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Project Report

Lecture Business Forecasting

Mine Case Study II

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I Table of Contents

1. INTRODUCTION

For Mini Case Study II, the decision maker was interested in understanding the Effects of Global Warming on the city of Magdeburg. The monthly data on Average Temperature, Total Rain and Total Sunshine along with Daily Rainfall and Sunshine from January 1989 to May 2019 was given. The task was to use both, State Space Models and ARIMA Models in order to develop an appropriate Forecasting method.

2. PROCEDURE FOLLOWED

The PIVASE Framework was used to understand which model performs better on the given dataset. The **Purpose** of this is to end with a better forecasting model for the given data and the **Information** given is the Magdeburg Weather Data where the Estimation sample is from January 1989 to December 2015 and Holdout Sample is from January 2016 to May 2019. The **Value** is to understand the effect of global warming on a local community and based on our **Analysis**, the Average Temperature and Daily rainfall datasets were chosen. The reason being that variation in temperature and rainfall is more likely to reflect the climate change than the Sunshine Hours. The plots clearly indicate that the seasonality is extremely high for both Average Temperature and Daily Rainfall as shown in Figure 1. The **System** used was the R software and our **Evaluation** is as below.

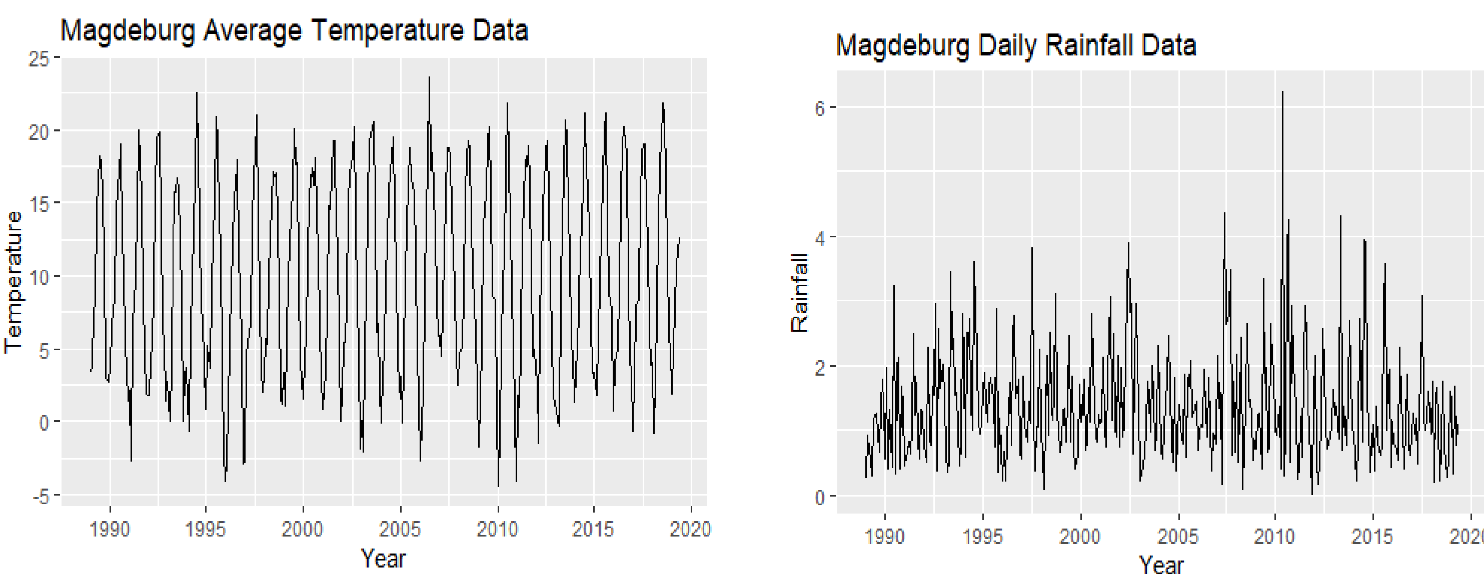

Figure 1: Depicts the Seasonality for Average Temperature and Daily Rainfall

2.1. Benchmarking Method

Benchmarking Method was the first step we had to establish and as shown in Table 1 it is very clear that the Seasonal Naïve method works better for the estimation sample of Average Temperature while Average method is for Daily Rainfall.

Dataset	Benchmarking Method	RMSE
Average Temperature	Average Method	6.664984
	Naïve Method	4.087647
	Seasonal Naïve Method	2.79143
Daily Rainfall	Average Method	0.9023452
	Naïve Method	1.219596
	Seasonal Naïve Method	1.218276

Table 1: Benchmarking Method Comparison

2.2. State Space Models

ETS function automatically selects the optimal method by determining the components error (E), trend (T) and seasonality (S). This was used to determine the optimal State Space Model and as shown in Table 2, the respective models are chosen. To verify if any negligible trend component was missing, the Holt Winter's methods were executed.

Dataset	State Space Models	RMSE
Average Temperature	ANA model	1.905787
	Holt Winter's Additive	2.036115
Daily Rainfall	MNM model	0.8332603
	Holt Winter's Multiplicative	0.9669651

Table 2: State Space Models Comparison

2.3. ARIMA Model

Since the seasonality is very high, Seasonal ARIMA modelling is used. The ACF and PACF plots help us to identify the non-stationarity of the data and if differencing is needed to attain Stationarity. Differencing was done on the Average Temperature data while not on the Daily Rainfall data.

Based on the ACF and PACF plots obtained after differencing, we estimated the [p, q] and [P, Q] values and multiple combinations were run and the Best Solution obtained is reflected in Table 3.

Dataset	Arima model	RMSE
Average Temperature	Arima [2,0,1] [1,1,2] $_{m=12}$	1.872427
Daily Rainfall	Arima [2,0,1] [2,1,1] $_{m=12}$	0.8265921

Table 3: ARIMA Models Chosen

3. RESULT

ARIMA models obtained for Average Temperature and Daily Rainfall perform better on the given Holdout Sample and this is clearly reflected in Table 4. RMSE was the Scale Dependent Error that we have used as the Comparison Criterion for all the models tested.

Dataset	Benchmark Method	State Space Model	ARIMA Model
Average Temperature	2.799076	1.799833	1.064053
Daily Rainfall	0.6702996	0.6270849	0.5353389

Table 4: Final Comparison of all Models

4.CONCLUSION

Climate change can be indicated not only by a higher variance in temperature with hotter summers and colder winters, but also by the intensity and frequency of weather extremes like erratic rainfall, longer summers with extreme heat waves and milder winters with a decrease in snow falling and longer frost-free seasons. With our data spread across years 1989 to 2019, there has also been many changes in the city of Magdeburg like increasing population and automobiles, industrial development and growth of real estate. Considering all the above factors, to what degree and how direct is this influence cannot be estimated with the given data set. The areas surrounding Magdeburg also play a vital role and we cannot forecast this with our present dataset.

We can only observe a few erratic fluctuations but not determine the exact factor that governs these fluctuations. Hence, Global Warming definitely is a factor in climate change but the extent is undeterminable.

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