Kaufman_McNeill_ENV797_Project

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2024-04-10

```r
# load required packages
library(lubridate)
```

```
##
## Attaching package: 'lubridate'

## The following objects are masked from 'package:base':
##
##     date, intersect, setdiff, union
```

```r
library(ggplot2)
library(forecast)
```

```
## Registered S3 method overwritten by 'quantmod':
##   method            from
##   as.zoo.data.frame zoo
```

```r
library(Kendall)
library(tseries)
library(outliers)
library(tidyverse)
```

```
## -- Attaching core tidyverse packages ------------------------ tidyverse 2.0.0 --
## v dplyr   1.1.3     v stringr 1.5.0
## v forcats 1.0.0     v tibble  3.2.1
## v purrr   1.0.2     v tidyr   1.3.0
## v readr   2.1.4

## -- Conflicts ------------------------------------------ tidyverse_conflicts() --
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()    masks stats::lag()
## i Use the conflicted package (<http://conflicted.r-lib.org/>) to force all conflicts to become errors
```

```r
library(smooth)
```

```
## Loading required package: greybox
## Package "greybox", v2.0.0 loaded.
##
```

```
##
## Attaching package: 'greybox'
##
## The following object is masked from 'package:tidyr':
##
##     spread
##
## The following object is masked from 'package:lubridate':
##
##     hm
##
## This is package "smooth", v4.0.0
```

```r
library(dplyr)
library(cowplot)
```

```
##
## Attaching package: 'cowplot'
##
## The following object is masked from 'package:lubridate':
##
##     stamp
```

```r
library(corrplot)
```

```
## corrplot 0.92 loaded
```

```r
library(kableExtra)
```

```
## Warning: package 'kableExtra' was built under R version 4.3.2
```

```
##
## Attaching package: 'kableExtra'
##
## The following object is masked from 'package:dplyr':
##
##     group_rows
```

```r
library(gridExtra)
```

```
##
## Attaching package: 'gridExtra'
##
## The following object is masked from 'package:dplyr':
##
##     combine
```

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 forecasts 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, we examine the best 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.

(add more about objectives?)

Dataset information Provide information on how the dataset for this analysis were collected (source), the data contained in the dataset (format). Describe how you wrangled/processed your dataset to get the time series object.

Add a table that summarizes your data structure (variables, units, ranges and/or central tendencies, data source if multiple are used, etc.). This table should inserted as a `kable` function in an R chunk. Just show the first 10 rows of your data. Do not include the code used to generate your table.

The dataset for this analysis was 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 the 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 while Well LT2 represents the southern confined portion. 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.

```
## [1] "/Users/jennifermcneill/TSA_Spring2024/TSA_Spring2024/FinalProject"
```

```
##  [1] -12.23 -12.22 -12.19 -12.25 -12.27 -12.27 -12.28 -12.25 -12.24 -12.28
## [11] -12.33 -12.33 -12.32 -12.34 -12.35 -12.38 -12.35 -12.33 -12.31 -12.31
## [21] -12.32 -12.30 -12.28 -12.22 -12.20   0.00   0.00 -12.27 -12.28 -12.28
## [31] -12.27 -12.29 -12.29 -12.27 -12.28 -12.28 -12.27 -12.29 -12.31 -12.32
## [41] -12.31 -12.33 -12.34 -12.35 -12.35 -12.36 -12.36 -12.37 -12.36 -12.38
```

```
##  [1] -5.50 -5.47 -5.47 -5.43 -5.52 -5.53 -5.43 -5.47 -5.41 -5.42 -5.42 -5.46
## [13] -5.41 -5.51 -5.49 -5.42 -5.47 -5.52 -5.45 -5.43 -5.51 -5.48 -5.58 -5.55
## [25]  0.00  0.00  0.00 -5.30 -5.30 -5.27  0.00  0.00  0.00  0.00  0.00  0.00
## [37] -5.33 -5.34 -5.34 -5.29 -5.38 -5.43 -5.35 -5.46 -5.57  0.00 -5.50 -5.49
## [49] -5.50 -5.56
```

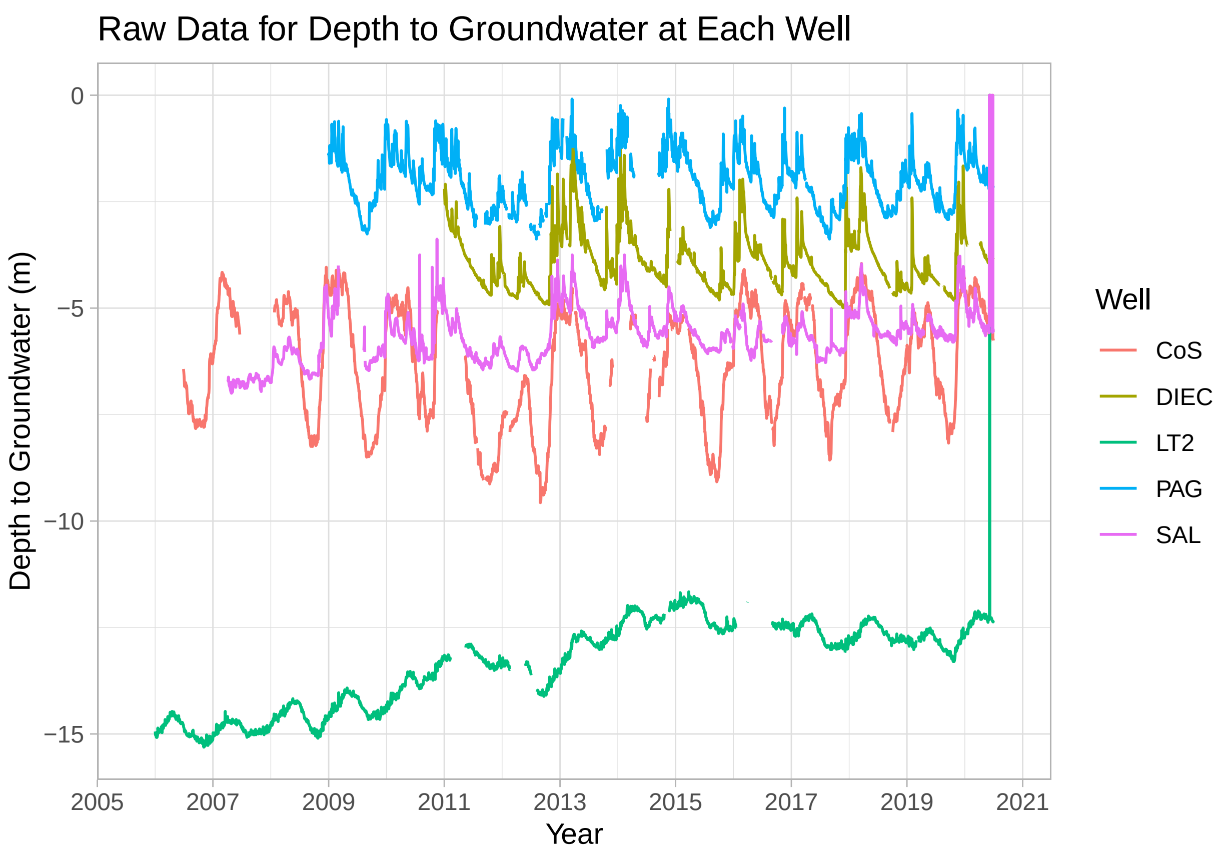


Figure 1: Raw Depth to Groundwater Series

```
##  [1] -1.87 -1.89 -1.93 -1.97 -2.00 -2.02 -2.06 -2.00 -1.71 -1.81 -1.89 -1.97
## [13] -2.02 -2.04 -2.06 -2.11 -2.09 -2.06 -2.07 -2.14 -2.15 -2.17 -2.21 -2.11
## [25] -2.10 -2.14 -2.14 -2.12 -2.12 -2.02 -2.01 -2.07 -2.07 -1.82 -1.88 -1.94
## [37] -1.54 -1.37 -1.57 -1.70 -1.78 -1.85 -1.92 -1.97 -2.03 -2.04 -2.10 -2.14
## [49] -2.15 -2.17
```

```
##  [1] -5.13 -5.16 -5.13 -5.17 -5.21 -5.28 -5.31 -5.24 -5.19 -5.22 -5.29 -5.37
## [13] -5.42 -5.41 -5.43 -5.47 -5.54 -5.47 -5.46 -5.54 -5.53 -5.58 -5.63 -5.60
## [25]  0.00  0.00  0.00 -5.75 -5.78 -5.74 -5.63 -5.60 -5.63 -5.59 -5.51 -5.50
## [37] -5.45 -5.37 -5.33 -5.37 -5.39 -5.39 -5.44 -5.51 -5.59  0.00 -5.71 -5.73
## [49] -5.73 -5.76
```

```
##  [1] -3.75 -3.77 -3.80 -3.83 -3.84 -3.85 -3.85 -3.86 -3.85 -3.87 -3.87 -3.88
## [13] -3.89 -3.90 -3.91 -3.93 -3.93 -3.92 -3.93 -3.94 -3.94 -3.95 -3.95 -3.88
## [25] -2.95 -3.13 -3.33 -3.38 -3.52 -3.60 -3.68 -3.75 -3.79 -3.79 -3.82 -3.83
## [37] -3.80 -3.75 -3.79 -3.80 -3.78 -3.79 -3.81 -3.82 -3.82 -3.83 -3.84 -3.84
## [49] -3.84 -3.85
```

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.

```
## Scale for x is already present.
## Adding another scale for x, which will replace the existing scale.
```

```
## Scale for x is already present.
## Adding another scale for x, which will replace the existing scale.
```

Analysis (Methods and Models) Describe the analysis and tests that were performed. Described the components of the time series you identified. List any packages and functions used. Include visualizations of your dataset (i.e. time series plot, ACF, PACF, etc).

Format your R chunks so that graphs are displayed but code is not displayed. Accompany these graphs with text sections that describe the visualizations and provide context for further analyses.

Each figure should be accompanied by a caption, and referenced within the text if applicable.

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. 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.

Table 1: Auser Aquifer Data Head 10 Rows

Date	05-17-11	05-18-11	05-19-11	05-20-11	05-21-11	05
Rainfall_Gallicano	0.0	0.0	0.0	0.8	0.0	0.
Rainfall_Pontetetto	0	0	0	0	0	0
Rainfall_Monte_Serra	0	0	0	0	0	0
Rainfall_Orentano	0.0	0.0	0.0	0.2	0.0	0.
Rainfall_Borgo_a_Mozzano	0	0	0	0	0	0
Rainfall_Piaggione	0	0	0	0	0	0
Rainfall_Calavorno	0	0	0	0	0	2
Rainfall_Croce_Arcana	0.0	0.0	0.0	0.0	1.0	0.
Rainfall_Tereglio_Coreglia_Antelminelli	0.0	0.0	0.0	0.6	0.0	0.
Rainfall_Fabbriche_di_Vallico	0.0	0.0	0.0	0.4	0.0	0.
Depth_to_Groundwater_LT2	-12.97	-12.93	-12.92	-12.93	-12.92	-1
Depth_to_Groundwater_SAL	-5.92	-5.93	-5.95	-5.95	-5.95	-5
Depth_to_Groundwater_PAG	-2.34	-2.46	-2.41	-2.48	-2.43	-2
Depth_to_Groundwater_CoS	-6.22	-6.27	-6.32	-6.39	-6.49	-6
Depth_to_Groundwater_DIEC	-3.79	-3.80	-3.80	-3.81	-3.81	-3
Temperature_Orentano	16.05	17.20	19.25	20.65	20.40	21
Temperature_Monte_Serra	12.80	15.25	15.35	16.40	17.60	18
Temperature_Ponte_a_Moriano	17.20	19.00	19.95	20.15	21.35	22
Temperature_Lucca_Orto_Botanico	17.45	19.00	20.10	21.60	21.15	22
Volume_POL	-9936.0	-9936.0	-9936.0	-9936.0	-9936.0	-9
Volume_CC1	-16377.12	-16377.12	-16377.12	-16377.12	-16377.12	-1
Volume_CC2	-12823.49	-12823.49	-12823.49	-12823.49	-12823.49	-1
Volume_CSA	0	0	0	0	0	0
Volume_CSAL	0	0	0	0	0	0
Hydrometry_Monte_S_Quirico	0.17	0.18	0.16	0.15	0.15	0.
Hydrometry_Piaggione	-1.04	-1.04	-1.04	-1.04	-1.05	-1

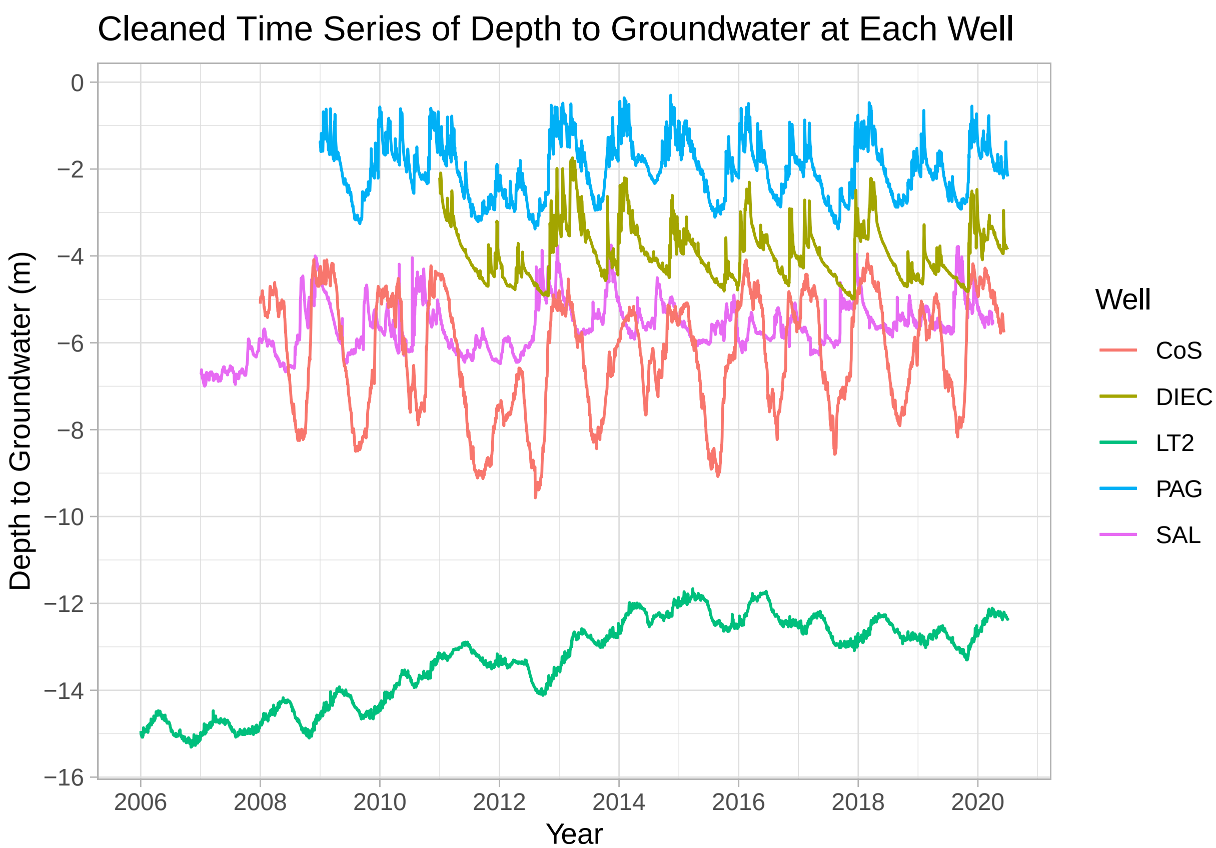


Figure 2: Depth to Groundwater Time Series

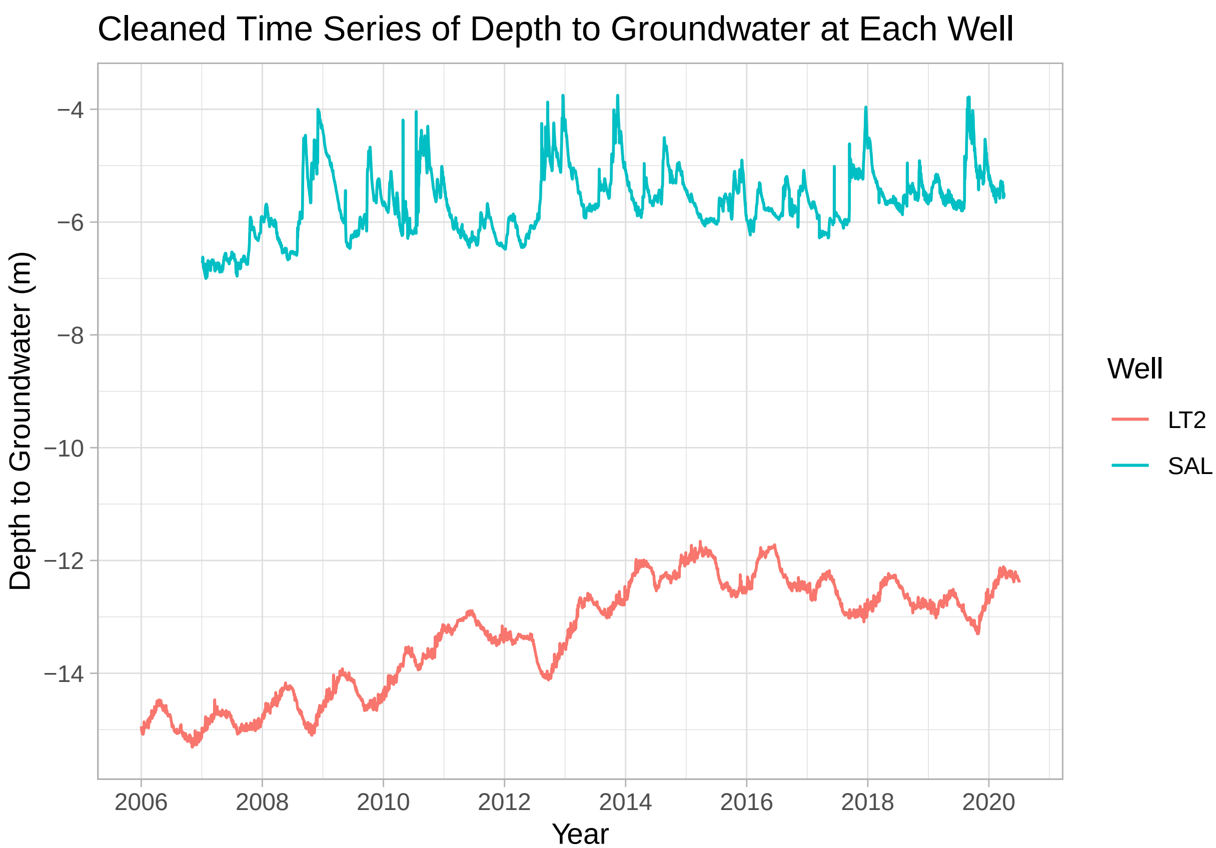
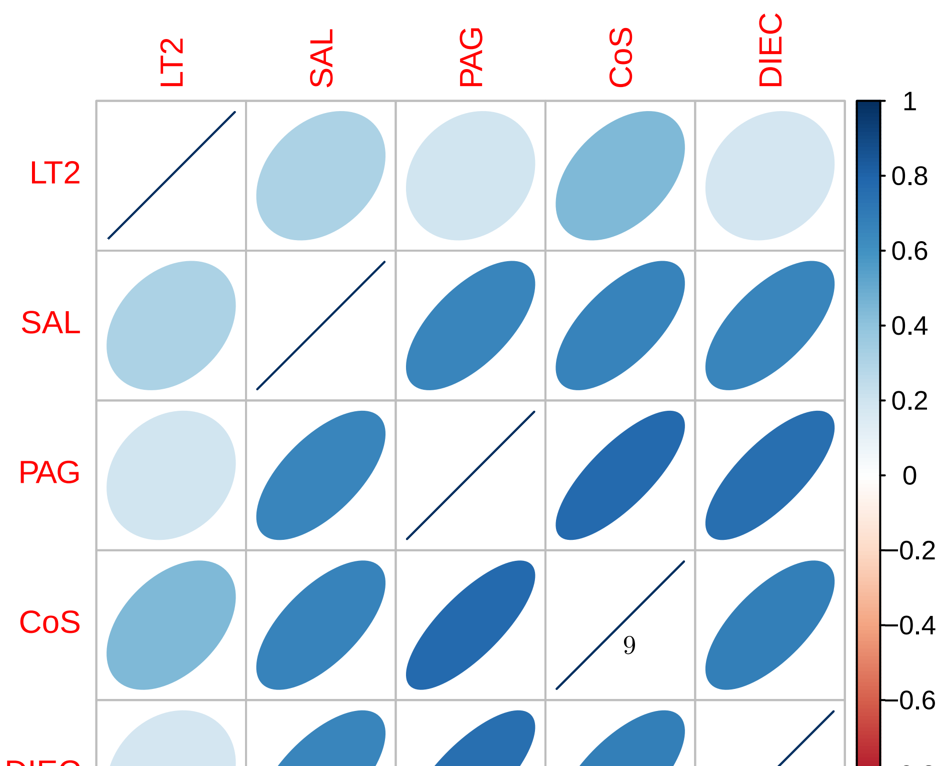
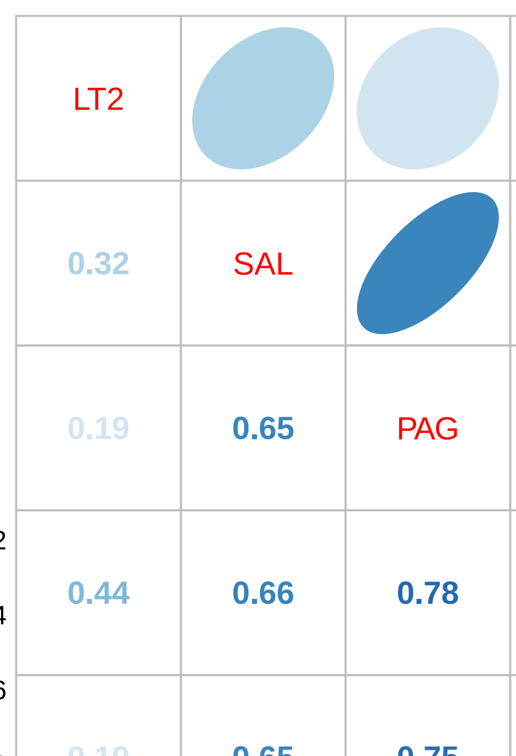


Figure 3: LT2 and SAL Time Series

Table 2: 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	





We 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. Both ACF graphs show peaks and troughs at regular intervals, so we know that our data has yearly seasonality. Knowing what we know about temperature and rainfall affecting aquifer storage, it makes sense that the depth to groundwater in the aquifer is changing with respect to the season.

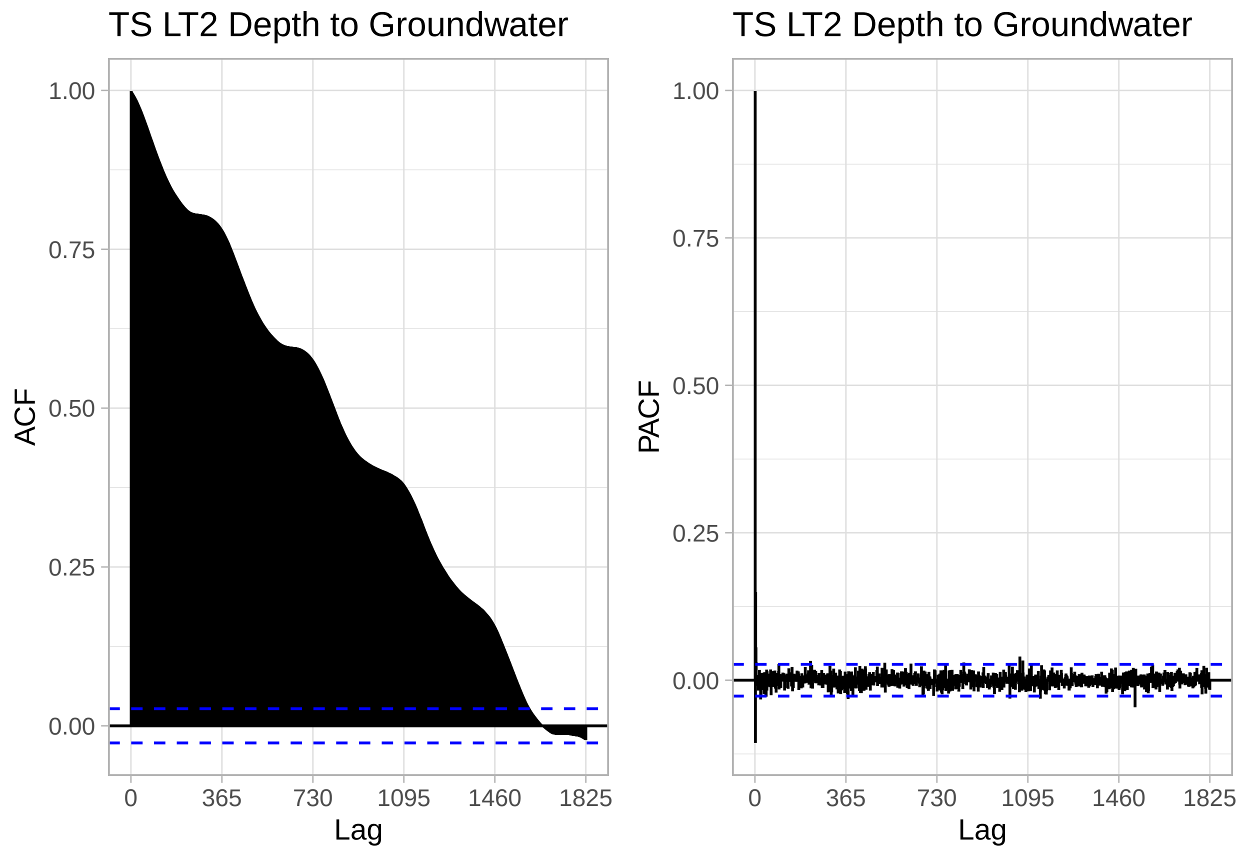


Figure 4: ACF and PACF for Depth to Groundwater at Well LT2

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 with both the additive and multiplicative methods. **WRITE SOMETHING ABOUT CHOOSING WHICH METHOD IS BETTER MOVING FORWARD? OR MAYBE JUST REMOVE WHICHEVER ONE WE DECIDE TO NOT USE?

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 deseasoned 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.

Table 3: Trend Conclusions from the Augmented Dickey Fuller and Mann Kendall Test Results

	SAL North Well	LT2 South Well
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

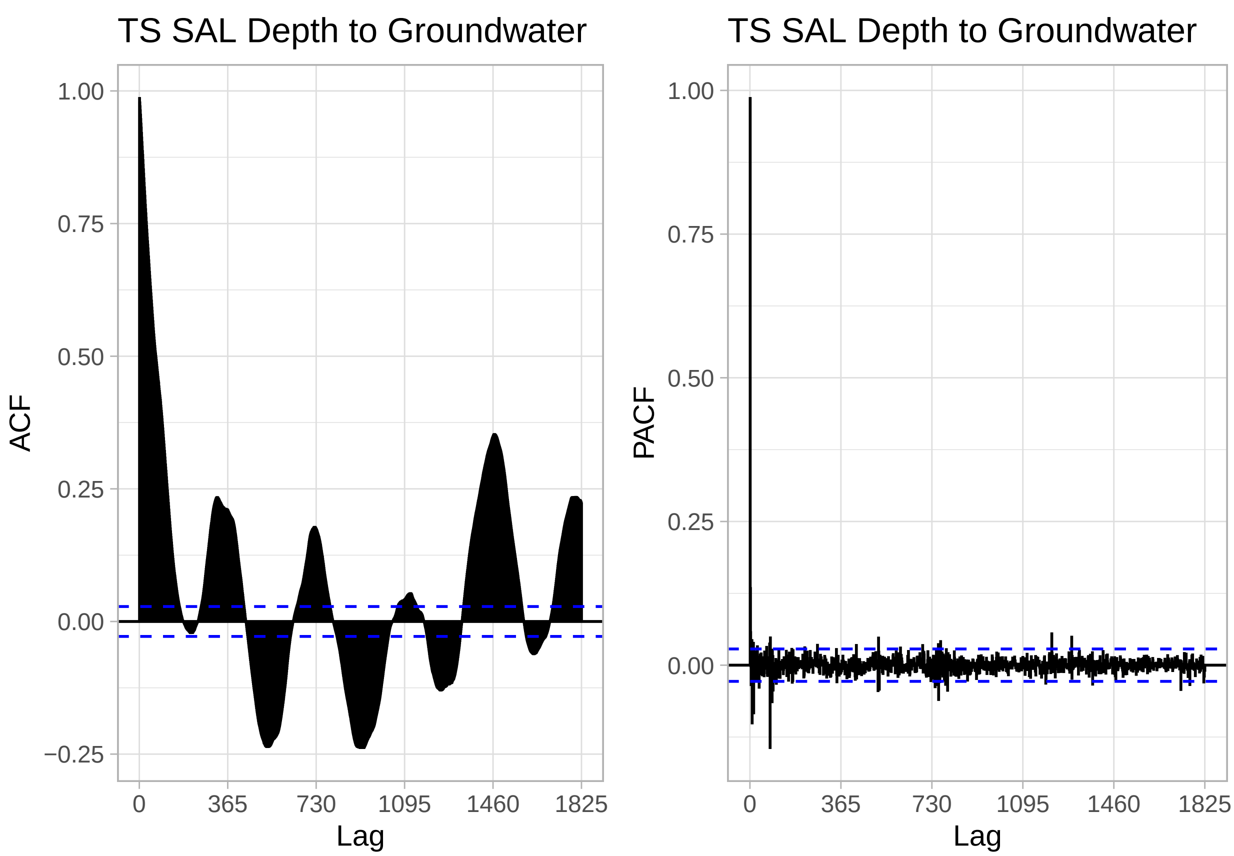


Figure 5: ACF and PACF for Depth to Groundwater at Well SAL

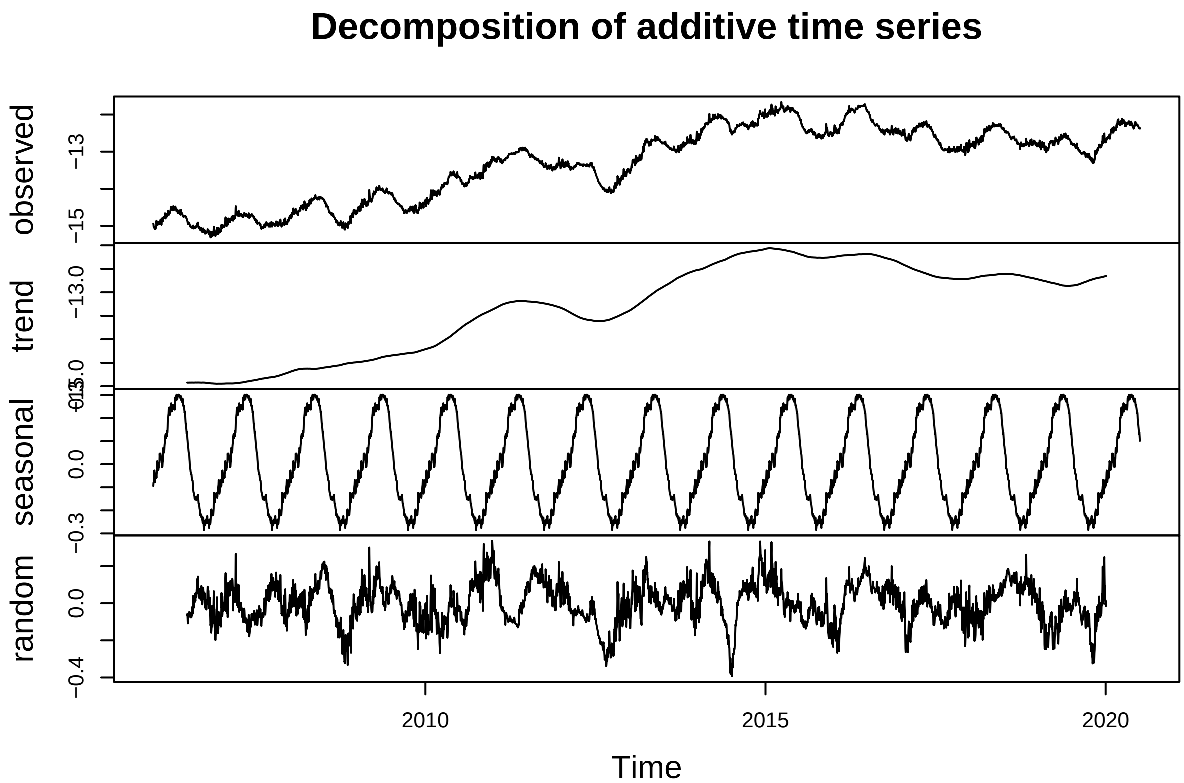


Figure 6: Decomposition of Depth to Groundwater at Well LT2

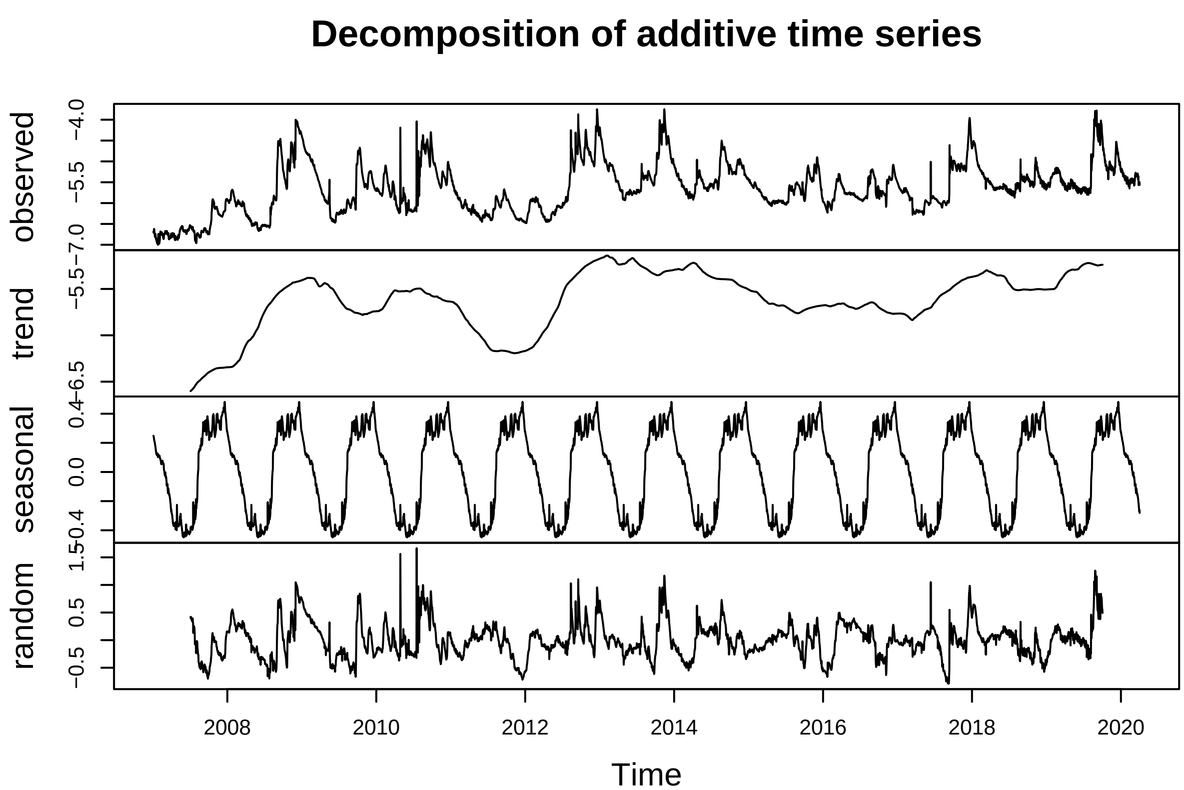


Figure 7: Decomposition of Depth to Groundwater at Well SAL

```
## Scale for x is already present.
## Adding another scale for x, which will replace the existing scale.
```

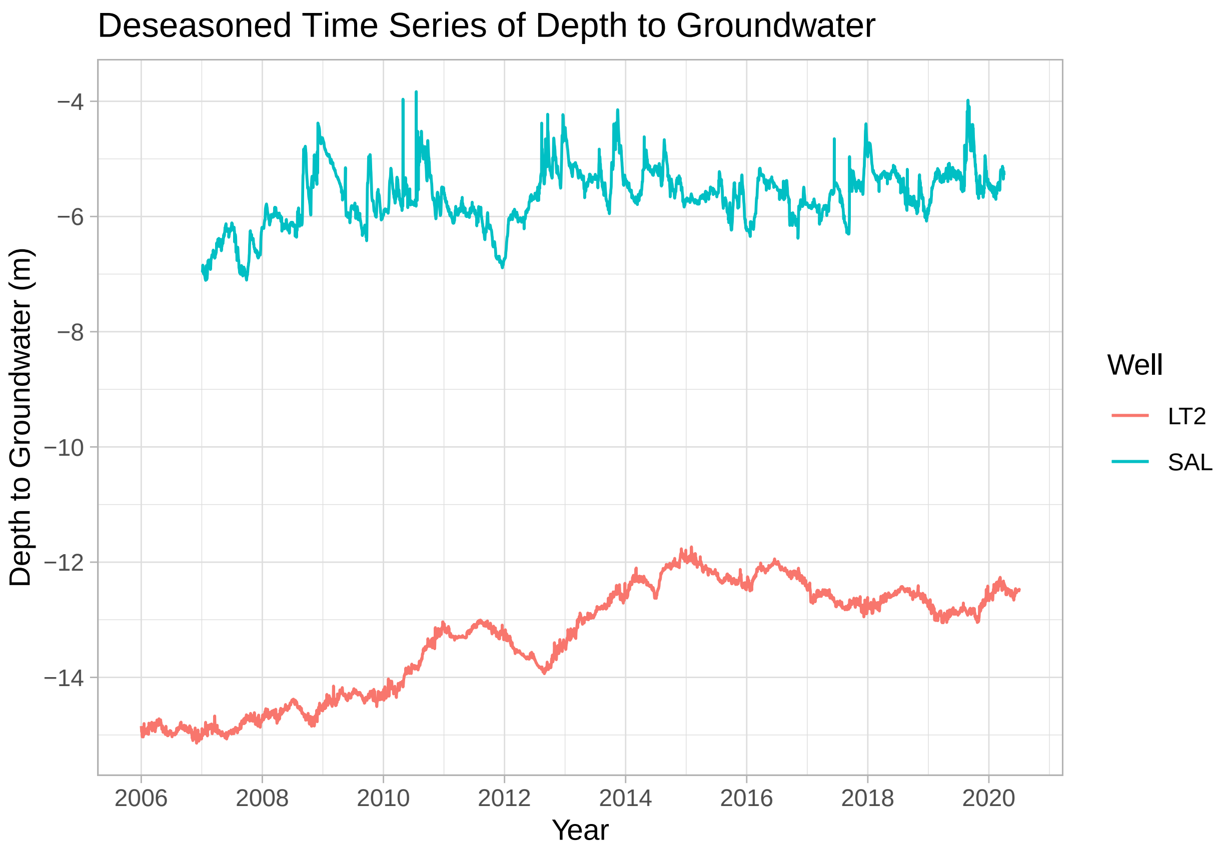


Figure 8: Trend Visualization for Deseasoned Time Series of Depth to Groundwater at Wells LT2 and SAL

Once we analyzed the time series, we were ready to start fitting models. Our process for fitting models was to fit four models on each well by holding out a year of data. The following section shows the results of testing the four models against the actual time series values for the final year.

SARIMA

ETS

SSES

Neural Network **NOTE PLEASE CHECK THE NAMES OF THESE MODELS TO SEE IF THEYRE RIGHT?? After running the Auto Sarima (SARIMA), the Exponential Smoothing State Space Model (ETS), the Simple Exponential Smoothing (SSES), and the Neural Network (NN) models, we plotted all tested models together on a graph and compared the predicted values for each model to the original data using the accuracy() function.

Table 4: 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	-0.16525	0.28518	0.21675	1.25945	1.68108	0.98750	7.73611

Table 5: 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	0.30061	0.55009	0.36378	-6.70215	7.80958	0.97940	6.80660

Performance

```
## 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.

Improving Performance with Exogenous Variables

```
## The best LT2 Well Sarima model by RMSE is: SARIMA w/ TEMP
```

```
## The best SAL Well Sarima model by RMSE is: SARIMA w/ TEMP
```

Summary and Conclusions Summarize your major findings from your analyses in a few paragraphs and plots. What conclusions do you draw from your findings? Any insights on how to improve the model?

Table 6: 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

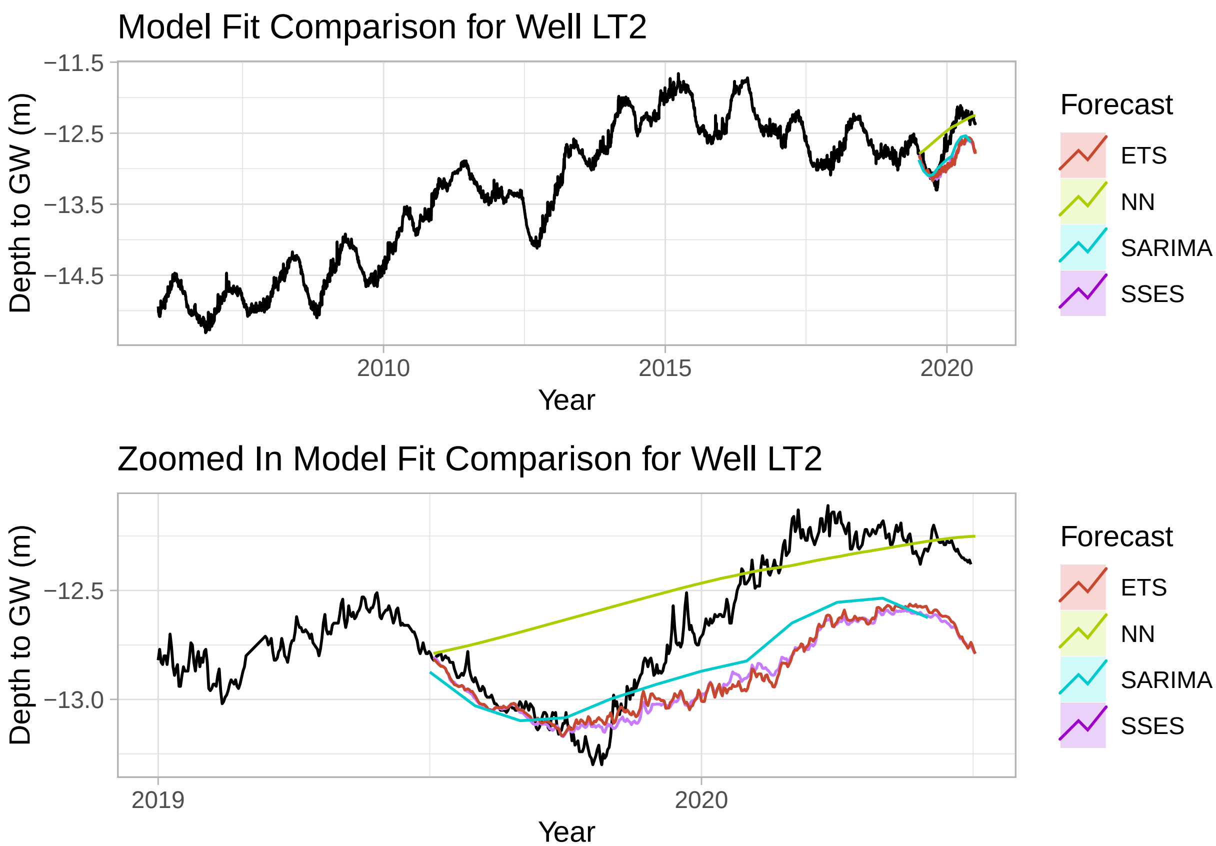
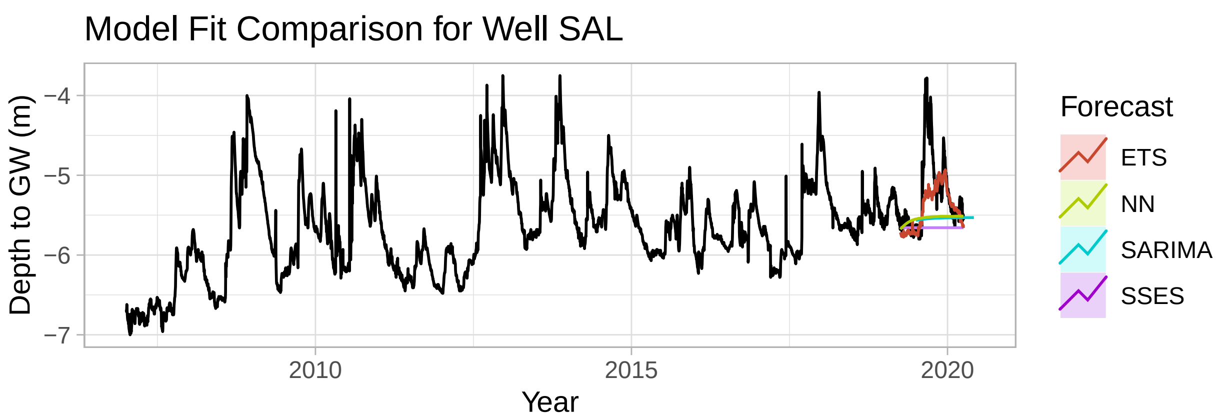


Figure 9: Model Fit Comparisons for Well LT2

Table 7: 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



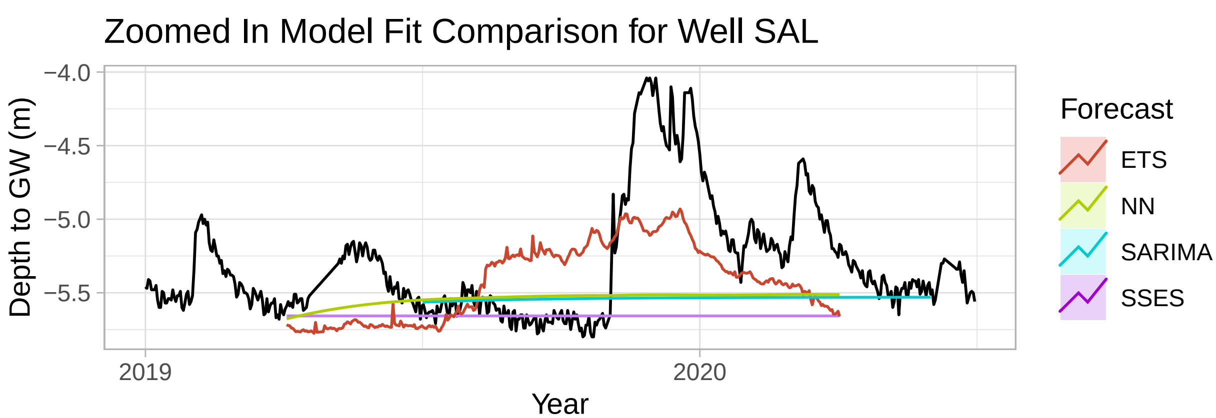


Figure 10: Model Fit Comparisons for Well SAL

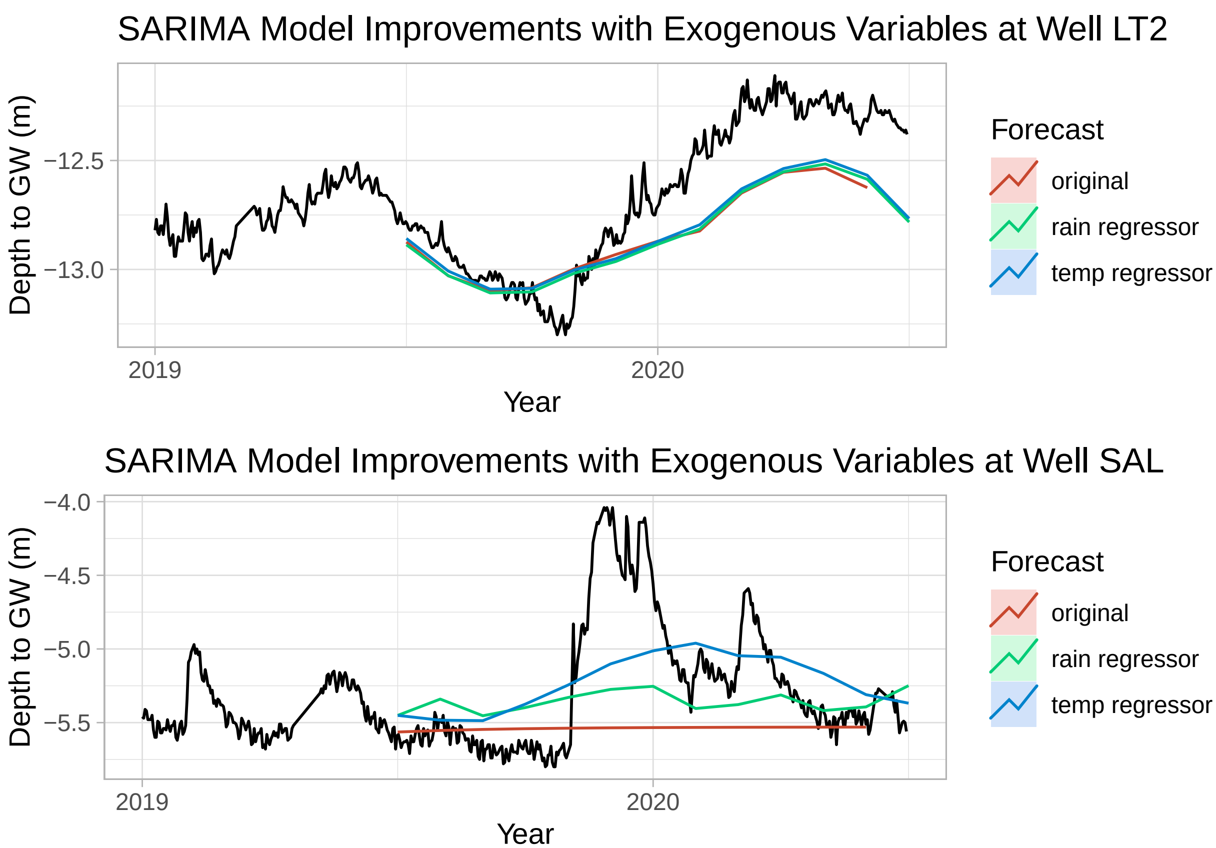


Figure 11: SARIMA Model Improvements when Exogenous Variables are Included at Wells LT2 and SAL

Bibliography Un world water development report 2022 ‘Groundwater: Making the invisible visible.’ (n.d.). UN-Water. Retrieved April 18, 2024, from https://www.unwater.org/news/un-world-water-development-report-2022-%E2%80%98groundwater-making-invisible-visible%E2%80%99

antimo musone, Aredhel Bergström, Federico, Luisa Marotta, Maggie, Maurizio Lucchesi. (2020). Acea Smart Water Analytics. Kaggle. https://kaggle.com/competitions/acea-water-prediction