Time Series Forecasting of Freshwater Withdrawals in Germany Using ARIMA and Prophet

1. Introduction

This section aims to forecast freshwater withdrawals in Germany using time series analysis. Freshwater withdrawals are a key indicator of national water demand and are closely linked to sustainability metrics such as GDP and water stress. Two forecasting models are employed: ARIMA, a classical statistical method, and Prophet, a modern additive time series model developed by Facebook. The goal is to evaluate their performance and generate reliable short-term forecasts.

2. R Packages and Tools Used

Package	Purpose
forecast	Classical ARIMA modeling
prophet	Decomposable time series forecasting
tidyverse	Data wrangling and visualization
lubridate	Date parsing and manipulation

3. Variable and Country Selection Rationale

3.1. Target Variable: Freshwater Withdrawals

Freshwater withdrawals were chosen as the target variable because they represent total water demand across all economic sectors. This variable is directly involved in the calculation of other key indicators: GDP (USD) is computed as the product of water productivity and withdrawals, while water stress is derived from the ratio of withdrawals to renewable water resources, multiplied by 100. These mathematical relationships highlight the centrality of withdrawals in understanding both economic performance and environmental pressure. Forecasting this variable therefore supports broader insights into sustainability and development trends.

3.2. Target Country: Germany

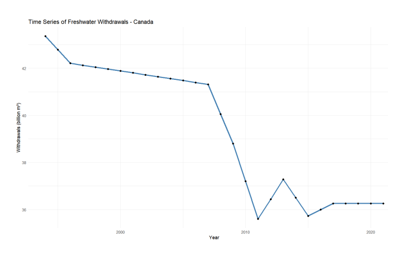	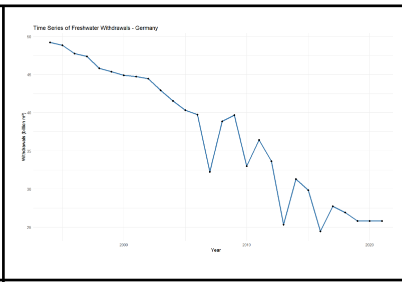	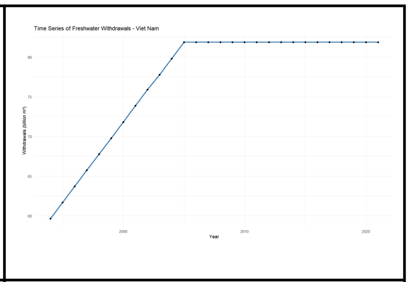
Canada("CAN")	Germany("DEU")	Vietnam("VNM")

Figure 1. Time Series of Freshwater Withdrawals of various countries

Germany was selected after reviewing the freshwater withdrawal patterns of numerous countries. Its time series exhibits a clear and consistent long-term downward trend, with moderate year-to-year variability that provides structure without excessive noise. Also, there are no long flat segments, which often limit model learning, and the values remain within a stable, realistic range, avoiding outliers or sudden regime shifts. In contrast, many countries showed less favorable patterns—some, like Vietnam, had time series that became completely flat in recent years, offering no meaningful variation to model. Others, such as Canada, displayed irregular drops and prolonged stagnation, which reduced forecastability. Therefore, Germany proved to be the most suitable candidate for time series forecasting.

4. Forecasting Framework

As previously mentioned, both the AutoRegressive Integrated Moving Average (ARIMA) model and the Facebook Prophet model were applied to model the historical freshwater withdrawals in Germany. Conceptual explanations of these models are provided in Appendix D.

4.1. ARIMA Forecasting

The forecasting procedure followed a two-step approach. First, the model was trained on the full available time span to produce a five-year forecast for future withdrawals. This was used primarily for visualization and exploratory insight. Then, a separate evaluation was conducted using a holdout method: the dataset was split into a training period (up to 2017) and a test period (2018–2021). A new ARIMA model was fitted on the training data alone, and its predictive accuracy was assessed on the test set using MAE, RMSE, and MAPE. This workflow ensured that model performance was evaluated fairly, based on a held-out test set.

```
# Convert to time series object
ts_germany <- ts(df$Value, start = min(df$Year), frequency = 1)
# frequency = 1 means yearly data (as opposed to monthly = 12, quarterly = 4).

# Fit ARIMA model: This uses the auto.arima() function to automatically determine
# the best-fitting ARIMA model for the time series.
arima_model <- auto.arima(ts_germany)

# Forecast for 5 future years
arima_forecast <- forecast(arima_model, h = 5)
```

Figure 2. Code snippet – ARIMA model design and forecasting logic.

The time series was explicitly defined with frequency = 1 to indicate annual observations, distinguishing it from monthly or quarterly data where seasonal components would be more relevant. The auto.arima() function from the forecast package was used to automatically select the best-fitting ARIMA model by minimizing the corrected Akaike Information Criterion (AICc). This process identifies the optimal combination of autoregressive (AR), differencing (I), and moving average (MA) terms without requiring manual specification.

4.2 Prophet Forecasting

As with ARIMA, Prophet was first fitted on the full dataset to produce a five-year forecast for visualization. Then, a second model was trained on data up to 2017 and evaluated on the 2018–2021 period using MAE, RMSE, and MAPE. This consistent two-step approach was adopted to enable a direct and fair comparison between the Prophet and ARIMA models.

```
# Prepare data for Prophet
prophet_df <- df %>%
  rename(ds = Year, y = Value) %>%
  mutate(ds = ymd(paste0(ds, "-01-01")))

# Fit Prophet model with yearly seasonality disabled (not needed for annual data)
prophet_model <- prophet(prophet_df, yearly.seasonality = FALSE)

# Create future dates (5 years ahead)
future <- make_future_dataframe(prophet_model, periods = 5, freq = "year")

# Forecast future withdrawals
forecast_prophet <- predict(prophet_model, future)
```

Figure 3. Code snippet – Prophet model setup and forecasting logic.

Prophet is an additive time series model that decomposes the data into trend, seasonality, and holiday effects, and is particularly effective for handling irregular trends and missing values. In this case, only the trend component was modeled, as the data is annual and does not exhibit seasonal patterns. The input data was formatted to match Prophet's required structure, with the time variable renamed to ds and the target variable to y.

5. Forecasting Results and Evaluation

5.1. ARIMA Forecasting

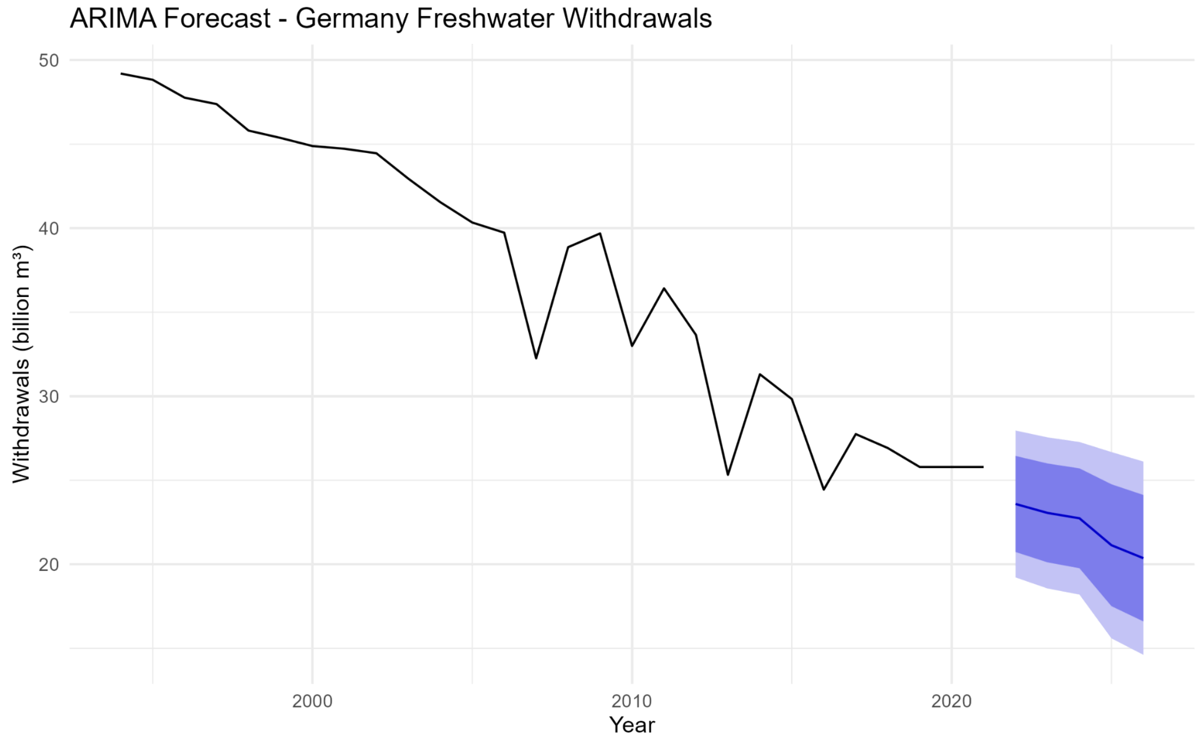

Figure 4. ARIMA Forecast of Germany's Freshwater Withdrawals (2022–2026)

This plot illustrates the five-year forecast generated by the ARIMA model trained on the full historical dataset. The black line represents the observed data up to 2021, while the blue line extends the forecasted trend through 2026. The shaded areas denote the 80% and 95% confidence intervals, capturing increasing uncertainty further into the forecast horizon. The model projects a continued decline in freshwater withdrawals, consistent with the long-term trend observed in the past data.

	A	B
1	Year	Forecast
2	2022	23.59159
3	2023	23.05934
4	2024	22.73899
5	2025	21.13809
6	2026	20.36587

Figure 5. Forecasted Values from the ARIMA Model (2022–2026)

This table lists the exact forecasted values corresponding to the ARIMA plot shown earlier, which provides a numerical reference. Together with the visual forecast in Figure 4, these results offer a practical basis for future decision-making and water resource policy planning.

```
> summary(arima_model)
Series: ts_germany
ARIMA(2,1,0) with drift

Coefficients:
          ar1      ar2    drift
      -0.7582  -0.6711  -0.9060
s.e.   0.1335   0.1259   0.1721

sigma^2 = 4.968:  log likelihood = -59.08
AIC=126.15   AICc=127.97   BIC=131.34

Training set error measures:
                     ME     RMSE      MAE        MPE     MAPE      MASE     ACF1
Training set 0.01225276 2.063632 1.283608 -0.2315765 3.962897 0.5439712 0.114933
```

Figure 6. ARIMA Model Summary

The final model selected by auto.arima() was an ARIMA(2,1,0) with drift, indicating that the time series was differenced once and modeled using two autoregressive terms. All estimated coefficients, including the drift term (−0.9060), were statistically significant, as their absolute values exceeded approximately twice their respective standard errors—a common rule of thumb when formal p-values are not reported. The negative drift reflects a consistent downward trend in the data.
Model selection was based on the corrected Akaike Information Criterion (AICc), which is the default criterion. The selected model yielded AIC = 126.15, AICc = 127.97, and BIC = 131.34. On the full dataset, it achieved a MAPE of 3.96%, indicating a strong in-sample fit. The residual autocorrelation at lag 1 (ACF1 = 0.11) was low, meaning that the model captured most of the patterns in the data, and there was little leftover structure in the residuals.

5.2. Prophet Forecasting

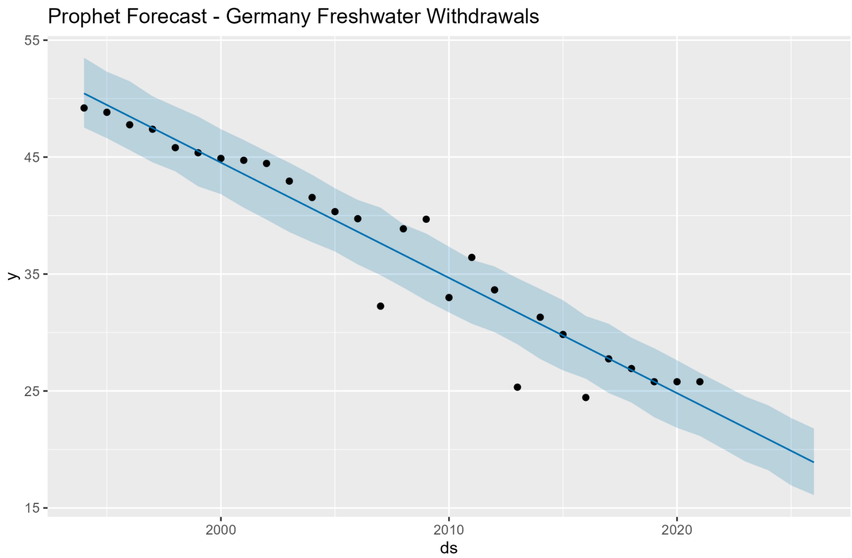

Figure 7. Prophet Forecast of Germany's Freshwater Withdrawals (2022–2026)

This plot presents the five-year forecast generated by the Prophet model trained on the full dataset. The blue line represents the model's predicted trend, while the shaded area shows the model’s uncertainty interval. The black dots represent actual historical observations. Most data points fall within the shaded region, indicating that the model effectively captures the underlying trend and variability of the historical data. Prophet forecasts a continued decline in withdrawals, consistent with the long-term trend.

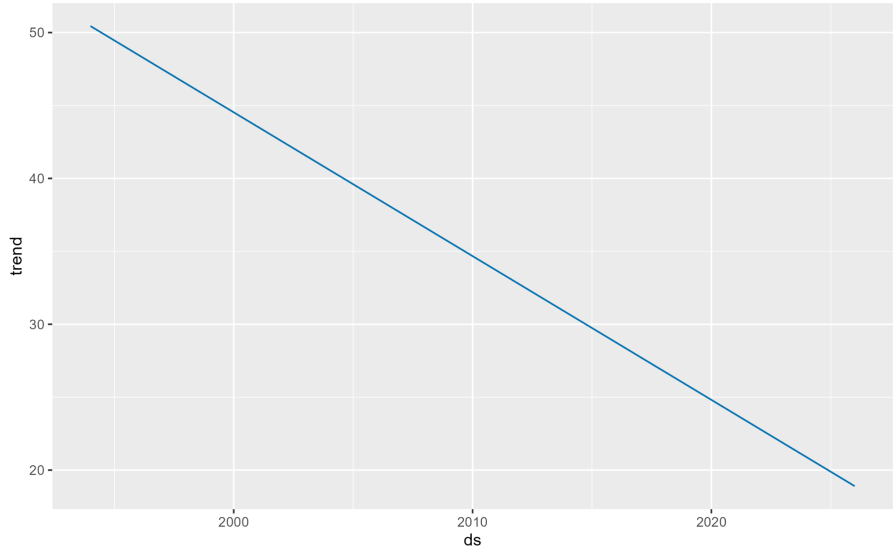

Figure 8. Prophet Forecast Components – Germany's Freshwater Withdrawals (2022–2026)

Note: Since the seasonality and holiday effect are absent, the line in the graph is identical to that of *Figure 7*.

30	#######	22.84169	20.07409	25.55233
31	#######	21.85656	18.97046	24.52072
32	#######	20.87142	18.22946	23.76917
33	#######	19.88358	16.93172	22.68717
34	#######	18.89845	16.10444	21.78603

Figure 9. Forecasted and Fitted Values from the Prophet Model

This table contains the Prophet model’s output across the full time span. The yhat column contains fitted values for historical years (1994–2021) and forecasted values for future years (2022–2026), with yhat_lower and yhat_upper indicating uncertainty bounds. (Only the five forecasted values are displayed in the figure due to image size constraints.)

5.3. Model Performance Evaluation and Comparison

As previously mentioned, both ARIMA and Prophet were trained on data up to 2017 and evaluated on a held-out test set spanning 2018 to 2021 to compare model performance. Forecast accuracy was measured using three standard metrics: MAE, RMSE, and MAPE. The results for each model are summarized below.

```
> cat("ARIMA Metrics:\n")
ARIMA Metrics:
> cat("MAE: ", MAE, "\nRMSE:", RMSE,
"\nMAPE:", MAPE, "%\n")
```

```
> cat("Prophet Metrics:\n")
Prophet Metrics:
> cat("MAE: ", MAE, "\nRMSE:", RMSE,
"\nMAPE:", MAPE, "%\n")
```

MAE: 2.011173 RMSE: 2.262085 MAPE: 7.778954 %	MAE: 1.457615 RMSE: 1.676682 MAPE: 5.620193 %
ARIMA	Prophet

Metric	**Description**
MAE (Mean Absolute Error)	Average magnitude of the forecast errors, regardless of direction.
RMSE (Root Mean Squared Error)	Penalizes larger errors more heavily by squaring them before averaging.
MAPE (Mean Absolute Percentage Error)	Average absolute error expressed as a percentage of the actual values.

Overall, both ARIMA and Prophet delivered highly accurate forecasting performance, successfully capturing the long-term declining trend in Germany's freshwater withdrawals. ARIMA achieved a MAPE of 7.78%, while Prophet yielded an even lower value of 5.62%. According to the commonly referenced scale by Lewis (1982), forecasts with a MAPE below 10% are considered highly accurate, and both models meet this criterion. This indicates that either approach could serve as a valid forecasting method in this context.
That said, Prophet consistently outperformed ARIMA across all three metrics (MAE, RMSE, and MAPE), suggesting better generalization and smoother trend modeling. While ARIMA remains a reliable and interpretable baseline, Prophet proved to be more effective in this case.
One possible reason for Prophet's superior performance lies in its flexible approach to modeling trends using changepoints. As observed in the historical time series of Germany's freshwater withdrawals, the data exhibits a clear long-term downward trend, punctuated by several sudden level shifts and periods of moderate fluctuation. Prophet's ability to automatically detect and adapt to such structural changes—without requiring manual specification—makes it particularly well-suited for capturing these dynamics.
In contrast, ARIMA relies on fixed linear differencing and assumes stationary behavior after transformation, which may not fully accommodate these intermittent changes in slope or volatility. Given the piecewise nature of the trend and the presence of multiple non-periodic deviations, it is plausible that Prophet's design was better suited to the characteristics of the data, which may have contributed to its superior forecasting accuracy.

6. Interpretation of Forecast Results and Conditional Policy Recommendations

The forecasting results for Germany's freshwater withdrawals, generated by both ARIMA and Prophet models, suggest a continued downward trend in the near future. By 2026, ARIMA projects withdrawals to decline to approximately 20.4 billion m³, while Prophet offers a similar estimate of 18.9 billion m³ — both down from roughly 26 billion m³ in 2021. While the models demonstrate strong statistical performance, it is important to recognize that such forecasts may reflect a range of underlying factors. A declining withdrawal trend could indicate positive developments, such as improved water-use efficiency or structural economic shifts, but it might also result from less favorable conditions, including economic downturns or climate-related constraints. Interpreting these results in context is therefore essential, particularly when deriving policy recommendations.

6.1. Potential Drivers Behind the Forecasted Withdrawal Trend

Several plausible scenarios may explain the observed and predicted reduction in withdrawals:

Cause Type	Possible Explanation
Efficiency Gains	Improved irrigation systems, industrial reuse, household conservation.
Economic Restructuring	Shift toward less water-intensive sectors such as services.
Economic Decline	Contraction in manufacturing or agriculture reducing demand.
Climate Impact	Droughts or groundwater depletion limiting actual withdrawal capacity.
Data Artefacts	Changes in monitoring methods or definitions over time.

Each scenario carries very different policy implications. For example, efficiency gains may justify infrastructure optimization, whereas climate-driven reductions may require emergency preparedness and adaptation investment.
To clarify which possibilities may be driving the observed trend, further analysis will be conducted in subsequent sections using exploratory data analysis (EDA), linear regression, and potentially classification techniques. These methods aim to uncover patterns and predictors that help explain the trajectory of withdrawals more clearly and inform targeted policy interventions.

6.2. Scenario-Based Policy Recommendations

The table below outlines appropriate responses based on the dominant driver of the withdrawal trend:

Scenario	Policy Direction
Efficiency improvements	Expand support for innovation, precision agriculture, smart water systems.
Sectoral shift	Align infrastructure plans with new economic structures and long-term demand.
Economic downturn	Avoid irreversible cuts in supply capacity; adopt flexible, modular planning.

Climate-related decline	Strengthen drought resilience, water storage, and non-traditional supply methods.
Measurement changes	Improve data transparency, harmonize indicators, and monitor consistency.

These recommendations are not mutually exclusive; multiple causes may operate simultaneously. Therefore, it is desirable that Policymakers adopt adaptive frameworks that can respond dynamically as new information emerges.

7. Conclusion

This study has presented a time series analysis of Germany's freshwater withdrawals using two forecasting approaches: ARIMA and Prophet. Both models demonstrated high forecasting accuracy, with mean absolute percentage errors (MAPE) of 7.78% for ARIMA and 5.62% for Prophet. Prophet slightly outperformed ARIMA across all evaluation metrics, possibly suggesting its greater flexibility in modeling non-linear trends and structural changes.

Both models projected a continued downward trend in withdrawals through 2026. While these projections are statistically reliable, their real-world interpretation requires caution. A declining trend may reflect favorable developments such as improved efficiency or structural economic shifts, but it could also signal more concerning drivers such as economic slowdown or climate-related constraints. The time series models capture the "what," but not the "why."

To address this limitation, further analysis will be conducted in the next phase of the research using exploratory data analysis, regression analysis, and potentially classification techniques. These tools will help clarify the underlying causes of withdrawal changes and provide a more nuanced understanding of the observed patterns.

Ultimately, this study lays the foundation for a broader research framework that combines accurate forecasting with causal interpretation. By integrating time series forecasting with complementary analytical methods, this research aims to support more informed, adaptive, and sustainable water resource planning — both within Germany and in other countries facing similar water management challenges.