    df[f"{column}_seasonal"] = decomp.seasonal
```

```python
fig, ax = plt.subplots(ncols=2, nrows=4, sharex=True, figsize=(16,8))

for i, column in enumerate(['temperature', 'depth_to_groundwater']):

    res = seasonal_decompose(df[column], freq=52, model='additive', extrapolate_trend
='freq')

    ax[0,i].set_title('Decomposition of {}'.format(column), fontsize=16)
    res.observed.plot(ax=ax[0,i], legend=False, color='dodgerblue')
    ax[0,i].set_ylabel('Observed', fontsize=14)

    res.trend.plot(ax=ax[1,i], legend=False, color='dodgerblue')
    ax[1,i].set_ylabel('Trend', fontsize=14)

    res.seasonal.plot(ax=ax[2,i], legend=False, color='dodgerblue')
    ax[2,i].set_ylabel('Seasonal', fontsize=14)

    res.resid.plot(ax=ax[3,i], legend=False, color='dodgerblue')
    ax[3,i].set_ylabel('Residual', fontsize=14)

plt.show()
```



LAG:

We want to calculate each variable with a `shift()` (lag) to compare the correlationwith the other variables.

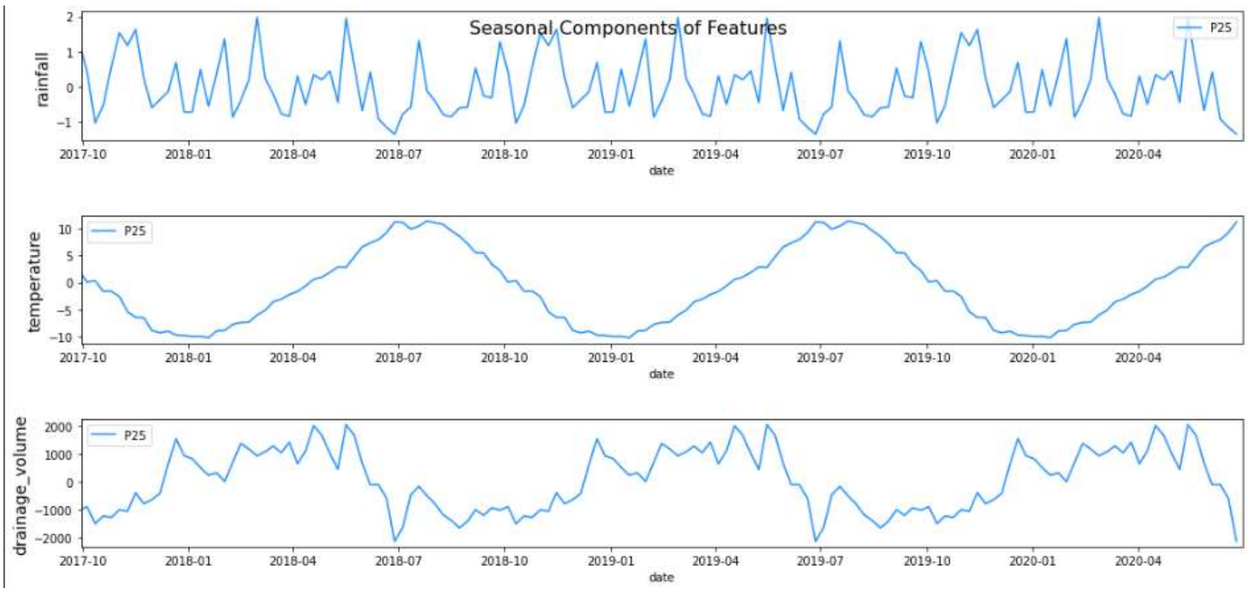
```
weeks_in_month = 4

for column in core_columns:
    df[f'{column}_seasonal_shift_b_2m'] = df[f'{column}_seasonal'].shift(-2 * weeks_in_month)
    df[f'{column}_seasonal_shift_b_1m'] = df[f'{column}_seasonal'].shift(-1 * weeks_in_month)
    df[f'{column}_seasonal_shift_1m'] = df[f'{column}_seasonal'].shift(1 * weeks_in_month)
    df[f'{column}_seasonal_shift_2m'] = df[f'{column}_seasonal'].shift(2 * weeks_in_month)
    df[f'{column}_seasonal_shift_3m'] = df[f'{column}_seasonal'].shift(3 * weeks_in_month)
```

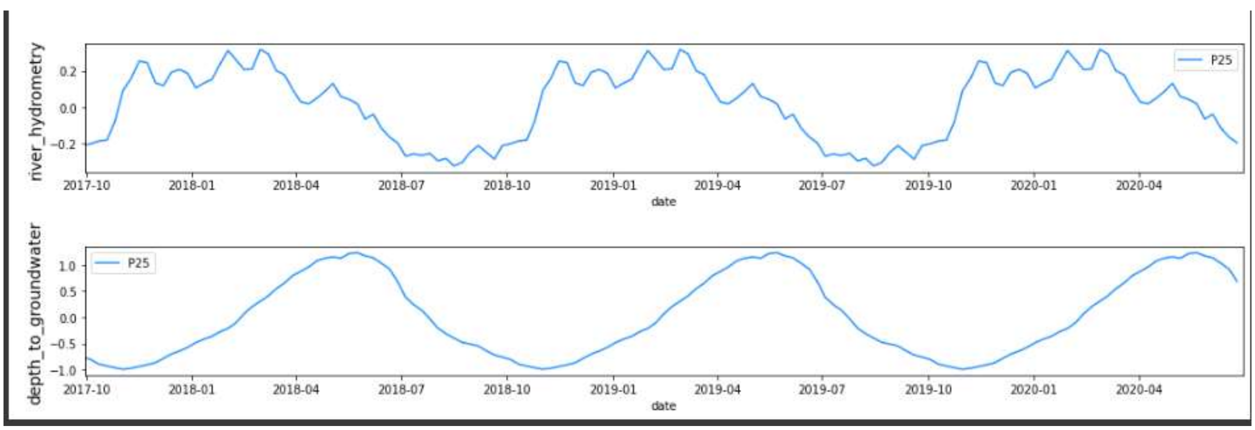
EXPLORATORY DATA ANALYSIS:

Now, we are going to plot the data and try to extract some knowledge.

```
f, ax = plt.subplots(nrows=5, ncols=1, figsize=(15, 12))
f.suptitle('Seasonal Components of Features', fontsize=16)
```

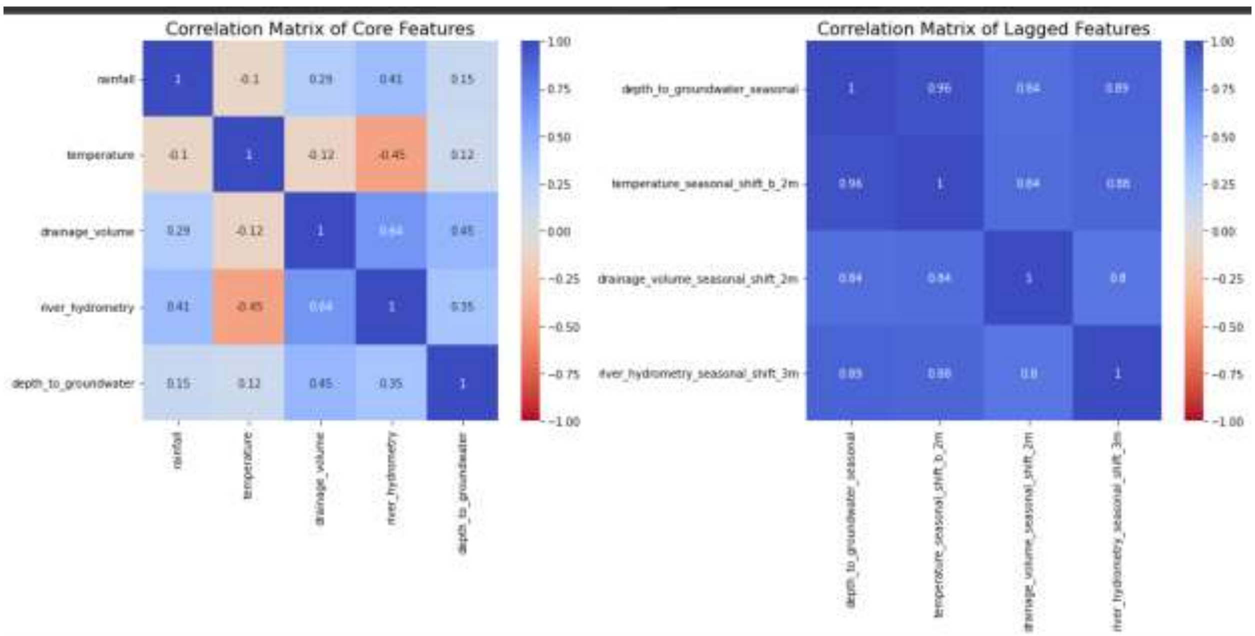
```
for i, column in enumerate(core_columns):
    sns.lineplot(x=df['date'], y=df[column + '_seasonal'], ax=ax[i], color='dodge
rblue', label='P25')
    ax[i].set_ylabel(ylabel=column, fontsize=14)
    ax[i].set_xlim([date(2017, 9, 30), date(2020, 6, 30)])

plt.tight_layout()
plt.show()
```






```
f, ax = plt.subplots(nrows=1, ncols=2, figsize=(16, 8))

corrmat = df[core_columns].corr()

sns.heatmap(corrmat, annot=True, vmin=-1, vmax=1, cmap='coolwarm_r', ax=ax[0])
ax[0].set_title('Correlation Matrix of Core Features', fontsize=16)

shifted_cols = [
    'depth_to_groundwater_seasonal',
```

```
    'temperature_seasonal_shift_b_2m',
    'drainage_volume_seasonal_shift_2m',
    'river_hydrometry_seasonal_shift_3m'
]
cormat = df[shifted_cols].corr()

sns.heatmap(cormat, annot=True, vmin=-1, vmax=1, cmap='coolwarm_r', ax=ax[1])
ax[1].set_title('Correlation Matrix of Lagged Features', fontsize=16)


plt.tight_layout()
plt.show()
```



MODELING:

Time series can be either univariate or multivariate:

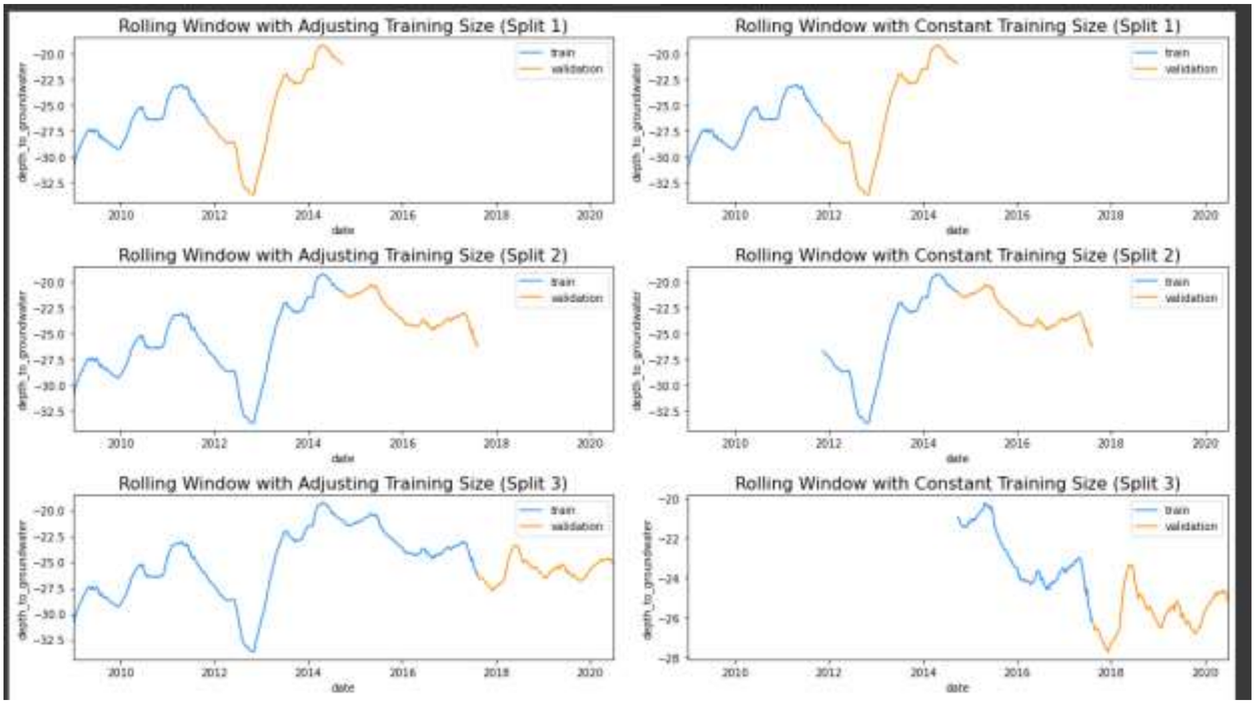
- **Univariate** time series only has a single time-dependent variable.
- **Multivariate** time series have a multiple time-dependent variable.

But, first of all we are going to see how does cross-validation technic works in TimeSeries Analysis

```
from sklearn.model_selection import TimeSeriesSplit

N_SPLITS = 3

X = df['date']
```

```
y = df['depth_to_groundwater']

folds = TimeSeriesSplit(n_splits=N_SPLITS)
```

```
f, ax = plt.subplots(nrows=N_SPLITS, ncols=2, figsize=(16, 9))

for i, (train_index, valid_index) in enumerate(folds.split(X)):
    X_train, X_valid = X[train_index], X[valid_index]
    y_train, y_valid = y[train_index], y[valid_index]

    sns.lineplot(
        x=X_train,
        y=y_train,
        ax=ax[i,0],
        color='dodgerblue',
        label='train'
    )
    sns.lineplot(
        x=X_train[len(X_train) - len(X_valid):(len(X_train) - len(X_valid) + len(X_valid))],
        y=y_train[len(X_train) - len(X_valid):(len(X_train) - len(X_valid) + len(X_valid))],
        ax=ax[i,1],
        color='dodgerblue',
        label='train'
    )

    for j in range(2):
        sns.lineplot(x= X_valid, y= y_valid, ax=ax[i, j], color='darkorange', label='validation')
    ax[i, 0].set_title(f"Rolling Window with Adjusting Training Size (Split {i+1})", fontsize=16)
    ax[i, 1].set_title(f"Rolling Window with Constant Training Size (Split {i+1})", fontsize=16)

for i in range(N_SPLITS):
    ax[i, 0].set_xlim([date(2009, 1, 1), date(2020, 6, 30)])
    ax[i, 1].set_xlim([date(2009, 1, 1), date(2020, 6, 30)])

plt.tight_layout()
plt.show()
```


Rolling Window with Adjusting Training Size (Split 1)
Rolling Window with Constant Training Size (Split 1)
Rolling Window with Adjusting Training Size (Split 2)
Rolling Window with Constant Training Size (Split 2)
Rolling Window with Adjusting Training Size (Split 3)
Rolling Window with Constant Training Size (Split 3)
train
validation
depth_to_groundwater
date