Swiss Tourism - Forecasting visitors from 10/2023 to 12/2024

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1 Introduction

Tourism is a significant sector for Switzerland's economy, contributing greatly to its GDP and employment. Accurate forecasting of tourist arrivals is essential for effective planning and decision-making in the tourism industry. This project aims to predict the total number of visitors to Vaud from October 2023 to December 2024 as well as the number of visitors from the Philippines to Ticino during the same period. Utilizing historical data from 2005 to September 2023, we apply various forecasting techniques, integrating exogenous variables such as GDP and weather conditions to enhance the accuracy of our predictions.

1.1 Objectives

The primary objectives of this project are:

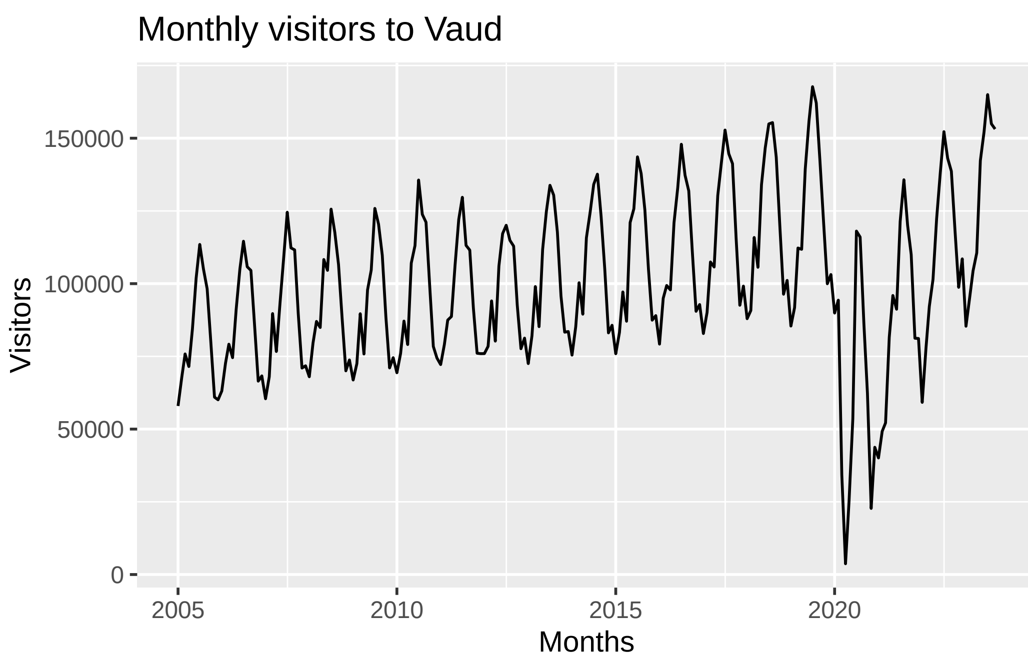
- To forecast the total number of visitors to the canton of Vaud from October 2023 to December 2024.
- To forecast the number of visitors from the Philippines to the canton of Ticino for the same period.

We aim to compare different time series models and include exogenous variables to improve forecast accuracy.

2 EDA

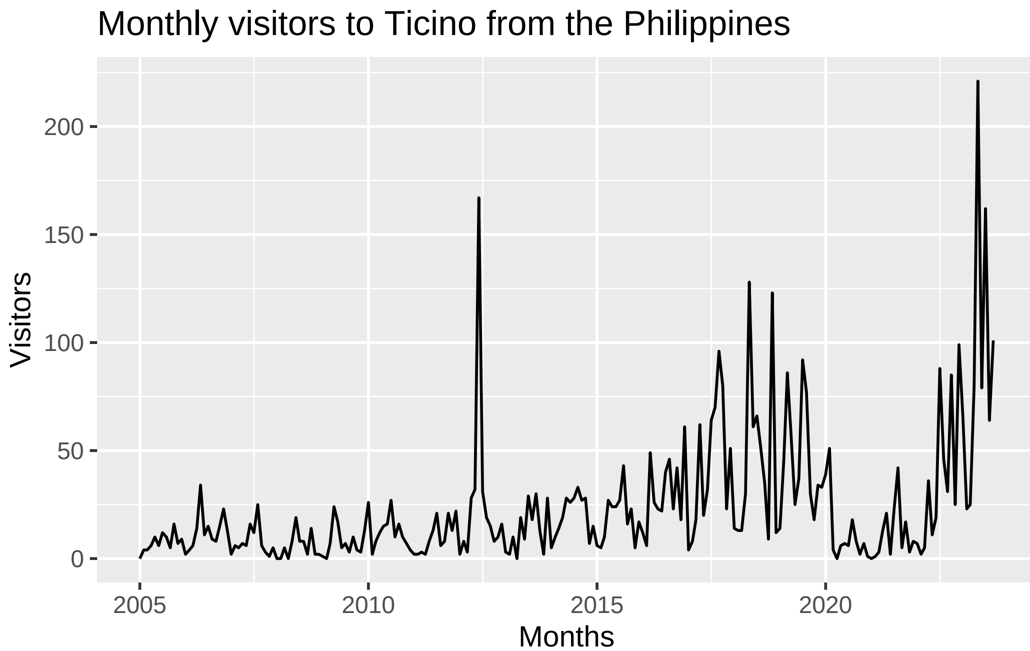
Before plotting the data, we translate german months to english, and create a date type column.

Here we plot the total visitors for canton Vaud for the entire time frame.



The time series plot of monthly visitors to Vaud from 2005 to 2023 reveals several key insights. There is a clear upward trend in visitor numbers, indicating growing tourism. The plot shows strong seasonal patterns, with regular peaks and troughs each year, reflecting typical tourist activity periods. A significant drop in visitors during the COVID-19 pandemic (2020-2022) is evident, illustrating the impact of global travel restrictions. Post-pandemic, visitor numbers recover, though with some variability. This highlights the need to account for trends, seasonality, and anomalies in our forecasting models.

Below is the plot for visitors to Ticino, from the Philippines



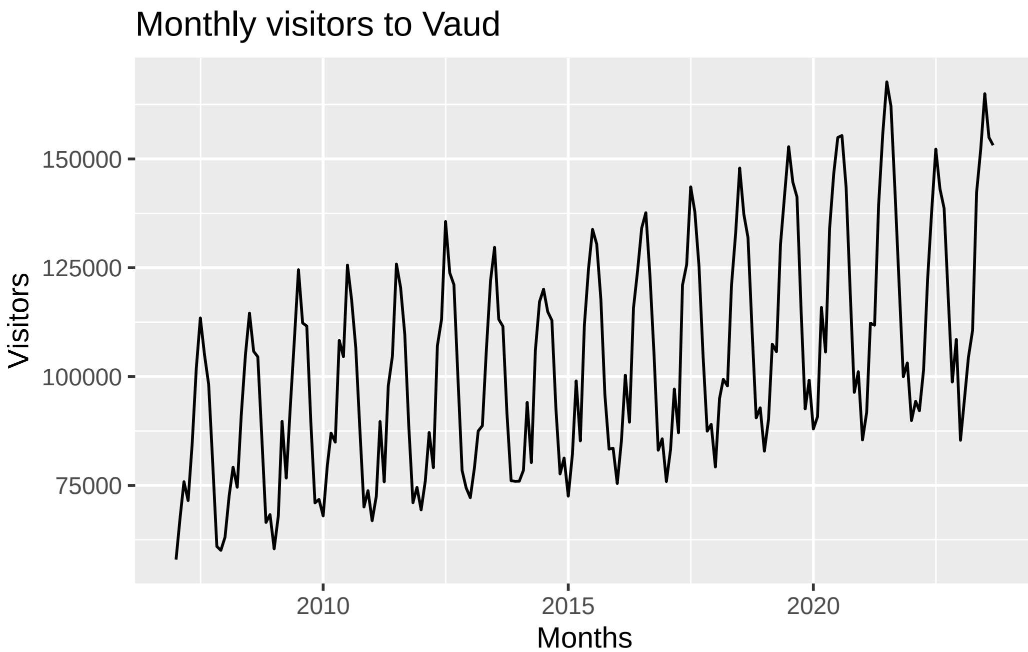
As the number of visitors is greatly reduced compared to the previous plot, we observe much more variability in the number of visitors across months. It is hard to make out any seasonality with the naked eye, but we do notice an upwards trend. The effect of COVID is also very noticeable, with a dip in the number of visitors between 2020 and 2022.

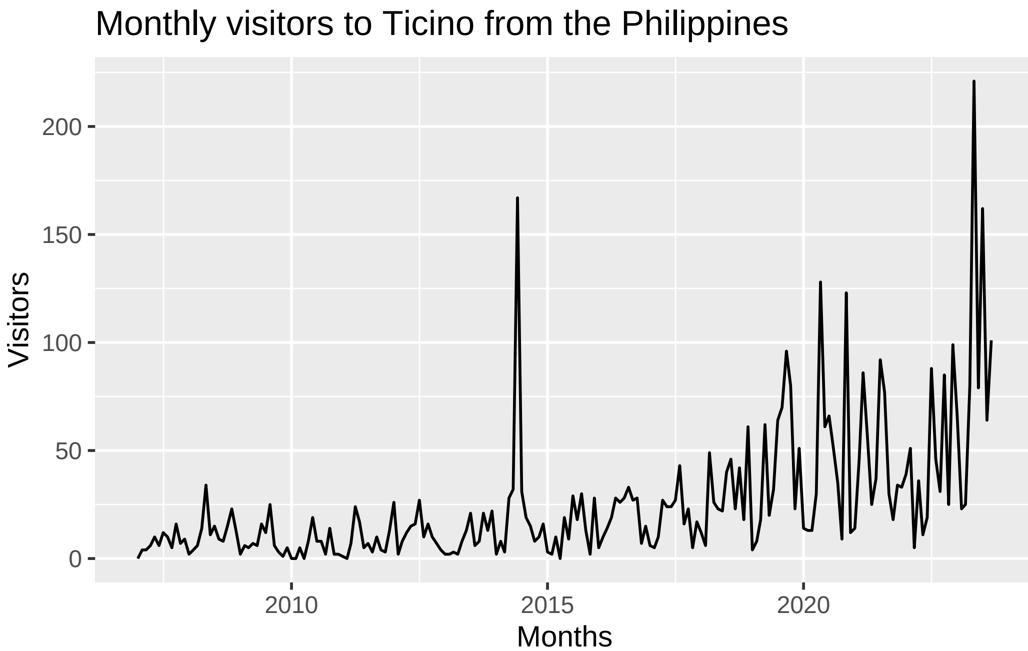
We produced an STL decomposition that highlighted the separate influences of trend, seasonality, and irregular components, as well as ACF and PACF plots that provided insight into autocorrelation. We also made scatterplot matrices to indicate the relationships between visitor numbers and exogenous variables (GDP, temperature and precipitation) presented in the modeling section. These plots are in the appendix.

3 Data cleaning/wrangling

We consider COVID to be a black swan, and a unique event, and we will assume that it will not happen again during the period that we are predicting (Oct 23 - Dec 24). Knowing this, we decided it would be best to completely remove the data during the lockdown period, as it would bias our forecasts. Lockdown in Switzerland started in March 2020, and all measures except masks were lifted indefinitely in February 2022, which gives us lockdown period of exactly 2 years. It's important that the data we remove is in multiples of 12 months, as it won't affect seasonality. To implement this, we create a new dummy variable called covid to our data frame, that will be set equal to 1 during this time frame, and 0 everywhere else.

We then remove all the data where covid = 1, and add 2 years to the data before March 2020, so there are no gaps in our tsibble. Below are plots for both cases.

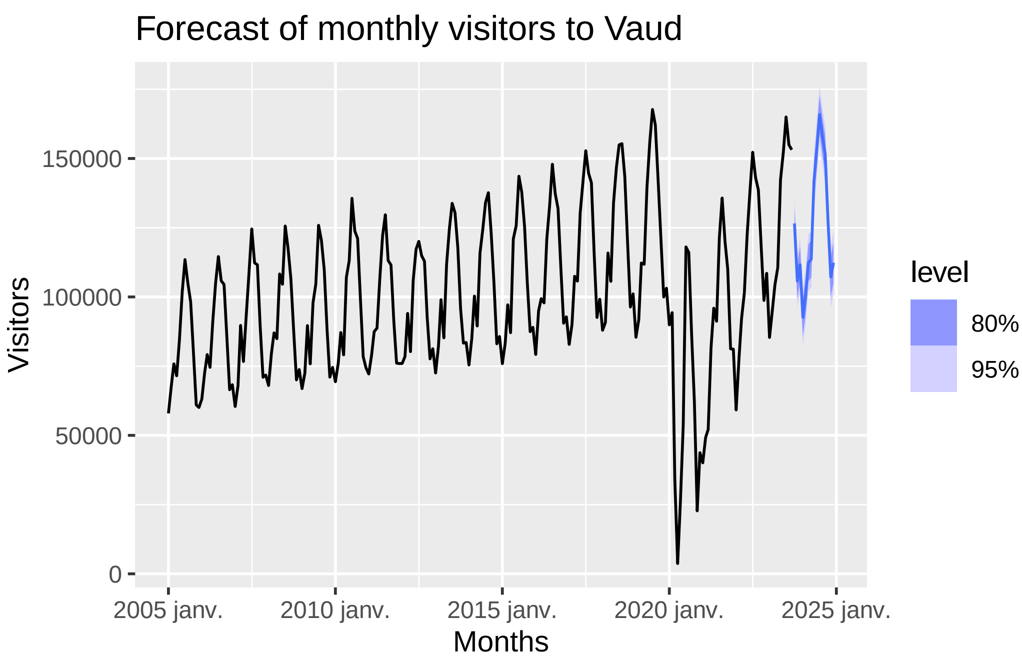




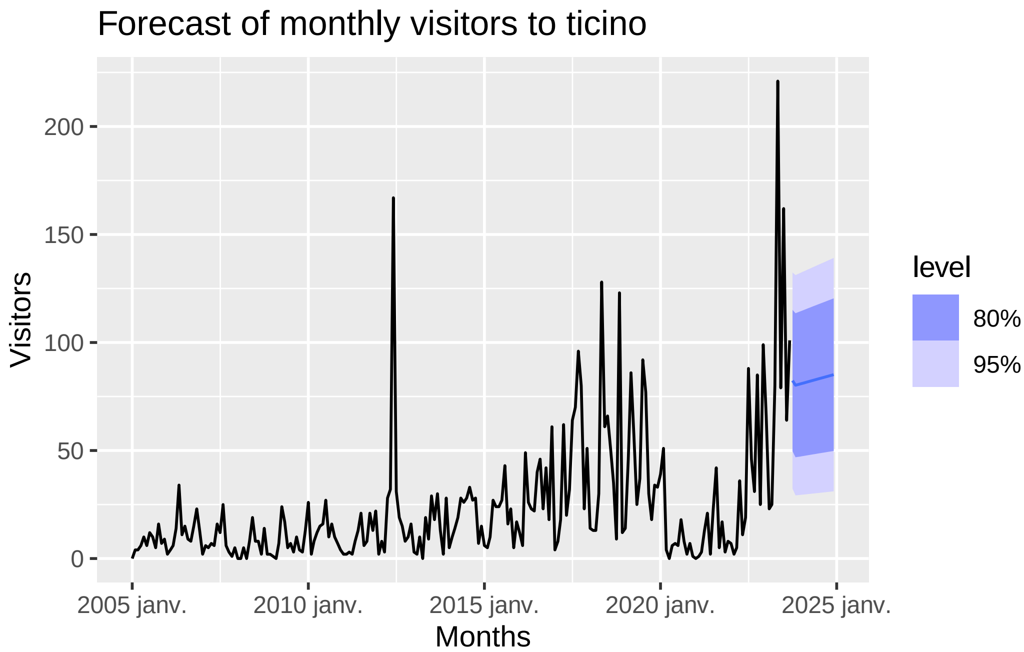
4 Modeling

We decided first to make an automatic ARIMA model to forecast visitors. Below are the automatic ARIMA models, the AIC and BIC values, and the forecasts for both cases.

```
Series: value
Model: ARIMA(0,0,3)(0,1,2)[12] w/ drift

Coefficients:
         ma1     ma2     ma3     sma1     sma2   constant
      0.3819  0.3574  0.3019  -0.5603  -0.1391  2672.4410
s.e.  0.0730  0.0698  0.0677   0.0770   0.0722   242.7348

sigma^2 estimated as 20137890:  log likelihood=-1858.22
AIC=3730.44   AICc=3731.06   BIC=3753.13
```




```
Series: value
Model: ARIMA(0,1,2) w/ drift

Coefficients:
          ma1      ma2  constant
      -0.8049  -0.0963    0.3780
s.e.   0.0657   0.0688    0.1947

sigma^2 estimated as 651.7:  log likelihood=-931.03
AIC=1870.05   AICc=1870.26   BIC=1883.25
```



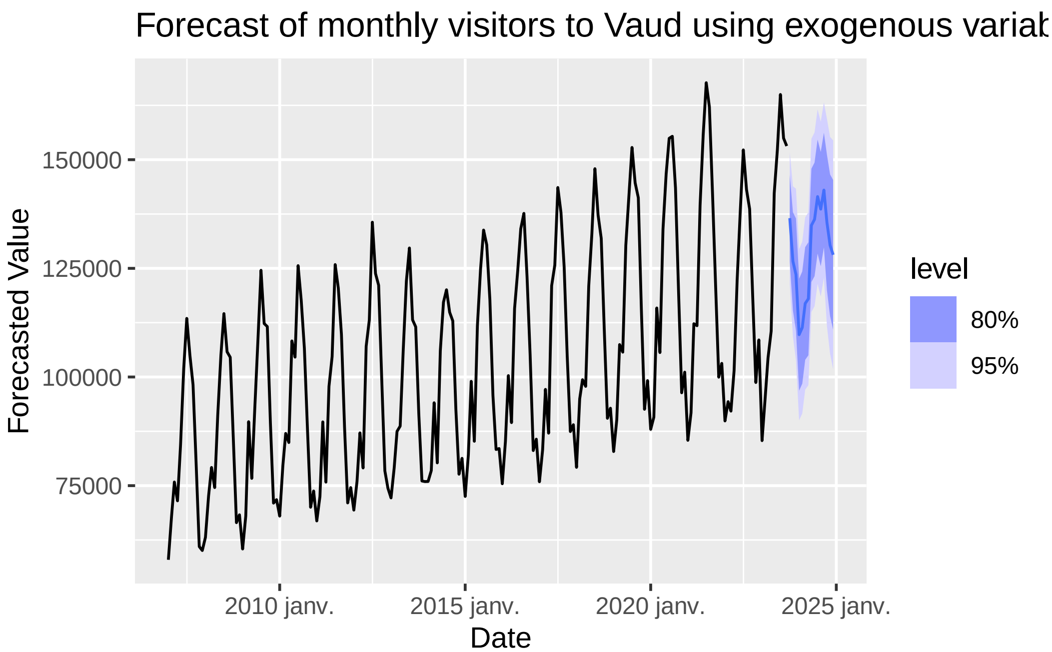
We notice that the forecast for Vaud visitors is quite precise, with a very small confidence interval. The model accounts for seasonality as well as the upwards trend. On the other hand, the forecast for Ticino visitors is very basic, resembling a naive model with a slight upwards trend, and without seasonality.

To improve our current model, we decided to add exogenous variables that we think are likely to impact the number of tourists in a region. The first exogenous variable is GDP per capita in Vaud and Ticino. The hypothesis we're making is that higher GDP will boost tourism. Looking at the overall visitors plot, we notice that there are considerably more visitors during summer months, when the weather is warm and precipitation is low, than in winter. This is why we've chosen the second and third exogenous variables to be temperature and precipitation. For Vaud, we use the monthly average temperature and precipitaion in the city of Payerne as a proxy for the canton. We do the same with the city of Lugano for Ticino.

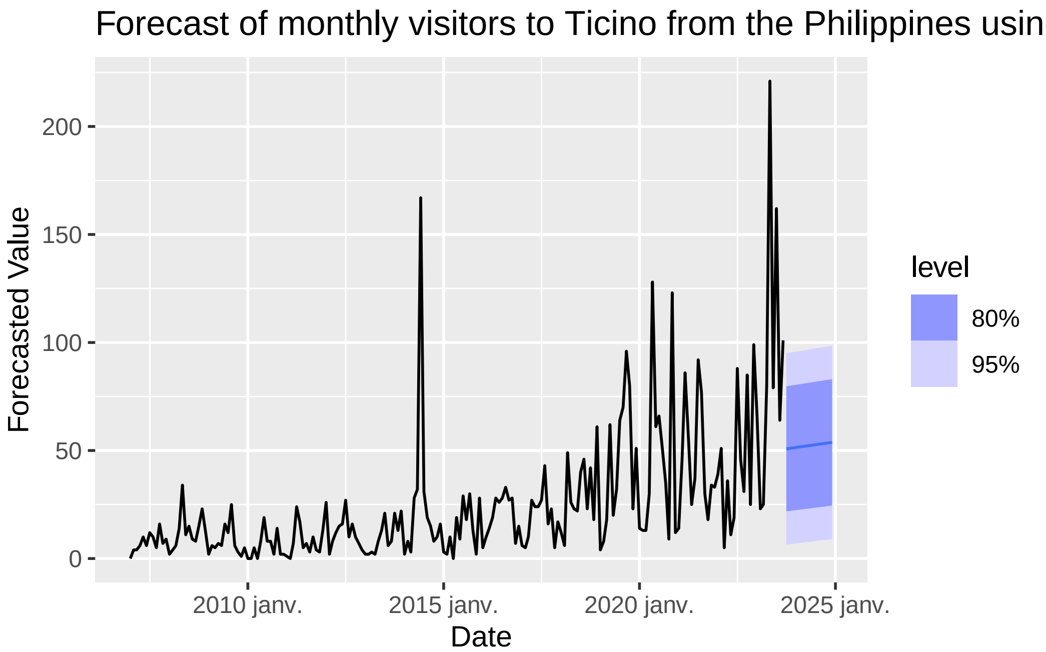
Below are the ARIMA models using these exogenous variables, with the forecasts.

```
Series: value
Model: LM w/ ARIMA(0,1,4)(0,0,2)[12] errors

Coefficients:
          ma1     ma2      ma3      ma4    sma1    sma2    GDP.V  Temperature
      -0.3554  0.0531  -0.0828  -0.4986  0.7157  0.5602  -0.0302     653.7395
s.e.   0.0737  0.0694   0.0731   0.0668  0.0869  0.0700   0.1592     242.5833
      Precipitation
```

```
            -12.1293
s.e.          8.8688

sigma^2 estimated as 44217798:  log likelihood=-1951.09
AIC=3922.17   AICc=3923.34   BIC=3955.16
```




```
Series: value
Model: LM w/ ARIMA(0,1,1) errors

Coefficients:
          ma1  GDP.T  Temperature  Precipitation  intercept
      -0.9604  4e-04       1.1101         0.0160     0.2130
s.e.   0.0257  1e-04       0.2562         0.0176     0.0829

sigma^2 estimated as 506.7:  log likelihood=-865.04
AIC=1742.08   AICc=1742.51   BIC=1761.87
```



We also created ETS models for both cantons, but these models cannot compete with our ARIMA models for reasons described in the next section. The forecasts are in the appendix for reference.

```
[1] 0
```

```
[1] 0
```

The exogenous variables have coefficients indicating a positive relationship with the dependent variable, particularly significant for temperature. However, the AIC and BIC values are significantly higher than the automatic ARIMA model without exogenous variables in Vaud, indicating a more complex model without necessarily providing a proportionate improvement in fit as per the increase in complexity. For Ticino, the AIC is lower for our exogenous variables model.

5 Forecast and validation

After modeling the forecasts for both Vaud and Ticino, we will opt for our first model, the automatic ARIMA, for Vaud. Firstly, this model is simpler than our exogenous variables model, and we generally prefer to use simpler models, unless our complex model is proven to have superior forecasts. In our case, we don't have the future data, so we are unable to measure the accuracy of both models. We can however look at indicators such as the AIC and BIC, which tell us that the simple model is superior in the case of Vaud, where we have enough data to make a decent forecast. This model also provided us with the lowest error metrics, including a Mean Absolute Percentage Error (MAPE) of 4.22% shown in the appendix.

For the Ticino model, the amount of visitors is so low, and the variance is so high, that even the automatic ARIMA model has difficulty forecasting the future, and the confidence levels are very high. We thought about using a mean or naive model for this forecast, but these would not take into account the upwards trend in visitors, which we assume to be true. Although the ARIMAX (exogenous variables) model is more complex, it showed improvements in Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE) over the simple ARIMA model. These accuracy metrics are shown in the appendix. The inclusion of GDP, temperature, and precipitation helped explain some of the variability in the visitor numbers, so we decided it would be more suitable to use this model for the Ticino forecast.

In regards to our ETS models, the Vaud forecast is very similar to the automatic ARIMA model, but the confidence intervals are much too small, which is why we opted for ARIMA. For the Ticino forecast, the ETS model failed to take into account the upwards trend in visitors, so we opted for ARIMA with exogenous variables.

6 Limits and Discussion

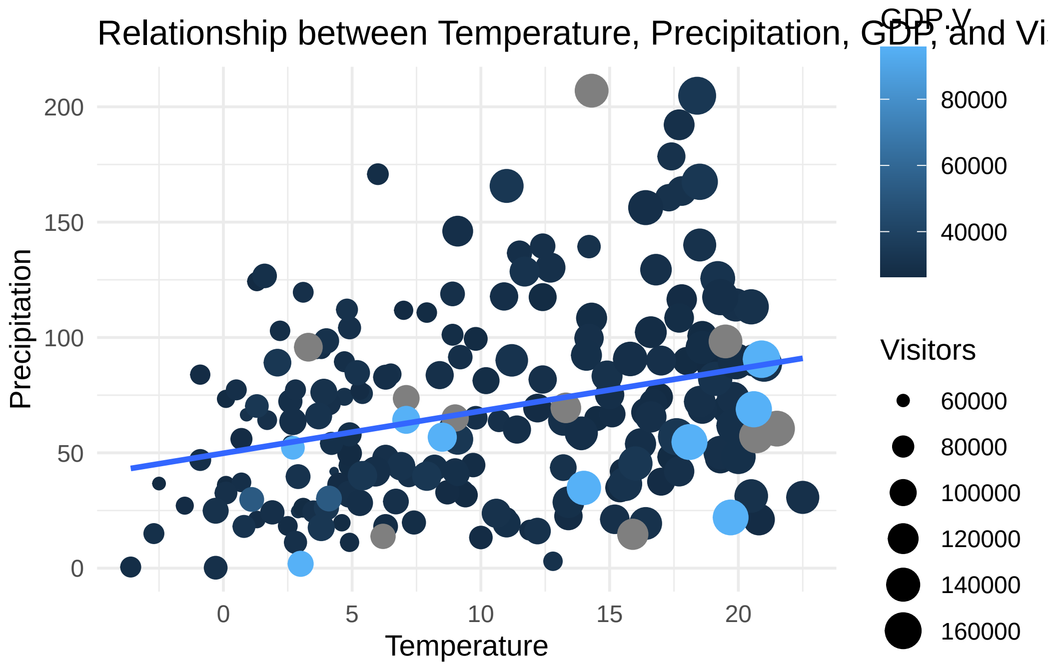
The forecasting models used in this analysis, including ARIMA, ARIMA with exogenous variables (ARIMAX), and ETS, each have their strengths and limitations. While ARIMA models effectively captured the seasonality and trends in the data, they assume linear relationships and stationarity, which may not always hold true. The ARIMAX models included GDP, temperature, and precipitation as exogenous variables to account for external influences on tourism, yet these proxies might not fully capture all relevant factors, such as political stability or marketing efforts.

Additionally, the exclusion of the COVID-19 period helped avoid anomalies but also introduced bias in understanding long-term trends. The ETS model, though robust in handling seasonality, faces similar limitations regarding assumptions and data quality. Future improvements could involve incorporating more exogenous variables, exploring advanced machine learning techniques, and continuously validating models with real-time data. External factors like economic conditions and climate change also play significant roles in tourism patterns and should be considered in long-term forecasts.

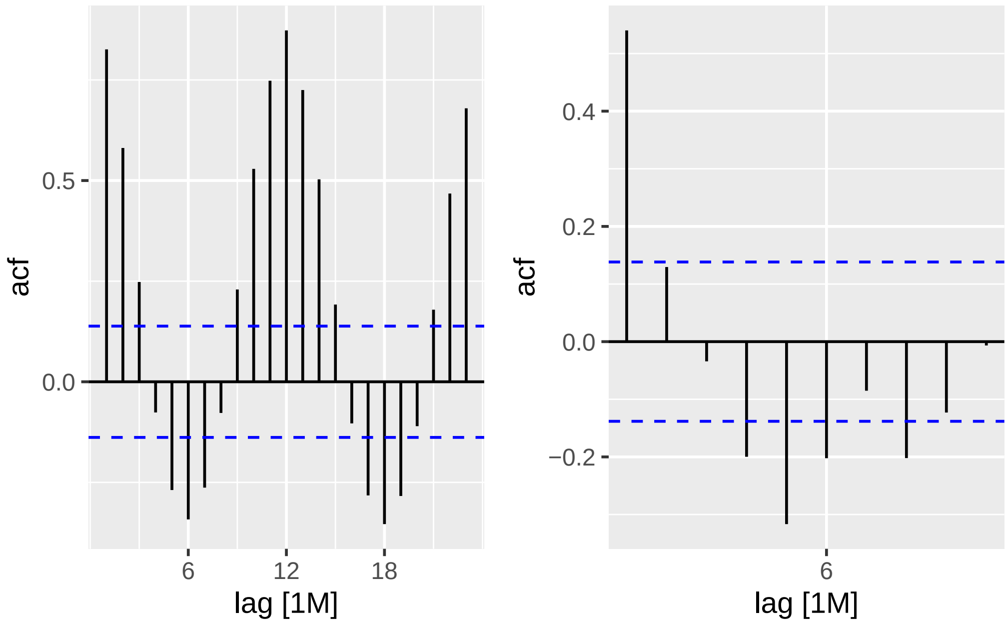
Despite these challenges, the selected models, automatic ARIMA without for Vaud and ARIMA with exogenous variables for Ticino, will hopefully provide decent forecasts to support tourism planning in these regions.

7 Appendix

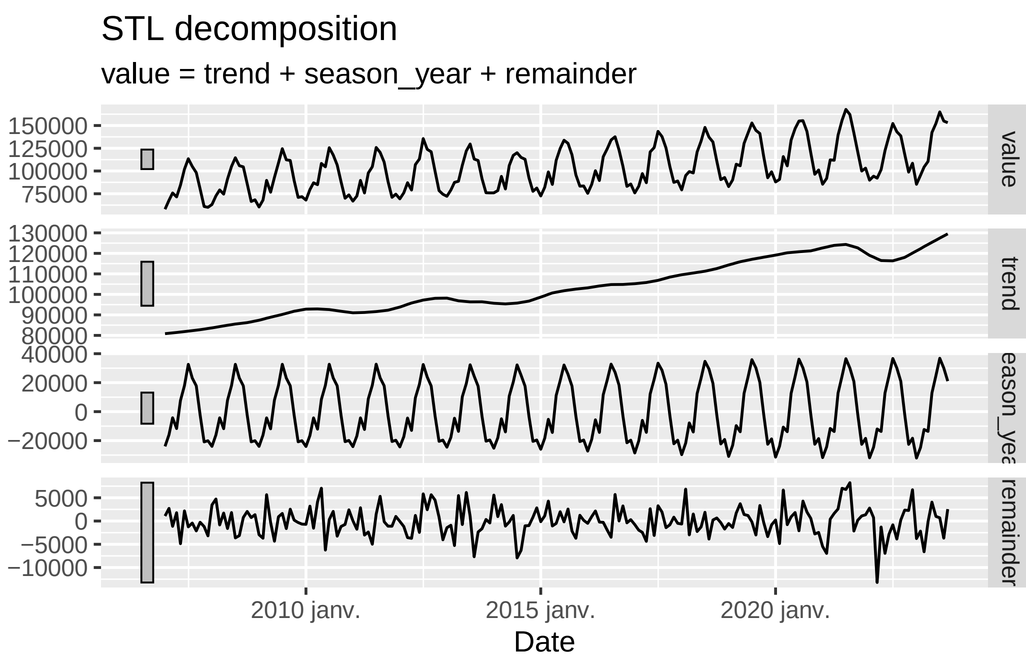
Vaud scatterplot matrix to see relationship between variables



Vaud ACF plot



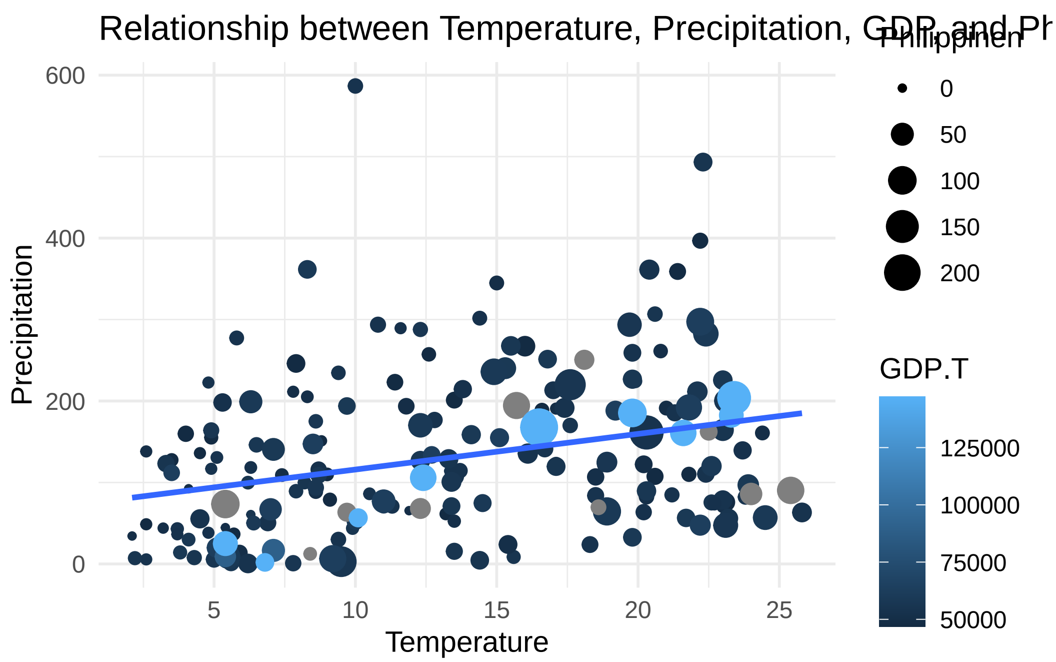
Vaud STL decomposition



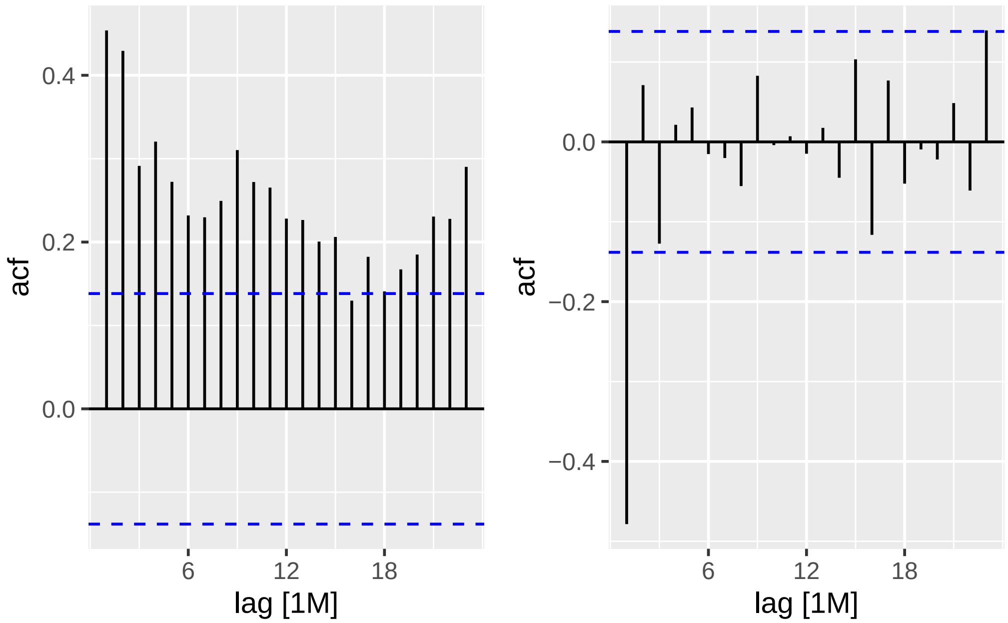
Ticino scatterplot matrix to see relationship between variables

```r
print(ticino_scatterplot_matrix)
```

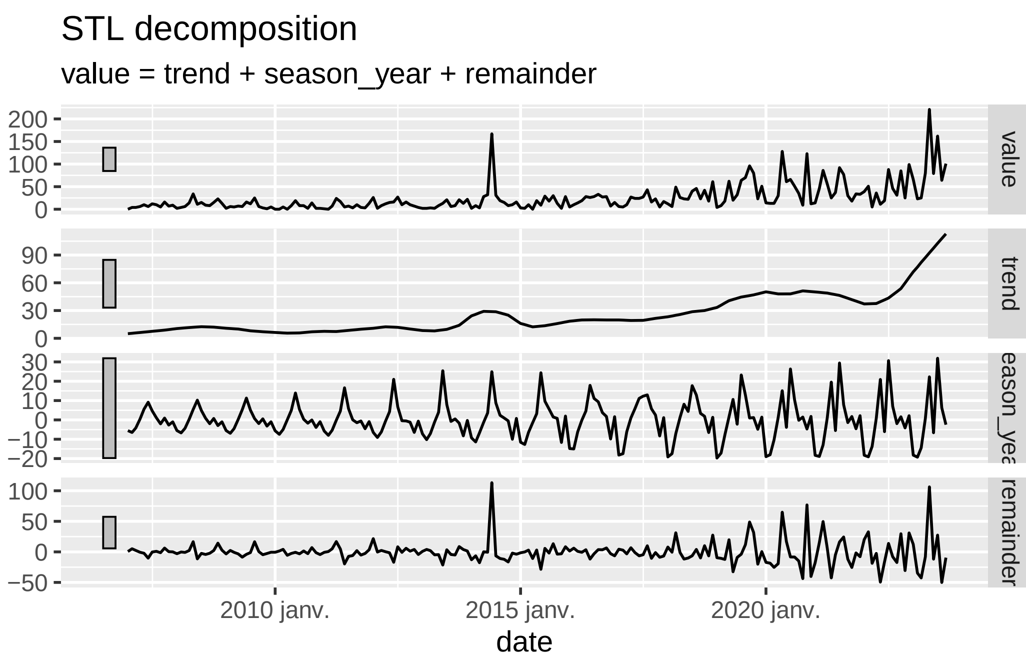
```
`geom_smooth()` using formula = 'y ~ x'
```



Ticino ACF plot



Ticino STL decomposition



Accuracy Metrics for Vaud

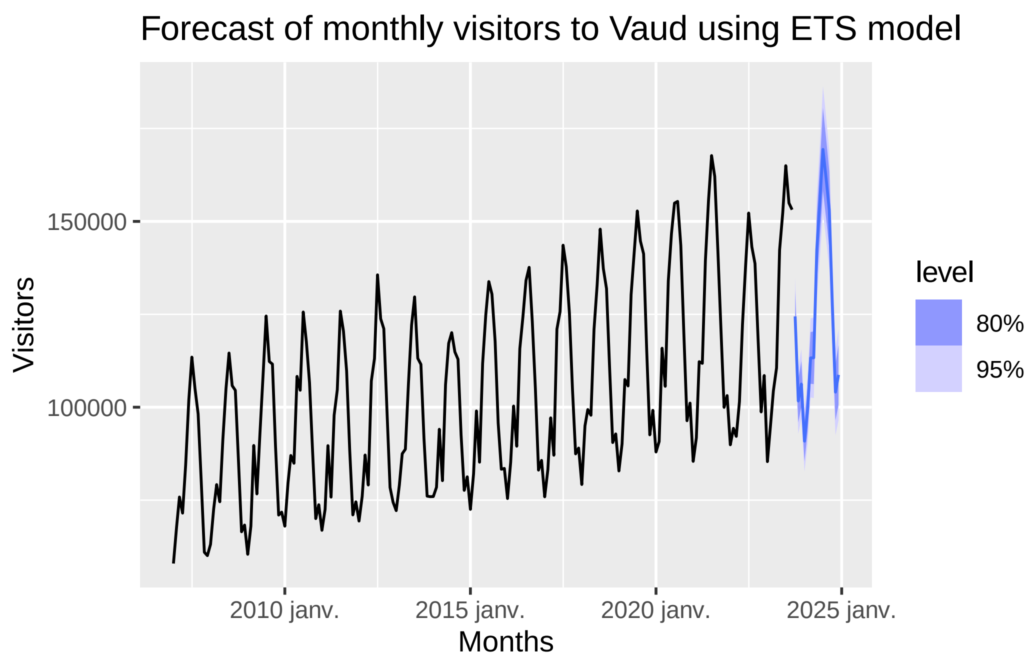
```
                              Model   ME RMSE  MAE   MPE MAPE MASE RMSSE
1 ARIMA without exogenous variables 45.2 71.5 53.4  24.8 58.7   NA    NA
2    ARIMA with exogenous variables 19.5 57.1 41.0 -15.0 59.8   NA    NA
3                         ETS model 45.2 71.5 53.4  25.0 58.5   NA    NA
      ACF1
1  0.00267
2 -0.14400
3  0.00504
```

Accuracy Metrics for Ticino

```
                              Model   ME RMSE  MAE   MPE MAPE MASE RMSSE
1 ARIMA without exogenous variables 45.2 71.5 53.4  24.8 58.7   NA    NA
2    ARIMA with exogenous variables 19.5 57.1 41.0 -15.0 59.8   NA    NA
3                         ETS model 45.2 71.5 53.4  25.0 58.5   NA    NA
      ACF1
1  0.00267
2 -0.14400
3  0.00504
```

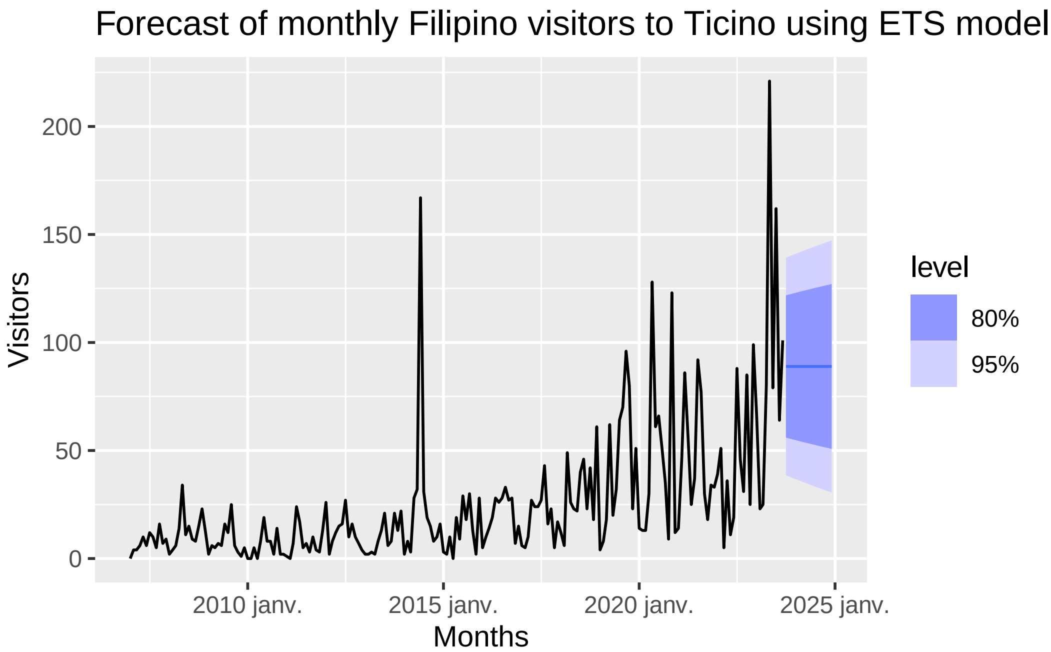
ETS model for Vaud

```
Series: value
Model: ETS(M,A,M)
  Smoothing parameters:
    alpha = 0.2115592
    beta  = 0.0001000386
    gamma = 0.2227596

  Initial states:
     l[0]     b[0]      s[0]     s[-1]     s[-2]    s[-3]    s[-4]    s[-5]
 83355.95 250.2777 0.7641147 0.7684332 0.9651906 1.203249 1.243203 1.375393
    s[-6]    s[-7]     s[-8]     s[-9]    s[-10]    s[-11]
 1.210834 1.091756 0.8742811 0.9479082 0.8226419 0.7329945

  sigma^2:  0.0019

     AIC     AICc      BIC
4452.547 4455.892 4508.704
```



ETS Model for Ticino

```
Series: value
Model: ETS(A,N,N)
  Smoothing parameters:
    alpha = 0.1563349

  Initial states:
     l[0]
 6.415333

  sigma^2:  660.4141

     AIC     AICc      BIC
2375.021 2375.142 2384.930
```


Forecast of monthly Filipino visitors to Ticino using ETS model
Visitors
200
150
100
50
0
2010 janv.
2015 janv.
2020 janv.
2025 janv.
Months
level
80%
95%