ENV 797 Final Project

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2024-04-10

Introduction, Motivation, Relevance, Objectives This project focuses on predicting water availability in an Italian aquifer managed by Acea Group, a leading Italian utility operator. The group provides water services to 9 million inhabitants across Italy.

In order to best service their customers, the Acea group must understand how much water is available in the water bodies from which they extract. Forecasting water availability in a water body is necessary to ensure daily consumption needs are met.

The UN reported that groundwater provides "half of the volume of water withdrawn for domestic use by the global population" and that water use is expected to grow 1% per year over the next thirty years (UN, 2022). Thus, it is important to explore how much groundwater will be available in the future. If groundwater levels are forecasted to drop dramatically, these models can be used to urge for more efficient water use practices and investments into groundwater recharge strategies.

We focused our study in Italy due to the comprehensive data we were able to access in the region. In the following report, our objective is to examine the best models and exogenous variables that can help accurately predict groundwater levels. We hope that these findings offer insight about how to focus groundwater forecasting efforts in other regions across the globe.

Dataset information The data for this analysis were collected from the Acea Group Smart Water Analytics Competition on Kaggle. As a utility operator, they are concerned with preserving their water bodies which include a combination of water springs, lakes, rivers, and aquifers. The nine unique datasets from this kaggle competition each had different attributes and characteristics. For our final project, we focused our time series modeling and forecasting on the Auser Aquifer. Our objective is to predict the amount of water in the Auser Aquifer by modeling depth to groundwater and simultaneously evaluating how rainfall and temperature may impact our predictions as exogenous variables.

The dataset for the Auser Aquifer includes daily depth to groundwater measurements (in meters) from five different wells across the north and south sectors. Wells SAL, PAG, CoS, and DIEC represent the northern unconfined portion of the aquifer, while Well LT2 represents the southern confined portion of the aquifer. We also have daily temperature data at four sites, daily rainfall data at ten sites, and daily volume data from five different water treatment facilities that extract water from this aquifer. A sample of these data are shown in Tables 1 and 2, and the units for the measurements are found in Table 3.

Table 1: Example Auser Aquifer Data Rows 1-5

Date	05-17-11	05-18-11	05-19-11	05-20-11	05-21-11
Rainfall_Gallicano	0.0	0.0	0.0	0.8	0.0
Rainfall_Pontetetto	0	0	0	0	0
Rainfall_Monte_Serra	0	0	0	0	0
Rainfall_Orentano	0.0	0.0	0.0	0.2	0.0
Rainfall_Borgo_a_Mozzano	0	0	0	0	0
Rainfall_Piaggione	0	0	0	0	0
Rainfall_Calavorno	0	0	0	0	0
Rainfall_Croce_Arcana	0.0	0.0	0.0	0.0	1.0
Rainfall_Tereglio_Coreglia_Antelminelli	0.0	0.0	0.0	0.6	0.0
Rainfall_Fabbriche_di_Vallico	0.0	0.0	0.0	0.4	0.0
Depth_to_Groundwater_LT2	-12.97	-12.93	-12.92	-12.93	-12.92
Depth_to_Groundwater_SAL	-5.92	-5.93	-5.95	-5.95	-5.95
Depth_to_Groundwater_PAG	-2.34	-2.46	-2.41	-2.48	-2.43
Depth_to_Groundwater_CoS	-6.22	-6.27	-6.32	-6.39	-6.49
Depth_to_Groundwater_DIEC	-3.79	-3.80	-3.80	-3.81	-3.81
Temperature_Orentano	16.05	17.20	19.25	20.65	20.40
Temperature_Monte_Serra	12.80	15.25	15.35	16.40	17.60
Temperature_Ponte_a_Moriano	17.20	19.00	19.95	20.15	21.35
Temperature_Lucca_Orto_Botanico	17.45	19.00	20.10	21.60	21.15
Volume_POL	-9936.0	-9936.0	-9936.0	-9936.0	-9936.0
Volume_CC1	-16377.12	-16377.12	-16377.12	-16377.12	-16377.12
Volume_CC2	-12823.49	-12823.49	-12823.49	-12823.49	-12823.49
Volume_CSA	0	0	0	0	0
Volume_CSAL	0	0	0	0	0
Hydrometry_Monte_S_Quirico	0.17	0.18	0.16	0.15	0.15
Hydrometry_Piaggione	-1.04	-1.04	-1.04	-1.04	-1.05

Table 2: Example Auser Aquifer Data Head Rows 6-10

Date	05-22-11	05-23-11	05-24-11	05-25-11	05-26-11
Rainfall_Gallicano	0.0	0.0	0.0	0.0	0.0
Rainfall_Pontetetto	0	0	0	0	0
Rainfall_Monte_Serra	0	0	0	0	0
Rainfall_Orentano	0.0	0.0	0.0	0.0	0.0
Rainfall_Borgo_a_Mozzano	0	0	0	0	0
Rainfall_Piaggione	0	0	0	0	0
Rainfall_Calavorno	2	0	0	0	0
Rainfall_Croce_Arcana	0.2	0.0	0.0	0.0	0.0
Rainfall_Tereglio_Coreglia_Antelminelli	0.0	0.0	0.0	0.0	0.0
Rainfall_Fabbriche_di_Vallico	0.0	0.0	0.0	0.0	0.0
Depth_to_Groundwater_LT2	-12.91	-12.93	-12.94	-12.94	-12.93
Depth_to_Groundwater_SAL	-5.97	-6.01	-6.03	-6.05	-6.09
Depth_to_Groundwater_PAG	-2.54	-2.46	-2.47	-2.59	-2.61
Depth_to_Groundwater_CoS	-6.62	-6.70	-6.70	-6.72	-6.72
Depth_to_Groundwater_DIEC	-3.82	-3.83	-3.84	-3.84	-3.85
Temperature_Orentano	21.65	22.15	24.35	23.30	23.85
Temperature_Monte_Serra	18.65	20.25	20.20	21.30	20.25
Temperature_Ponte_a_Moriano	22.60	23.70	24.30	24.95	24.25
Temperature_Lucca_Orto_Botanico	22.55	23.60	24.05	24.60	24.70
Volume_POL	-9439.2	-9936.0	-9936.0	-9936.0	-9936.0
Volume_CC1	-15558.26	-16377.12	-16377.12	-16377.12	-16377.12
Volume_CC2	-12182.31	-12823.49	-12823.49	-12823.49	-12823.49
Volume_CSA	0	0	0	0	0
Volume_CSAL	0	0	0	0	0
Hydrometry_Monte_S_Quirico	0.15	0.15	0.14	0.15	0.14
Hydrometry_Piaggione	-1.05	-1.05	-1.05	-1.05	-1.06

Table 3: Acea Group Auser Aquifer Data Structure

Variables	Units
Date	Date
Rainfall_Gallicano	Millimeters
Rainfall_Pontetetto	
Rainfall_Monte_Serra	
Rainfall_Orentano	
Rainfall_Borgo_a_Mozzano	
Rainfall_Piaggione	
Rainfall_Calavorno	
Rainfall_Croce_Arcana	
Rainfall_Tereglio_Coreglia_Antelminelli	
Rainfall_Fabbriche_di_Vallico	
Depth_to_Groundwater_LT2	Meters
Depth_to_Groundwater_SAL	
Depth_to_Groundwater_PAG	
Depth_to_Groundwater_CoS	
Depth_to_Groundwater_DIEC	
Temperature_Orentano	Celcius
Temperature_Monte_Serra	
Temperature_Ponte_a_Moriano	
Temperature_Lucca_Orto_Botanico	
Volume_POL	Cubic Meters
Volume_CC1	
Volume_CC2	
Volume_CSA	
Volume_CSAL	
Hydrometry_Monte_S_Quirico	Meters
Hydrometry_Piaggione	

Data Wrangling The first obstacle with wrangling our data came when we realized that the data for each variable started at a different date. We found this issue by plotting the five depth to groundwater lines and seeing a large lag before the data started, NA values within each series, and a few random "zero" values that we assumed to be errors. To rectify this issue, we converted all "zero" values to NA, found the start date for each well's data, and then converted each well's data into a time series object. When we plotted these five time series together, we still had gaps of NA data. We ran the tsclean() function to fill in the gaps of missing data with interpolated values and then had five clean series with no data gaps, as displayed in Figure 1 below.

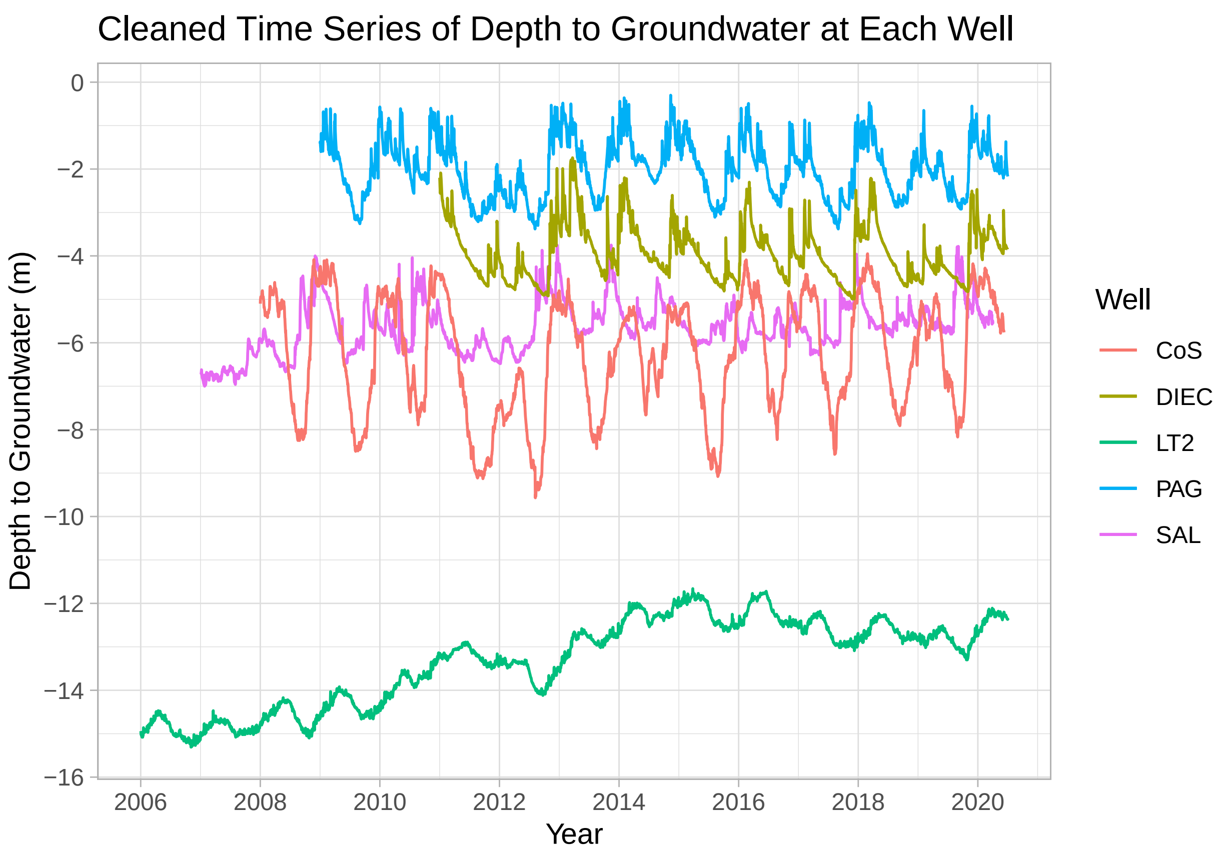

Figure 1: Depth to Groundwater Time Series

Analysis (Methods and Models) The first step of analysis that we performed was running the correlation function on our depth to groundwater data to discern whether the depth to groundwater values at the five wells were correlated to one another, as shown in Figure 2. We found that the four north wells had similar correlation values to one another and that the one south well was weakly correlated to the others. Because there were not strong correlations between the wells, we decided to focus the rest of our analysis on one north, confined well (SAL) and one south, unconfined well (LT2). These two wells had the most complete time series data, as displayed in Figure 3.

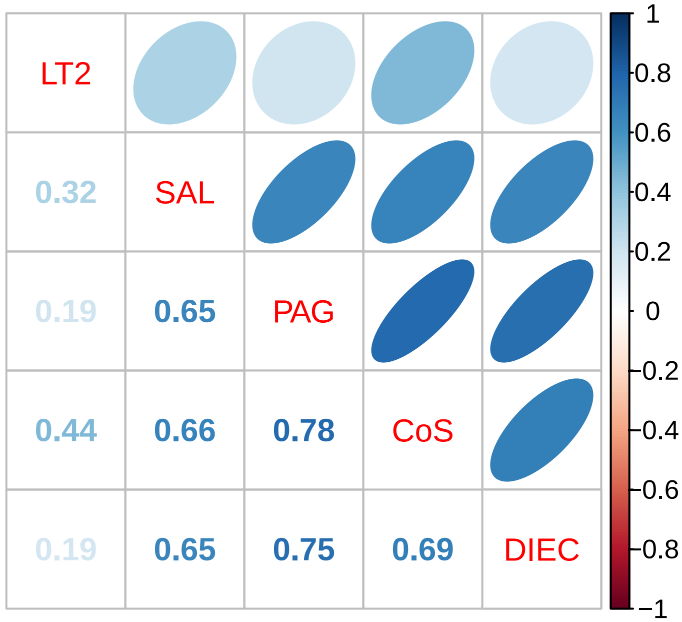

Figure 2: Correlation of Well Depths in Auser Aquifer

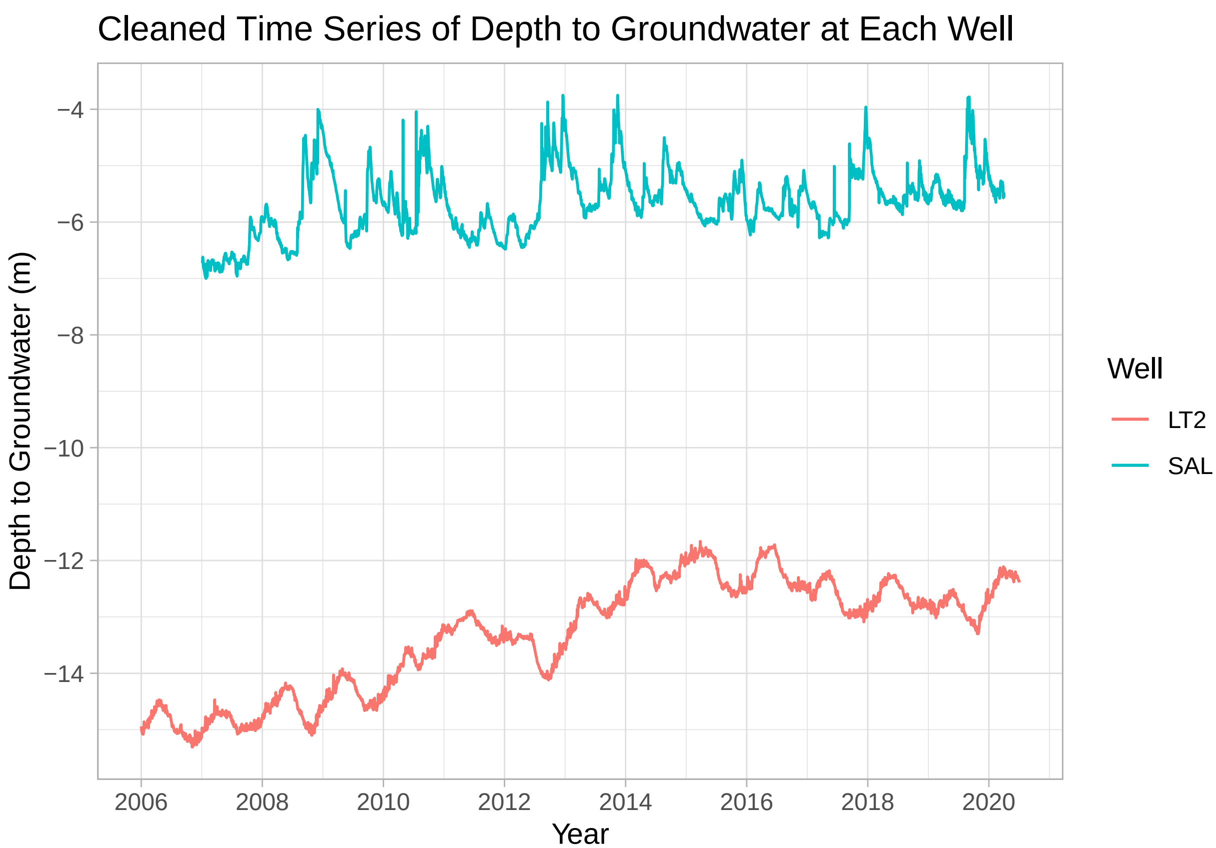

Figure 3: LT2 and SAL Time Series

We then plotted the ACF and PACF for each well using a lag time of five years to get a sense for whether our data had seasonal patterns, displayed in Figure 4. Both ACF graphs show peaks and troughs at regular intervals, so we determined that our data have yearly seasonality. Knowing that temperature and rainfall affect aquifer storage, it makes sense that the depth to groundwater in the aquifer is changing with respect to the season.

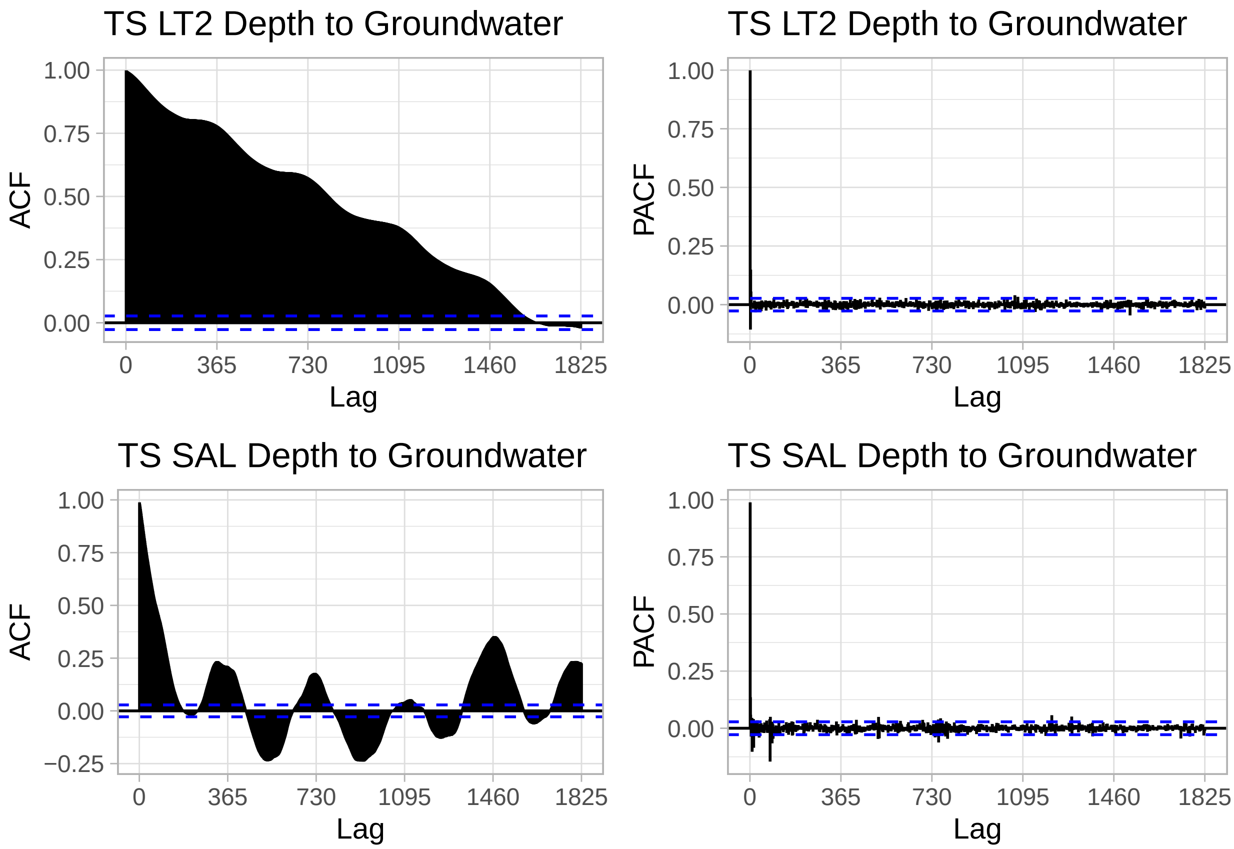

Figure 4: ACF and PACFs for Depth to Groundwater at Wells LT2 and SAL

In order to visualize our data in another way, we decomposed the time series for each well into its seasonal, trend, and random components using the decompose() function, shown in Figure 5 and Figure 6 below.

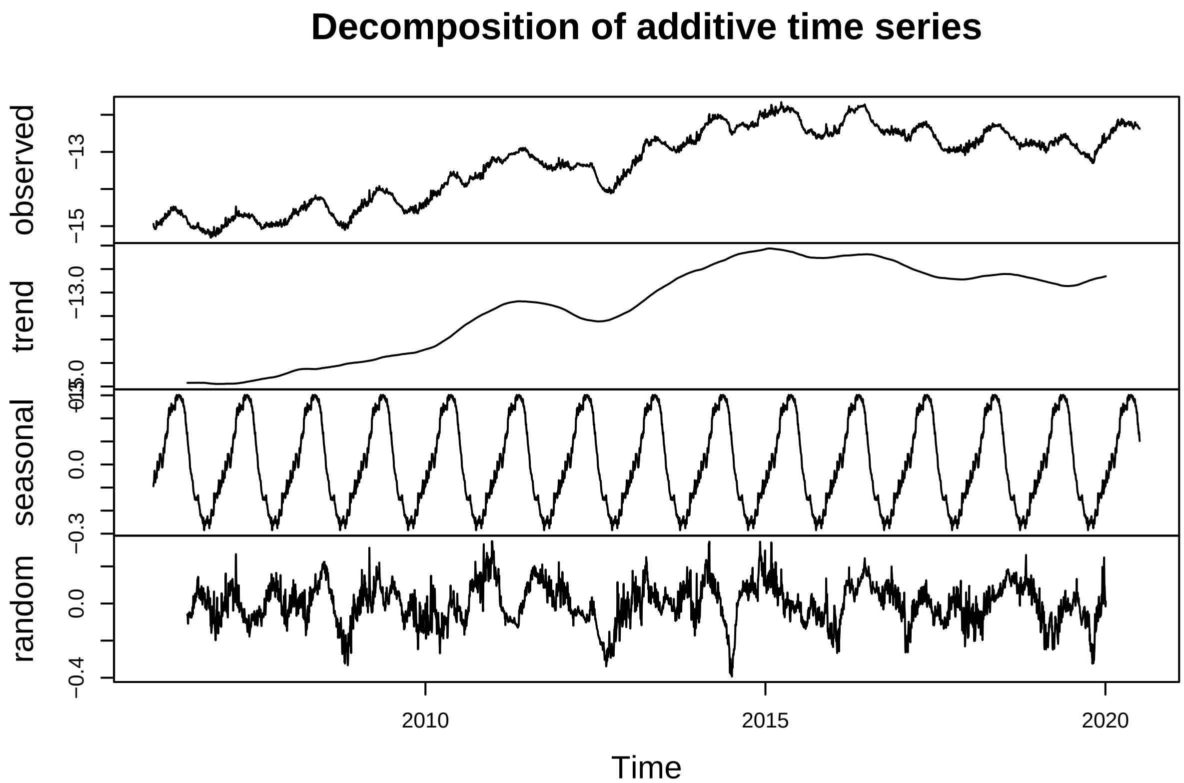

Figure 5: Decomposition of Depth to Groundwater at Well LT2

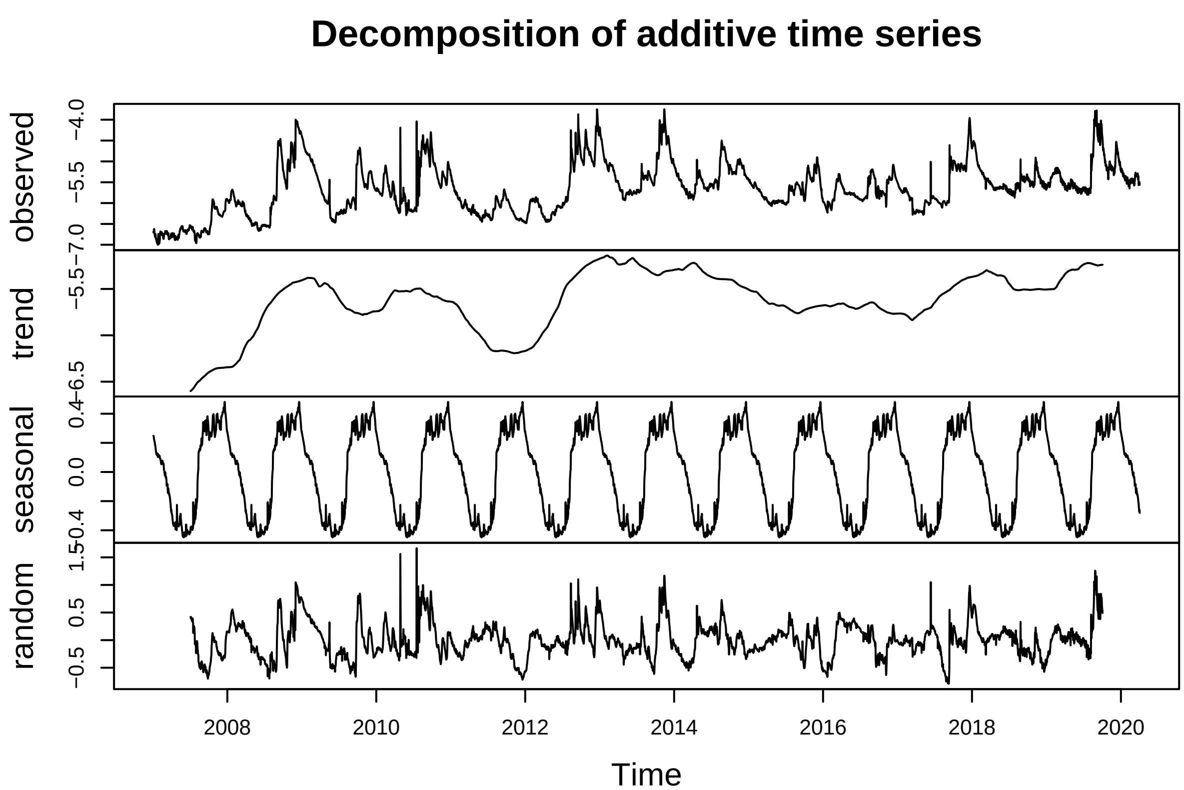

Figure 6: Decomposition of Depth to Groundwater at Well SAL

According to the decomposition, both of our wells showed depth to groundwater values that trended upwards over time. To model our data, we felt it was important to understand whether the trends were monotonic or stochastic. To arrive at an answer, we de-seasoned the time series and then ran tests on them to classify their trends. The LT2 well in the confined portion of the aquifer turned out to have a stochastic trend, while the SAL well in the unconfined aquifer turned out to have a deterministic trend. A summary of the statistical tests used to determine this are seen in Table 4 below. We hypothesized that these different trends are due to the fact that wells are monitoring different kinds of aquifers, confined and unconfined.

Table 4: Trend Conclusions from the Augmented Dickey Fuller and Mann Kendall Test Results

	SAL North Well (confined)	LT2 South Well (unconfined)
ADF Test	p-value = 0.01	p-value = 0.9466
Result	Reject Null	Fail to Reject Null
MK Test	p-value =< 2.22e-16	NA
Result	Reject Null	NA
Conclusion	Deterministic Trend	Stochastic Trend

Once we analyzed the time series, we were ready to start fitting models. Our process for fitting models was to fit them on each well by holding out a year of data. We then evaluated model performance on the final year of held out data.

The results of the Auto Sarima (SARIMA), the Exponential Smoothing State Space (ETS), the State Space Exponential Smoothing (SSES), and the Neural Network (NN) models compared to the observed data are shown in Figures 7 and 8 below. A summary of the model performance metrics against the held-out test data are in Tables 5 and 6.

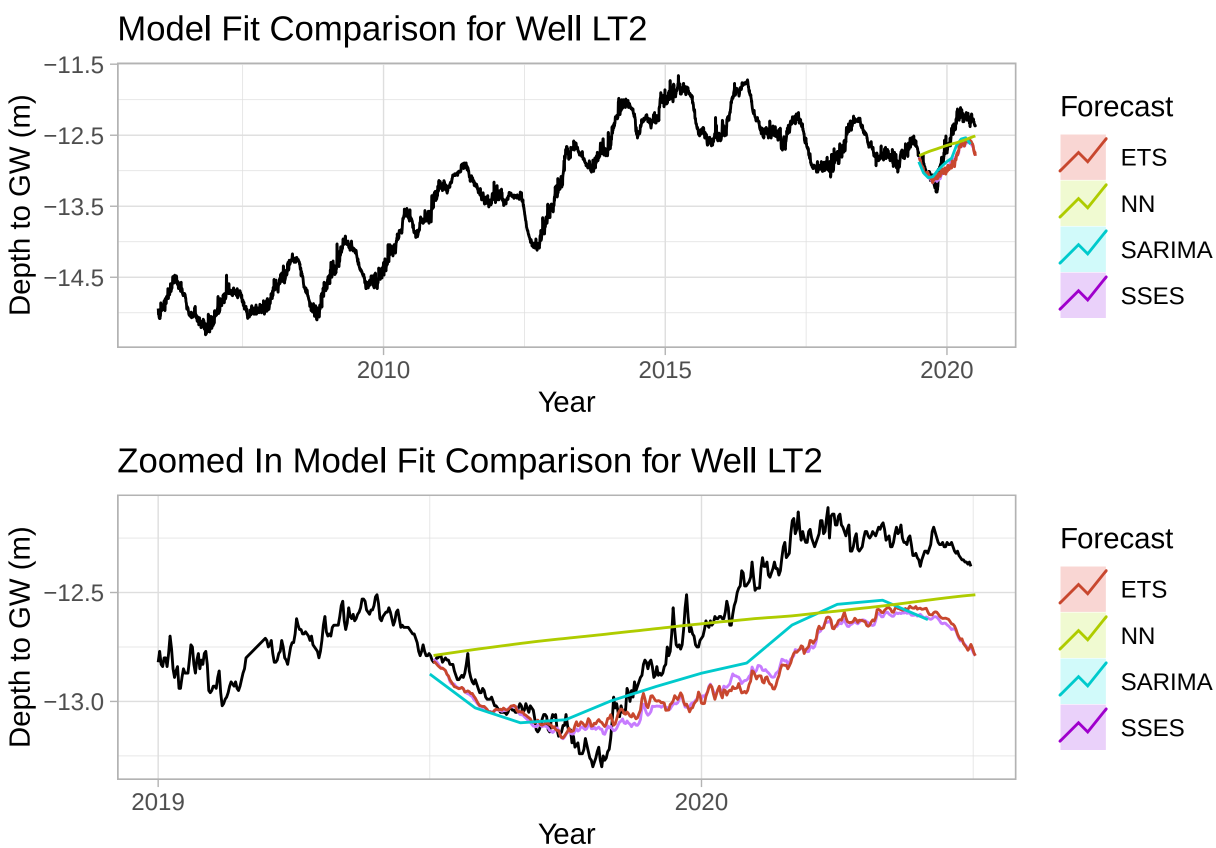

Figure 7: Model Fit Comparisons for Well LT2

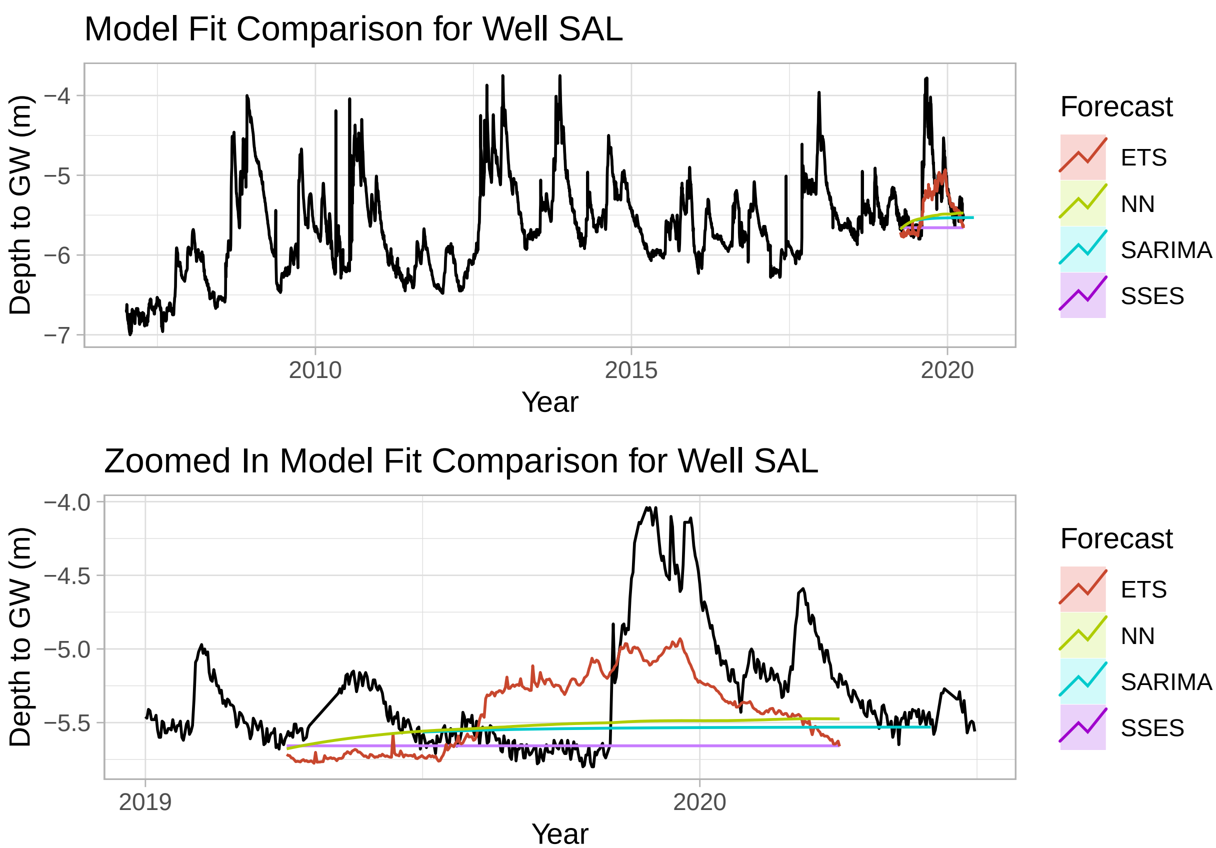

Figure 8: Model Fit Comparisons for Well SAL

Table 5: Forecast Accuracy for Seasonal Data at Well LT2

	ME	RMSE	MAE	MPE	MAPE	ACF1	Theil's U
SARIMA	0.18533	0.25429	0.20708	-1.50064	1.66526	0.78460	1.76030
ETS	0.22956	0.30488	0.25138	-1.85643	2.02133	0.97974	8.71599
SSES	0.23689	0.30485	0.25382	-1.91339	2.04135	0.97877	8.72128
NN	-0.00701	0.29381	0.25686	-0.00883	2.02747	0.99236	8.17006

Table 6: Forecast Accuracy for Seasonal Data at Well SAL

	ME	RMSE	MAE	MPE	MAPE	ACF1	Theil's U
SARIMA	0.28294	0.51523	0.35878	-6.16268	7.50082	0.47825	1.27277
ETS	0.18165	0.40155	0.24084	-4.12608	5.22038	0.96610	5.06406
SSES	0.41811	0.63229	0.43603	-8.99277	9.30487	0.98020	7.73355
NN	0.28931	0.54263	0.35200	-6.48076	7.58163	0.97916	6.73221

```
## The best LT2 Well model by RMSE is: SARIMA
```

```
## The best SAL Well model by RMSE is: ETS
```

According to our results, the SARIMA model resulted in the lowest root mean square error (RMSE) for the LT2 well, and the ETS model resulted in the lowest RMSE for the SAL well. To continue our analysis, we wanted to improve upon these basic models by adding in exogenous variables and seeing if our RMSE values decreased. For each well, we started by adding rain as an exogenous variable and then added temperature as an exogenous variable in the SARIMA model. Adding the exogenous variables successfully improved the accuracy of our model fit in the last year of data. the SARIMA model results with exogenous variables are seen in Figure 10 below. Tables 7 and 8 compare performance metrics of the SARIMA model without exogenous variables and for the models that included rainfall and temperature. We found that at each of the wells, the SARIMA model with temperature as an exogenous variable had the lowest RMSE and MAPE.

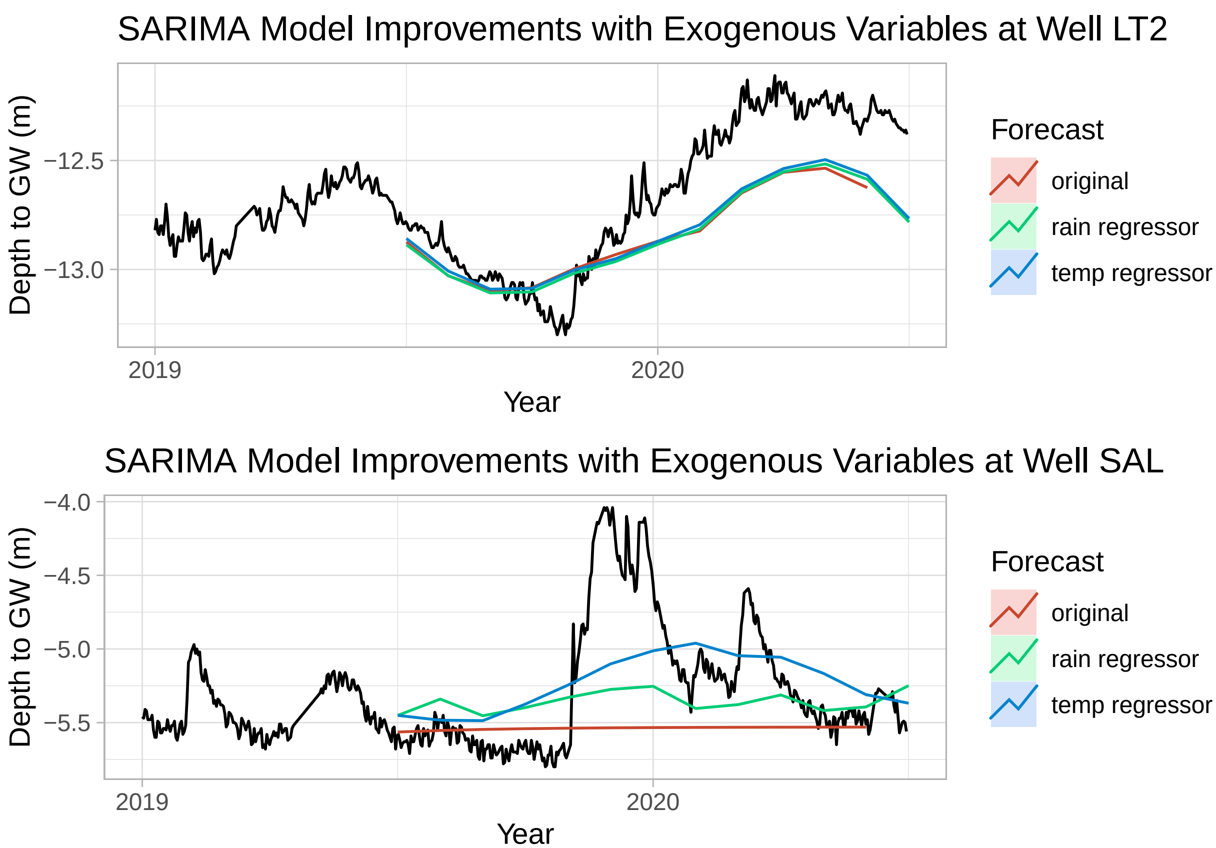

Figure 9: SARIMA Model Improvements when Exogenous Variables are Included at Wells LT2 and SAL

Table 7: Forecast Accuracy for Sarima with Regressors at Well LT2

	ME	RMSE	MAE	MPE	MAPE	ACF1	Theil's U
SARIMA	0.18533	0.25429	0.20708	-1.50064	1.66526	0.78460	1.76030
SARIMA w/ RAIN	0.18855	0.25089	0.20714	-1.52366	1.66434	0.78531	1.73493
SARIMA w/ TEMP	0.17090	0.23875	0.19216	-1.38419	1.54510	0.78406	1.65290

Table 8: Forecast Accuracy for Sarima with Regressors at Well SAL

	ME	RMSE	MAE	MPE	MAPE	ACF1	Theil's U
SARIMA	0.28294	0.51523	0.35878	-6.16268	7.50082	0.47825	1.27277
SARIMA w/ RAIN	0.11106	0.41086	0.32007	-2.80383	6.51817	0.42753	0.99058
SARIMA w/ TEMP	-0.03167	0.35584	0.28774	0.03923	5.75457	0.32779	0.84574

Summary and Conclusions We used four different models to predict depth to groundwater at two wells within confined and unconfined portions of the Auser Aquifer. These included a seasonal arima, exponential smoothing, state space exponential smoothing, and a neural network model. We first explored model performance without exogenous variables and found that ETS best predicted depth to groundwater in the confined aquifer, and the seasonal auto arima best predicted depth to groundwater in the unconfined aquifer, as determined by RMSE and MAPE scores on a final year of holdout data. The model performances are seen in Figures 7 and 8, and forecast accuracy metrics are displayed in Tables 5 and 6.

We then incorporated exogenous variables into our seasonal auto arima model and found that this improved model performance for both wells, as seen in Figure 9, and the forecast accuracy metrics of Tables 7 and 8. For both of the wells we explored, using temperature as an exogenous variable improved model accuracy the greatest.

The well within the unconfined aquifer (SAL) had more significant improvement in model forecast when including exogenous variables than the well within the confined aquifer (LT2). This is likely due to the fact that groundwater levels within the unconfined aquifer fluctuate with greater frequency due to climatic factors. Rain can recharge unconfined aquifers faster than an confined aquifer, and extreme heat would cause more evaporation in an unconfined aquifer than a confined one.

That being said, these climatic factors definitely influence depth to groundwater, so it makes sense that variables of temperature and rainfall both improved model performance when used an exogenous variables. We expected that rainfall would improve model performance more than temperature when predicting depth to groundwater, but perhaps there is a lag in the correlation that we were unable to account for and could be explored further to improve the model even more.

These results help us conclude that if we were to forecast our models into the future using the seasonal arima model, we would want to be sure to use temperature as an exogenous variable. This information is valuable because it can help utilities prioritize the data that they are collecting at their sites. If utilities prioritize obtaining temperature data as well as aquifer storage data, they can more accurately predict future aquifer storage.

Bibliography
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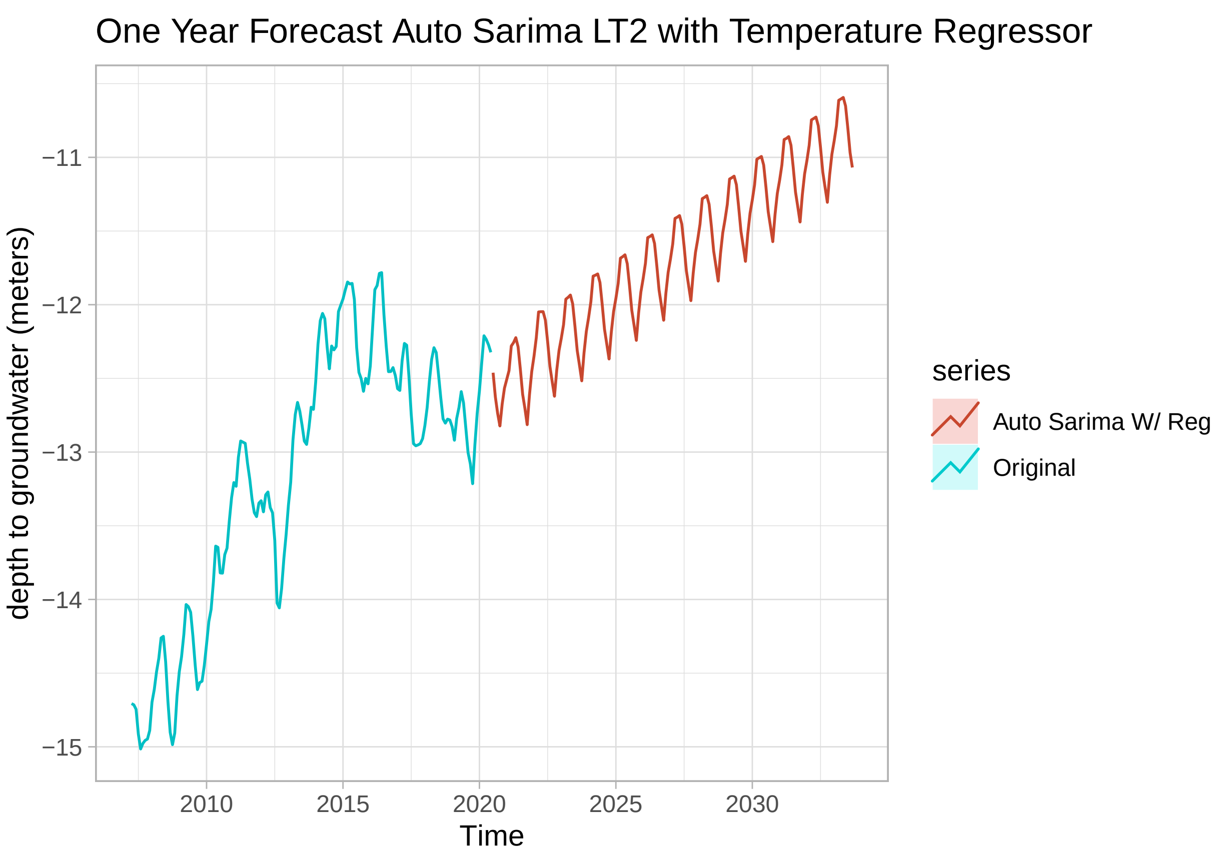
Appendix For further analysis, we attempted to run a forecast of the seasonal arima one year into the future to see what future groundwater availability in these two wells would look like. We ran into an issue where our forecast with temperature as an exogenous variable ended up forecasting 12 years into the future instead of 12 months. After multiple attempts, we were not able to figure out how to rectify the issue. Although these forecasts are not what we had hoped for, we still found the results interesting and wanted to include them in our report. Below we have shown our code and the resulting plots for reference.

```
ts_LT2_monthly_reg <- tsclean(ts(LT2_for_reg[,2],start=c(2007,04,01),frequency=12))
ts_SAL_monthly_reg <- tsclean(ts(SAL_for_reg[,2],start=c(2007,04,01),frequency=12))
ts_rain_monthly_reg <- tsclean(ts(rain_reg_monthly[,2],start=c(2007,04,01),frequency=12))
ts_temp_monthly_reg <- tsclean(ts(temp_reg_monthly[,2],start=c(2007,04,01),frequency=12))

auto_LT2_future <- auto.arima(ts_LT2_monthly_reg, xreg=ts_temp_monthly_reg)

auto_LT2_future_forecast <- forecast(auto_LT2_future, h=12, xreg=ts_temp_monthly_reg)

#plot model + observed data
autoplot(ts_LT2_monthly_reg, series = "Original") +
  autolayer(auto_LT2_future_forecast, series = "Auto Sarima W/ Reg", PI = FALSE) +
  ylab("depth to groundwater (meters)") +
  ggtitle("One Year Forecast Auto Sarima LT2 with Temperature Regressor") +
  theme_light()
```




```
auto_SAL_future <- auto.arima(ts_SAL_monthly_reg, xreg=ts_temp_monthly_reg)

auto_SAL_future_forecast <- forecast(auto_SAL_future, h=12, xreg=ts_temp_monthly_reg)
```

```
#plot model + observed data
autoplot(ts_SAL_monthly_reg, series = "Original") +
  autolayer(auto_SAL_future_forecast, series = "Auto Sarima W/ Reg", PI = FALSE) +
  ylab("depth to groundwater (meters)") +
  ggtitle("One Year Forecast Auto Sarima SAL with Temperature Regressor") +
  theme_light()
```