Homework 8

Time Series Analysis (STAT 6391)

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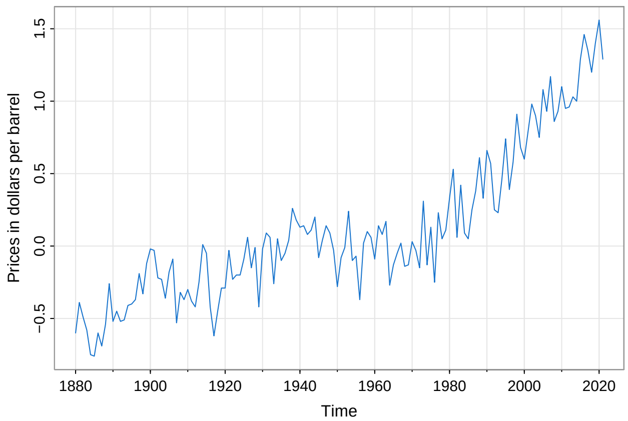
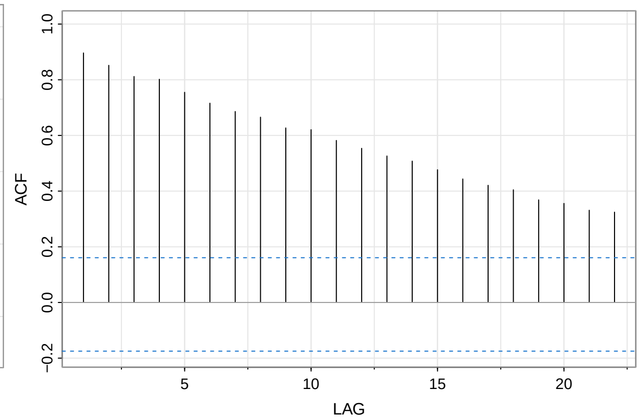
Problem 5.4

We fit an ARIMA(p,d,q) model to `gtemp_land`, the land-based global temperature data, and perform all of the necessary diagnostics; including a model choice analysis.



(a) Annual temperature anomalies (in degress centigrade) averaged over the Earth's land area from 1880 to 2021.



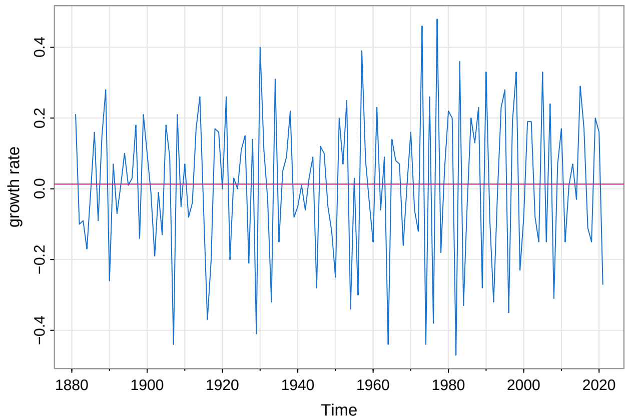
(b) Sample ACF of the growth rate

Figure 1: Exploring the land-based global temperature data.

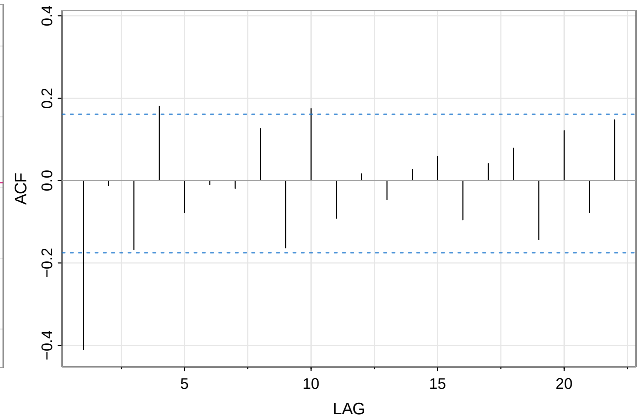
The series exhibits a strong non-linear trend. We see a sign of slow decay in the sample ACF, suggesting that an ARIMA model is an appropriate choice to consider.

Based on our initial observations about the data, we decided that differencing the data will be helpful. Plot (a) in Figure 2 shows a time series plot of the differenced data of order 1 (d=1), which shows that differencing the data resulted in a stable process.

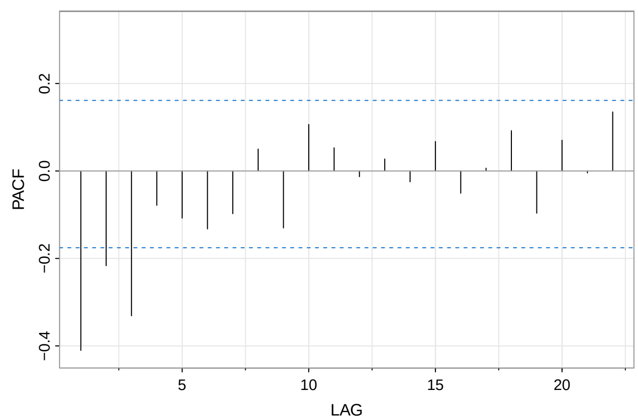
To decide on the appropriate choice of p and q for the ARIMA model to start with, we generated sample ACF and PACF plots as shown in Figure 2. The ACF appears to be tailing off while the PACF cuts off at lag 3 which suggests an ARMA(3,0) to the differenced data or ARIMA(3,1,0) to the actual data. It is also not unreasonable to assume that the ACF is cutting off after lag 1, and if we further assume that the PACF is tailing off, then this will suggest an ARMA(0,1) or MA(1) to the differenced series.



(a) First differenced series of the land-based global temperature.



(b) Sample ACF



(c) Sample PACF

Figure 2: Exploring the first differenced series of the land-based global temperature data.

Parameter Estimation

The foregoing analysis suggested two candidate models, ARIMA(3,0,0) or AR(3) and ARIMA(0,0,1) or MA(1) for the differenced series. The mean of the differenced series is slightly above zero so we fitted models with constant terms.

Results in Tables 1 and 2show that all the regression coefficients including the constant term are significant (associated p-values are less than 5%).

	Estimate	SE	t.value	p.value
Coefficients				
AR1	-0.5729	0.0796	-7.1966	0.0000
AR2	-0.3835	0.0875	-4.3846	0.0000
AR3	-0.3295	0.0797	-4.1337	0.0001
Constant	0.0136	0.0064	2.1203	0.0358
Performance metrics				
Sigma^2	0.0299			
AIC	-0.5982			
AICc	-0.5962			
BIC	-0.4937			

Table 1: Parameter estimates and performance metrics for ARIMA(3,0,0) on the land-based global temperature data.

	Estimate	SE	t.value	p.value
Coefficients				
MA1	-0.7023	0.0601	-11.6793	0.0000
Constant	0.0139	0.0044	3.1382	0.0021
Performance metrics				
Sigma^2	0.0301			
AIC	-0.6195			
AICc	-0.6189			
BIC	-0.5568			

Table 2: Parameter estimates and performance metrics for ARIMA(0,0,1) on the land-based global temperature data.

Residual Diagnostics

Residual analysis results for the models considered are shown in Figures 3 and 4. There is no signs of departures from the model assumptions as the residuals look white (because the ACF of the residuals fall within the confidence bands and the Ljung-Box statistic p-values are all above the 5% significance level) and the distribution of the residuals looking reasonably normal.

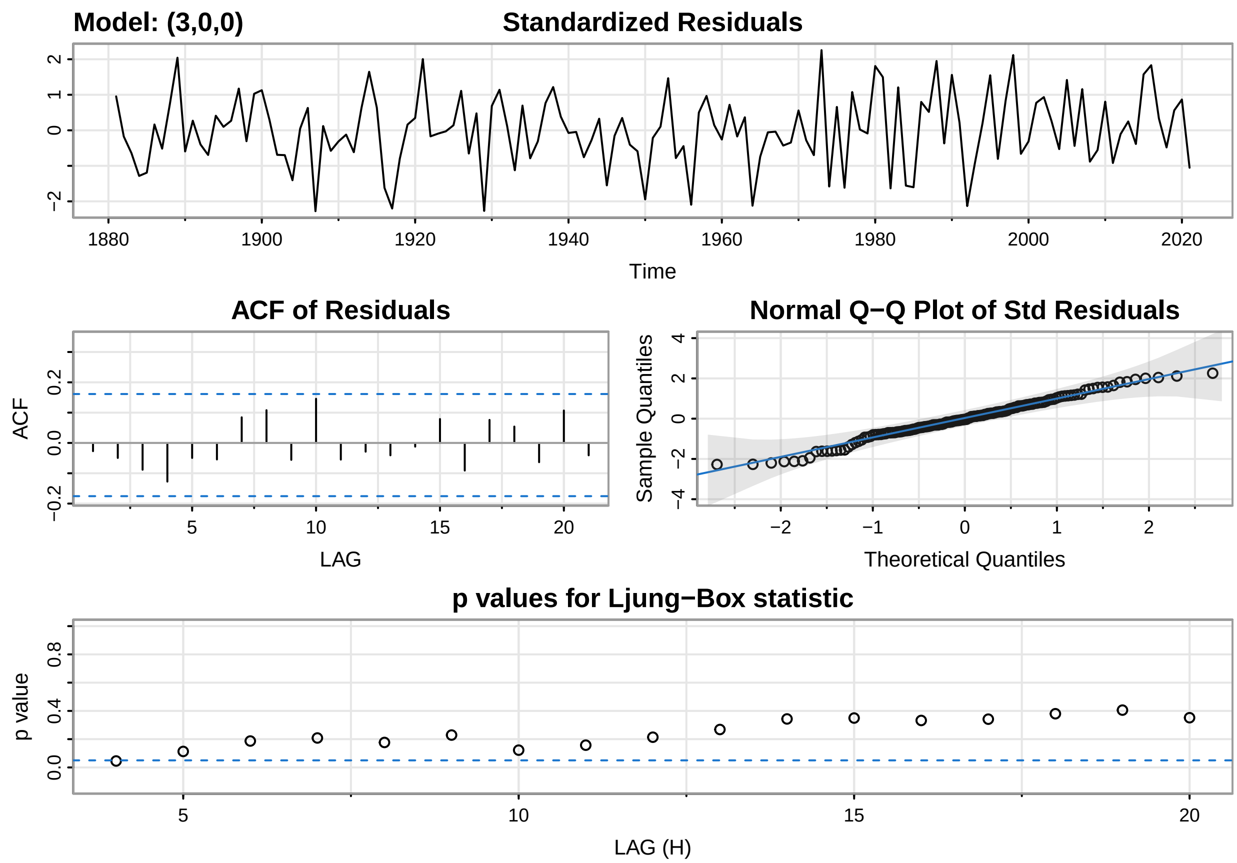


Figure 3: Residual analysis for the fitted ARMA(3,0) model

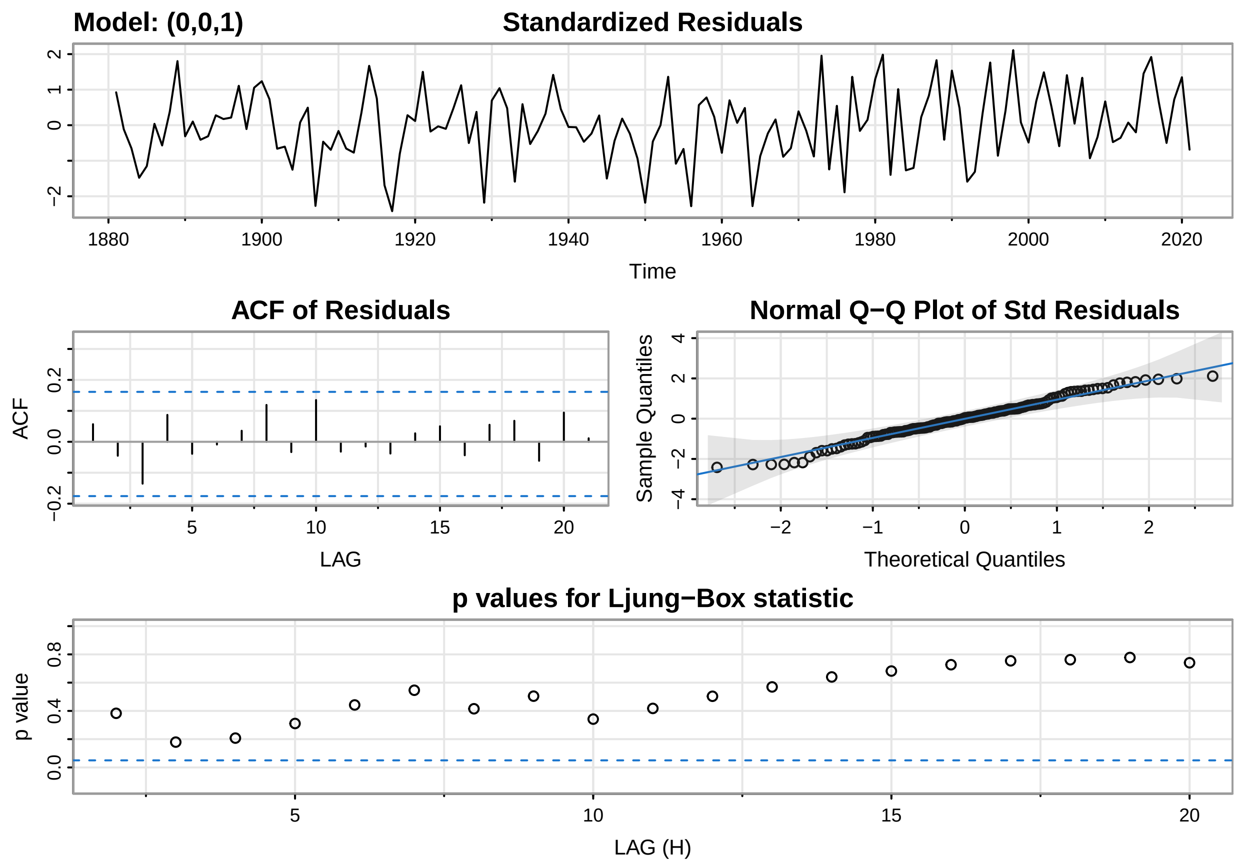


Figure 4: Residual analysis for the fitted ARMA(0,1) model

Model Choice Analysis

Results in 3 are presented for model comparison.

	AIC	AICc	BIC
ARMA(3,0)	-0.5982	-0.5962	-0.4937
ARMA(0,1)	-0.6195	-0.6189	-0.5568

Table 3: Performance metrics for ARMA models for the differenced land-based global temperature series

According to all three metrics, the ARMA(0,1) or MA(1) fit is preferred. The ARMA(3,0) is appears to fit the data quite well, however, for a more parsimonious model, we conclude that an ARMA(0,1) model for the differenced land-based global temperature series or an ARIMA(0,1,1) to the actual land-based gloval temperature series is most appropriate.

Forecasting

We then forecast the next 10 years land-based global temperature using the ARIMA(0,1,1) model selected as shown in Figure 5. The forecasts for the 10 years ahead were obtained as 1.387786, 1.401660, 1.415535, 1.429410, 1.443285 1.457160, 1.471035, 1.484910, 1.498784, and 1.512659. These forecasts are represented by the red circles in the Figure. We see that the forecasts increased with increasing years.

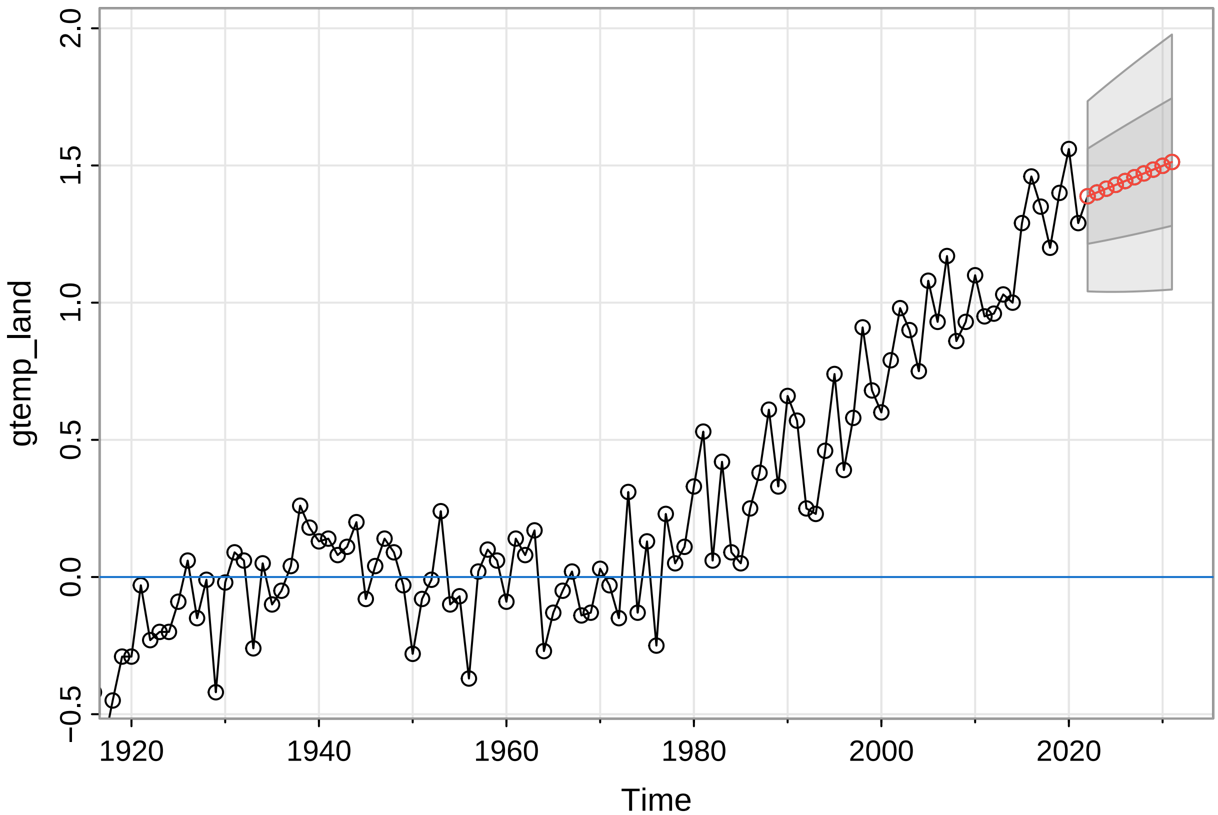


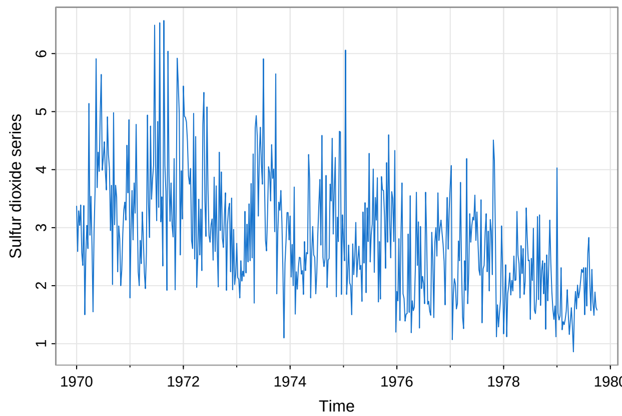
Figure 5: Next 10 years forecasts of the land-based global temperature series using the selected ARIMA(0,1,1) maodel

Problem 5.6

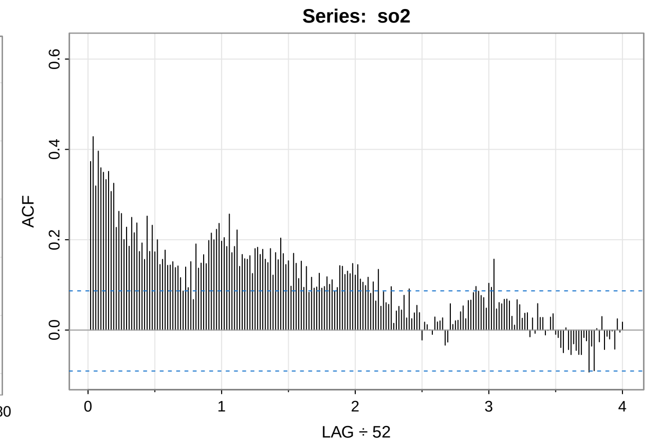
This problem considers the sulfur dioxide series, `so2` available in the `atsa` R package. The goal is to obtain an appropriate ARIMA(p, d, q) model for the series and then use the resulting model to forecast the data into the future four time periods ahead (about one month) and calculate 95% prediction intervals for each of the four forecasts.

As usual, we begin by exploring the series and performing some preliminary analysis to guide the whole model building process.

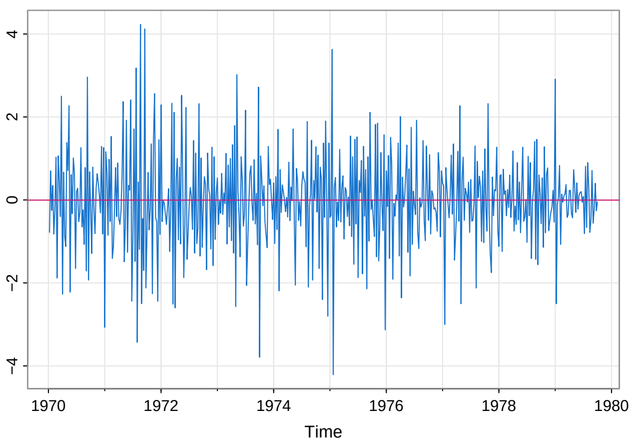
The differenced series looks like a stable process with zero mean. Look at the P/ACF plots, we can see that the ACF is cutting off at lag 3 and the PACF is tailing off. It is also reasonable to assume that the ACF tails off while the PACF cuts of at lags below 6.



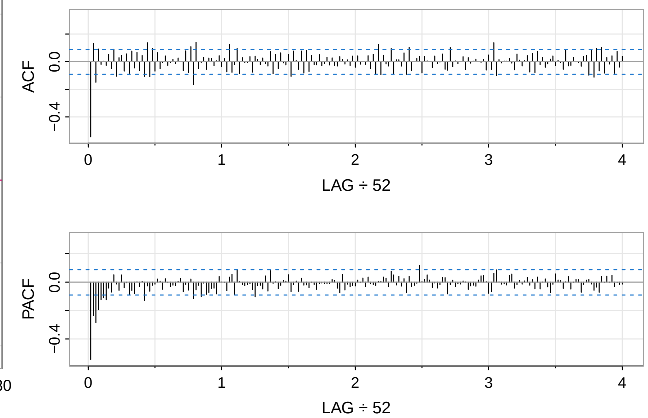
(a) Original sulfur series



(b) Sample ACF of the sulfur series



(c) Differenced sulfur series



(d) Sample ACF and PACF of the differenced series

Figure 6: Exploring the actual sulfur dioxide series and its first differenced series.

Parameter Estimation

The foregoing analysis suggested three candidate models, ARMA(3,0) or AR(3), ARMA(0,1) or MA(1) and ARMA(0,3) or MA(3) for the differenced series.

Results in Tables 4 and 5 and show that all the regression coefficients excluding the constant term are significant (associated p-values are less than 5%). However, for the ARMA(0,3) model, only the MA1 parameter is significant (See 6). The non-significant constant terms shows that the mean of the series is zero as we observed from the time series plot of the differenced data.

	Estimate	SE	t.value	p.value
Coefficients				
AR1	-0.7389	0.0426	-17.3624	0.000
AR2	-0.4256	0.0503	-8.4679	0.000
AR3	-0.2836	0.0425	-6.6791	0.000
Constant	-0.0029	0.0167	-0.1714	0.864
Performance metrics				
Sigma^2	0.8421			
AIC	2.6871			
AICc	2.6873			
BIC	2.7288			

Table 4: Parameter estimates for ARMA(3,0)

	Estimate	SE	t.value	p.value
Coefficients				
MA1	-0.8403	0.0275	-30.5410	0.0000
Constant	-0.0024	0.0063	-0.3801	0.7041
Performance metrics				
Sigma^2	0.7846			
AIC	2.6096			
AICc	2.6097			
BIC	2.6346			

Table 5: Parameter estimates for ARMA(0,1)

	Estimate	SE	t.value	p.value
Coefficients				
MA1	-0.8557	0.0450	-19.0244	0.0000
MA2	0.0790	0.0530	1.4912	0.1365
MA3	-0.0827	0.0490	-1.6883	0.0920
Constant	-0.0025	0.0056	-0.4431	0.6579
Performance metrics				
Sigma^2	0.7791			
AIC	2.6105			
AICc	2.6107			
BIC	2.6522			

Table 6: Parameter estimates for ARMA(0,3)

Residual Diagnostics

Figures 7, 8, and 9 show residual analysis for the three candidate models considered.

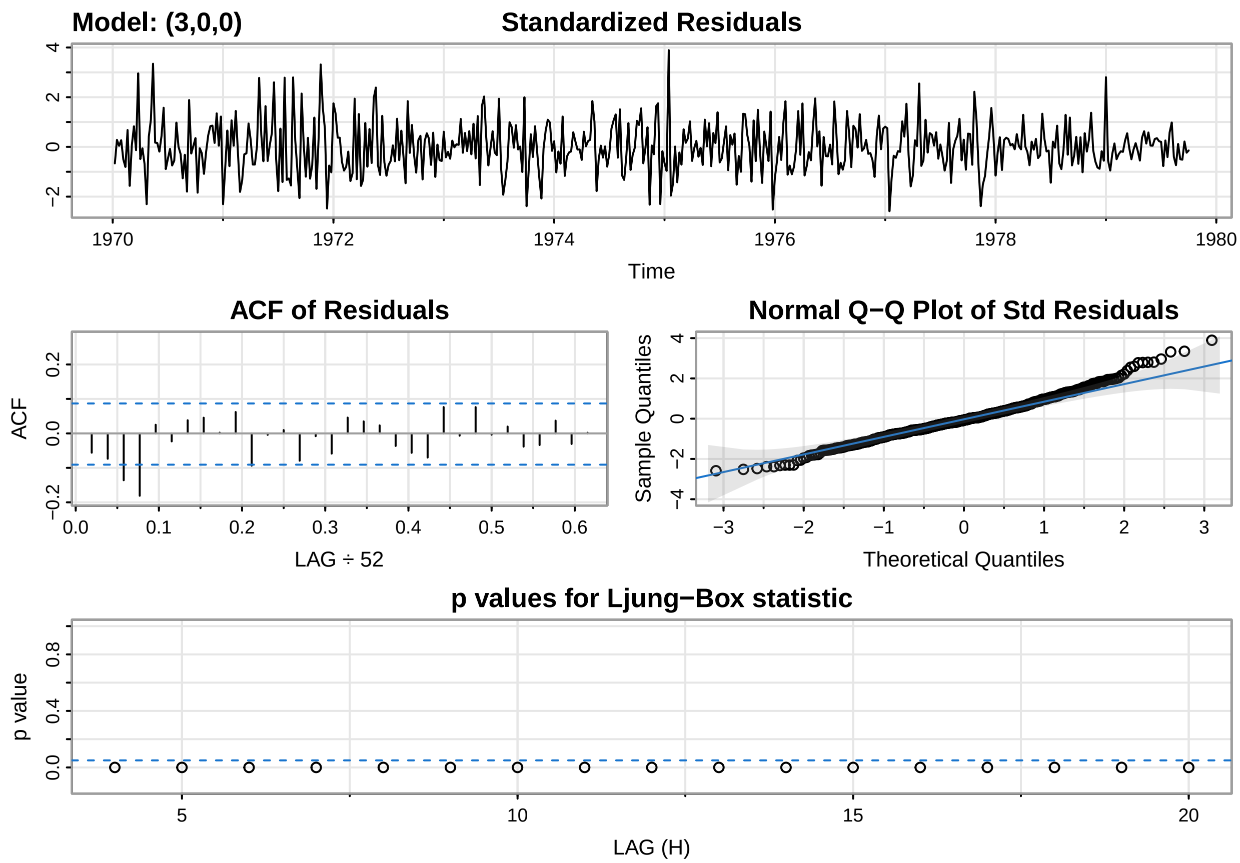


Figure 7: Residual analysis for the fitted ARMA(3,0) model

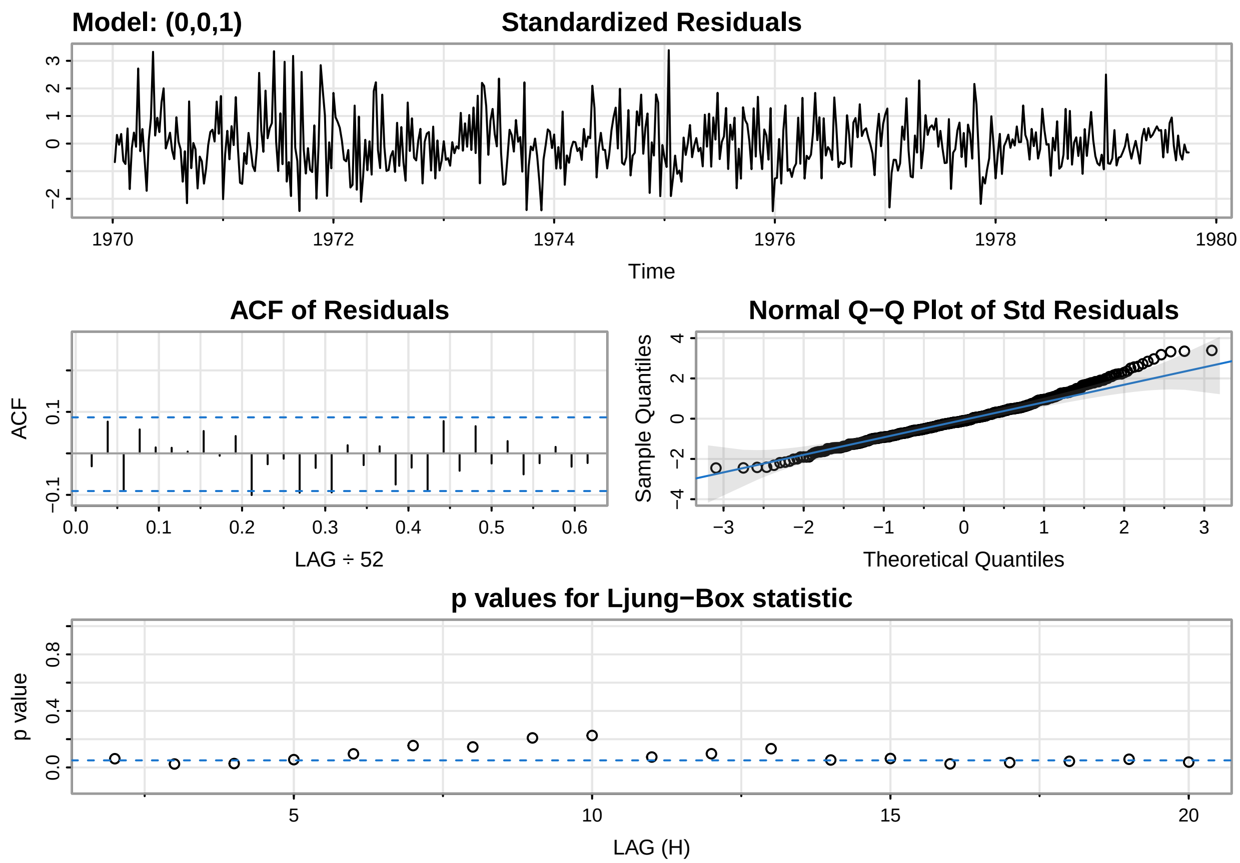


Figure 8: Residual analysis for the fitted ARMA(0,1) model

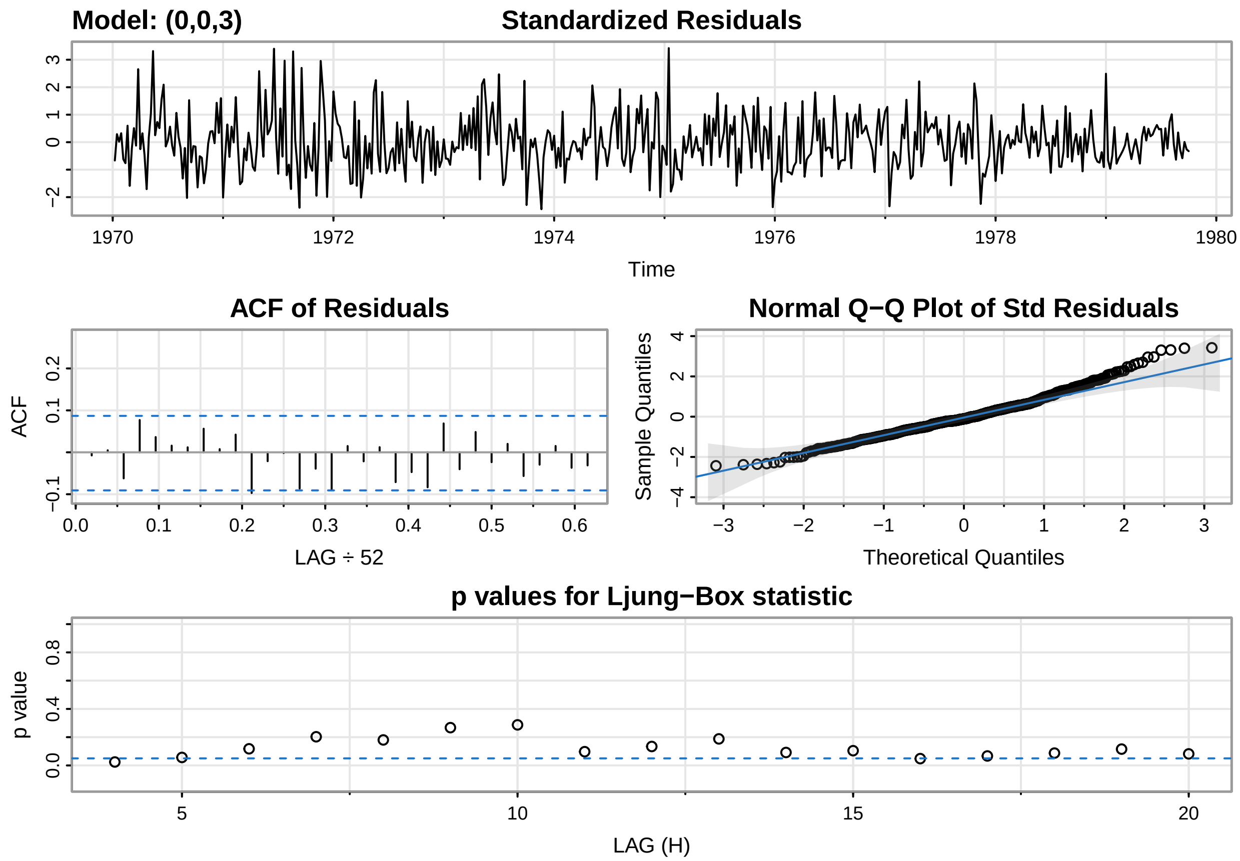


Figure 9: Residual analysis for the fitted ARMA(0,3) model

The residuals analysis for the two MA models to the differenced data look much decent compared to those for the AR model. To account for possibly additional autocorrelation remaining, we added another MA parameters (q=2,3) but the results (not shown) were not substantially different.

Model Choice Analysis

	AIC	AICc	BIC
ARMA(3,0)	2.6871	2.6873	2.7288
ARMA(0,1)	2.6096	2.6097	2.6346
ARMA(0,3)	2.6105	2.6107	2.6522

Table 7: Performance metrics for ARMA models for the differenced land-based global temperature series

According to all three metrics, the ARMA(0,1) or MA(1) fit is preferred even though the performance are quite close among the three models. Thus, we conclude that an ARMA(0,1) model for the differenced sulfur dioxide series or an ARIMA(0,1,1) to the actual sulfur series is the best model.

Finally, we forecast the sulfur dioxide data into the future four time periods ahead (about one month) and calculate 95% prediction intervals for each of the four forecasts as shown in 10. Note that we fitted the selected model without a constant term because it was found to insignificant. The four forecasts are about the same with approximate value **1.83**, but with slight increase in variance as depicted by the 95% confidence band.

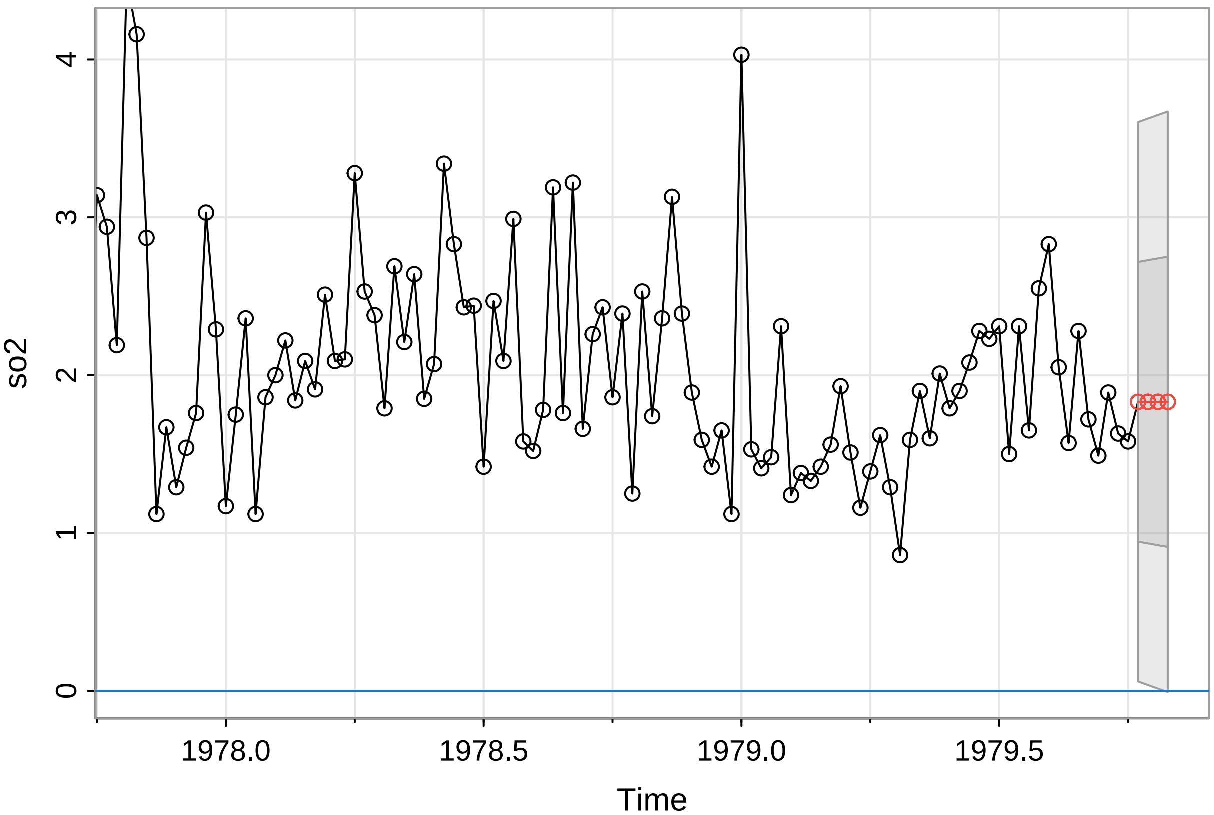
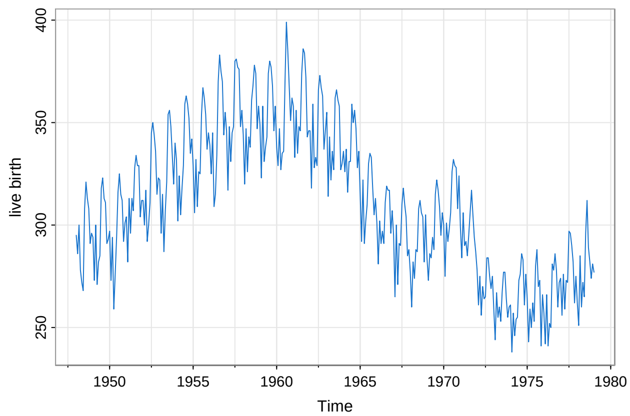


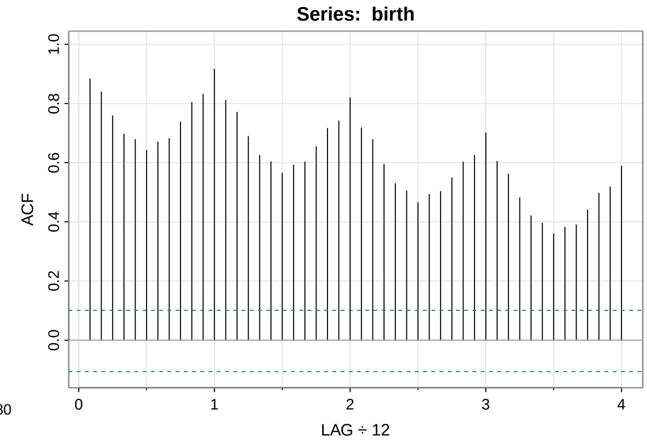
Figure 10: forecasts for the sulfur dioxide data into the future four time periods ahead (about one month) and calculated 95% prediction bands.

Problem 5.11

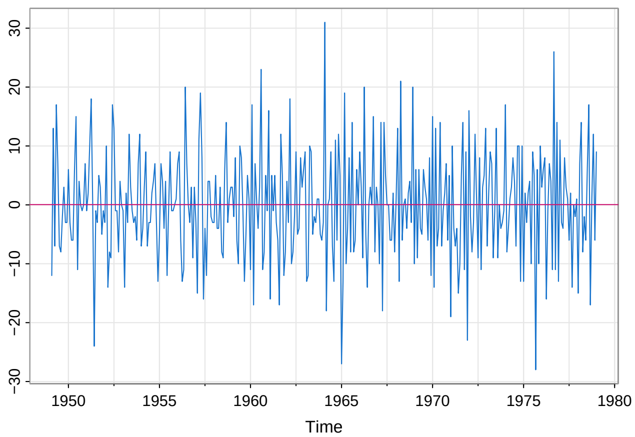
We aim to fit a seasonal ARIMA model to the U.S. Live Birth Series, `birth`, available in the `astsa` package. We begin the analysis with initial exploration of the data to help choose appropriate values for the parameters of the ARIMA model.



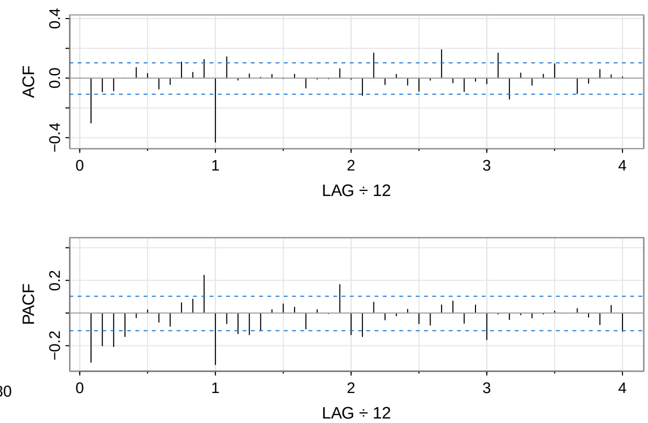
(a) Original Live Birth Series



(b) Sample ACF of the Live Birth series



(c) Differenced Live Birth series



(d) Sample ACF and PACF of the differenced series

Figure 11: Exploring the actual US Live Birth Series and its first differenced series.

Looking at the sample ACF and PACF of the differenced data at the first few lags, it appears as though the ACF is cuts off at lag 1, while the PACF is tailing off, suggesting an MA(1) within the seasons. Based on this result, an ARIMA(0,1,1) $\times(0,1,1)_{12}$ on the US Live Birth data appears to be a reasonable choice. Parameter estimates from a fit of the chosen model are given in 8.

	Estimate	SE	t.value	p.value
Coefficients				
MA1	-0.4734	0.0598	-7.9097	0
SMA1	-0.7861	0.0451	-17.4227	0
Sigma^2	47.4020			
Performance metrics				
AIC	6.7460			
AICc	6.7461			
BIC	6.7784			

Table 8: Parameter estimates model for the ARIMA(0,1,1)x(0,1,1) with S=12 on the differenced US Live Birth data.

The residual analysis displayed in Figure 12 look decent except that the p-values for Ljung-Box statistic fall slightly below the 5% significant level threshold.

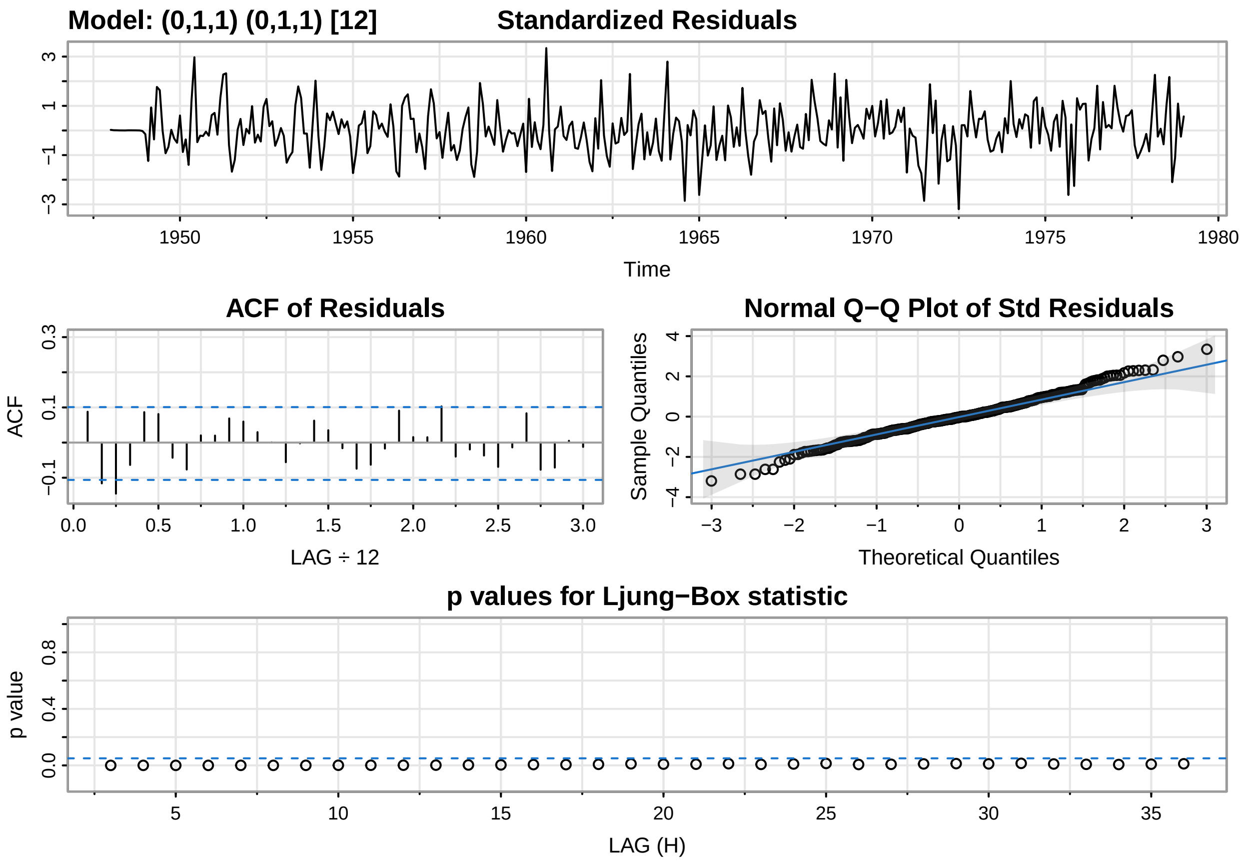
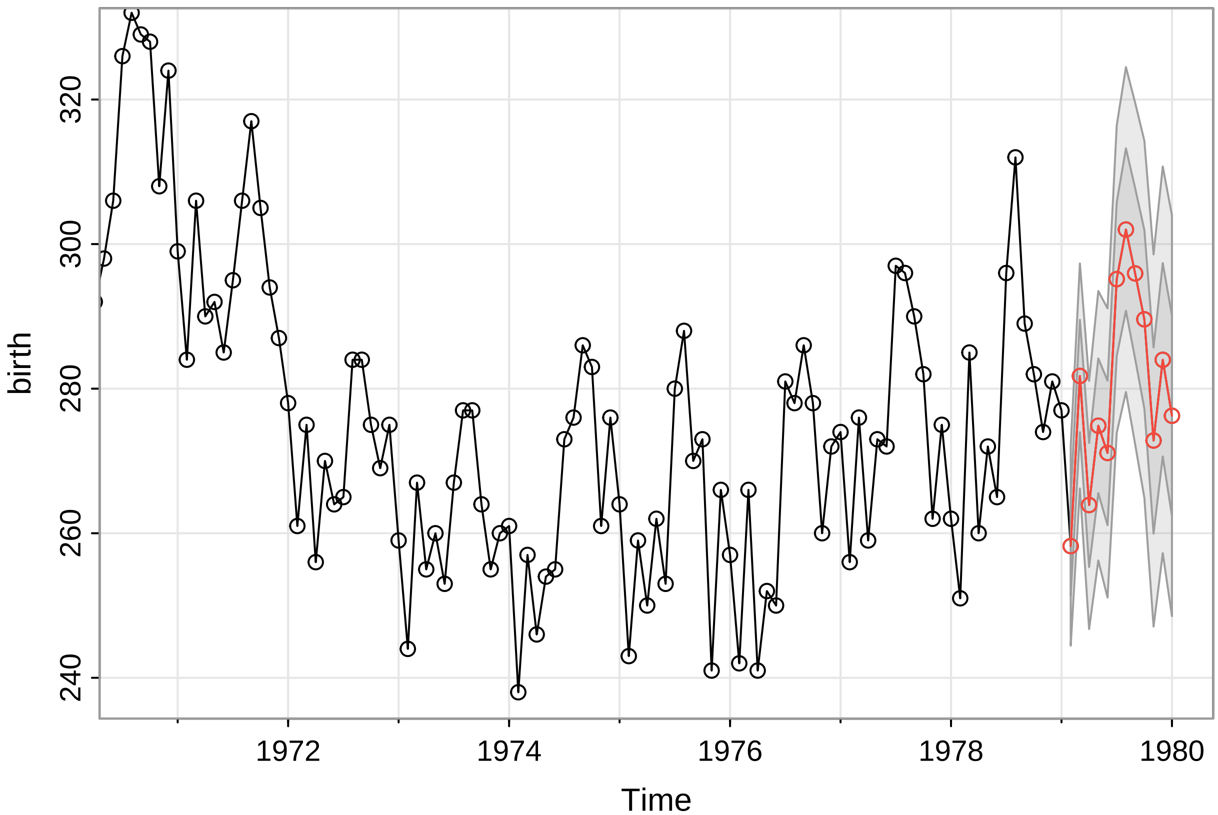


Figure 12: Residual analysis for the chosen seasonal ARIMA model

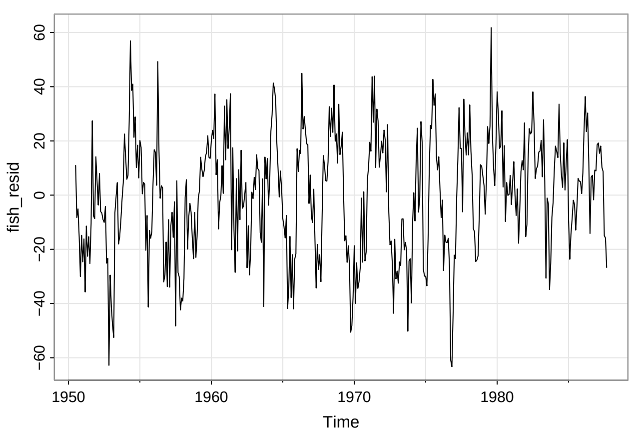
We now used the estimated model to forecast the next 12 months of live Births. The forecasts rise and fall over the 12 months.



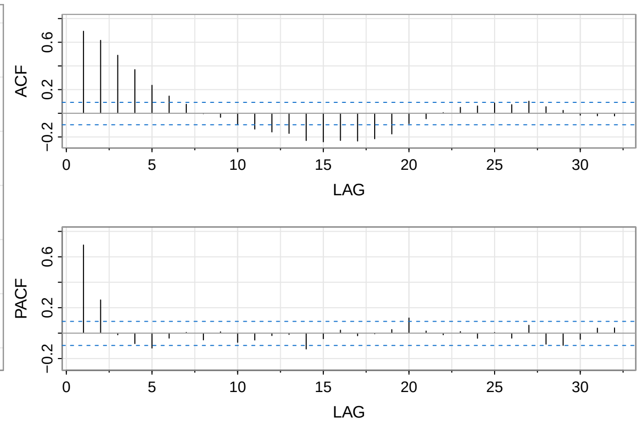
Problem 5.16

Part (a)

We fitted a dummy variable ordinary regression of recruitment. Plots of the sample ACF and PACF of the residuals are presented in 13, which indicate that an AR(2) model for the residual process might be appropriate since the ACF is tailing off and the PACF is cutting off after lag 2.



(a) Time series plot of the residuals



(b) Sample ACF and PACF

Figure 13: Sample ACF and PACF ofthe residuals from the OLS fit.

Part (b)

We fitted the dummy variable regression model assuming that the noise is correlated noise by fitting an AR(2) identified in part (a) for the residual process using `sarima()` from the `astsa` package.

The residual analysis results in Figure 13 looks good except for the presence of about two outliers (those observations in the standardized residuals plot exceeding 3 standard errors in magnitude). This signifies that the model adequately fit the data.

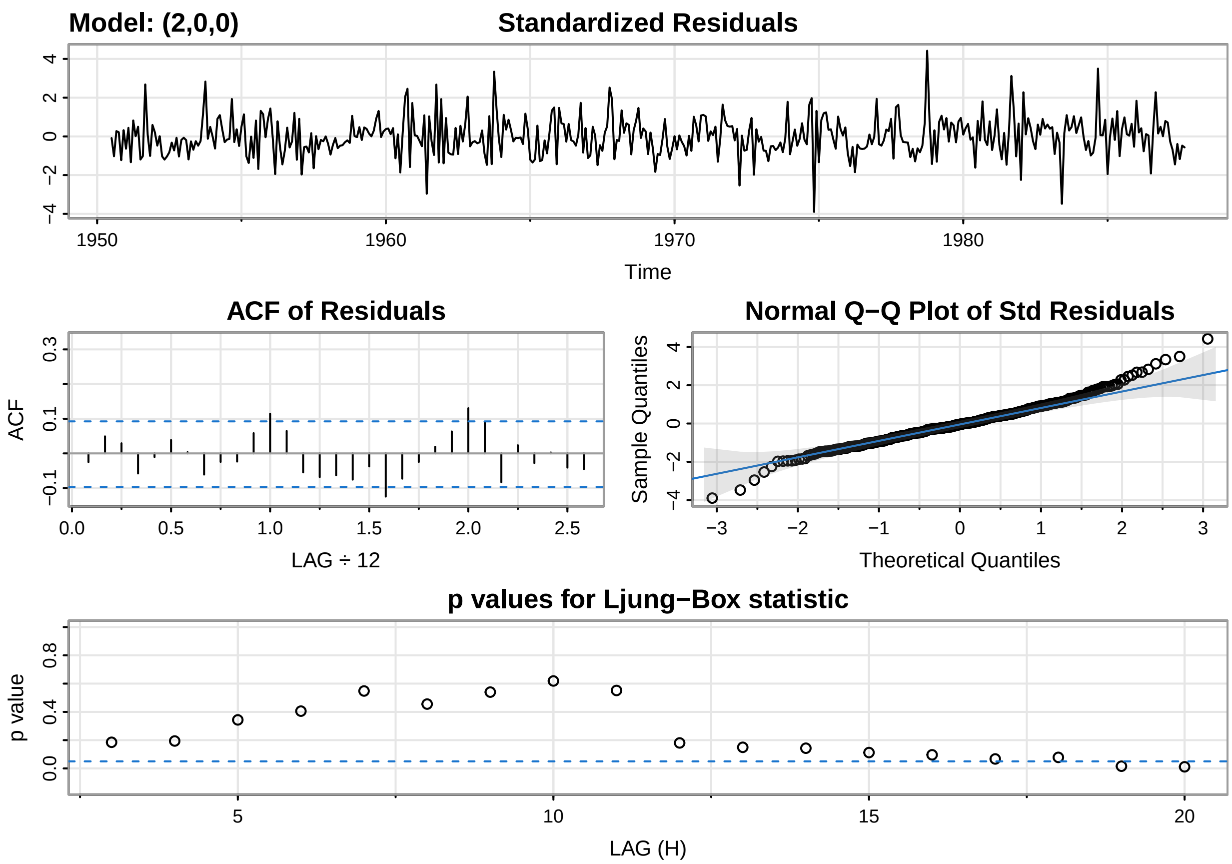


Figure 14: Residual analysis.

The parameter estimates with the corresponding standard errors are reported in Table 9. The noise variance (σ^2) was estimated as 89.8.

Comparing the results in Table 9 to the results of Example 3.14 in (Shumway and Stoffer 2019), we see that the estimates here have smaller standard errors (with the exception of the intercept), showing an improvement in performance over the initial model in EXample 3.14.

	Estimate	SE	t.value	p.value
AR1	1.3624	0.0440	30.9303	0.0000
AR2	-0.4703	0.0444	-10.5902	0.0000
Intercept	64.8028	4.1121	15.7590	0.0000
soiL6	8.6671	2.2205	3.9033	0.0001
dL6	-2.5945	0.9535	-2.7209	0.0068
soiL6 * dL6	-10.3092	2.8311	-3.6415	0.0003

Table 9: Parameter estimates for the dummy variable regression model with AR(2)

Part (c)

Here, we fitted a seasonal model of the form ARIMA(2,0,0)$\times(1,0,0)_{12}$ for the noise in the previous part and the parameter estimates for the model are displayed in 10. All the model parameters are statistically significant. The residual analysis shown in 15 look decent, indicating adequate model fit to the data.

	Estimate	SE	t.value	p.value
Coefficients				
AR1	1.3626	0.0437	31.1478	0.0000
AR2	-0.4660	0.0441	-10.5758	0.0000
SAR1	0.1222	0.0485	2.5200	0.0121
Intercept	64.4453	4.8162	13.3809	0.0000
soiL6	8.8235	2.1879	4.0330	0.0001
dL6	-2.4559	0.9516	-2.5808	0.0102
soiL6 * dL6	-9.7818	2.8182	-3.4710	0.0006
Performance metrics				
Sigma^2	85.5301			
AIC	7.3285			
BIC	7.4019			

Table 10: Parameter estimates

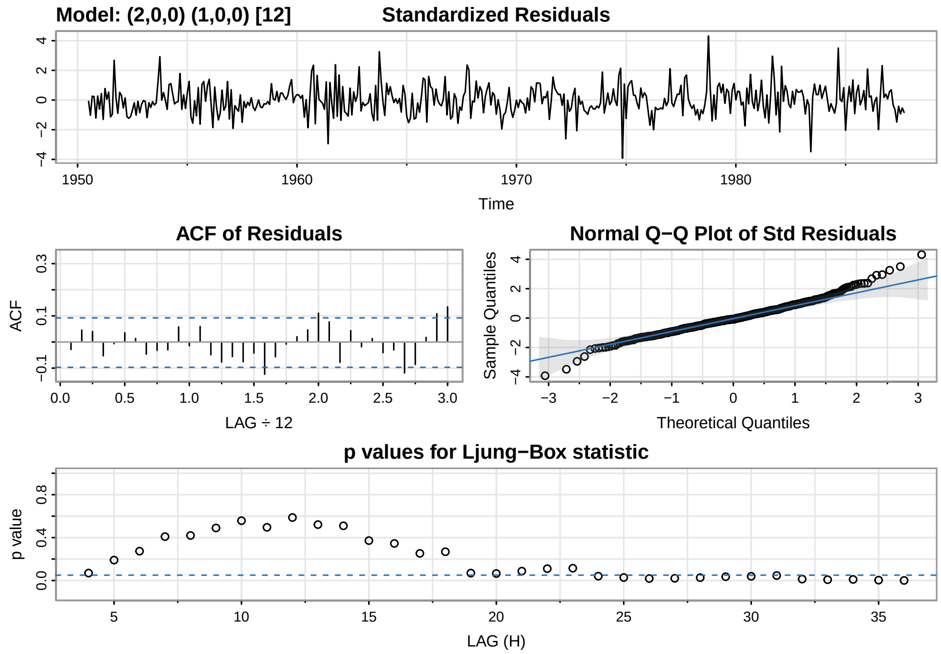


Figure 15: Sample ACF and PACF of the noise from part (b)

Appendix R Codes for the Analysis

```
# Set global options for output rendering
knitr::opts_chunk$set(eval = T, echo = F, warning = F, message = F,
                      fig.pos = "H", out.extra = "", fig.align = "center",
                      cache = F, comment="")

#----------------- Load required packages
# library(dplyr)
library(knitr)
library(kableExtra)
# library(broom)
library(stats)
library(astsa)


#----------------- set the current working directory to the file path
setwd(dirname(rstudioapi::getSourceEditorContext()$path))




##--------- Problem 5.4 codes

# plot the original series data
xt <- gtemp_land
tsplot(xt, col=4, ylab = "Prices in dollars per barrel")

sample_acf <- acf1(xt, main = "")

# plot of the first differenced series
xt_diff <- diff(xt)
tsplot(xt_diff, ylab = "growth rate", col = 4)
abline(h=mean(xt_diff), col=6)

sample_acf <- acf1(xt_diff, main = "")
sample_pacf <- acf1(xt_diff, pacf = T, main = "")
ar3 <- sarima(xt_diff, 3,0,0, details = F) # AR(3) on differenced series

# collect relevant model outputs into a table
result_tbl <- data.frame(rbind(
    ar3$ttable,
    c(ar3$fit$sigma2, rep(NA, 3)),
    c(ar3$AIC, rep(NA, 3)),
    c(ar3$AICc, rep(NA, 3)),
    c(ar3$BIC, rep(NA, 3))
))
rownames(result_tbl) <- c("AR1", "AR2", "AR3", "Constant", "Sigma^2", "AIC", "AICc", "BIC")

## display table of results
options(knitr.kable.NA='')  # suppress NAs from table output
result_tbl |>
    kable(booktabs=T, linesep="", align = "lcccc", digits=4,
          caption = "Parameter estimates and performance metrics for ARIMA(3,0,0)  on the land-based gl
    pack_rows("Coefficients", 1, 4) |>
```

```
    pack_rows("Performance metrics", 5, 8) |>
    kable_styling(latex_options = c("HOLD_position")) |>
    kable_classic()
ma1 <- sarima(xt_diff, 0,0,1, details = F) # MA(3) on differenced series

# collect relevant model outputs into a table
result_tbl <- data.frame(rbind(
    ma1$ttable,
    c(ma1$fit$sigma2, rep(NA, 3)),
    c(ma1$AIC, rep(NA, 3)),
    c(ma1$AICc, rep(NA, 3)),
    c(ma1$BIC, rep(NA, 3))
))
# rownames(result_tbl) <- c("MA1", "MA2", "MA3", "Constant", "Sigma^2", "AIC", "AICc", "BIC")
rownames(result_tbl) <- c("MA1", "Constant", "Sigma^2", "AIC", "AICc", "BIC")


## display table of results
options(knitr.kable.NA='')  # suppress NAs from table output
result_tbl |>
    kable(booktabs=T, linesep="", align = "lcccc", digits=4,
          caption = "Parameter estimates and performance metrics for ARIMA(0,0,1)  on the land-based gl
    pack_rows("Coefficients", 1, 2) |>
    pack_rows("Performance metrics", 3, 6) |>
    kable_styling(latex_options = c("HOLD_position")) |>
    kable_classic()
ar32 <- capture.output(sarima(xt_diff, 3,0,0)) # suppress convergence output


ma12 <- capture.output(sarima(xt_diff, 0,0,1))

# collect relevant model outputs into a table
result_tbl <- data.frame(rbind(

    c(ar3$AIC, ar3$AICc, ar3$BIC),
    c(ma1$AIC, ma1$AICc, ma1$BIC)
))
names(result_tbl) <- c("AIC", "AICc", "BIC")
rownames(result_tbl) <- c("ARMA(3,0)", "ARMA(0,1)")

## display table of results
result_tbl |>
    kable(booktabs=T, linesep="", align = "ccc", digits=4,
          caption = "Performance metrics for ARMA models for the differenced land-based global temperat
    kable_styling(latex_options = c("HOLD_position")) |>
    kable_classic()
gtemp_land_for <- sarima.for(gtemp_land, n.ahead=10, 0,1,1, no.constant = F)
abline(h=0, col=4) # display the zero mean

##--------- Problem 5.6 codes

# plot the original series data
```

```r
tsplot(so2, col=4, ylab = "Sulfur dioxide series")

sample_acf <- acf1(so2)

# plot of the first differenced series
so2_diff <- diff(so2)
tsplot(so2_diff, ylab = "", col = 4)
abline(h=mean(so2_diff), col=6)


par(mfrow=c(2,1))
sample_acf <- acf1(so2_diff, main = "")
sample_pacf <- acf1(so2_diff, pacf = T, main = "")

ar3 <- sarima(so2_diff, 3,0,0, details = F, no.constant = F) # AR(3) on differenced series

# collect relevant model outputs into a table
result_tbl <- data.frame(rbind(
    ar3$ttable,
    c(ar3$fit$sigma2, rep(NA, 3)),
    c(ar3$AIC, rep(NA, 3)),
    c(ar3$AICc, rep(NA, 3)),
    c(ar3$BIC, rep(NA, 3))
))
rownames(result_tbl) <- c("AR1", "AR2", "AR3", "Constant", "Sigma^2", "AIC", "AICc", "BIC")

## display table of results
options(knitr.kable.NA='')  # suppress NAs from table output
result_tbl |>
    kable(booktabs=T, linesep="", align = "lcccc", digits=4,
          caption = "Parameter estimates for ARMA(3,0)", na="") |>
    pack_rows("Coefficients", 1, 4) |>
    pack_rows("Performance metrics", 5, 8) |>
    kable_styling(latex_options = c("HOLD_position")) |>
    kable_classic()

# try MA 1 or 2
arma04 <- sarima(so2_diff, 0,0,1, details = F, no.constant = F)

# collect relevant model outputs into a table
result_tbl <- data.frame(rbind(
    arma04$ttable,
    c(arma04$fit$sigma2, rep(NA, 3)),
    c(arma04$AIC, rep(NA, 3)),
    c(arma04$AICc, rep(NA, 3)),
    c(arma04$BIC, rep(NA, 3))
))
rownames(result_tbl) <- c("MA1", "Constant", "Sigma^2", "AIC", "AICc", "BIC")

## display table of results
options(knitr.kable.NA='')  # suppress NAs from table output
result_tbl |>
    kable(booktabs=T, linesep="", align = "lcccc", digits=4,
```

```
          caption = "Parameter estimates for ARMA(0,1)", na="") |>
    pack_rows("Coefficients", 1, 2) |>
    pack_rows("Performance metrics", 3, 6) |>
    kable_styling(latex_options = c("HOLD_position")) |>
    kable_classic()
arma05 <- sarima(so2_diff, 0,0,3, details = F, no.constant = F)

# collect relevant model outputs into a table
result_tbl <- data.frame(rbind(
    arma05$ttable,
    c(arma05$fit$sigma2, rep(NA, 3)),
    c(arma05$AIC, rep(NA, 3)),
    c(arma05$AICc, rep(NA, 3)),
    c(arma05$BIC, rep(NA, 3))
))
rownames(result_tbl) <- c("MA1", "MA2", "MA3", "Constant", "Sigma^2", "AIC", "AICc", "BIC")

## display table of results
options(knitr.kable.NA='')  # suppress NAs from table output
result_tbl |>
    kable(booktabs=T, linesep="", align = "lcccc", digits=4,
          caption = "Parameter estimates for ARMA(0,3)", na="") |>
    pack_rows("Coefficients", 1, 4) |>
    pack_rows("Performance metrics", 5, 8) |>
    kable_styling(latex_options = c("HOLD_position")) |>
    kable_classic()

ar32 <- capture.output(sarima(so2_diff, 3,0,0)) # suppress convergence output
arma042 <- capture.output(sarima(so2_diff, 0,0,1))
arma052 <- capture.output(sarima(so2_diff, 0,0,3))
# collect relevant model outputs into a table
result_tbl <- data.frame(rbind(

    c(ar3$AIC, ar3$AICc, ar3$BIC),
    c(arma04$AIC, arma04$AICc, arma04$BIC),
    c(arma05$AIC, arma05$AICc, arma05$BIC)
))

names(result_tbl) <- c("AIC", "AICc", "BIC")
rownames(result_tbl) <- c("ARMA(3,0)", "ARMA(0,1)", "ARMA(0,3)")

## display table of results
result_tbl |>
    kable(booktabs=T, linesep="", align = "ccc", digits=4,
          caption = "Performance metrics for ARMA models for the differenced land-based global temperatu
    kable_styling(latex_options = c("HOLD_position")) |>
    kable_classic()
arma04_for <- sarima.for(so2, n.ahead=4, 0,1,1, details = F, no.constant = T)
abline(h=0, col=4) # display the zero mean

##--------- Problem 5.11 codes

# plot the original series data
```

```
tsplot(birth, col=4, ylab = "live birth")

sample_acf <- acf1(birth)

# plot of the first differenced series
birth_diff <- diff(birth)
birth_diff <- diff(diff(birth, 12))
tsplot(birth_diff, ylab = "", col = 4)
abline(h=mean(birth_diff), col=6)


par(mfrow=c(2,1))
sample_acf <- acf1(birth_diff, main = "")
sample_pacf <- acf1(birth_diff, pacf = T, main = "")

sarima_mod <- sarima(birth, p=0,d=1,q=1, P=0, D=1, Q=1, S=12, details = F) #p=1,P=1, (0,1)


# collect relevant model outputs into a table
result_tbl <- data.frame(rbind(
    sarima_mod$ttable,
    c(sarima_mod$fit$sigma2, rep(NA, 3)),
    c(sarima_mod$AIC, rep(NA, 3)),
    c(sarima_mod$AICc, rep(NA, 3)),
    c(sarima_mod$BIC, rep(NA, 3))
))
rownames(result_tbl) <- c("MA1", "SMA1", "Sigma^2", "AIC", "AICc", "BIC")

## display table of results
options(knitr.kable.NA='')  # suppress NAs from table output
result_tbl |>
    kable(booktabs=T, linesep="", align = "lcccc", digits=4,
          caption = "Parameter estimates model for the ARIMA(0,1,1)x(0,1,1) with S=12 on the difference
    pack_rows("Coefficients", 1, 3) |>
    pack_rows("Performance metrics", 4, 6) |>
    kable_styling(latex_options = c("HOLD_position")) |>
    kable_classic()

dd <- capture.output(sarima(birth, p=0,d=1,q=1, P=0, D=1, Q=1, S=12))
sarima_for <- sarima.for(birth, 12, p=0,d=1,q=1, P=0, D=1, Q=1, S=12)

#---------- Problem 5.6 codes

library(zoo)
dummy = ifelse(soi<0, 0, 1)
fish <- as.zoo(ts.intersect(rec, soiL6=lag(soi,-6), dL6=lag(dummy,-6)))
fish_fit <- lm(rec~ soiL6*dL6, data=fish, na.action=NULL)
# summary(fish_fit)
fish_resid <- resid(fish_fit)

tsplot(time(fish), fish_resid)
sample_acf <- acf2(fish_resid, main = "")
# sample_pacf <- acf1(fish_resid, pacf = T)
```

```
soiL6 <- fish$soiL6
dL6 <- fish$dL6
dd<-capture.output(sarima(fish$rec, 2, 0, 0, xreg = cbind(soiL6, dL6, soiL6*dL6)))
cor_mod <- sarima(fish$rec, 2, 0, 0, xreg = cbind(soiL6, dL6, soiL6*dL6), details = F)
# collect relevant model outputs into a table
result_tbl <- data.frame(rbind(
    cor_mod$ttable
    # c(cor_mod$fit$sigma2, rep(NA, 3)),
    # c(cor_mod$AIC, rep(NA, 3)),
    # c(cor_mod$AICc, rep(NA, 3)),
    # c(cor_mod$BIC, rep(NA, 3))
))
rownames(result_tbl) <- c("AR1", "AR2", "Intercept", "soiL6", "dL6", "soiL6 * dL6")

## display table of results
options(knitr.kable.NA='')  # suppress NAs from table output
result_tbl |>
    kable(booktabs=T, linesep="", align = "lcccc", digits=4,
          caption = "Parameter estimates for the dummy variable regression model with AR(2)", na="") |>
    # pack_rows("Coefficients", 1, 4) |>
    # pack_rows("Performance metrics", 5, 8) |>
    kable_styling(latex_options = c("HOLD_position")) |>
    kable_classic()
sarima_mod2 <- sarima(fish$rec, 2, 0, 0, P=1, D=0, Q=0, S=12,
       xreg = cbind(soiL6, dL6, soiL6*dL6), details = F)

# collect relevant model outputs into a table
result_tbl <- data.frame(rbind(
    sarima_mod2$ttable,
    c(sarima_mod2$fit$sigma2, rep(NA, 3)),
    c(sarima_mod2$AIC, rep(NA, 3)),
    # c(sarima_mod2$AICc, rep(NA, 3)),
    c(sarima_mod2$BIC, rep(NA, 3))
))

rownames(result_tbl) <- c("AR1", "AR2", "SAR1", "Intercept", "soiL6", "dL6", "soiL6 * dL6", "Sigma^2",


## display table of results
options(knitr.kable.NA='')  # suppress NAs from table output
result_tbl |>
    kable(booktabs=T, linesep="", align = "lcccc", digits=4,
          caption = "Parameter estimates", na="") |>
    pack_rows("Coefficients", 1, 7) |>
    pack_rows("Performance metrics", 8, 10) |>
    kable_styling(latex_options = c("HOLD_position")) |>
    kable_classic()



dd <- capture.output(sarima(fish$rec, 2, 0, 0, P=1, D=0, Q=0, S=12,
       xreg = cbind(soiL6, dL6, soiL6*dL6)))
```

References

Shumway, Robert, and David Stoffer. 2019. *Time Series: A Data Analysis Approach Using r*. CRC Press.