Environmental analysis: weather influence on phosphorus in swiss lakes

Introduction

This report present the results and interpretation of the analysis of environmental data about phosphorus concentration in lakes in Switzerland, as well as weather data (insolation, rainfall, temperature, fresh snow) in several locations in the country. This work aim to identify tendancies and changes over time. But the main objective is to show if there is any potential correlations between the concentration of phosphorus and climate in swiss lakes.

Datasets

This work is based on two datasets available on opendata.swiss:

- Klimadaten: Sonnenscheindauer, Niederschlag, Temperatur und Neuschnee (Climate data: insolation time, precipitation, temperature and fresh snowfall)
- Phosphorgehalt in Seen (Phosphorus content in lakes).

The climate dataset consist in four sheets (insolation time in h per year, precipitation in cumulative mm per year, temperature in mean °C per year, and fresh snowfall in cumulative cm per year) of data for 13 locations (Basel-Binningen, Bern- Zollikofen, Davos, Geneva-Cointrin, Locarno-Monti, Lugano, Lucerne, Neuchâtel, Säntis, Sion, St-Gallen and Zurich-Fluntern) from 1931 to 2024. The phosphorus dataset consist in a table of the annual measurements of phosphorus concentration in µg/l in six lakes (lake Lucerne, lake Hallwil, lake Neuchâtel, lake Constance, lake Zug and lake Geneva) from 1951 (first data from 1957) to 2023.

In [1]:
```
# Importing required package for the analyses
import pandas as pd
from scipy.stats import linregress
import matplotlib.pyplot as plt
import json
import numpy as np
import seaborn as sns
import statsmodels.api as sm
from sklearn.linear_model import Ridge, Lasso
from sklearn.metrics import r2_score, root_mean_squared_error
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestRegressor
```

Cleaning and importing the data

First, the datasets have been cleaned in LibreOffice Calc. Next to making the files more easily usable with Python, the cleaning was also usefull to get rid of all irrelevant cells and data within the file. This particularly concerns the locations in the climate dataset.

The phosphorus dataset covers six lakes, whereas the climate dataset covers 13 locations, most of which being quite remote from the said lakes. So, in order to get the most accurate climate data for the lakes, only the locations closest to the lakes were retained in the climate dataset. For Lake Lucerne, Lake Neuchâtel and Lake Geneva, the locations retained were quite obviously Lucerne, Neuchâtel and Geneva-Cointrin, since they are next to the lakes. For the Lake Constance and Lake Zug, St-Gallen and Lucerne respectively were retained since they are the closest location in proximity and altitude. Concerning Lake Hallwil, both Lucerne and Zurich-Fluntern are the best candidates in terms of proximity and altitude. However, Lucerne was chosen since the city is a bit smaller than Zurich, slighlty reducing the influence of urbanism. In addition, there are several peaks between the lake and Zurich, whereas the space between the lake and Lucerne is a bit flatter, potentially resulting in a bigger climatic difference between the lake and Zurich than between the lake and Lucerne. Zurich-Fluntern was nevertheless kept in the dataset, for comparison purposes.

After the cleaning, the spreadsheet files were imported using the pandas package.

In [3]:
```
# Importing the datasets
phosphorus = pd.read_excel("00-cleaned-data/phosphorus-lakes.xlsx", na_values=["...
insolation = pd.read_excel("00-cleaned-data/weather-data.xlsx", sheet_name="Insolat
rainfall = pd.read_excel("00-cleaned-data/weather-data.xlsx", sheet_name="Rainfall"
temperature = pd.read_excel("00-cleaned-data/weather-data.xlsx", sheet_name="Temper
snow = pd.read_excel("00-cleaned-data/weather-data.xlsx", sheet_name="Fresh snow",
```

Exploratory analysis

Descriptive statistics

Before looking for possible correlations, some basic analyses were performed. First, the descriptive statistics of each dataset were calculated.

In [5]:
```
# Function to generate descriptive statistics
def desc_stat(df, x_col, y_col):
    stats = df[[x_col, y_col]].iloc[:, 1:].describe().to_dict()
    return stats
```

Data trends

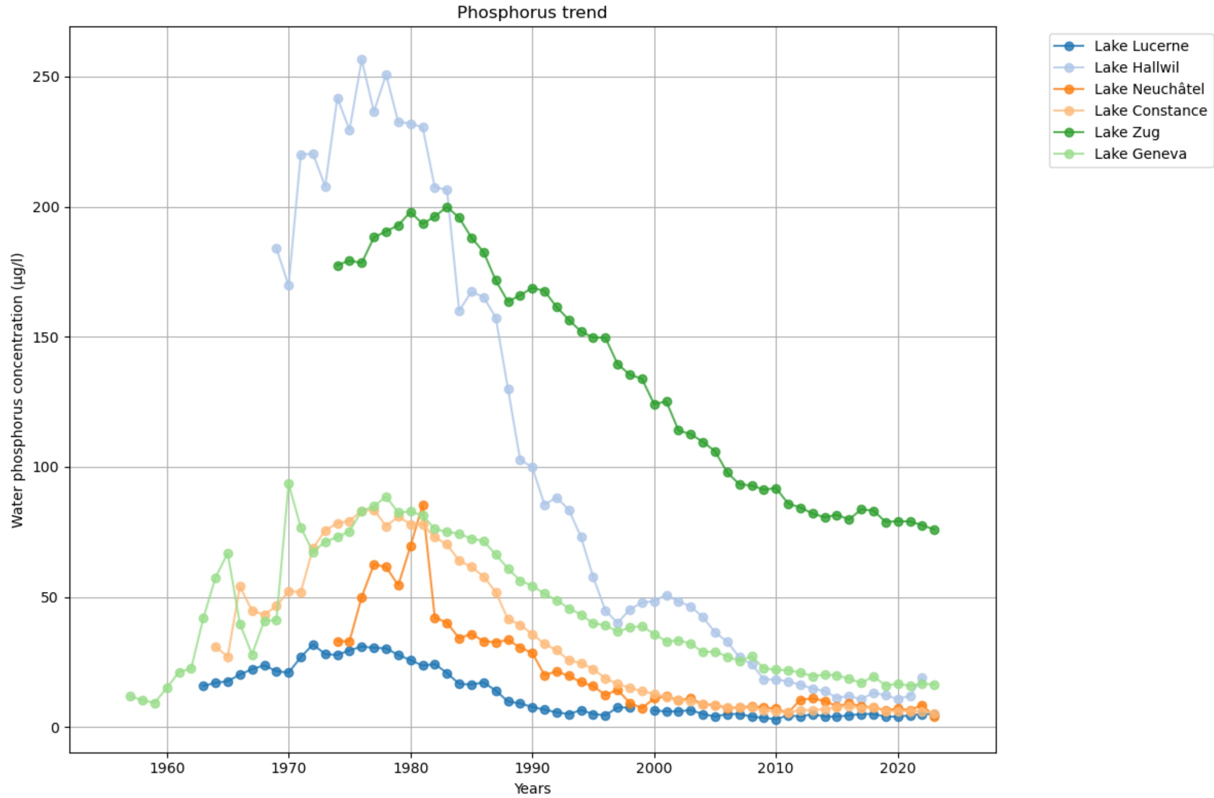
Then, these datasets were analyzed to identify linear trends, and the data were plotted in scatter plots, so that the trends could be visualized. Finally, the descriptive statistics, trend analysis results, and trend comparisons between the variables were stored in a JSON file, for easier access.

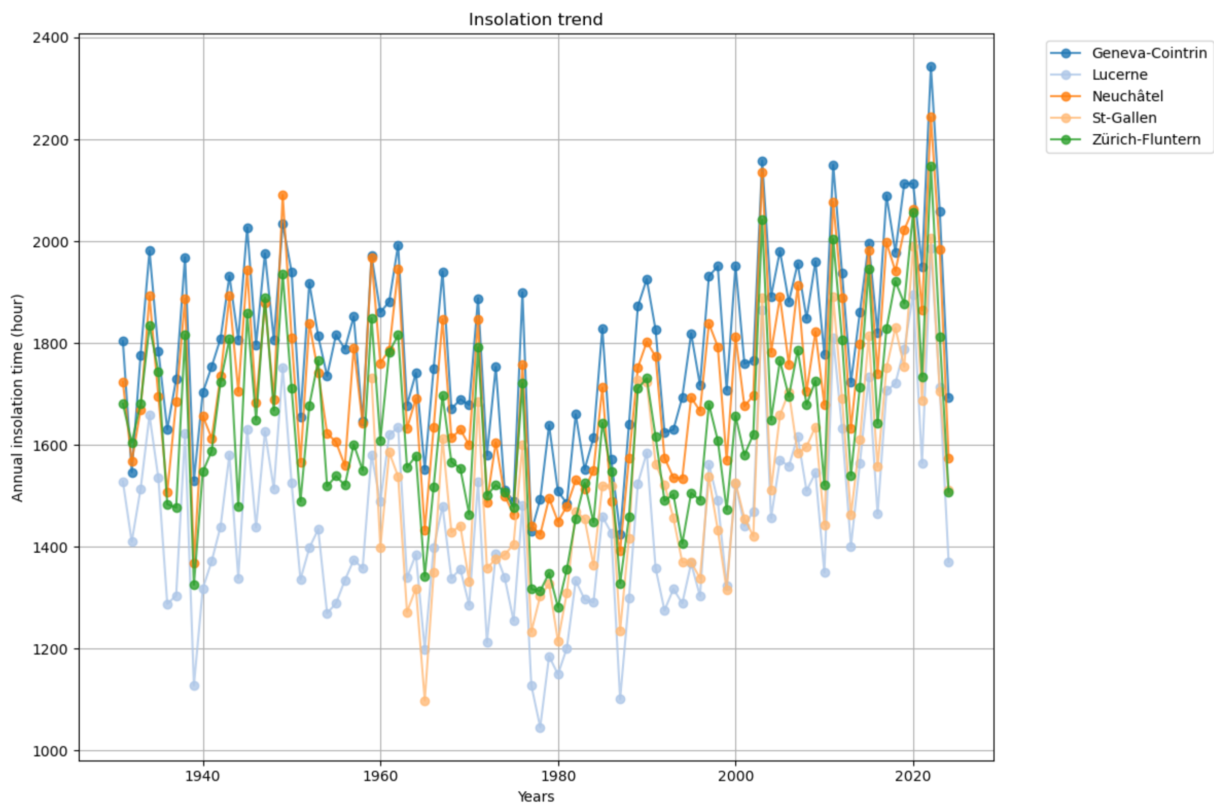
Note: all the files and figures produced by the analyses are also present as individual files in the corresponding directories ("Exploratory analysis outputs" and "Regression models outputs"); figures are named in order of appearences in this notebook.

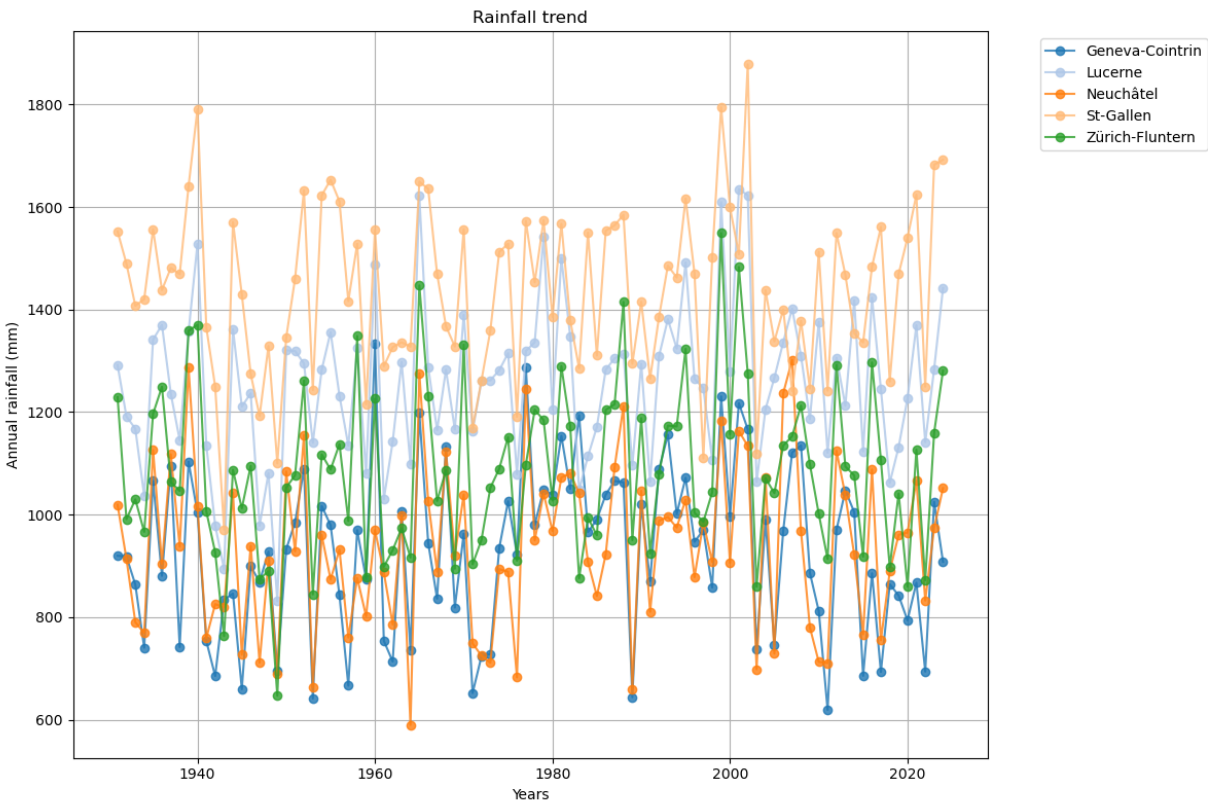
In [7]:
```
# Function for analysing linear trends
def detect_trends(df, x_col, y_col):
    # Removing NaN values for both columns
    valid_data = df[[x_col, y_col]].dropna()

    # Making sure there is enough values for the analysis
    if len(valid_data) > 1:
        x = valid_data[x_col].astype(float)
        y = valid_data[y_col].astype(float)
        regression = linregress(x, y)
        trend = "positive" if regression.slope > 0 else "negative"
        return {"slope": regression.slope, "intercept": regression.intercept, "r_va
    else:
        return None

# Function for plotting graphs
def plot_graph(dataframes, x_col, y_cols, title, xlab, xlim_inf, xlim_sup, ylab):
    plt.figure(figsize=(12, 8))

    cmap = plt.get_cmap("tab20") # Use color map with 20 different colors
    num_colors = cmap.N # Get the number of colors in the color map

    for i, (df, y_col, label) in enumerate(dataframes):
        color = cmap(i % num_colors) # Cycle through the color map
        plt.plot(df[x_col], df[y_col], marker = "o", linestyle = "-", label = label

    plt.title(title)
    plt.xlabel(xlab)
    plt.ylabel(ylab)
    plt.grid(True)
    plt.xlim(xlim_inf,xlim_sup)
    plt.legend(bbox_to_anchor = (1.05, 1), loc = "upper left") # Avoid overlapping
    plt.tight_layout()
    plt.show()

# Function for comparing trends
def compare_trends(trend1, trend2):
    if trend1["trend"] == trend2["trend"]:
        return "Trends are similar."
    else:
        return "Trends are opposite."
```

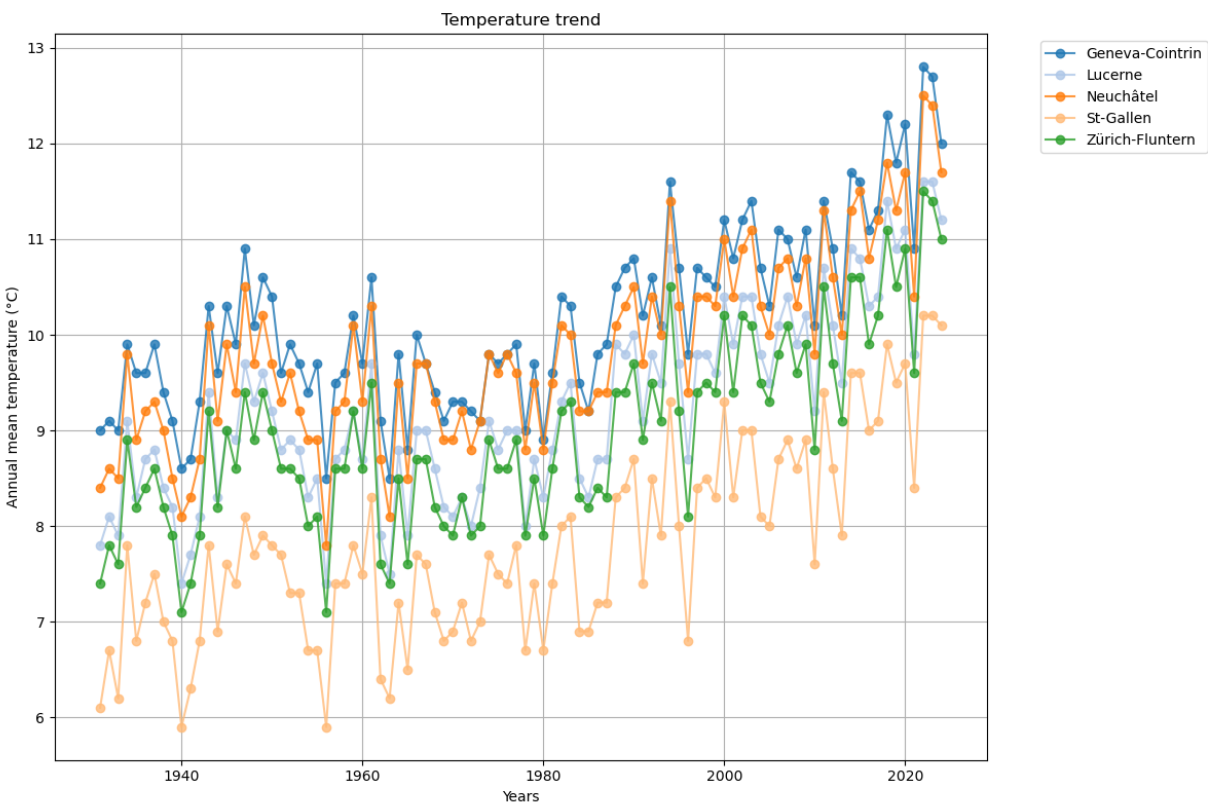
In [9]:
```
# Trends detection for each dataset
trends_results = {}
descriptive_stats = {}
comparisons = {}

# Phosphorus analysis
lakes = phosphorus.columns[1:]
data_to_plot = []
```

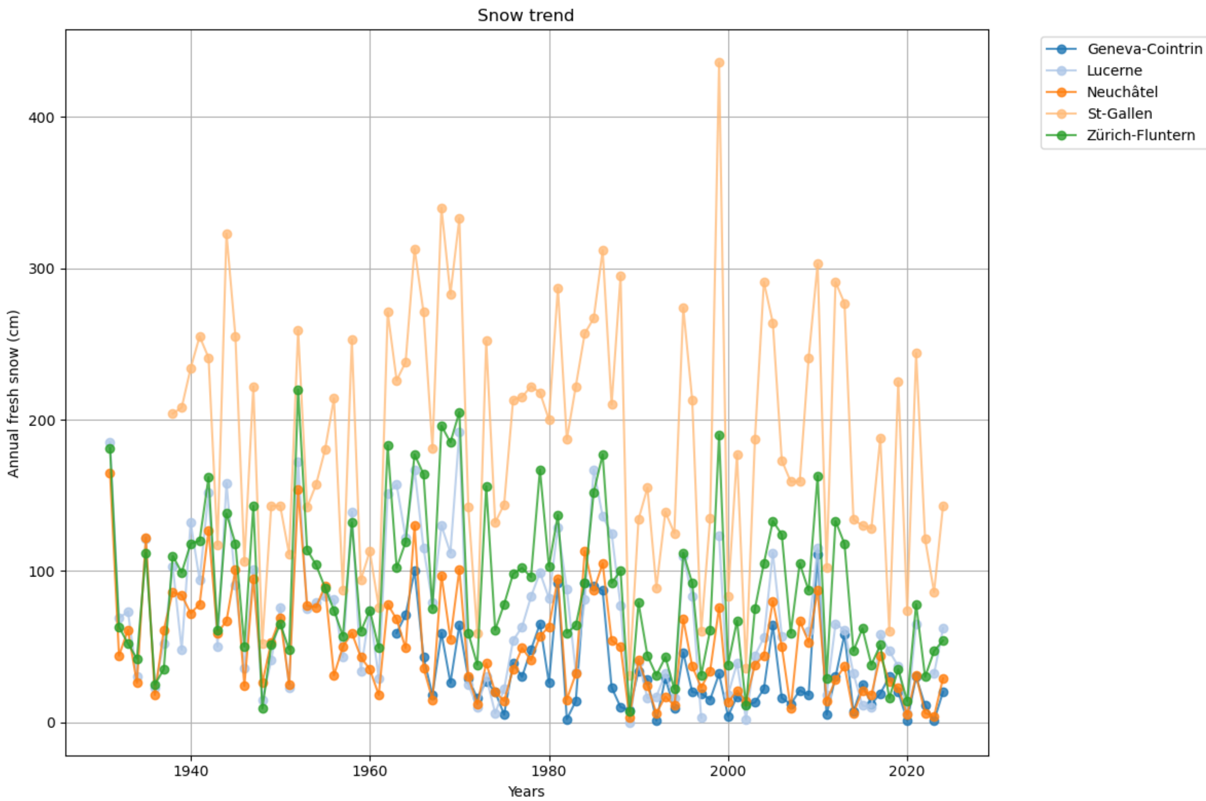
```
trends_results["Phosphorus"] = {}
descriptive_stats["Phosphorus"] = {}
for lake in lakes:
    trend = detect_trends(phosphorus, "Year", lake)
    stats = desc_stat(phosphorus, "Year", lake)
    if trend:
        trends_results["Phosphorus"][lake] = trend
        descriptive_stats["Phosphorus"][lake] = stats
        data_to_plot.append((phosphorus, lake, lake))
plot_graph(data_to_plot, "Year", lakes, "Phosphorus trend", "Years", 1952, 2028, "W

# Weather analysis
for dataset_name, dataset, y_legend in [("Insolation", insolation, "Annual insolati
    stations = dataset.columns[1:]
    data_to_plot = []
    trends_results[dataset_name] = {}
    descriptive_stats[dataset_name] = {}

    for station in stations:
        trend = detect_trends(dataset, "Year", station)
        stats = desc_stat(dataset, "Year", station)

        if trend:
            trends_results[dataset_name][station] = trend
            descriptive_stats[dataset_name][station] = stats
            data_to_plot.append((dataset, station, station))

    plot_graph(data_to_plot, "Year", stations, f"{dataset_name} trend", "Years", 19

# Comparing trends
for lake, phos_trend in trends_results["Phosphorus"].items():
    for climate_type in ["Insolation", "Rainfall", "Temperature", "Snow"]:
        for station, climate_trend in trends_results[climate_type].items():
            comparison = compare_trends(phos_trend, climate_trend)
            comparisons[f"{lake} vs {station} ({climate_type})"] = comparison

for climate_type1 in ["Insolation", "Rainfall", "Temperature", "Snow"]:
    for station1, trend1 in trends_results[climate_type1].items():
        for climate_type2 in ["Insolation", "Rainfall", "Temperature", "Snow"]:
            if climate_type1 != climate_type2:
                for station2, trend2 in trends_results[climate_type2].items():
                    comparison = compare_trends(trend1, trend2)
                    comparisons[f"{station1} ({climate_type1}) vs {station2} ({clim

# Saving trends results
with open("01-exploratory-analysis-outputs/trends_results.json", "w") as f:
    json.dump({"Descriptive statistics": descriptive_stats, "Trends analysis result

print("Trends analysis completed. The results are saved in 'trends_results.json'.")
```


Phosphorus trend
Water phosphorus concentration (µg/l)
Years
Lake Lucerne
Lake Hallwil
Lake Neuchâtel
Lake Constance
Lake Zug
Lake Geneva


Insolation trend
Annual insolation time (hour)
Years
Geneva-Cointrin
Lucerne
Neuchâtel
St-Gallen
Zürich-Fluntern


Rainfall trend
Annual rainfall (mm)
Years
Geneva-Cointrin
Lucerne
Neuchâtel
St-Gallen
Zürich-Fluntern


Temperature trend
Annual mean temperature (°C)
Years
Geneva-Cointrin
Lucerne
Neuchâtel
St-Gallen
Zürich-Fluntern




```
Trends analysis completed. The results are saved in 'trends_results.json'.
```

Correlations

Correlations between the phosphorus concentration and the climate data (insolation time, annual rainfall, mean annual temperature, annual fresh snow) were calculated. The correlations between the climate variables themselves were also calculated, in case of multicolinearity.

In [11]:
```
# Requirements for the analyses

# Dictionnary for correspondance between lakes (phosphorus) and stations (weather)
lake_to_station = {
        "Lake Lucerne": "Lucerne",
        "Lake Hallwil": "Lucerne",
        "Lake Neuchâtel": "Neuchâtel",
        "Lake Constance": "St-Gallen",
        "Lake Zug": "Lucerne",
        "Lake Geneva": "Geneva-Cointrin"
        }

# Melting the dataframes
phosphorus_melted = phosphorus.melt(id_vars="Year", var_name="Lake", value_name="Ph
insolation_melted = insolation.melt(id_vars="Year", var_name="Station", value_name=
rainfall_melted = rainfall.melt(id_vars="Year", var_name="Station", value_name="Rai
temperature_melted = temperature.melt(id_vars="Year", var_name="Station", value_nam
snow_melted = snow.melt(id_vars="Year", var_name="Station", value_name="Snow")

# Mapping lakes to stations
phosphorus_melted["Station"] = phosphorus_melted["Lake"].map(lake_to_station)
```

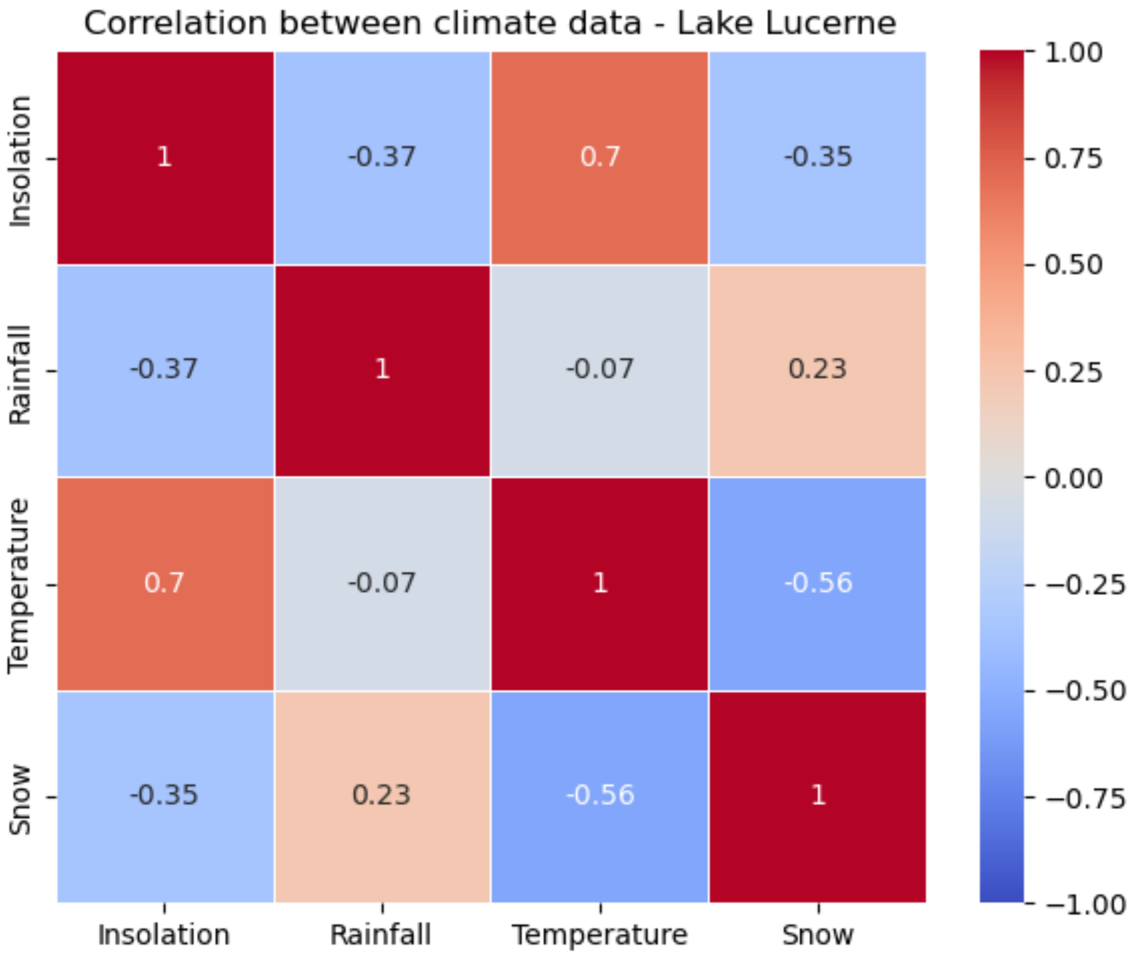
```
# Merging dataframes together
merged_inso = pd.merge(phosphorus_melted, insolation_melted, on=["Year", "Station"]
merged_rain = pd.merge(phosphorus_melted, rainfall_melted, on=["Year", "Station"],
merged_temp = pd.merge(phosphorus_melted, temperature_melted, on=["Year", "Station"
merged_snow = pd.merge(phosphorus_melted, snow_melted, on=["Year", "Station"], how=

weather_full = insolation_melted \
        .merge(rainfall_melted, on=["Year", "Station"], how="outer") \
        .merge(temperature_melted, on=["Year", "Station"], how="outer") \
        .merge(snow_melted, on=["Year", "Station"], how="outer")

phospho_weather = pd.merge(phosphorus_melted, weather_full, on=["Year", "Station"],
```

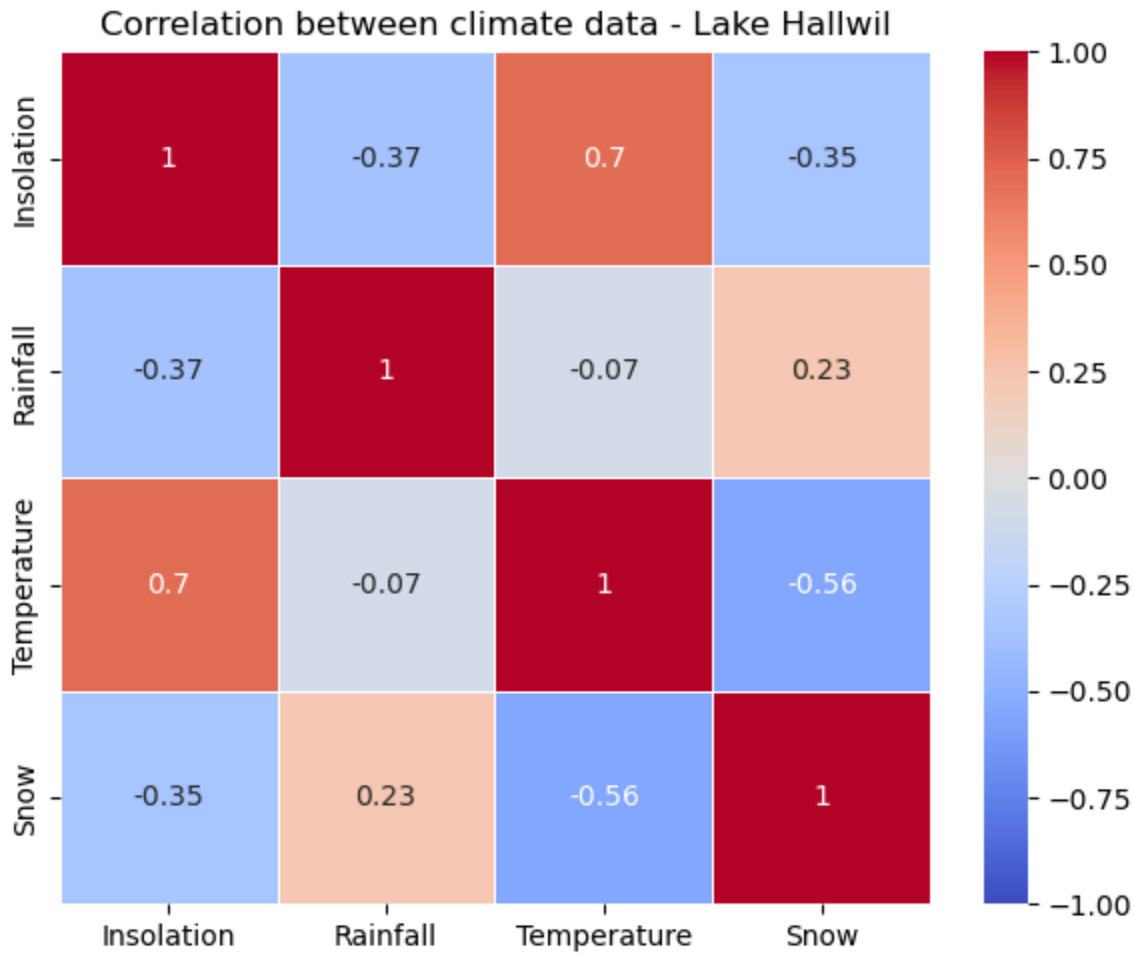
In [13]:
```
# Correlation beetwen phosphorus and climate data per lake
for lake in phospho_weather["Lake"].unique():
    subset = phospho_weather[phospho_weather["Lake"] == lake]
    print(f"\nCorrelation for {lake.title()}:")
    print(subset[["Phosphorus", "Insolation", "Rainfall", "Temperature", "Snow"]].c
```

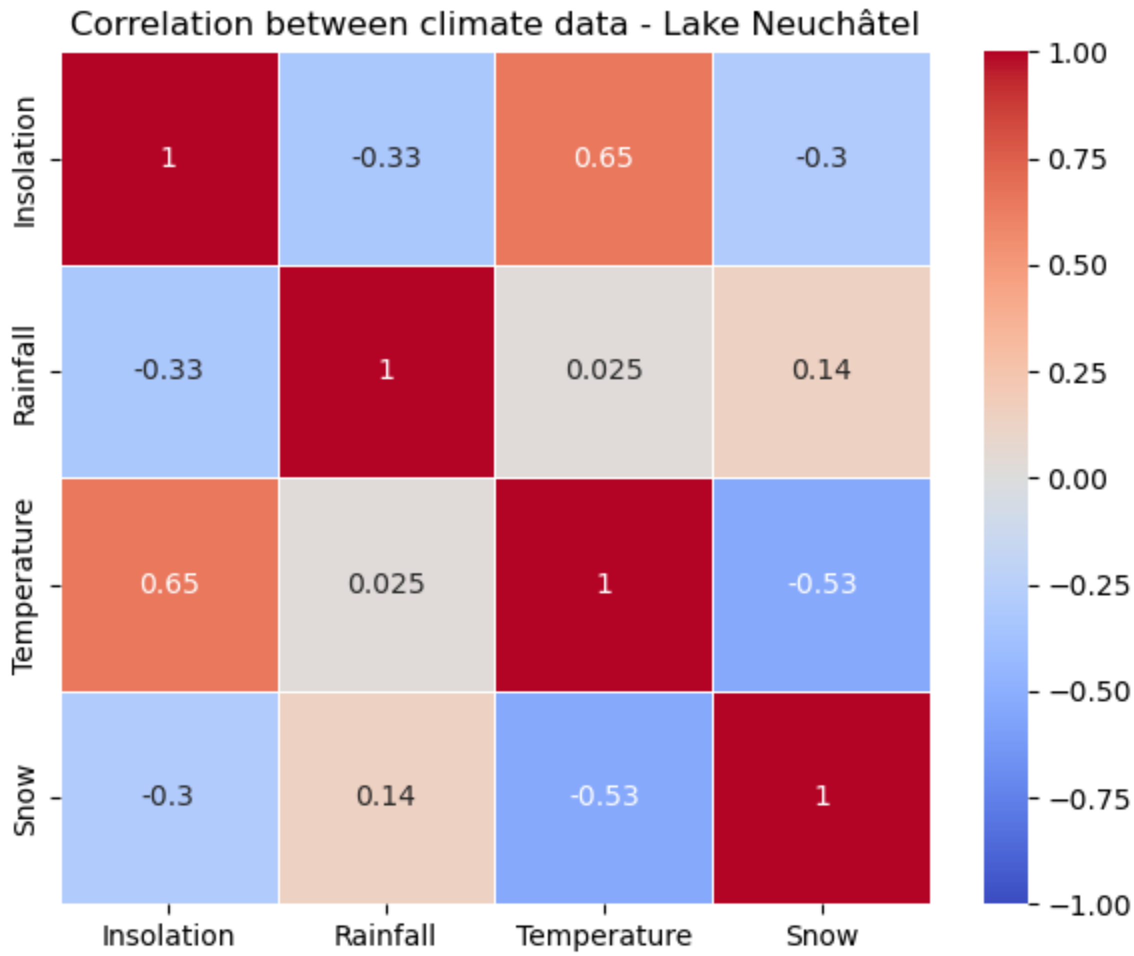
```
Correlation for Lake Lucerne:
Phosphorus     1.000000
Insolation    -0.602580
Rainfall      -0.002264
Temperature   -0.730045
Snow           0.258308
Name: Phosphorus, dtype: float64

Correlation for Lake Hallwil:
Phosphorus     1.000000
Insolation    -0.673539
Rainfall      -0.015579
Temperature   -0.780711
Snow           0.235270
Name: Phosphorus, dtype: float64

Correlation for Lake Neuchâtel:
Phosphorus     1.000000
Insolation    -0.671244
Rainfall       0.119720
Temperature   -0.675271
Snow           0.345293
Name: Phosphorus, dtype: float64

Correlation for Lake Constance:
Phosphorus     1.000000
Insolation    -0.552265
Rainfall      -0.017011
Temperature   -0.691314
Snow           0.180090
Name: Phosphorus, dtype: float64

Correlation for Lake Zug:
Phosphorus     1.000000
Insolation    -0.757725
Rainfall       0.026652
Temperature   -0.779252
Snow           0.315647
Name: Phosphorus, dtype: float64

Correlation for Lake Geneva:
Phosphorus     1.000000
Insolation    -0.697869
Rainfall       0.258101
Temperature   -0.577597
Snow           0.331701
Name: Phosphorus, dtype: float64
```

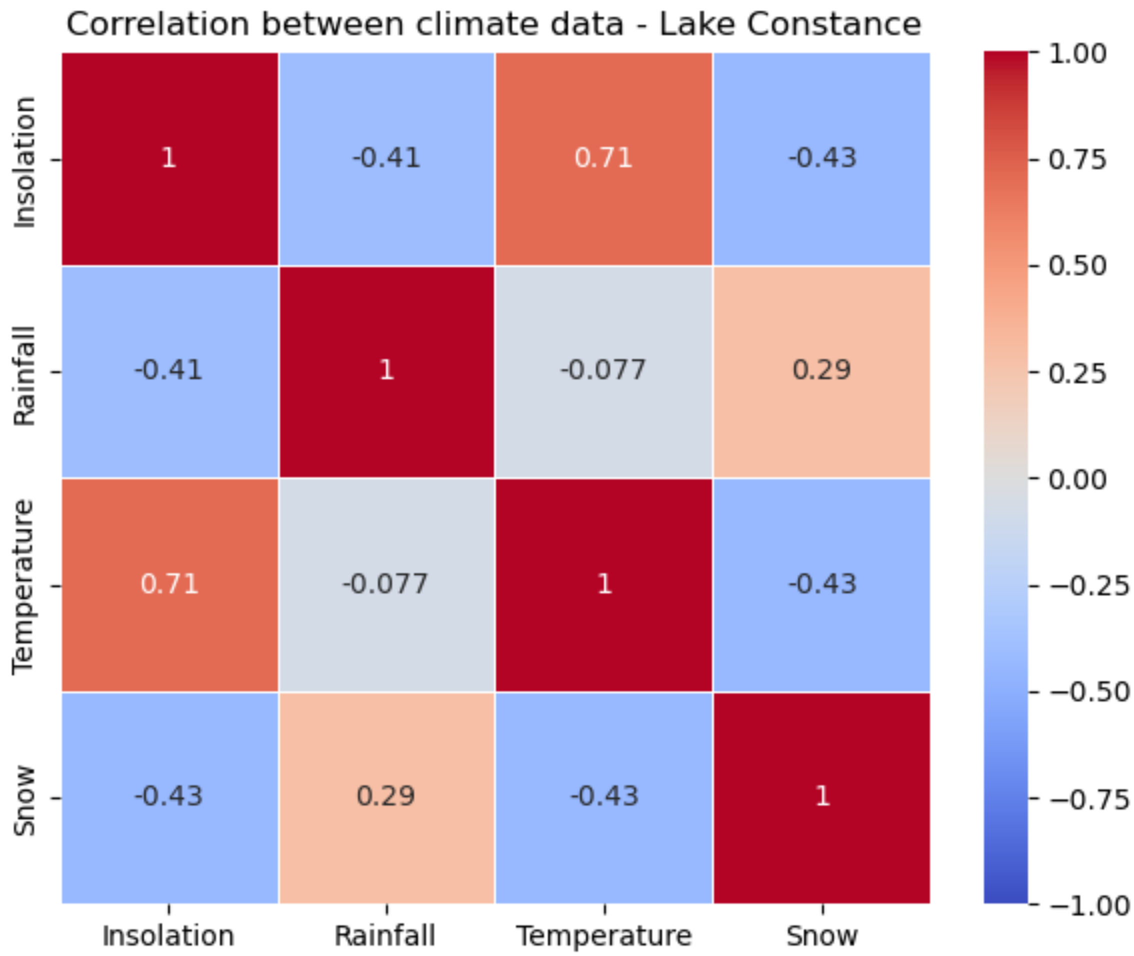
In [15]:
```
# Heatmap of the correlations within climate data for each lake
for lake in phospho_weather["Lake"].unique():
    subset = phospho_weather[phospho_weather["Lake"] == lake]
    corr = subset[["Phosphorus", "Insolation", "Rainfall", "Temperature", "Snow"]].

    # Deleting phosphorus to avoid correlating to itself
    corr_trimmed = corr.drop("Phosphorus").drop("Phosphorus", axis=1)
```

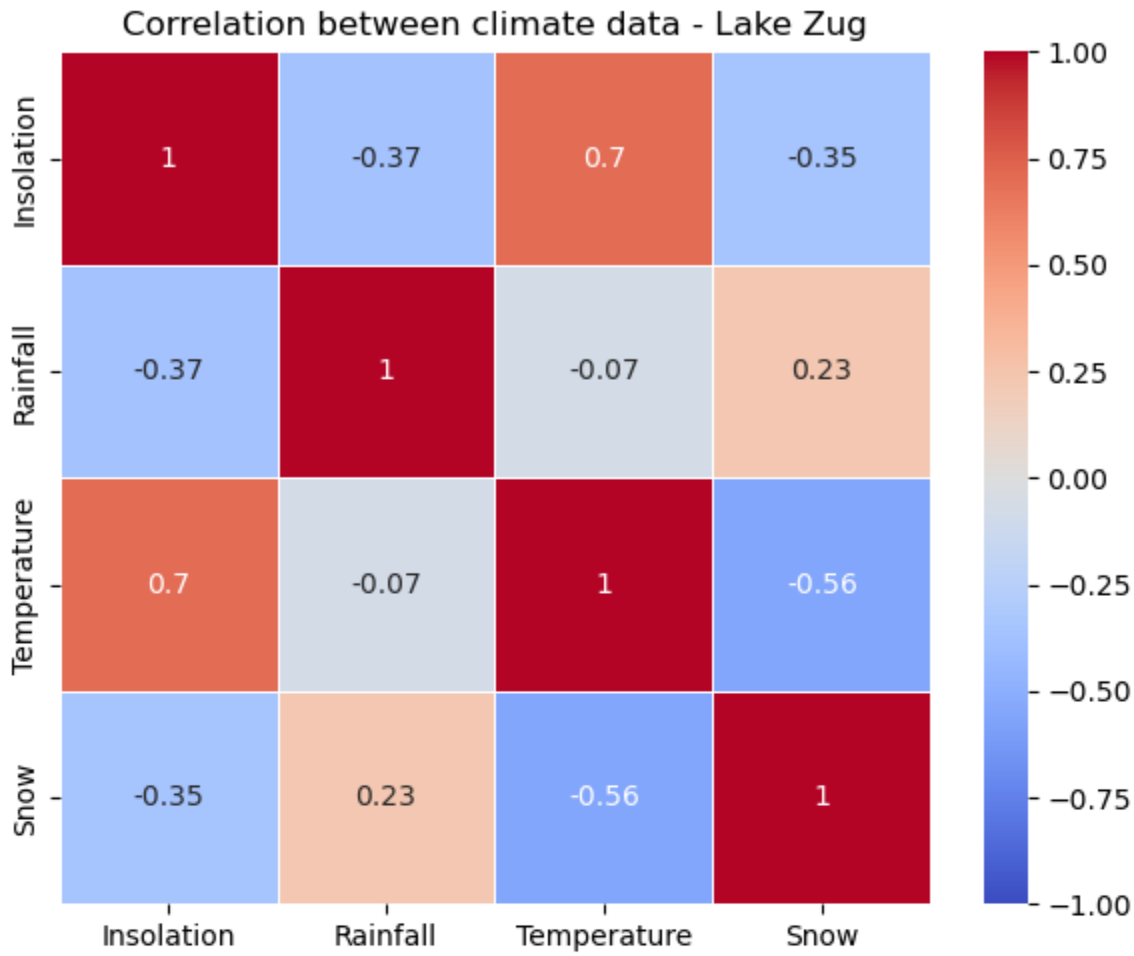
```
plt.figure(figsize=(6, 5))
sns.heatmap(corr_trimmed, annot=True, cmap="coolwarm", center=0, linewidths=0.5
plt.title(f"Correlation between climate data - {lake}")
plt.tight_layout()
plt.show()
```

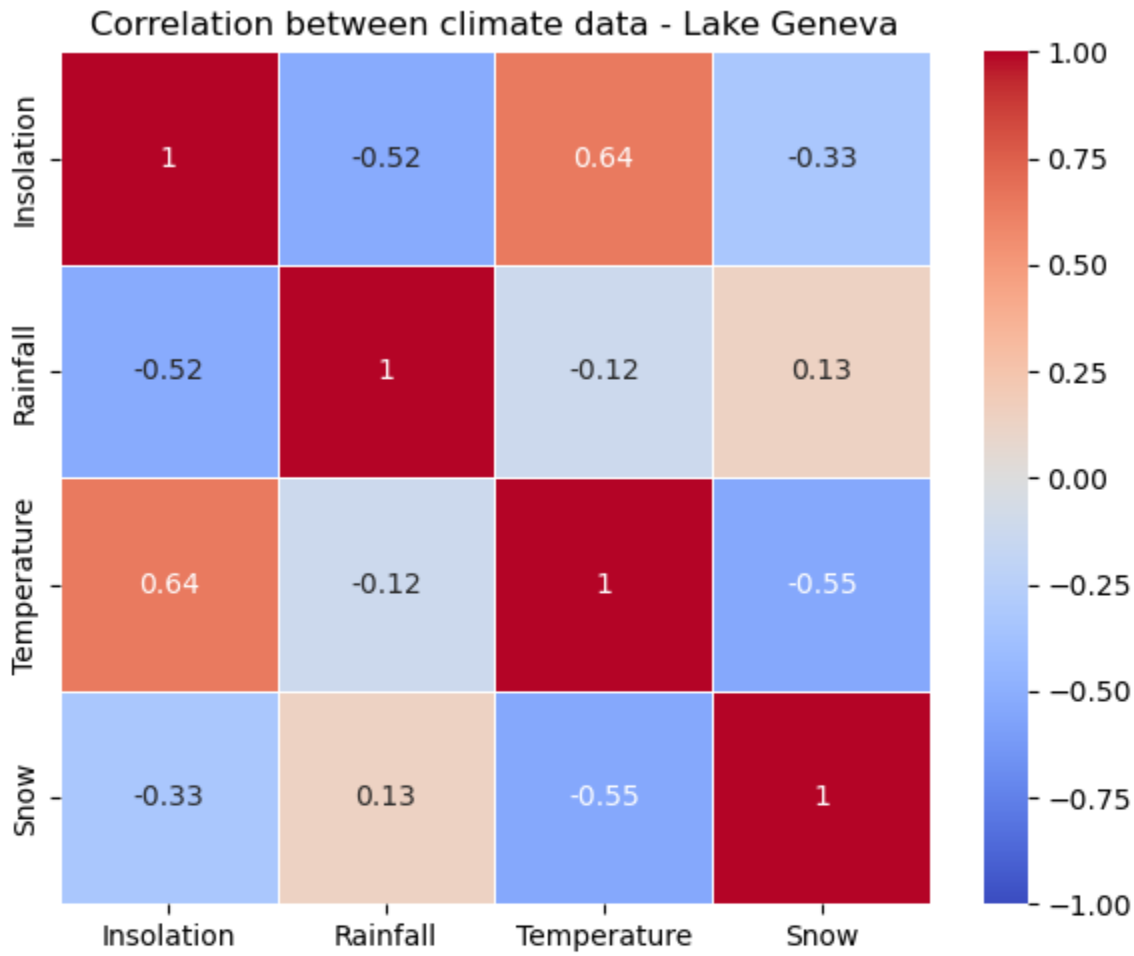



Correlation between climate data - Lake Hallwil
Insolation
Rainfall
Temperature
Snow
1
-0.37
0.7
-0.35
-0.37
1
-0.07
0.23
0.7
-0.07
1
-0.56
-0.35
0.23
-0.56
1
Insolation
Rainfall
Temperature
Snow
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00


Correlation between climate data - Lake Neuchâtel
Insolation
Rainfall
Temperature
Snow
1
-0.33
0.65
-0.3
-0.33
1
0.025
0.14
0.65
0.025
1
-0.53
-0.3
0.14
-0.53
1
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00


Correlation between climate data - Lake Constance
Insolation
Rainfall
Temperature
Snow
1
-0.41
0.71
-0.43
-0.41
1
-0.077
0.29
0.71
-0.077
1
-0.43
-0.43
0.29
-0.43
1
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00


Correlation between climate data - Lake Zug
Insolation
Rainfall
Temperature
Snow
1
-0.37
0.7
-0.35
-0.37
1
-0.07
0.23
0.7
-0.07
1
-0.56
-0.35
0.23
-0.56
1
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00



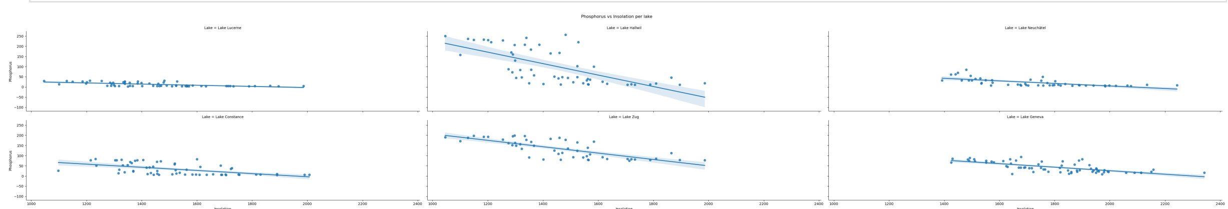
Modelisation

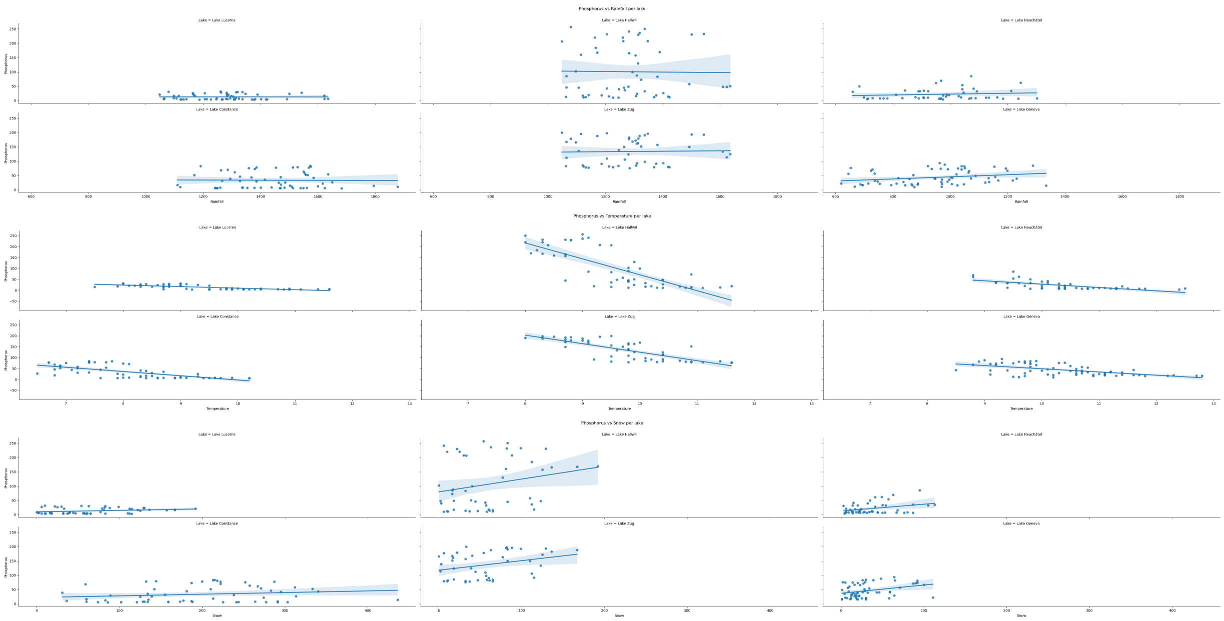
Then, regression models were applied.

Linear regressions

The first models are simple and multilple linear regression models, as a starting point.

In [17]:
```
# Linear regression scatter plot
for var in ["Insolation", "Rainfall", "Temperature", "Snow"]:
    sns.lmplot(data=phospho_weather, x=var, y="Phosphorus", col="Lake", col_wrap=3,
    plt.subplots_adjust(top=0.9)
    plt.suptitle(f"Phosphorus vs {var} per lake")
    plt.show()
```

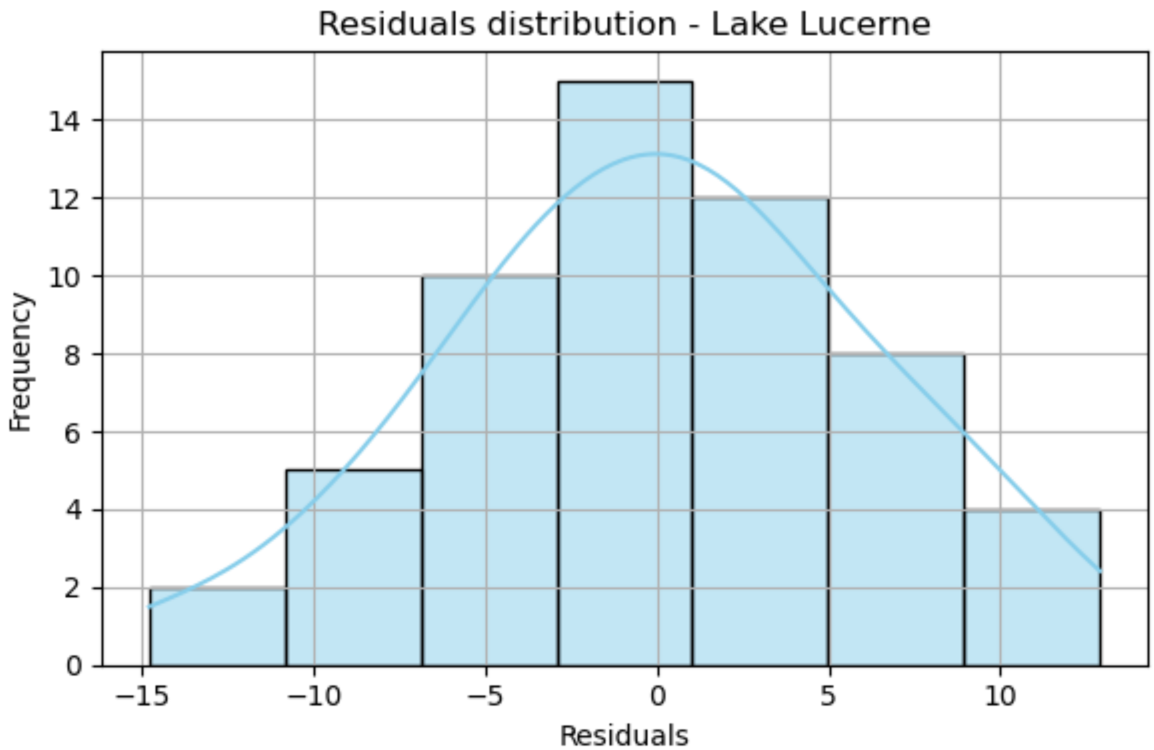


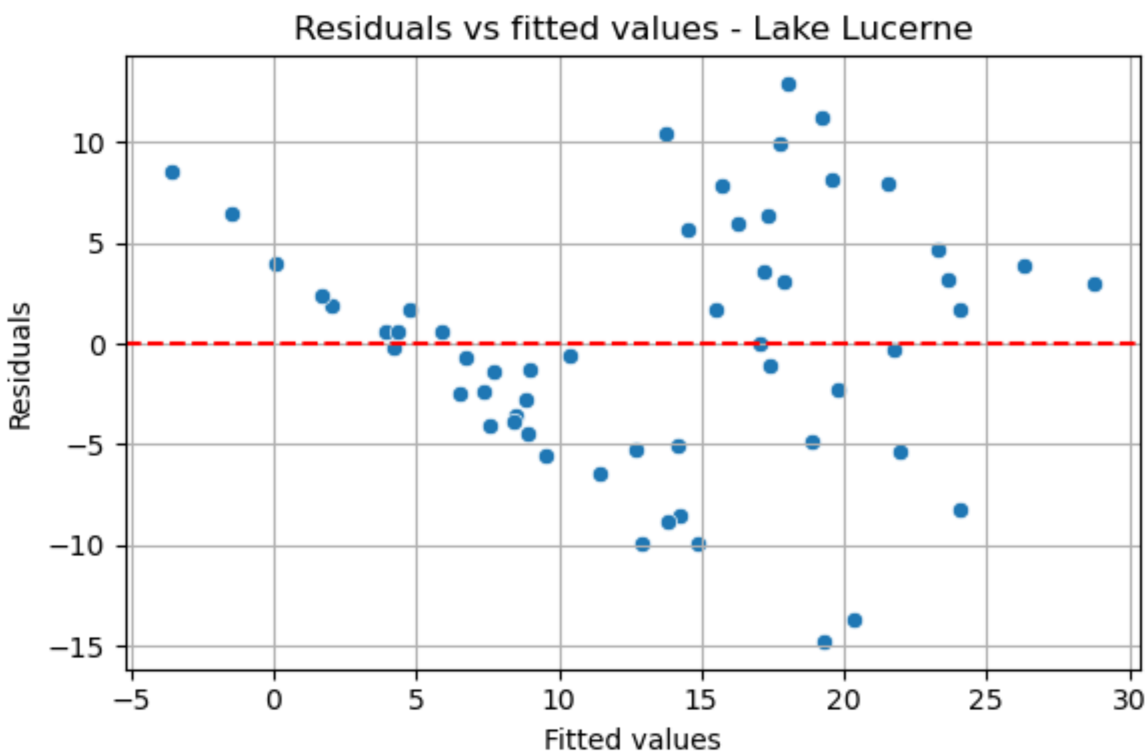


In [19]:
```python
# Multiple linear regression
results_list = []

for lake in phospho_weather["Lake"].unique():
    subset = phospho_weather[phospho_weather["Lake"] == lake].dropna()
    x = subset[["Insolation", "Rainfall", "Temperature", "Snow"]]
    y = subset["Phosphorus"]
    x = sm.add_constant(x) # Add constant for intercept
    model = sm.OLS(y, x).fit()
    summary = model.summary2().tables[1] # Get coefficient and P-values
    significant = summary[summary["P>|t|"] < 0.05].index.tolist()
    if "const" in significant:
        significant.remove("const")
    print(f"\n{lake.title()} - Linear regression:")
    print(model.summary())
    residuals = model.resid
    fitted = model.fittedvalues

    results_list.append({
        "lake": lake,
        "R²": round(model.rsquared, 3),
        "Adj. R²": round(model.rsquared_adj, 3),
        "Significant predictors": ",".join(significant) if significant else "None",
        "Cond. no": int(np.linalg.cond(x)), # Rough multicollinearity indicator
        "multicollinearity": "Yes" if np.linalg.cond(x) > 3000 else "No"
        })

    # Residuals distribution
    plt.figure(figsize=(6, 4))
    sns.histplot(residuals, kde=True, color="skyblue")
    plt.title(f"Residuals distribution - {lake}")
    plt.xlabel("Residuals")
    plt.ylabel("Frequency")
    plt.grid(True)
    plt.tight_layout()
    plt.show()
```

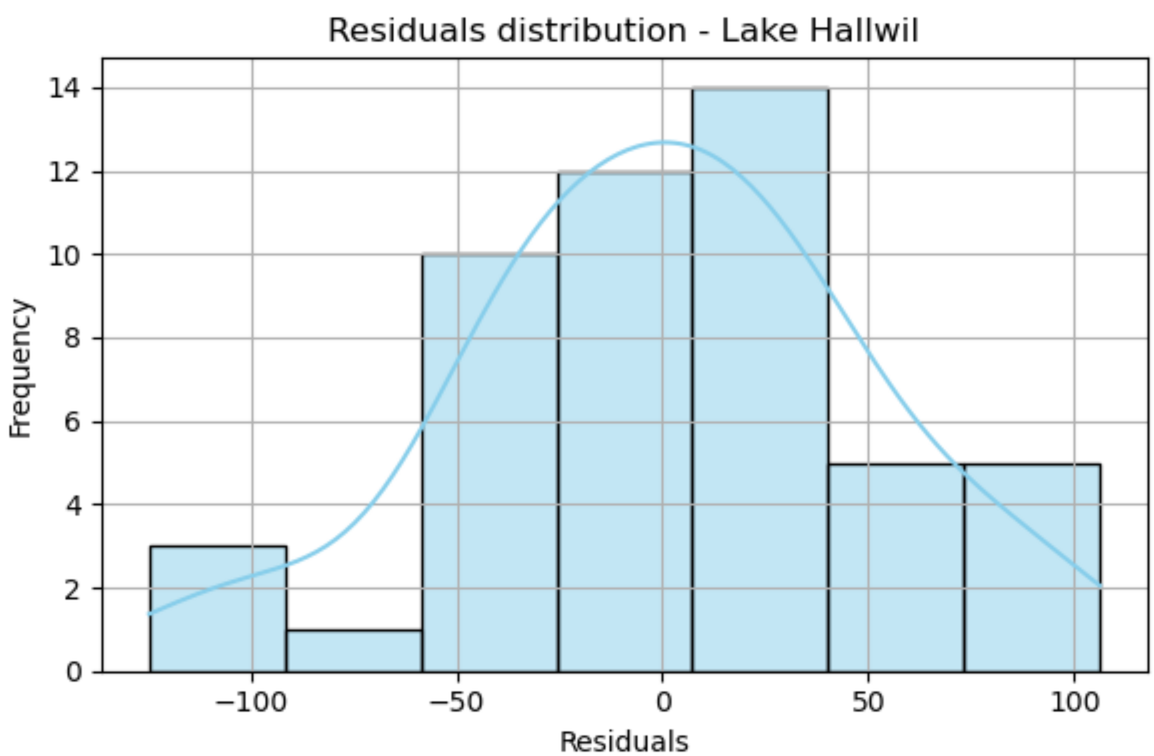
```
    # Residuals vs fitted values
    plt.figure(figsize=(6, 4))
    sns.scatterplot(x=fitted, y=residuals)
    plt.axhline(0, linestyle="--", color="red")
    plt.title(f"Residuals vs fitted values - {lake}")
    plt.xlabel("Fitted values")
    plt.ylabel("Residuals")
    plt.grid(True)
    plt.tight_layout()
    plt.show()

summary_df = pd.DataFrame(results_list)
print(summary_df)
```

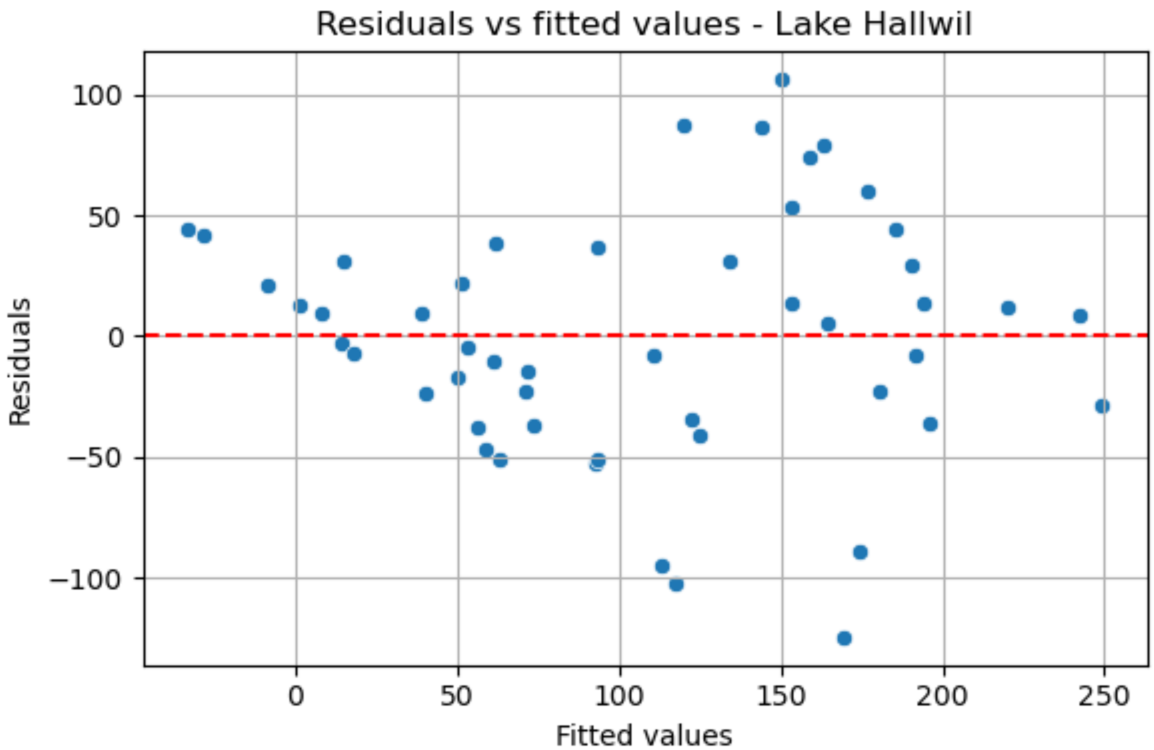
```
Lake Lucerne - Linear regression:
                            OLS Regression Results
==============================================================================
Dep. Variable:             Phosphorus   R-squared:                       0.593
Model:                            OLS   Adj. R-squared:                  0.561
Method:                 Least Squares   F-statistic:                     18.54
Date:                Tue, 27 May 2025   Prob (F-statistic):           1.84e-09
Time:                        10:58:35   Log-Likelihood:                -181.21
No. Observations:                  56   AIC:                             372.4
Df Residuals:                      51   BIC:                             382.6
Df Model:                           4
Covariance Type:            nonrobust
===============================================================================
                  coef    std err          t      P>|t|      [0.025      0.975]
-------------------------------------------------------------------------------
const         107.6496     13.949      7.717      0.000      79.646     135.653
Insolation     -0.0091      0.007     -1.231      0.224      -0.024       0.006
Rainfall       -0.0065      0.007     -0.923      0.361      -0.021       0.008
Temperature    -7.3984      1.598     -4.629      0.000     -10.607      -4.190
Snow           -0.0476      0.023     -2.070      0.044      -0.094      -0.001
==============================================================================
Omnibus:                        0.270   Durbin-Watson:                   0.924
Prob(Omnibus):                  0.874   Jarque-Bera (JB):                0.425
Skew:                          -0.136   Prob(JB):                        0.809
Kurtosis:                       2.671   Cond. No.                     3.12e+04
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly spe
cified.
[2] The condition number is large, 3.12e+04. This might indicate that there are
strong multicollinearity or other numerical problems.
```


Residuals distribution - Lake Lucerne
Frequency
0
2
4
6
8
10
12
14
−15
−10
−5
0
5
10
Residuals

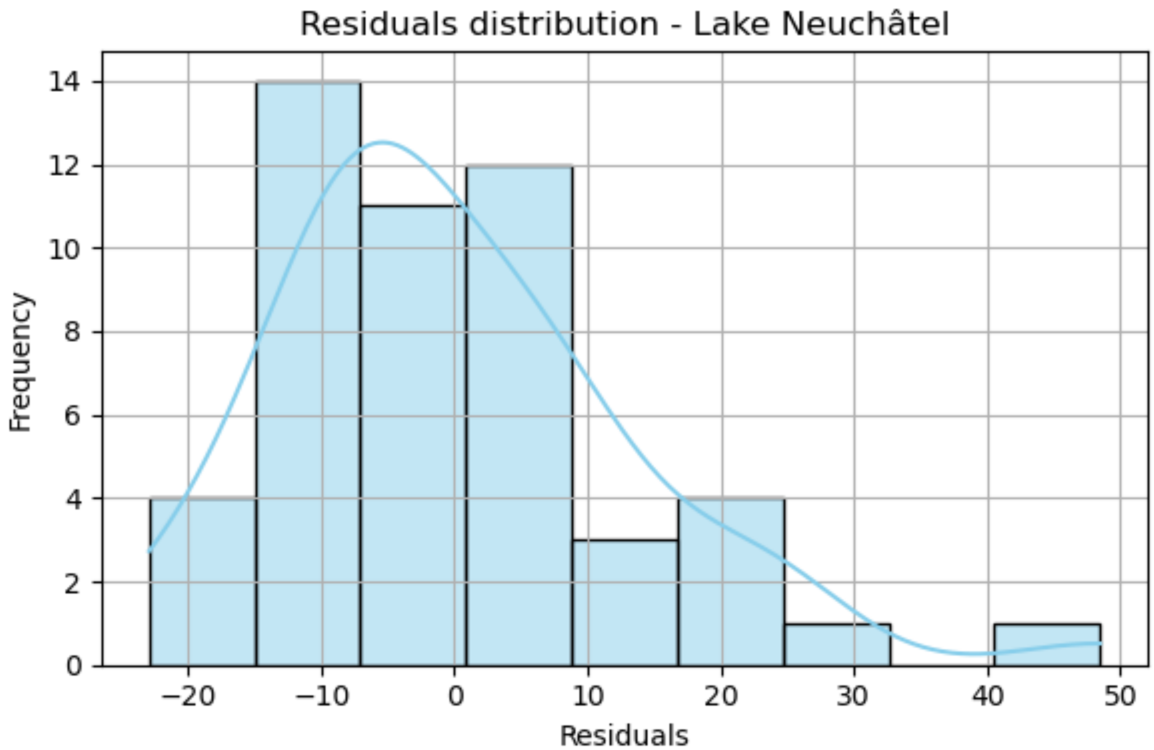

Residuals vs fitted values - Lake Lucerne
Residuals
−15
−10
−5
0
5
10
−5
0
5
10
15
20
25
30
Fitted values

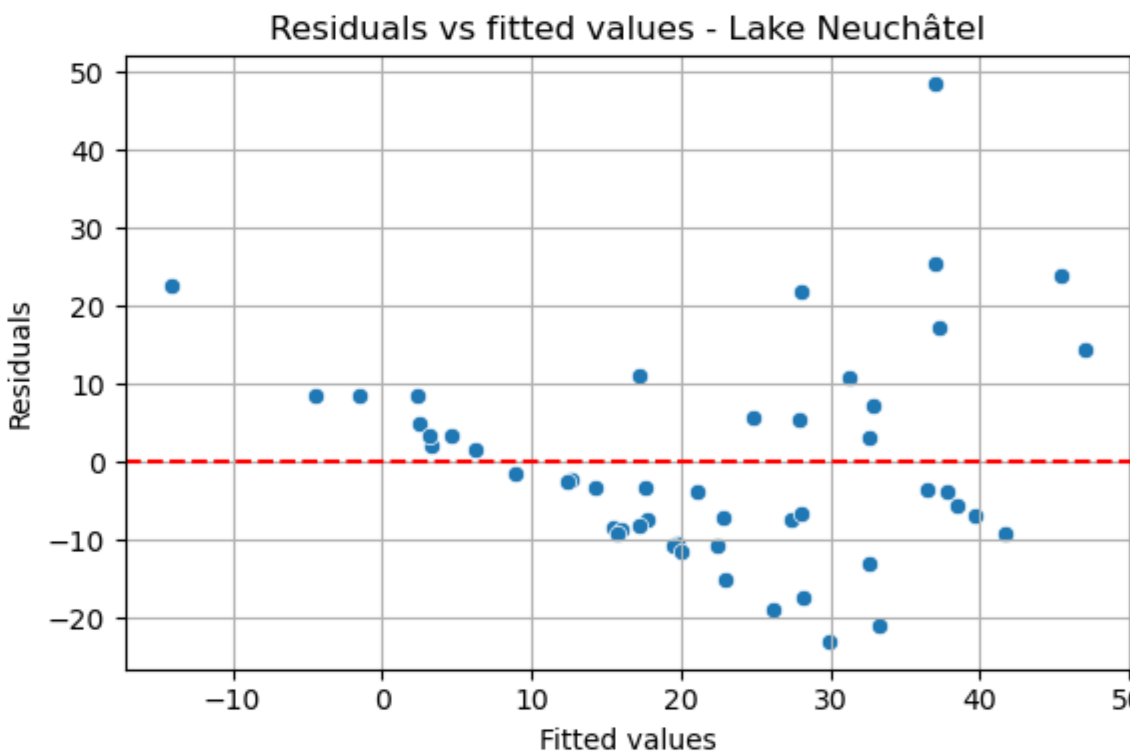
```
Lake Hallwil - Linear regression:
                            OLS Regression Results
==============================================================================
Dep. Variable:             Phosphorus   R-squared:                       0.678
Model:                            OLS   Adj. R-squared:                  0.650
Method:                 Least Squares   F-statistic:                     23.72
Date:                Tue, 27 May 2025   Prob (F-statistic):           1.35e-10
Time:                        10:58:35   Log-Likelihood:                -265.74
No. Observations:                  50   AIC:                             541.5
Df Residuals:                      45   BIC:                             551.0
Df Model:                           4
Covariance Type:            nonrobust
===============================================================================
                  coef    std err          t      P>|t|      [0.025      0.975]
-------------------------------------------------------------------------------
const        1014.8023    114.236      8.883      0.000     784.719    1244.885
Insolation     -0.1363      0.062     -2.214      0.032      -0.260      -0.012
Rainfall       -0.0783      0.060     -1.311      0.196      -0.199       0.042
Temperature   -62.3081     13.967     -4.461      0.000     -90.439     -34.177
Snow           -0.3207      0.194     -1.656      0.105      -0.711       0.069
==============================================================================
Omnibus:                        0.591   Durbin-Watson:                   1.314
Prob(Omnibus):                  0.744   Jarque-Bera (JB):                0.324
Skew:                          -0.197   Prob(JB):                        0.851
Kurtosis:                       3.012   Cond. No.                     3.01e+04
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly spe
cified.
[2] The condition number is large, 3.01e+04. This might indicate that there are
strong multicollinearity or other numerical problems.
```



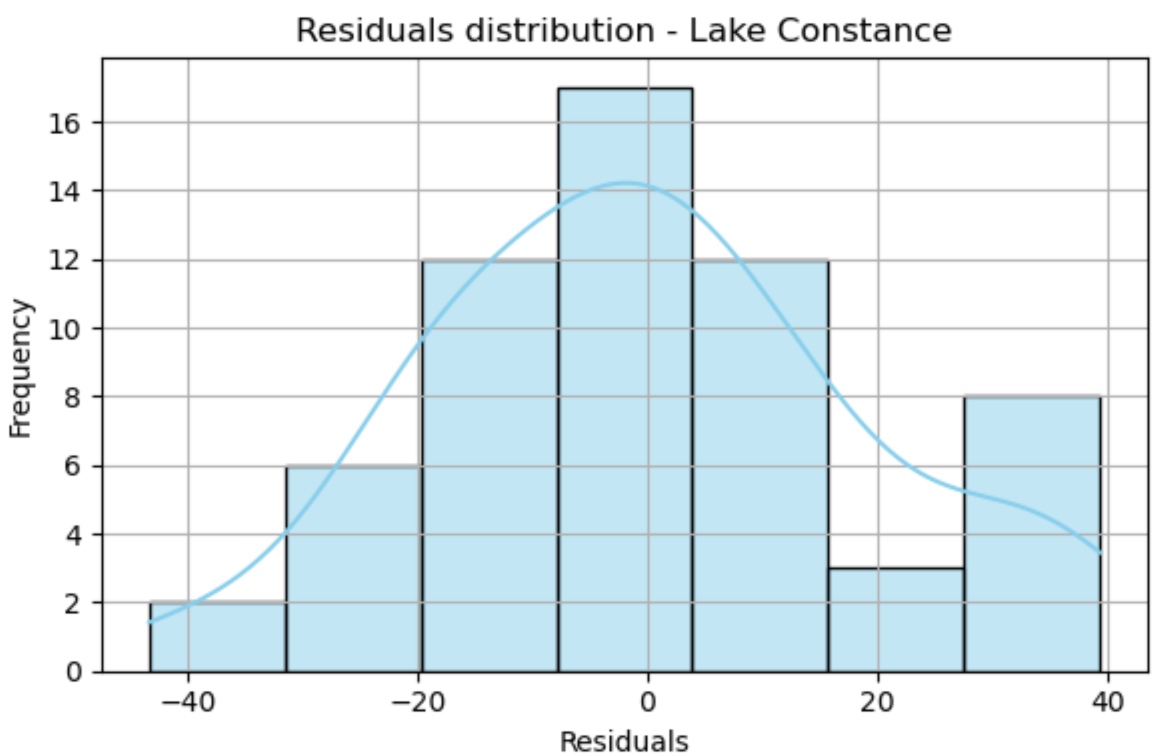


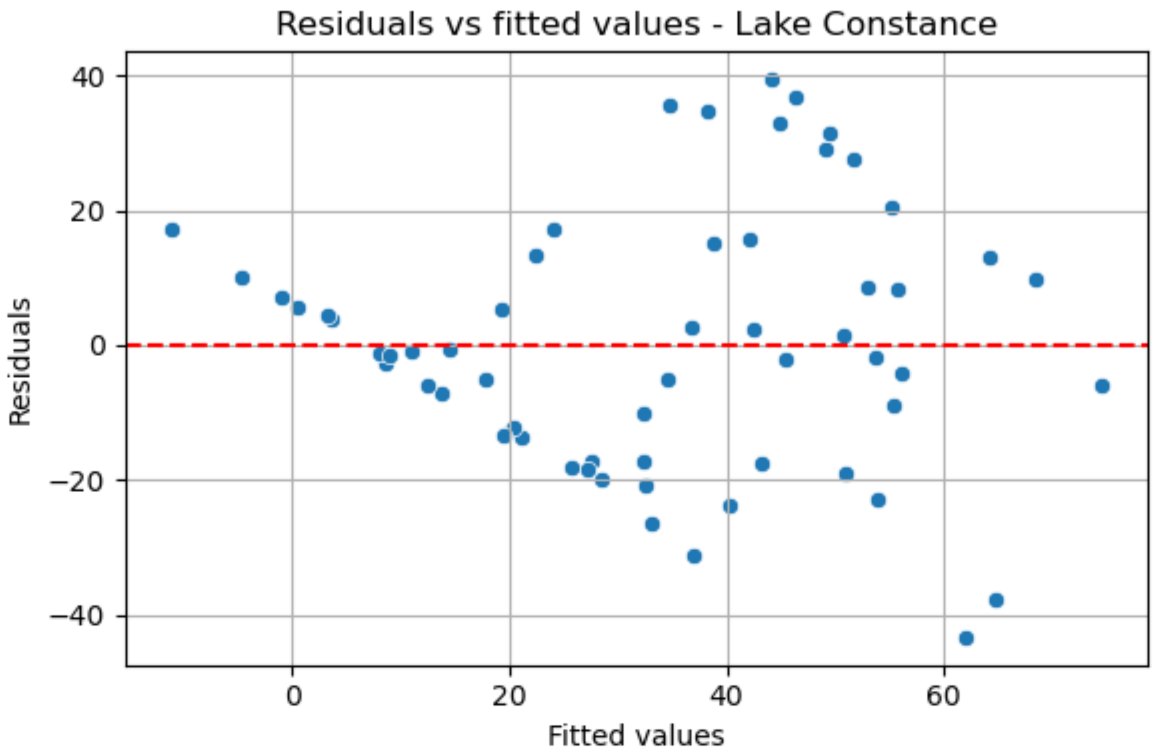

```
Lake Neuchâtel - Linear regression:
                            OLS Regression Results
==============================================================================
Dep. Variable:             Phosphorus   R-squared:                       0.511
Model:                            OLS   Adj. R-squared:                  0.467
Method:                 Least Squares   F-statistic:                     11.74
Date:                Tue, 27 May 2025   Prob (F-statistic):           1.30e-06
Time:                        10:58:36   Log-Likelihood:                -200.60
No. Observations:                  50   AIC:                             411.2
Df Residuals:                      45   BIC:                             420.8
Df Model:                           4
Covariance Type:            nonrobust
===============================================================================
                  coef    std err          t      P>|t|      [0.025      0.975]
-------------------------------------------------------------------------------
const         184.7573     36.477      5.065      0.000     111.290     258.225
Insolation     -0.0385      0.018     -2.108      0.041      -0.075      -0.002
Rainfall       -0.0084      0.015     -0.576      0.567      -0.038       0.021
Temperature    -8.4252      4.718     -1.786      0.081     -17.928       1.077
Snow           -0.0178      0.090     -0.199      0.843      -0.199       0.163
==============================================================================
Omnibus:                       14.719   Durbin-Watson:                   1.011
Prob(Omnibus):                  0.001   Jarque-Bera (JB):               17.454
Skew:                           1.095   Prob(JB):                     0.000162
Kurtosis:                       4.893   Cond. No.                     3.64e+04
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly spe
cified.
[2] The condition number is large, 3.64e+04. This might indicate that there are
strong multicollinearity or other numerical problems.
```


Residuals distribution - Lake Neuchâtel
Frequency
0
2
4
6
8
10
12
14
−20
−10
0
10
20
30
40
50
Residuals

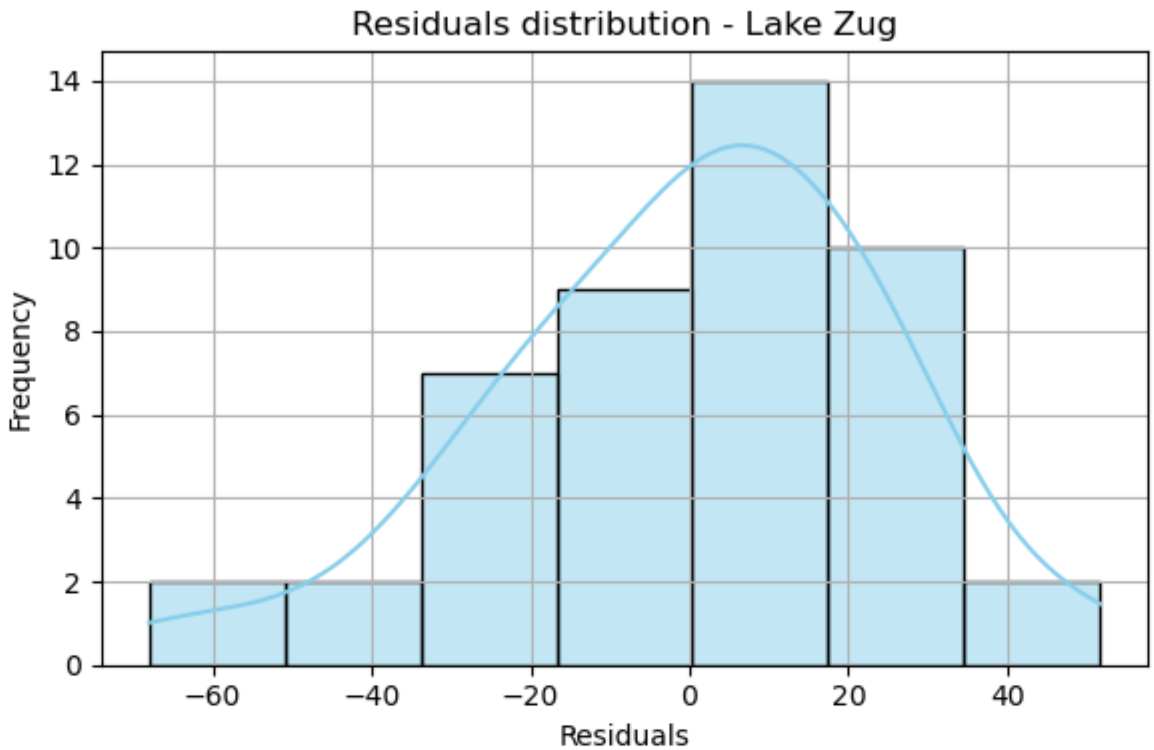

Residuals vs fitted values - Lake Neuchâtel
Residuals
50
40
30
20
10
0
−10
−20
−10
0
10
20
30
40
50
Fitted values

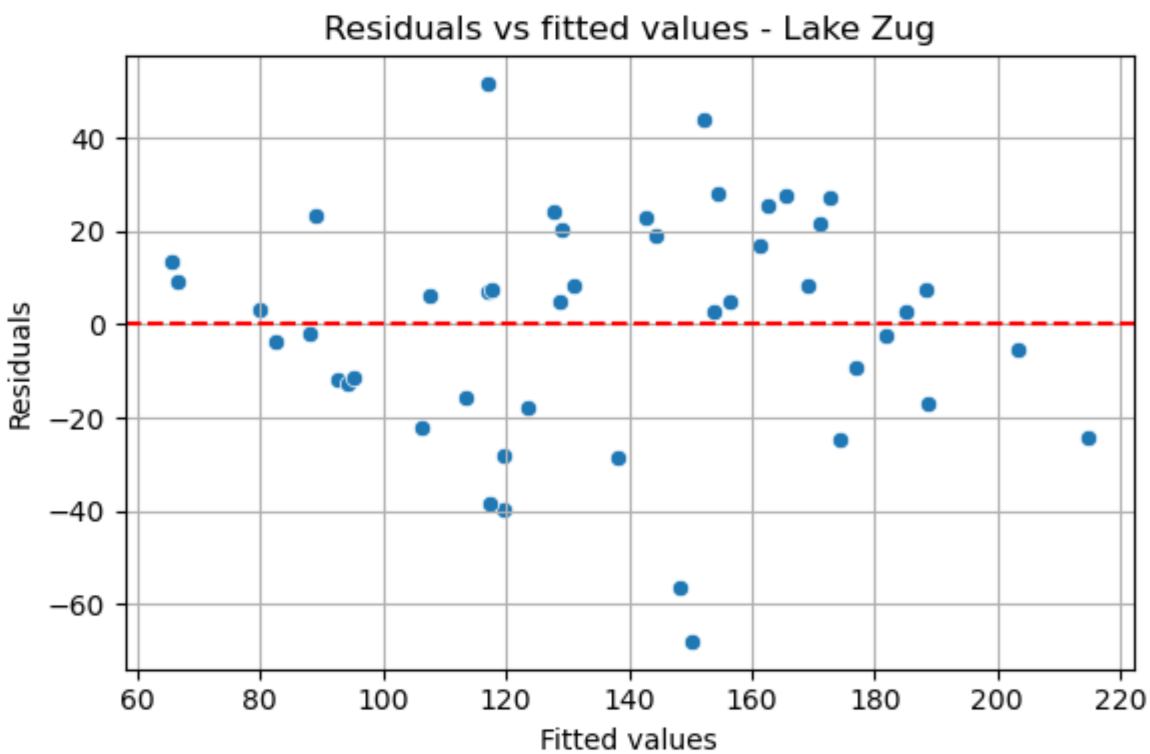
```
Lake Constance - Linear regression:
                            OLS Regression Results
==============================================================================
Dep. Variable:             Phosphorus   R-squared:                       0.527
Model:                            OLS   Adj. R-squared:                  0.493
Method:                 Least Squares   F-statistic:                     15.35
Date:                Tue, 27 May 2025   Prob (F-statistic):           1.73e-08
Time:                        10:58:37   Log-Likelihood:                -261.28
No. Observations:                  60   AIC:                             532.6
Df Residuals:                      55   BIC:                             543.0
Df Model:                           4
Covariance Type:            nonrobust
===============================================================================
                  coef    std err          t      P>|t|      [0.025      0.975]
-------------------------------------------------------------------------------
const         251.2768     41.506      6.054      0.000     168.096     334.457
Insolation     -0.0230      0.023     -0.984      0.329      -0.070       0.024
Rainfall       -0.0070      0.021     -0.337      0.737      -0.048       0.035
Temperature   -19.4659      4.672     -4.167      0.000     -28.828     -10.104
Snow           -0.0745      0.036     -2.046      0.046      -0.147      -0.002
==============================================================================
Omnibus:                        0.507   Durbin-Watson:                   0.824
Prob(Omnibus):                  0.776   Jarque-Bera (JB):                0.644
Skew:                           0.182   Prob(JB):                        0.725
Kurtosis:                       2.647   Cond. No.                     3.45e+04
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly spe
cified.
[2] The condition number is large, 3.45e+04. This might indicate that there are
strong multicollinearity or other numerical problems.
```



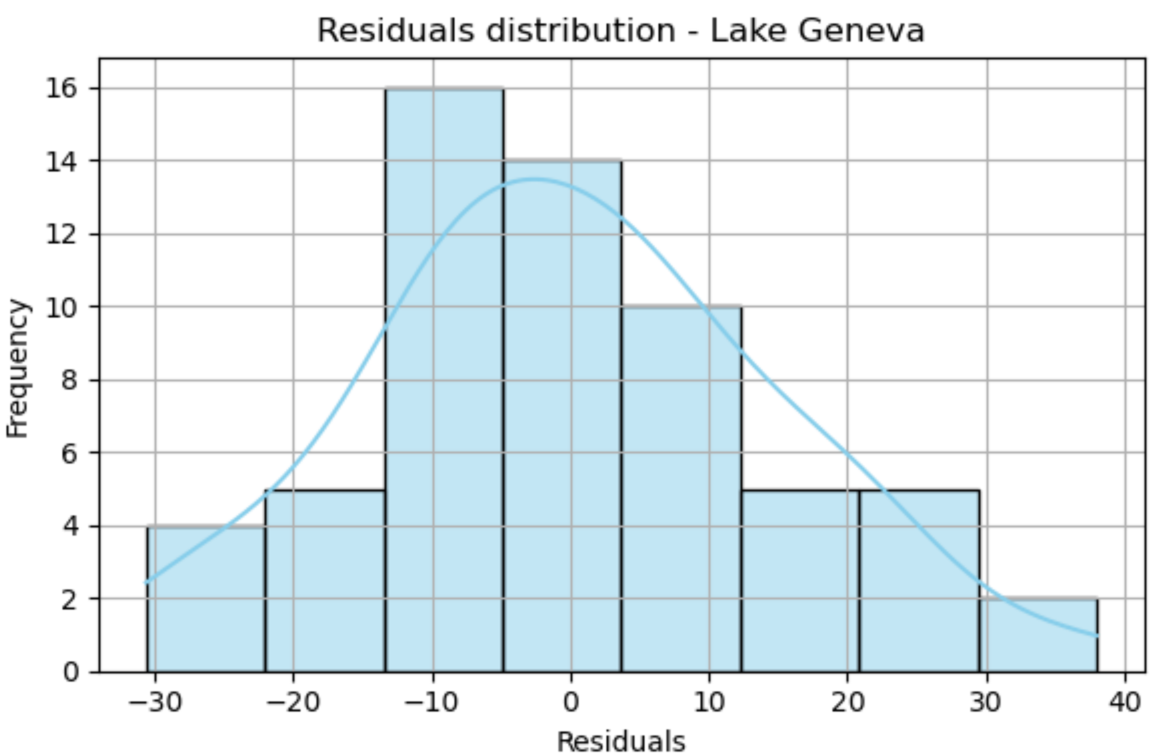


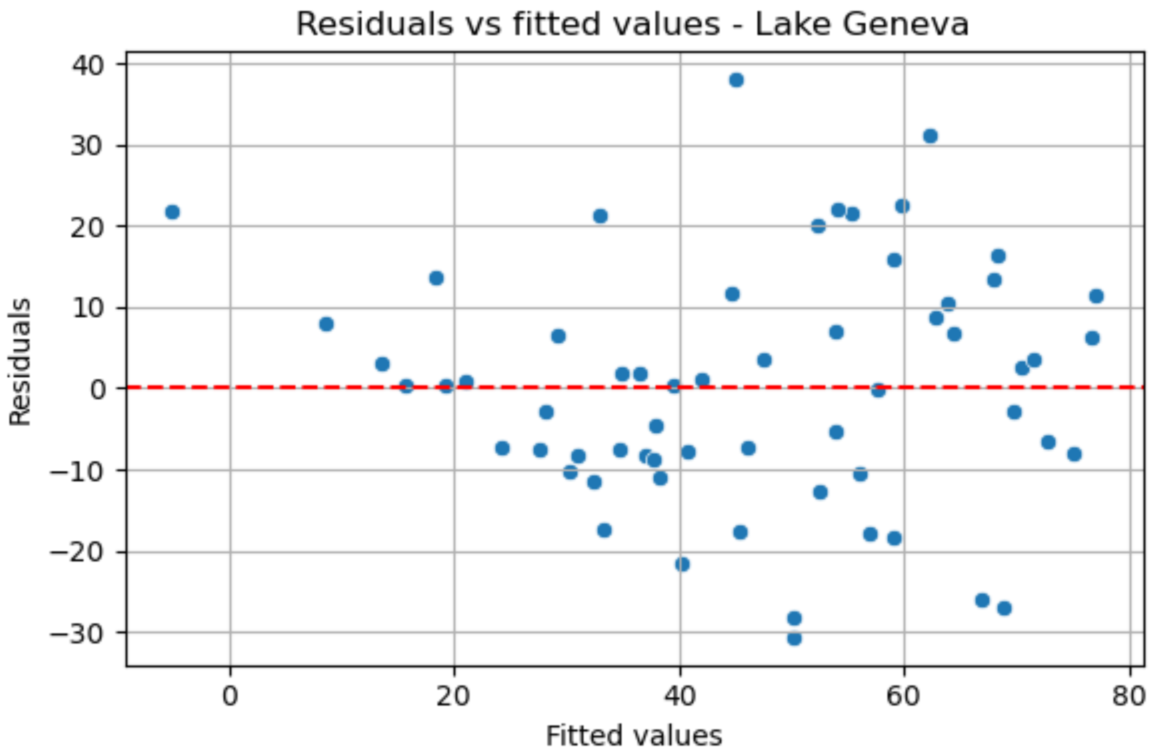

```
Lake Zug - Linear regression:
                            OLS Regression Results
==============================================================================
Dep. Variable:             Phosphorus   R-squared:                       0.695
Model:                            OLS   Adj. R-squared:                  0.665
Method:                 Least Squares   F-statistic:                     23.34
Date:                Tue, 27 May 2025   Prob (F-statistic):           4.12e-10
Time:                        10:58:38   Log-Likelihood:                -211.97
No. Observations:                  46   AIC:                             433.9
Df Residuals:                      41   BIC:                             443.1
Df Model:                           4
Covariance Type:            nonrobust
===============================================================================
                  coef    std err          t      P>|t|      [0.025      0.975]
-------------------------------------------------------------------------------
const         593.5325     63.702      9.317      0.000     464.884     722.181
Insolation     -0.1050      0.034     -3.102      0.003      -0.173      -0.037
Rainfall       -0.0500      0.030     -1.651      0.106      -0.111       0.011
Temperature   -24.0675      8.671     -2.776      0.008     -41.580      -6.555
Snow           -0.1166      0.118     -0.988      0.329      -0.355       0.122
==============================================================================
Omnibus:                        3.278   Durbin-Watson:                   1.413
Prob(Omnibus):                  0.194   Jarque-Bera (JB):                2.298
Skew:                          -0.518   Prob(JB):                        0.317
Kurtosis:                       3.357   Cond. No.                     3.28e+04
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly spe
cified.
[2] The condition number is large, 3.28e+04. This might indicate that there are
strong multicollinearity or other numerical problems.
```


Residuals distribution - Lake Zug
Frequency
Residuals
0
2
4
6
8
10
12
14
−60
−40
−20
0
20
40


Residuals vs fitted values - Lake Zug
Residuals
Fitted values
40
20
0
−20
−40
−60
60
80
100
120
140
160
180
200
220

```
Lake Geneva - Linear regression:
                            OLS Regression Results
==============================================================================
Dep. Variable:             Phosphorus   R-squared:                       0.618
Model:                            OLS   Adj. R-squared:                  0.590
Method:                 Least Squares   F-statistic:                     22.62
Date:                Tue, 27 May 2025   Prob (F-statistic):           3.70e-11
Time:                        10:58:39   Log-Likelihood:                -250.08
No. Observations:                  61   AIC:                             510.2
Df Residuals:                      56   BIC:                             520.7
Df Model:                           4
Covariance Type:            nonrobust
===============================================================================
                  coef    std err          t      P>|t|      [0.025      0.975]
-------------------------------------------------------------------------------
const         271.3012     34.357      7.897      0.000     202.477     340.126
Insolation     -0.0644      0.019     -3.449      0.001      -0.102      -0.027
Rainfall       -0.0173      0.016     -1.068      0.290      -0.050       0.015
Temperature    -8.8408      3.607     -2.451      0.017     -16.067      -1.614
Snow           -0.0294      0.087     -0.339      0.736      -0.203       0.145
==============================================================================
Omnibus:                        0.352   Durbin-Watson:                   1.220
Prob(Omnibus):                  0.839   Jarque-Bera (JB):                0.368
Skew:                           0.169   Prob(JB):                        0.832
Kurtosis:                       2.827   Cond. No.                     3.59e+04
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly spe
cified.
[2] The condition number is large, 3.59e+04. This might indicate that there are
strong multicollinearity or other numerical problems.
```






```
               lake     R²  Adj. R²  Significant predictors  Cond. no  \
0      Lake Lucerne  0.593    0.561        Temperature,Snow     31202
1      Lake Hallwil  0.678    0.650  Insolation,Temperature     30092
2    Lake Neuchâtel  0.511    0.467              Insolation     36437
3   Lake Constance  0.527    0.493        Temperature,Snow     34458
4          Lake Zug  0.695    0.665  Insolation,Temperature     32753
5       Lake Geneva  0.618    0.590  Insolation,Temperature     35888

  multicollinearity
0               Yes
1               Yes
2               Yes
3               Yes
4               Yes
5               Yes
```

Ridge, Lasso and Random Forest regression

The Ridge correlation model was tested, to see if a multi-variate model fits better. At the same time, a Lasso regression model was also tested, in case non-explanatory variables could have been excluded. The Random Forest regression model was also tested, to see if a non-linear model could better explain the data.

In [21]:
```
# Testing Ridge and Lasso regression models
models = {
        "Ridge": Ridge(alpha=1.0),
        "Lasso": Lasso(alpha=0.1, max_iter=10000)
        }

ridge_lasso_results = []
```

```
for lake in phospho_weather["Lake"].unique():
    subset = phospho_weather[phospho_weather["Lake"] == lake].dropna()
    x = subset[["Insolation", "Rainfall", "Temperature", "Snow"]]
    y = subset["Phosphorus"]

    # Standardisation
    scaler = StandardScaler()
    x_scaled = scaler.fit_transform(x)

    # Split
    x_train, x_test, y_train, y_test = train_test_split(x_scaled, y, test_size=0.2,

    for model_name, model in models.items():
        model.fit(x_train, y_train)
        y_pred = model.predict(x_test)

        ridge_lasso_results.append({
            "Lake": lake,
            "Model": model_name,
            "R² test": round(r2_score(y_test, y_pred), 3),
            "RMSE test": round(root_mean_squared_error(y_test, y_pred), 3),
            "Coefficients": dict(zip(x.columns, [round(c, 3) for c in model.coef_])
            })

# Printing test results, and coefficients in a separate table (coefficients too lon
ridge_lasso_df = pd.DataFrame(ridge_lasso_results)
print(f"Ridge and Lasso regression results \n")
for index, row in ridge_lasso_df.iterrows():
    print(f"Lake: {row['Lake']}, Model: {row['Model']}, R²: {row['R² test']}, RMSE:
coeffs_df = pd.DataFrame([row["Coefficients"] for index, row in ridge_lasso_df.iter
coeffs_df.index = ridge_lasso_df["Lake"] + "-" + ridge_lasso_df["Model"]
print(f"\nClimate variable coefficients per lake")
print(coeffs_df)
```

```
Ridge and Lasso regression results

Lake: Lake Lucerne, Model: Ridge, R²: 0.355, RMSE: 8.024
Lake: Lake Lucerne, Model: Lasso, R²: 0.345, RMSE: 8.08
Lake: Lake Hallwil, Model: Ridge, R²: 0.611, RMSE: 40.389
Lake: Lake Hallwil, Model: Lasso, R²: 0.591, RMSE: 41.461
Lake: Lake Neuchâtel, Model: Ridge, R²: -3.276, RMSE: 16.427
Lake: Lake Neuchâtel, Model: Lasso, R²: -3.301, RMSE: 16.475
Lake: Lake Constance, Model: Ridge, R²: 0.417, RMSE: 21.533
Lake: Lake Constance, Model: Lasso, R²: 0.42, RMSE: 21.492
Lake: Lake Zug, Model: Ridge, R²: 0.659, RMSE: 28.36
Lake: Lake Zug, Model: Lasso, R²: 0.654, RMSE: 28.537
Lake: Lake Geneva, Model: Ridge, R²: 0.224, RMSE: 19.754
Lake: Lake Geneva, Model: Lasso, R²: 0.215, RMSE: 19.88

Climate variable coefficients per lake
                      Insolation  Rainfall  Temperature    Snow
Lake Lucerne-Ridge        -1.454    -0.498       -7.207  -2.149
Lake Lucerne-Lasso        -1.112    -0.302       -7.522  -2.190
Lake Hallwil-Ridge       -25.927   -11.920      -58.685 -15.090
Lake Hallwil-Lasso       -24.395   -11.487      -61.782 -16.314
Lake Neuchâtel-Ridge      -9.207     0.290       -7.701  -0.027
Lake Neuchâtel-Lasso      -9.504     0.115       -7.573  -0.000
Lake Constance-Ridge      -4.688    -1.851      -17.581  -5.033
Lake Constance-Lasso      -3.822    -1.326      -18.605  -5.252
Lake Zug-Ridge           -19.240    -4.385      -22.607  -8.004
Lake Zug-Lasso           -19.133    -4.195      -23.633  -8.674
Lake Geneva-Ridge        -12.433    -1.322      -11.527  -1.651
Lake Geneva-Lasso        -12.556    -1.318      -11.616  -1.672
```

In [23]:

```python
# Testing Random Forest Regression
rf_results = []
for lake in phospho_weather["Lake"].unique():
    subset = phospho_weather[phospho_weather["Lake"] == lake].dropna()
    x = subset[["Insolation", "Rainfall", "Temperature", "Snow"]]
    y = subset["Phosphorus"]

    x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.2, random

    rf = RandomForestRegressor(n_estimators=100, random_state=42)
    rf.fit(x_train, y_train)
    y_pred = rf.predict(x_test)

    rf_results.append({
        "Lake": lake,
        "Model": "Random Forest",
        "R² test": round(r2_score(y_test, y_pred), 3),
        "RMSE test": round(root_mean_squared_error(y_test, y_pred), 3)
        })

rf_df = pd.DataFrame(rf_results)
print("Random Forest Regression results")
print(rf_df)
```

```
Random Forest Regression results
             Lake          Model  R² test  RMSE test
0    Lake Lucerne  Random Forest    0.304      8.331
1    Lake Hallwil  Random Forest    0.353     52.104
2  Lake Neuchâtel  Random Forest   -1.881     13.485
3  Lake Constance  Random Forest    0.175     25.623
4        Lake Zug  Random Forest    0.628     29.581
5     Lake Geneva  Random Forest    0.360     17.948
```

Results and interpretation

Concerning the trend analysis of the phosphorus, all trends are globally negative. However, when looking more in detail, we can see that for all lakes, the curves start with increasing values until the 70s - early 80s. From then on, the tendancy is inverted, with decreasing values, giving the globally negative trend.

Concerning the trend analysis of the weather data, it is a bit different. The trends are all positive for every locations for insolation time, rainfall and temperature. On the other hand, the fresh snow present negative trends for each locations. For a more detailed description, concerning insolation time, all locations present a slow decrease in values until a minimum around 1980, before a rapid increase in values. The rainfall and fresh snow global trends looks generally quite flat, although the values can vary significantly. Finally, the temperature show a clear increase in values over time, with what appears to be a positive exponential pattern.

The analysis of correlation between the phosphorus concentration and the climate data shows the same results for most locations. For every lakes except Lake Geneva, the climate parameter the most (negatively) correlated to the phosphorus concentration is the temperature (between -0.68 and -0.78), closely followed by the insolation time (between -0.55 and -0.75). The fresh snow is significantly less (positively) correlated (between 0.18 and 0.35), and then the rainfall is (negatively or positively) almost never correlated (between -0.02 and 0.12). As stated before, Lake Geneva is a bit different from the other lakes, since the climate parameter the most correlated to the phosphorus concentration is the insolation time (-0.70), followed by the temperature (-0.58). Another difference with the other lakes is the higher correlation values of the rainfall (0.26).

About the correlation between the climate variables themselves, for all lakes, the strongest correlation is between temperature and insolation time (between 0.64 and 0.71). Then comes the negative correlation between temperature and fresh snow (between -0.43 and -0.56). It is closely followed by the negative correlation between rainfall and insolation time (between -0.33 and -0.53). The fourth highest correlation, is the negative correlation between fresh snow and insolation time (between -0.30 and -0.43). Then rainfall is slighly less positively correlated to fresh snow (between 0.13 and 0.29). Finally, rainfall and temperature are almost not correlated at all (between -0.12 and 0.03).

In regard of the regression model, the one working the best is quite clearly the multiple linear regression model (R^2 comprised between 0.59 and 0.70, with Lake Neuchâtel and Constance having a lower value, respectively 0.51 and 0.53). However, for Lake Zug and Lake Hallwil, the Ridge and Lasso regression models have almost similar R^2 values (0.66 and 0.65 for Zug, 0.61 and 0.59 for Hallwil). But it is also important to remember that the locations used for the climate data of these lakes are not exactly next to the lakes themselves, but further away. This could also be because Hallwil and Zug are the two lakes with the highest phosphorus concentration in comparison to the other lakes, and with a much more important decrease than the others.

The multiple linear model being the best model seems to be consistent with the data. Indeed, according to the model the most significant predictors for the phosphorus concentration in the lakes are the temperature and the insolation. This make sense since the phosphorus concentration show an increase until ca. 1980 before decreasing until the present day. On the other hand, the insolation time show a decrease until ca. 1980 before increasing. And the temperature seems to be globally quite constant until ca. 1980 before also showing an increase in the values. So it appears quite clearly that the phosphorus concentration follow the opposite tendancy of the one displayed by the insolation time and the temperature. This therefore means that in regard to the climate, a higher insolation time and higher temperature result in a lower phosphorus concentration in the lakes, and vice versa.

It seems also that there is a slight correlation between the phosphorus concentration in the lakes and the fresh snow, in the sense that both are decreasing over time. But this could be an artifact due to the fact that, since the phosphorus concentration tends to decrease when the temperature increases, that increase in temperature can also obviously lead to a decrease in fresh snow.

Finally, it is important to keep in mind the limitation of this analysis. First, as mentioned before, climate data are not available directly for all lakes. Then, even if there is quite a significant amount of data for each location, this analysis is about only six lakes. It would therefore be appropriate to conduct a similar study on a higher number of lakes, at different places and different altitudes, to have more reliable results. Also, this study only concern four climate variables, but there are other climatic and environmental variables that most certainly have an influence on phosphorus concentration in lakes.

Conclusion

In conclusion, according to the analysis and the available data, it seems that the phosphorus concentration in the swiss lakes tend to follow the insolation time and the temperature. This relationship is linear and negative. This results in a decrease in the phosphoruse concentration in the lakes when the insolation time and the temperature increase, and vice versa. There could be also a positive relationship between the phosphorus concentration in the lakes and the fresh snow, but it was not clearly proven, and thus it is probably an artifact due to the negative correlation between fresh snow and temperature.

People should also keep in mind that not all climate data were directly available for every lakes, and this study only concern six lakes and four climate variables. It would be therefore relevant to do a similar study on a higher number of lakes, with climatic and environmental data recorded directly at every lakes.