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STAT 3504

Final Project

Analysis of NASA GISS Zonal Annual Mean Surface Temperature Deviations

ABSTRACT

This report explores a dataset of annual global mean temperature deviations from 1880-2017 compared to a baseline of temperatures from 1951-1980. This dataset exhibits characteristics of a random walk process, so an IMA(1,2) process was ultimately selected and determined to be a good fit for forecasting after a series of investigations through a number of statistical tests. Ultimately, the IMA(1,2) model was confirmed and used to forecast the global mean temperature deviations 33 years into the future through 2050. It was concluded that the annual global mean temperatures will continue to deviate positively from the baseline and could increase anywhere between 0.5 degrees to 1.6 degrees through 2050.

INTRODUCTION

The NASA Goddard Institute for Space Studies' Surface Temperature Analysis (GISTEMP) project is an endeavor to estimate global surface temperature change. This method of temperature analysis was established in the 1970s by American physicist James Hansen and is intended to be used for uncomplicated comparison with one-dimensional global climate models. The foundation of the method is “based on the finding that the correlation of temperature change was reasonably strong for stations separated by up to 1200 km, especially at middle and high latitudes” (NASA). This allows for the estimation of useful figures for global mean temperature changes. The data that will be analyzed in this report is a set of global annual mean temperature deviations from 1880 to 2017. The figures in this dataset are temperature deviations from a baseline of corresponding means from 1951-1980.

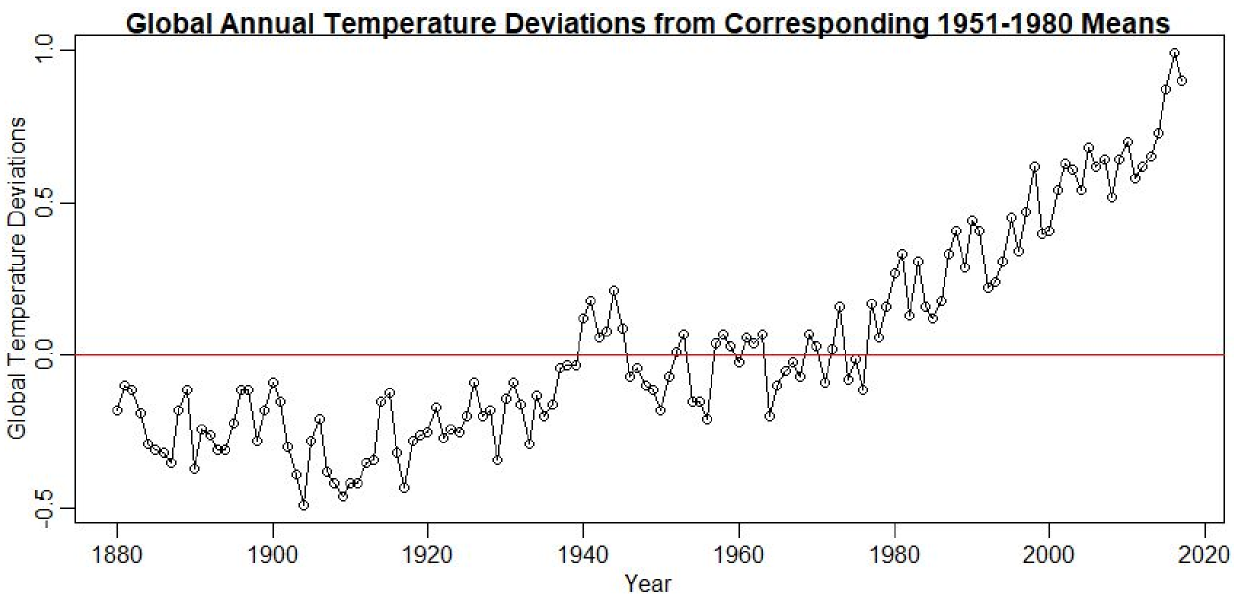

Figure 1. Global annual temperature deviations from 1880-2017 corresponding to 1951-1980 baseline (Appendix 1)

plot(x=antemp$Year, y=antemp$Glob, xlab="Year", ylab="Global Temperature Deviations", main = "Global Annual Temperature Deviations from Corresponding 1951-1980 Means", type = 'o')

abline(h=0, col=2)

Looking at a simple plot of the entire dataset, we can see that annual global temperature deviation is negative until approximately 1940, meaning that global mean temperatures were cooler on average from 1880 to 1940 compared to the 1951-1980 baseline. We also observe a relatively constant mean during this period from 1880 to roughly 1940. The data appears to then increase to a constant mean of approximately 0^o C from 1940 to 1980 which is obvious since this period is the baseline of which the dataset is being compared to. Finally, we observe a dramatic increase in annual temperature deviation after 1980 that appears to be linear, indicating that annual global temperatures became significantly warmer after 1980. The data as a whole does not appear to be stationary, as it does not have a constant mean, and looks similar to a random walk process. Therefore, it makes sense to first investigate if the data could be made stationary through differencing before we begin the selection process to model the data.

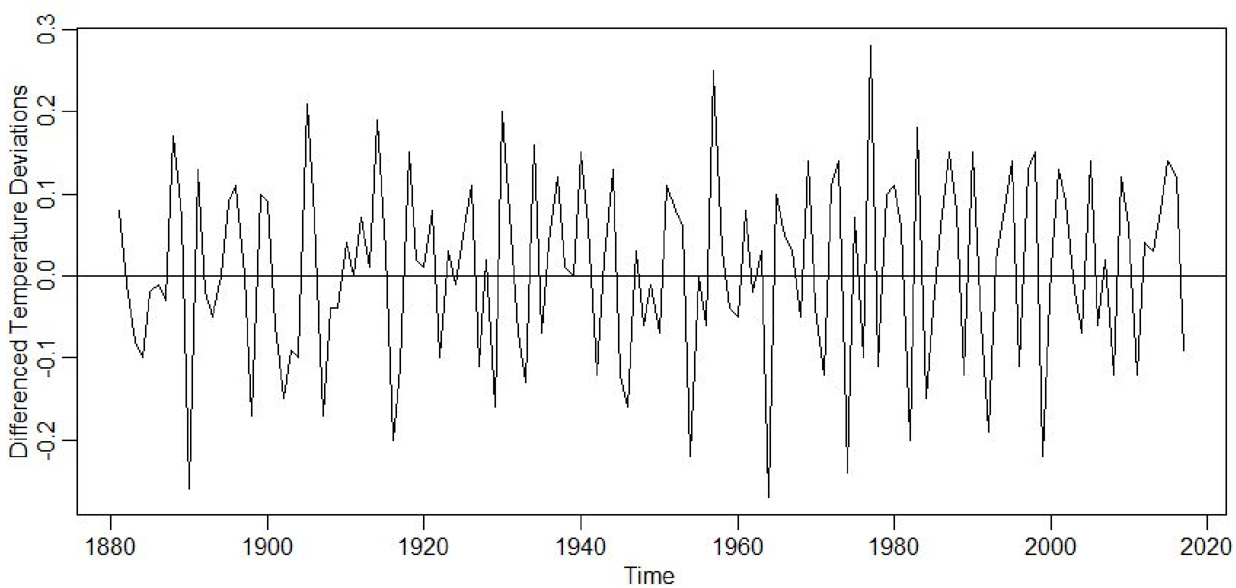

Figure 2. Time series plot of the differenced global annual mean temperature deviations

ts.plot(tempdiff, ylab='Differenced Temperature Deviations')

abline(h=0)

After applying first order differencing to the dataset, the differenced data looks much more like a constant, zero-mean process with constant variance. This signifies that some form of an ARIMA model would be a good fit for this dataset.

MODEL SPECIFICATION

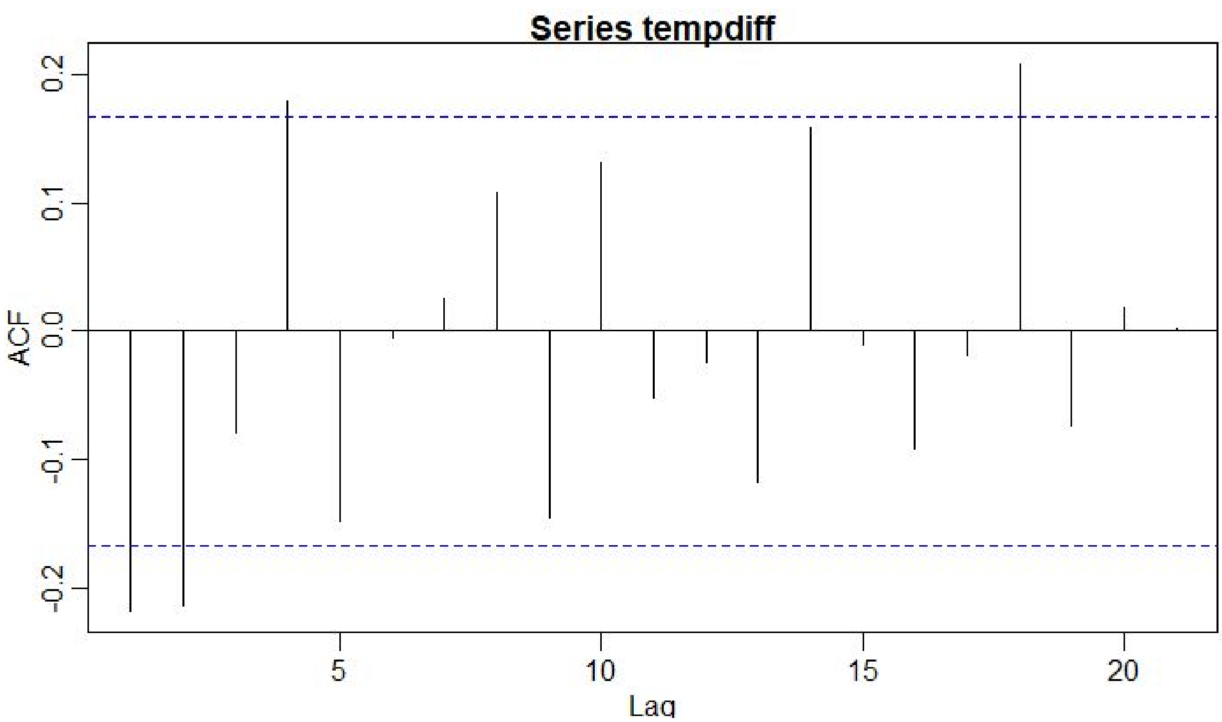

Figure 3. The plot of the autocorrelations for the differenced data

acf(tempdiff)

We see what could be a cut-off in autocorrelation after lag-2 in the ACF graph for the differenced data. This indicates that an IMA(1,2) model would be a good fit for the data, but there is a possibly significant autocorrelation at lag 18 which could be problematic.

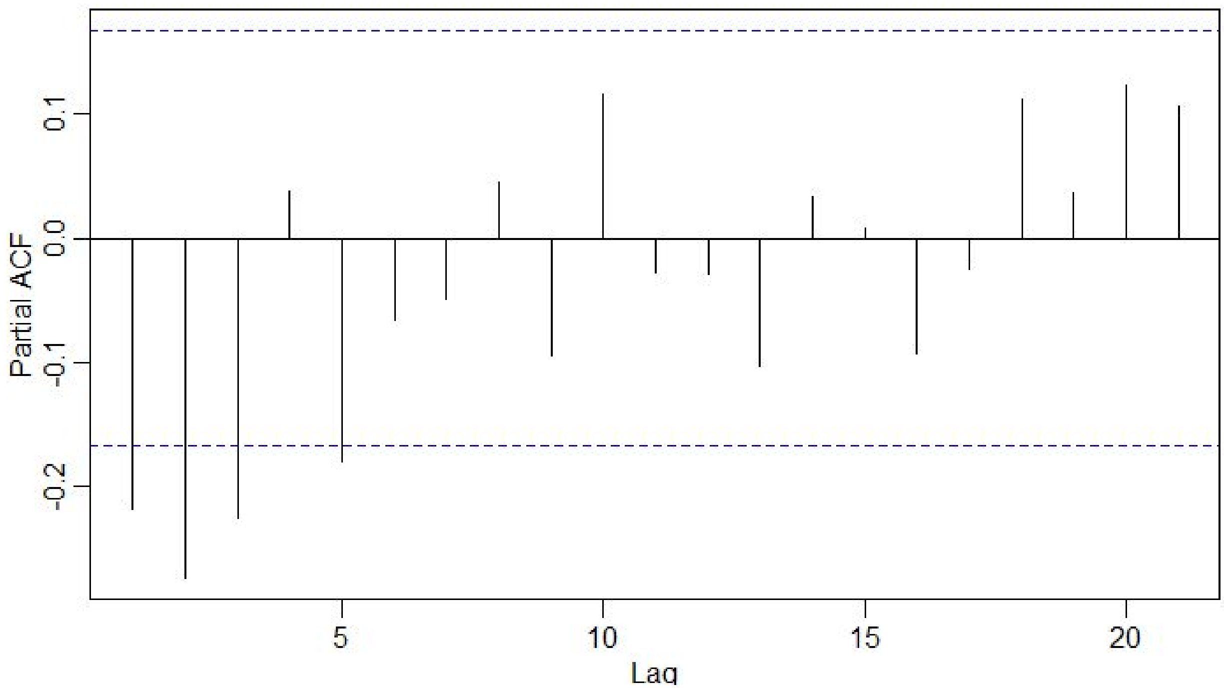

Figure 4. The plot of the partial autocorrelations for the differenced data

pacf(tempdiff)

It appears that the partial autocorrelations cut-off after lag-3, which indicates that an ARI(3,1) model could also be an appropriate fit for the data.

Since both the ACF and PACF plots for the differenced data appear to cutoff, we do not observe a model that will clearly, appropriately fit the dataset, therefore we will investigate further with EACF.

```
AR/MA
  0 1 2 3 4 5 6 7 8 9 10 11 12 13
0 x x o x o o o o o o o  o  o  o
1 x o o o o o o o o o o  o  o  o
2 x x x o o o o o o o o  o  o  o
3 o x x x o o o o o o o  o  o  o
4 x x x x o o o o o o o  o  o  o
5 x o x x o o o o o o o  o  o  o
6 x o o o x o o o o o o  o  o  o
7 x o o o x x o o o o o  o  o  o
```

Figure 5. The EACF grid for the differenced data

eacf(tempdiff)

Looking at the EACF grid of the differenced data, we once again do not see a model that is clearly most appropriate. It appears that the three most appropriate potential models given by the EACF are: ARI(3,1), ARIMA(1,1,1), and IMA(1,2).

We will therefore investigate each of these three models further.

```
Call:
arima(x = temp, order = c(1, 1, 1))

Coefficients:
         ar1      ma1
      0.3531  -0.7165
s.e.  0.1359   0.0954

sigma^2 estimated as 0.01089:  log likelihood = 115.1,  aic = -226.2
```

Figure 6. Summary of fitted ARIMA(1,1,1) model

model1 = arima(temp, order = c(1,1,1))

```
Call:
arima(x = temp, order = c(3, 1, 0))

Coefficients:
          ar1      ar2      ar3
      -0.3220  -0.3218  -0.2107
s.e.   0.0834   0.0836   0.0838

sigma^2 estimated as 0.01063:  log likelihood = 116.72,  aic = -227.44
```

Figure 7. Summary of fitted ARI(3,1) model

model2 = arima(temp, order = c(3,1,0))

```
Call:
arima(x = temp, order = c(0, 1, 2), method = "ML")

Coefficients:
          ma1      ma2
      -0.3408  -0.2108
s.e.   0.0797   0.0743

sigma^2 estimated as 0.01077:  log likelihood = 115.82,  aic = -227.63
```

Figure 8. Summary of fitted IMA(1,2) model
(note: maximum likelihood method was forced for parameter estimation because method of moments is an inappropriate method for an MA process)

model3 = arima(temp, order = c(0,1,2), method = 'ML')

Comparing the three models that were suggested by the EACF grid, we notice that the IMA(1,2) model has the smallest AIC and is therefore the most appropriate fit.

We will move forward with the IMA(1,2) model and perform diagnostics to determine if this model can be appropriately used to forecast our original data.

MODEL FITTING AND DIAGNOSTICS

Now that we have selected the IMA(1,2) model as the most appropriate model to fit the original data, we will perform a number of diagnostic tests to determine if this model can actually be used to forecast the data.

First, we test the significance of the estimated parameters given by the IMA(1,2) model:

Recall from Figure 8 that the parameter estimate for the MA1 term is given as -0.3408. Our null hypothesis in this case is that the parameter estimate is not significantly different from 0. (Appendix 2a)

```
[1] -0.4970091 -0.1845909
```

We see that the 95% confidence interval for the parameter estimate does not contain 0, and therefore we reject the null and conclude that the MA1 parameter estimate is significantly different from 0.

Repeating this process for the MA2 parameter estimate, which is given as -0.2108:

```
[1] -0.35642532 -0.06517468
```

Again, 0 is not included in the 95% confidence interval for the MA2 parameter estimate. We again reject the null and conclude that the MA2 parameter estimate is significantly different from 0.

Now that we know that the IMA(1,2) model has significant parameters, we will move forward to residual diagnostic tests.

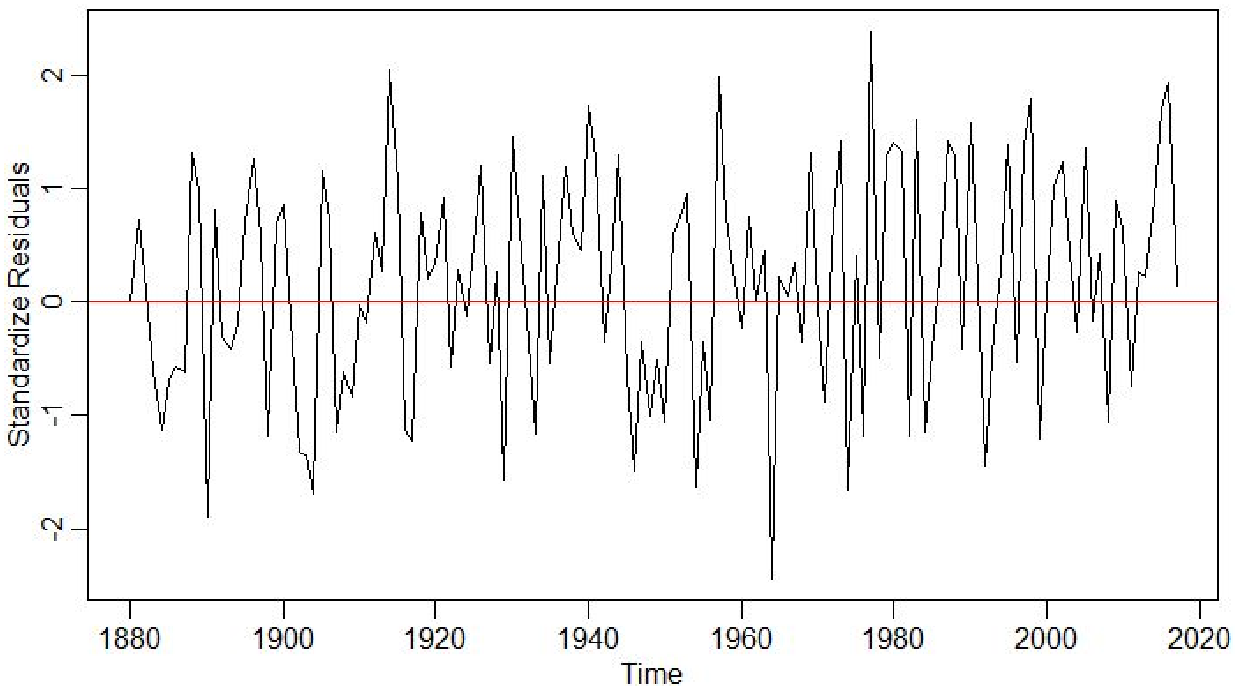

Figure 9. Simple plot of standardized residuals of fitted IMA(1,2) model over time

```
plot(rstandard(model3), ylab="Standardize Residuals")
abline(h=0, col = 2)
```

Looking at the simple plot of the standardized residuals, we see no trend and observe that the residuals are centered around zero and appear to have constant variance. These are all encouraging observations in regards to the accuracy of a forecast.

Next, we will investigate the normality of the standard residuals of this model.

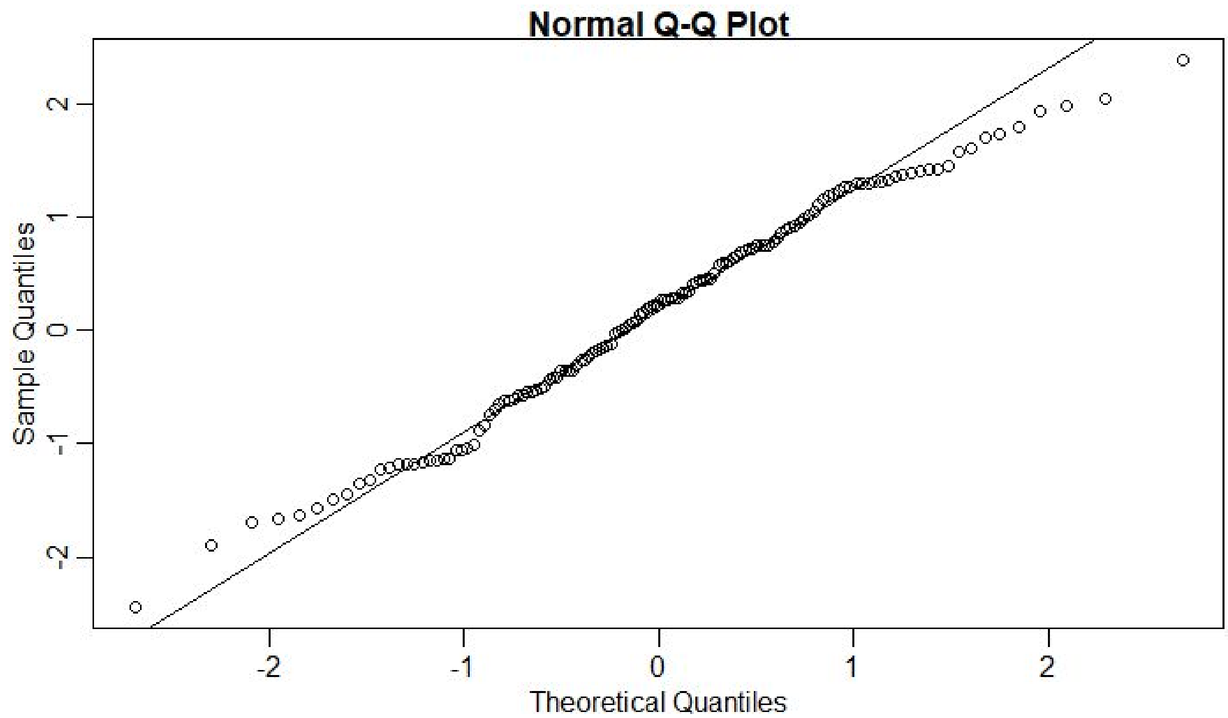

Figure 10. Normal Q-Q plot for the standardized residuals of the IMA(1,2) model

qqnorm(rstandard(model3))

The standardized residuals for the IMA(1,2) appear to be normally distributed, but also appear to have heavy tails. We will need to further investigate with a Shapiro-Wilk test for normality to conclude if the standardized residuals are, in fact, normally distributed.

```
        Shapiro-Wilk normality test

data:  rstandard(model3)
W = 0.9864, p-value = 0.1907
```

Figure 11. Shapiro-Wilk normality test for standardized residuals of IMA(1,2) model

shapiro.test(rstandard(model3))

The p-value given from the Shapiro test is much larger than a 0.05 significance level, so we fail to reject the Null and conclude that the standardized residuals of the IMA(1,2) model are, in fact, normally distributed.

We have concluded that the standardized residuals are both normally distributed, and stationary. This is what we expect from a good model fit, and we will move forward with the IMA(1,2) model.

Next, we will investigate the independence of the standardized residuals.

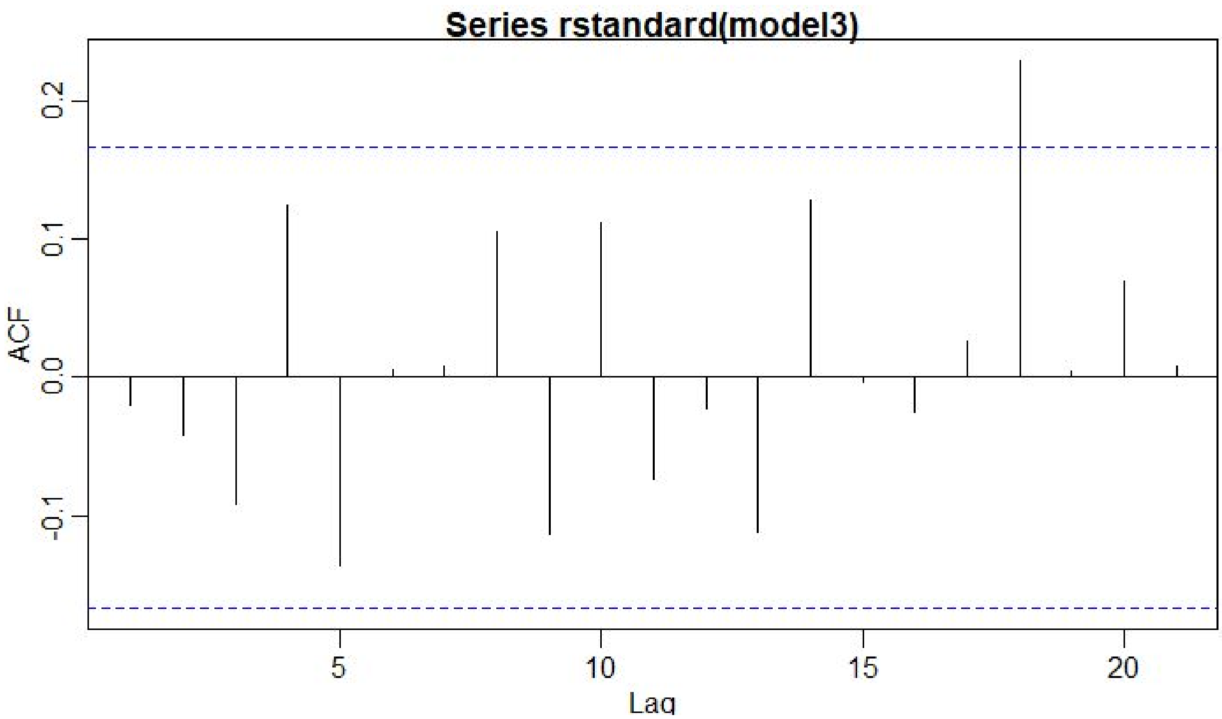

Figure 12. Autocorrelation plot of the standardized residuals of the IMA(1,2) model

We do observed a possibly significant autocorrelation at lag 18, but observe no significant autocorrelations for any other lags.

```
        Box-Ljung test

data:  rstandard(model3)
X-squared = 0.31166, df = 2, p-value = 0.8557
```

Figure 13. Box-Ljung test for standard residuals of IMA(1,2) model

The Box-Ljung test produces a very large p-value and we fail to reject the Null that the standardized residuals are uncorrelated and conclude that the standardized residuals are independent.

A runs test also yields a very large p-value and we confidently conclude that the standardized residuals are independent and the IMA(1,2) model continues to be an appropriate fit.

Finally, we decide to overfit the data with an IMA(1,3) model to determine if the IMA(1,2) model is the simplest and most appropriate model.

```
Call:
arima(x = temp, order = c(0, 1, 3))

Coefficients:
          ma1      ma2      ma3
      -0.3227  -0.2064  -0.0348
s.e.   0.0921   0.0753   0.0843

sigma^2 estimated as 0.01076:  log likelihood = 115.9,  aic = -225.8
```

Figure 14. Summary of the overfitted IMA(1,3) model

model4 = arima(temp, order = c(0,1,3))

Comparing the AIC of the overfitted IMA(1,3) model to the AIC of our selected IMA(1,2) model from Figure 8, we observe a smaller AIC in our selected IMA(1,2) model

We will now test if the estimated MA3 parameter from the overfitted IMA(1,3) model is significant: (Appendix 3)

```
[1] -0.200025  0.130425
```

This time, 0 is included in the 95% confidence interval for the MA3 parameter estimate. Therefore we fail to reject the Null, and conclude that the MA3 parameter estimate is not significantly different from 0.

We conclude that the IMA(1,3) model clearly overfits the data, and finally conclude that the IMA(1,2) model is appropriate and will produce a good forecast for our original data.

FORECASTING

Our selected IMA(1,2) model is written as:

Y_t - Y_{t-1} = e_t -0.3408 e_{t-1} -0.2108 e_{t-2}

Before we use the selected model to forecast the original data set, we will create a training subset of the data to evaluate the precision of our model forecasts. (Appendix 4)

Here, we have isolated 95% of the original data set to use for prediction and set aside the last 5% to evaluate the precision of the forecast.

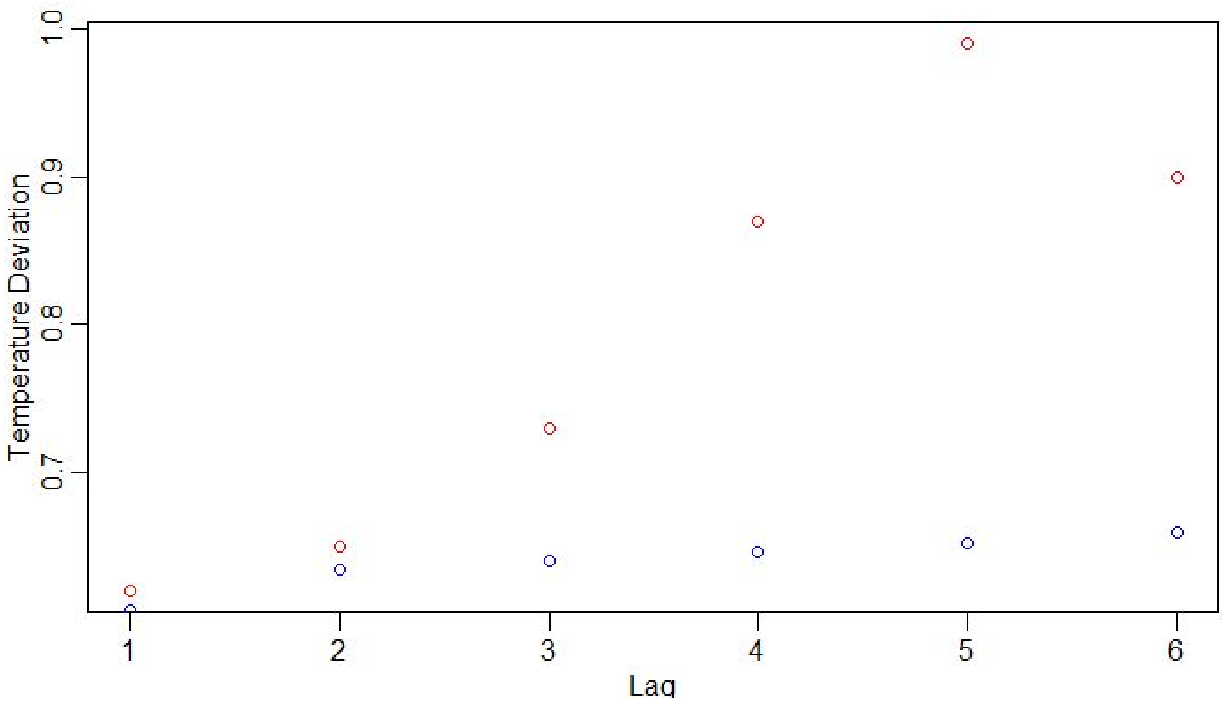

Figure 15. Actual and forecasted temperature deviations for final 6 points in data set

plot(check, col=2, ylab = "Temperature Deviation", xlab="Lag")
points(pred, col=4)

Here, we see the actual data points for the last 6 annual temperature deviations in the data set in red. Our model forecasts for the same years are in blue. We observe very small prediction errors for the first two lags, and large prediction errors for lags afterwards. The IMA(1,2) model appears to be sufficiently accurate for small time lags.

Therefore, we will finally use the selected IMA(1,2) model to forecast the annual global mean temperature deviations 33 years into the future (to 2050), realizing that our predictions will most likely be inaccurate after 2019.

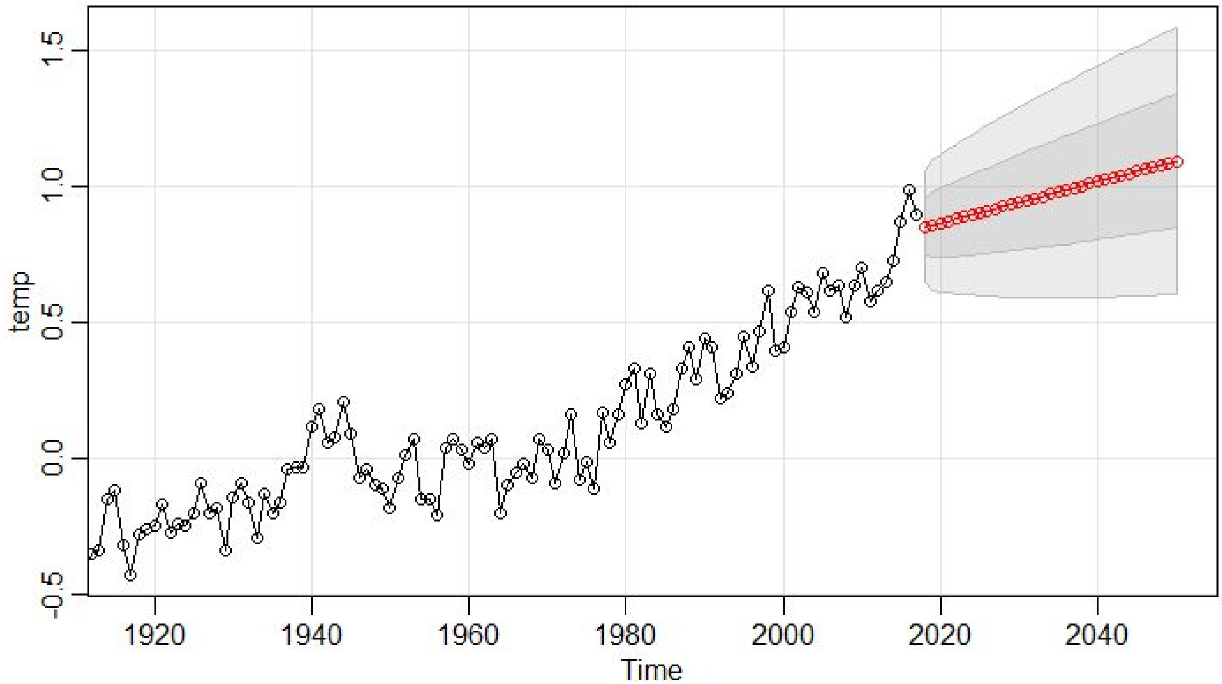

Figure 16. Global annual mean temperature deviations forecasted to 2050

sarima.for(temp,33,0,1,2)

CONCLUSION AND DISCUSSION

Speculating from the forecasts generated from the IMA(1,2) model, it is apparent that the annual global mean temperature will continue to deviate from the 1951-1980 baseline positively, between 0.6 and 1.6 degrees. The most extreme, but unlikely, possibilities include the annual global mean temperature stabilizing around 0.6 degrees warmer than the 1951-1980, or increasing drastically to 1.6 degrees warmer by 2050. If the unlikely drastic increase to a positive deviation of 1.6 degrees occurs, it would mean that mean global temperatures would have increased more drastically in the next 50 years (1.1 degrees) than they did in the 120 year period between 1880 and 2000 (1 degrees). A 1.6 degree deviation is alarming because climate research indicates that a 2 degree increase in global temperatures from baseline temperatures would have extreme consequences on the earth, including heat waves lasting longer, rain storms becoming more intense, and a large increase in sea level that could lead to the extinction of important ecosystems like coral reefs (Silberg). An deviation between the interval of 1.3 and 0.6 is more likely though through 2050, and while this is less of a drastic increase, a 1.5 degree increase from baseline would produce many of the same effects as a 2 degree increase, but these effects would be less severe (Silberg).

APPENDIX

Supplementary code:

1)

```
temp = ts(antemp$Glob, start=1880, end=2017, frequency=1)

tempdiff = diff(temp)
```

2a)

```
alpha = 0.05

c(-0.3408 - qnorm(1-alpha/2)*0.0797, -0.3408 + qnorm(1-alpha/2)*0.0797)
```

2b)

```
c(-0.2108 - qnorm(1-alpha/2)*0.0743, -0.2108 + qnorm(1-alpha/2)*0.0743)
```

3)

```
c(-0.0348 - qnorm(1-alpha/2)*0.0843, -0.0348 + qnorm(1-alpha/2)*0.0843)
```

4)

```
testing = temp[1:132]
test = sarima.for(testing,6,0,1,2)
pred = as.vector(test$pred)
check = temp[133:138]
```

REFERENCES

NASA, NASA, 24 Sept. 2018, data.giss.nasa.gov/gistemp/.

Silberg, Bob. "Why a Half-Degree Temperature Rise Is a Big Deal – Climate Change: Vital Signs of the Planet." *NASA*, NASA, 1 July 2016, climate.nasa.gov/news/2458/why-a-half-degree-temperature-rise-is-a-big-deal/.