Forcasting

2023-04-11

R Markdown

This is an R Markdown document. Markdown is a simple formatting syntax for authoring HTML, PDF, and MS Word documents. For more details on using R Markdown see http://rmarkdown.rstudio.com.

When you click the **Knit** button a document will be generated that includes both content as well as the output of any embedded R code chunks within the document. You can embed an R code chunk like this:

```
#Load/install required package here
library(lubridate)
```

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

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

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

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

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

```
## -- Attaching core tidyverse packages ------------------------ tidyverse 2.0.0 --
## v dplyr   1.1.0     v stringr 1.5.0
## v forcats 1.0.0     v tibble  3.2.1
## v purrr   1.0.1     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
```

```
library(smooth)
```

```
## Loading required package: greybox
## Package "greybox", v1.0.7 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", v3.2.0
```

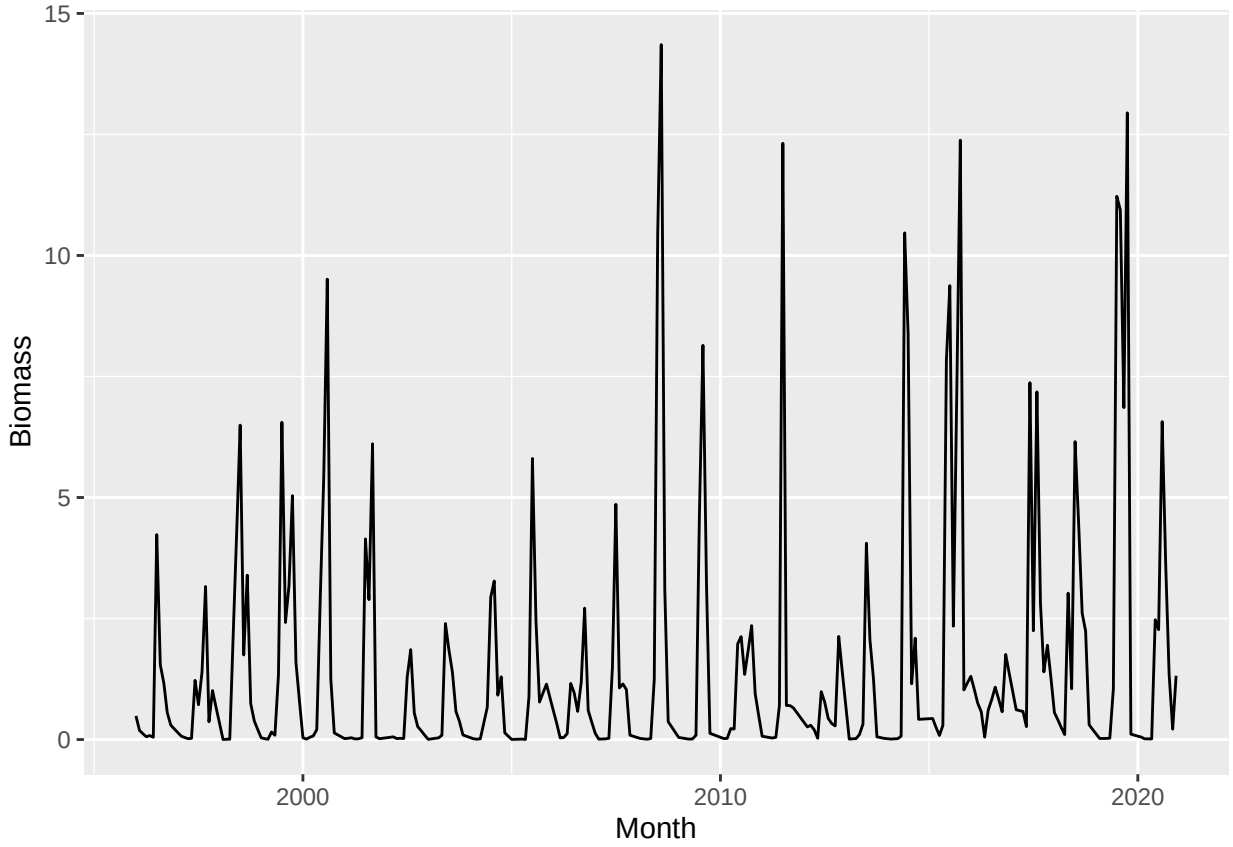
```
#New package for M9 to assist with tables
#install.packages("kableExtra")
library(kableExtra)
```

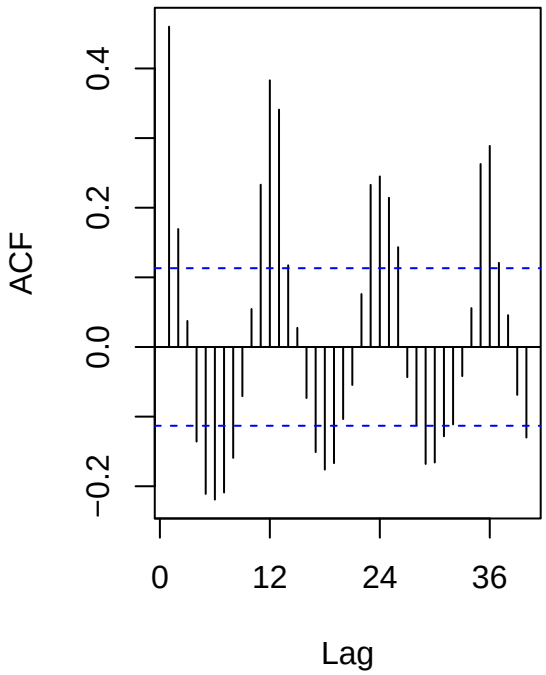
```
## Warning in !is.null(rmarkdown::metadata$output) && rmarkdown::metadata$output
## %in% : 'length(x) = 2 > 1' in coercion to 'logical(1)'
```

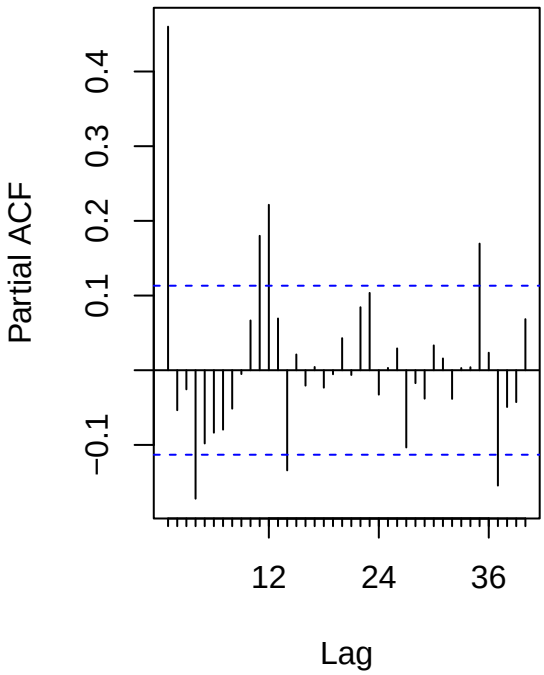
```
##
## Attaching package: 'kableExtra'
##
## The following object is masked from 'package:dplyr':
##
##     group_rows
```

Including Plots

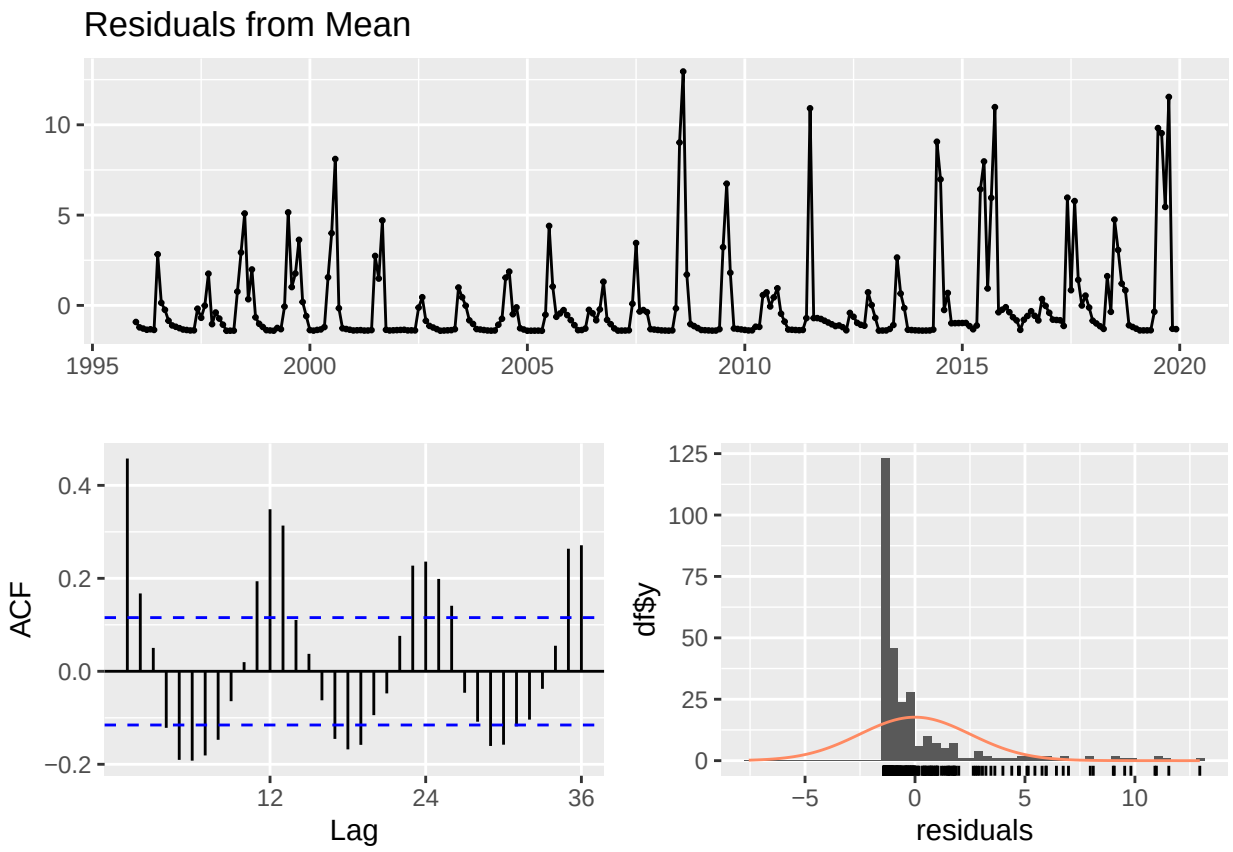
You can also embed plots, for example:







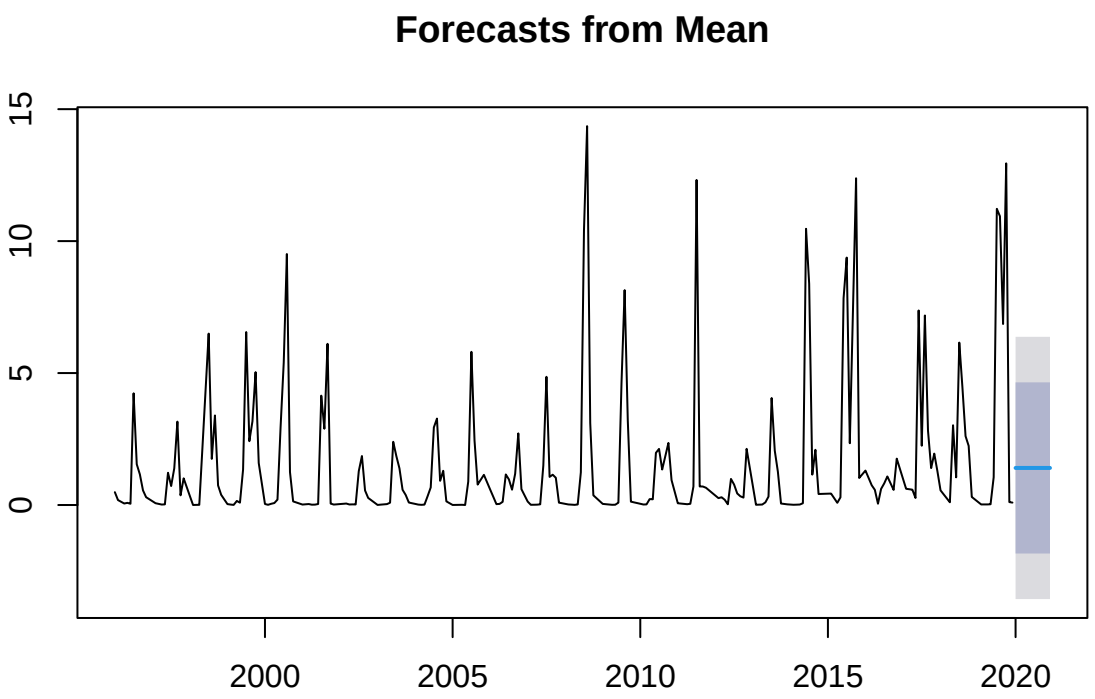

```
# Model 1: Arithmetic mean
# The meanf() has no holdout option
MEAN_seas <- meanf(y = ts_biomass, h = 12)
checkresiduals(MEAN_seas)
```



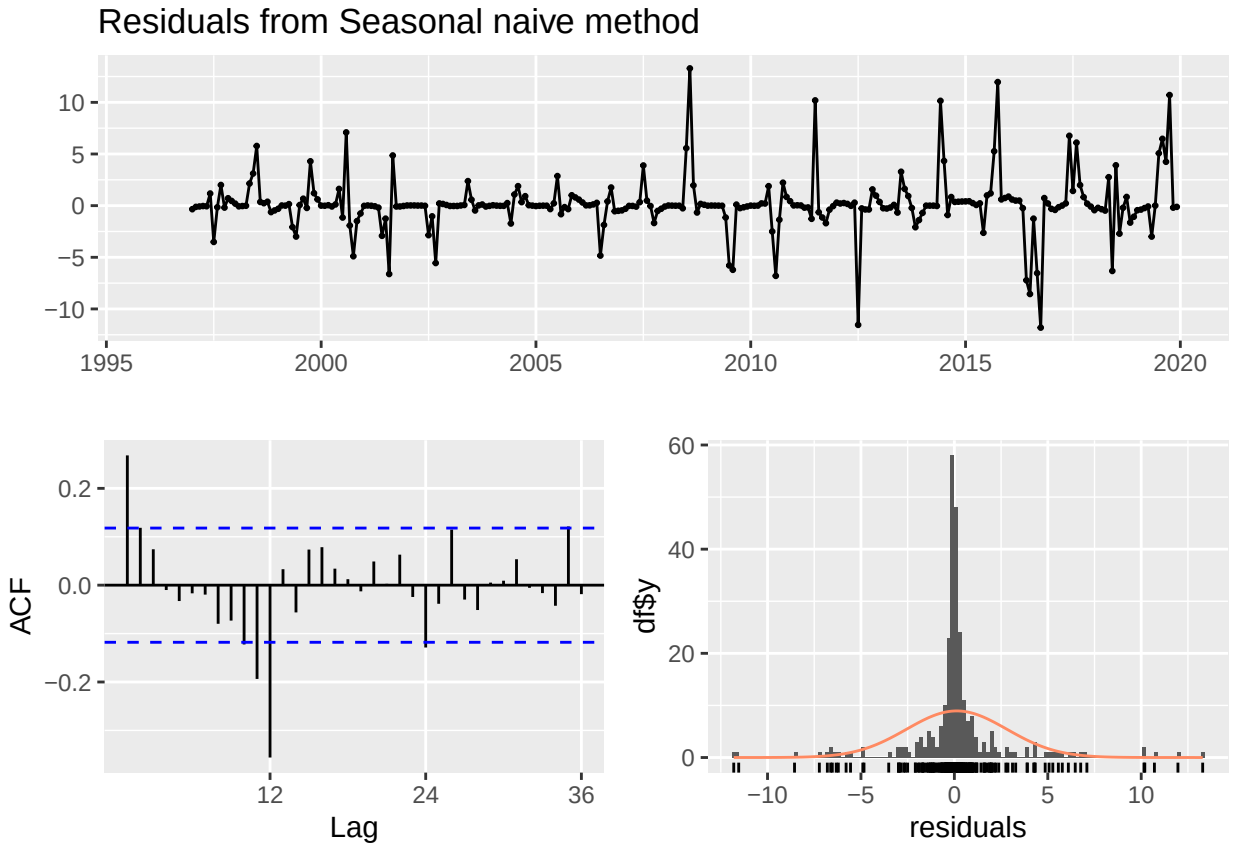

```
##
```

```
##  Ljung-Box test
##
## data:  Residuals from Mean
## Q* = 258.95, df = 23, p-value < 2.2e-16
##
## Model df: 1.   Total lags used: 24
```

```
plot(MEAN_seas)
```

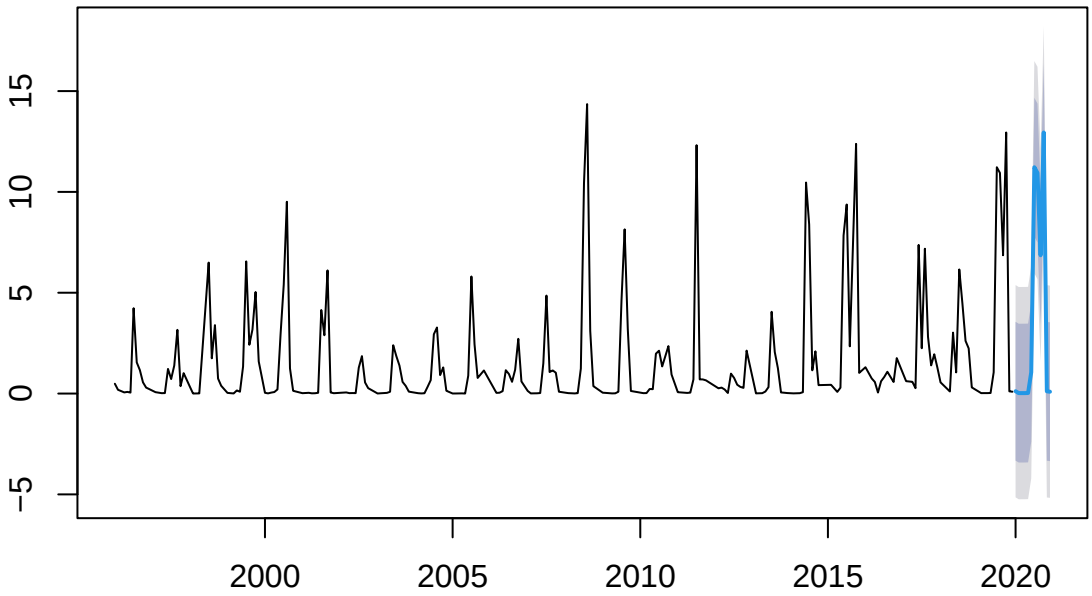



```
# Model 2: Seasonal naive
SNAIVE_seas <- snaive(ts_biomass, h=12, holdout=FALSE)
checkresiduals(SNAIVE_seas)
```

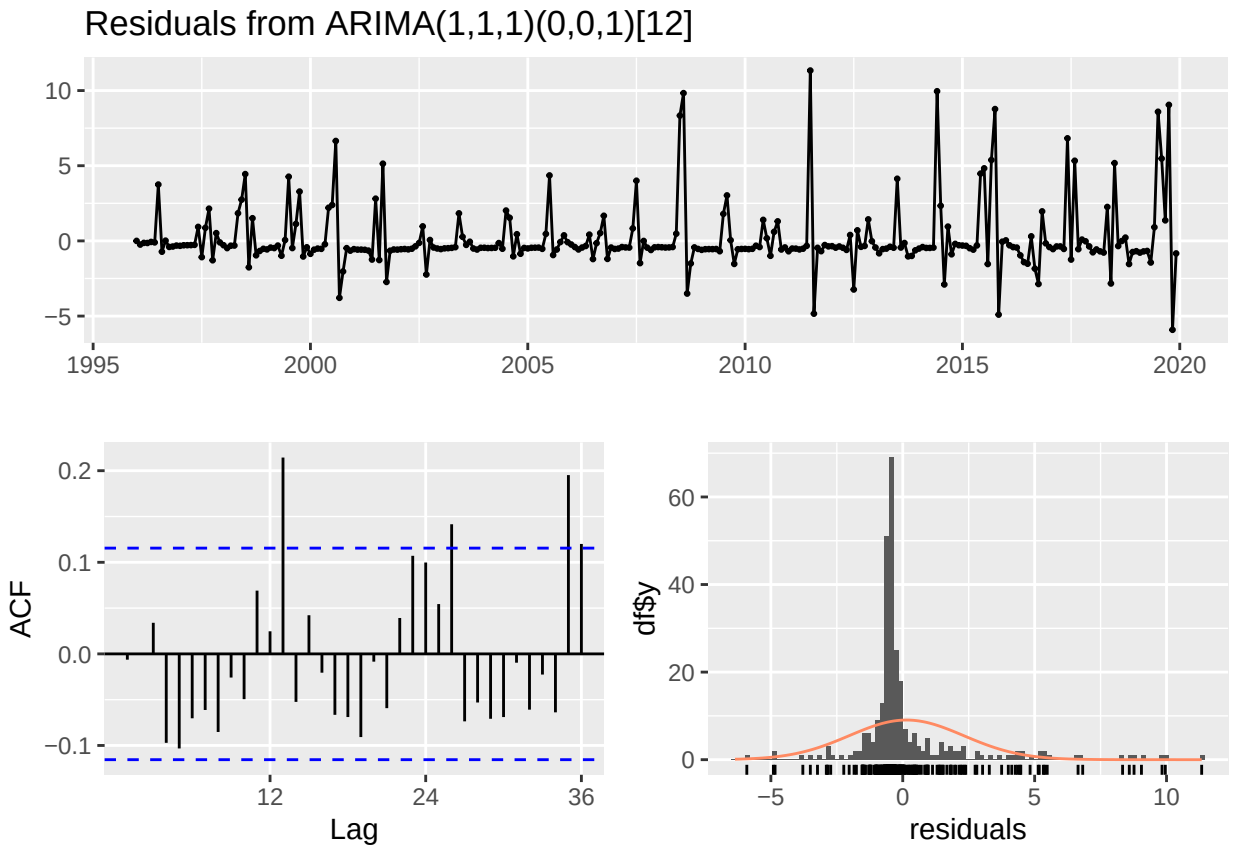



```
##
##  Ljung-Box test
##
## data:  Residuals from Seasonal naive method
## Q* = 93.651, df = 24, p-value = 3.556e-10
##
## Model df: 0.   Total lags used: 24
```

```
plot(SNAIVE_seas)
```



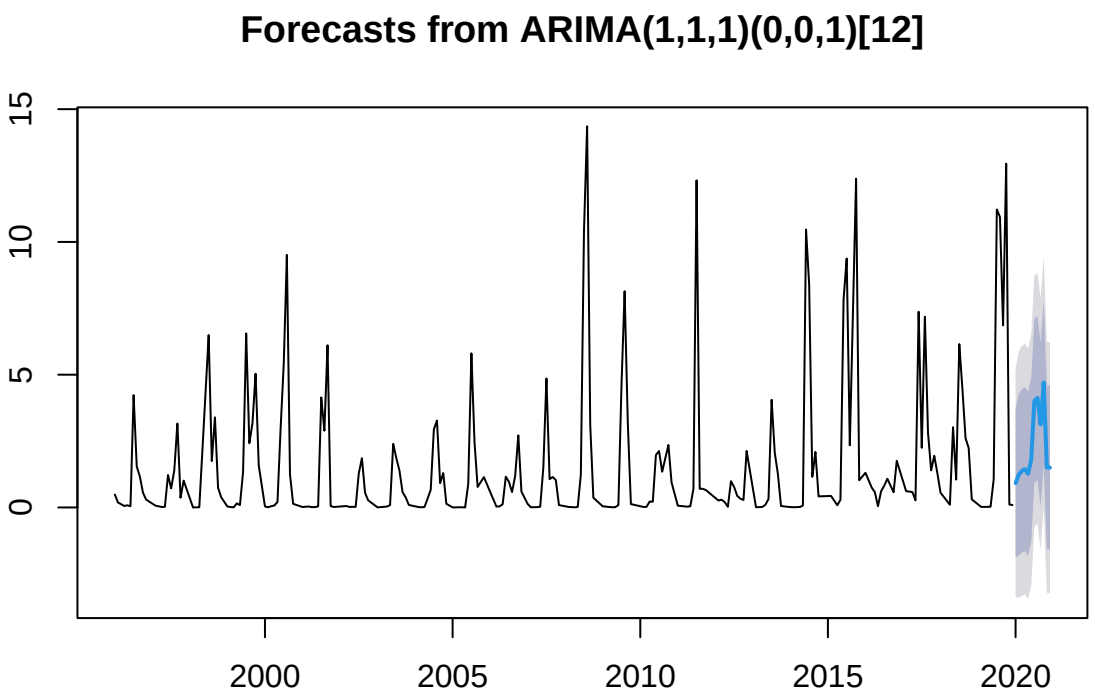

```
# Model 3: SARIMA

SARIMA_autofit <- auto.arima(ts_biomass)
checkresiduals(SARIMA_autofit)
```



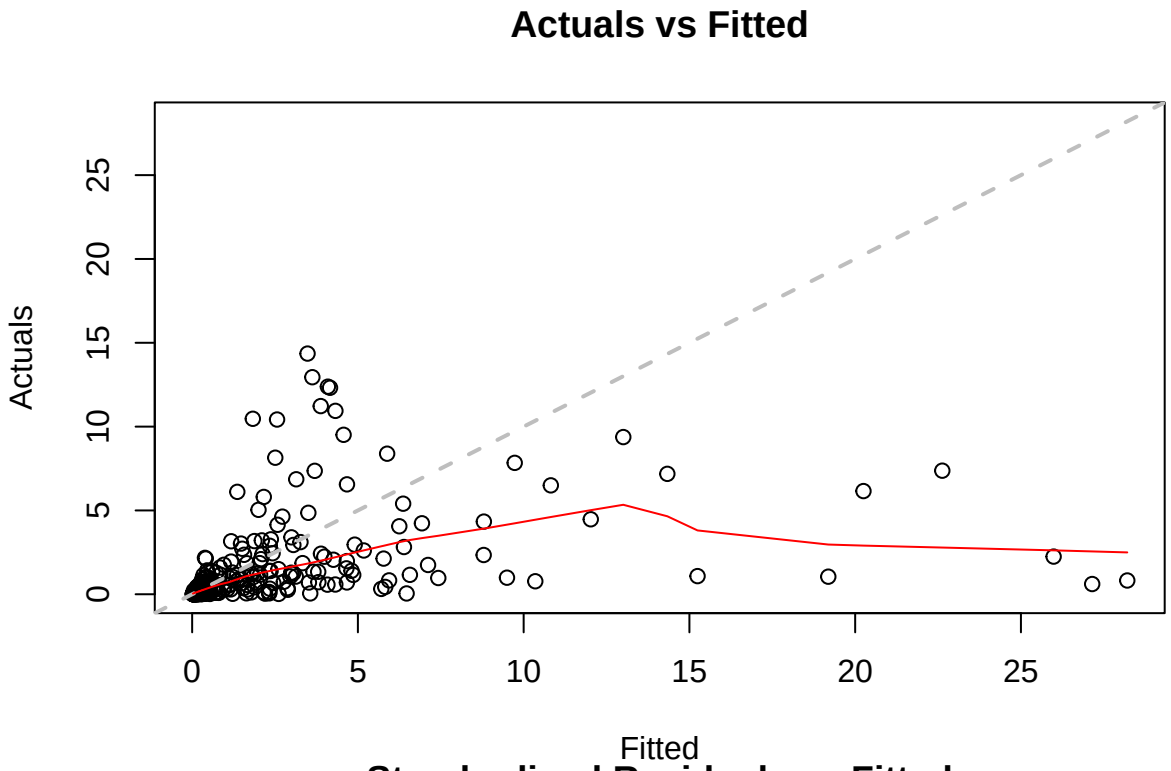

```
##
```

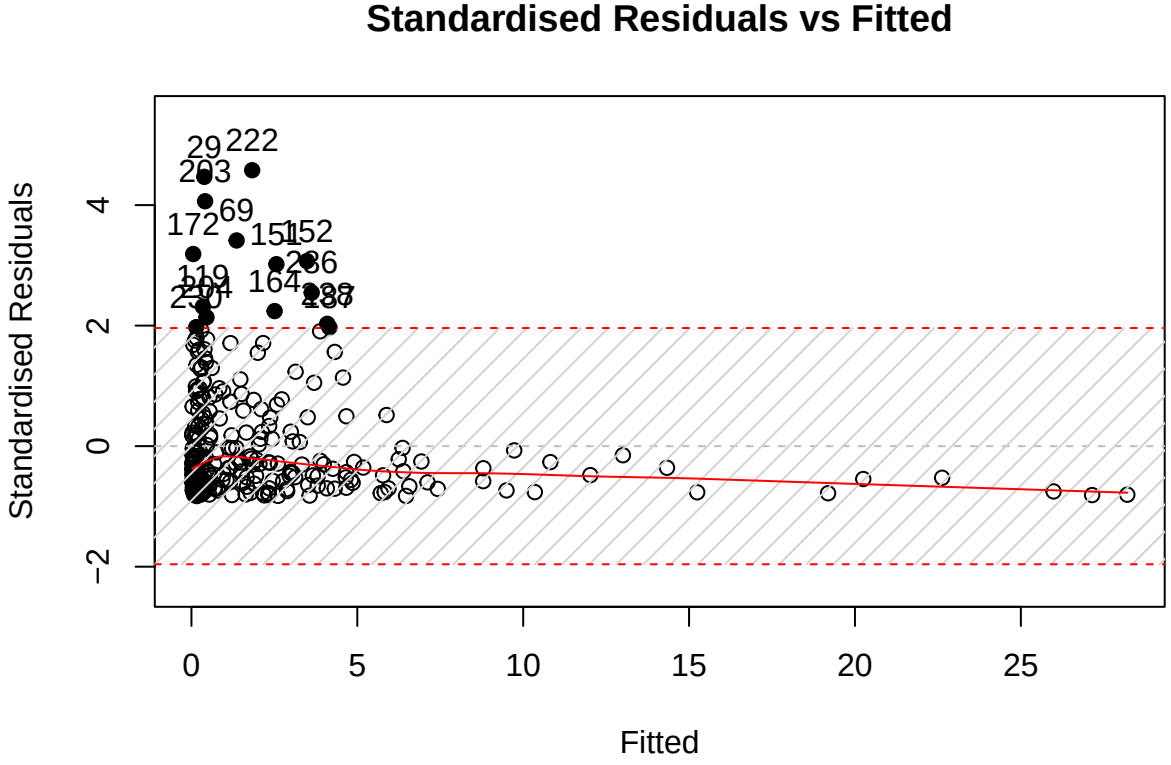
```
##  Ljung-Box test
##
## data:  Residuals from ARIMA(1,1,1)(0,0,1)[12]
## Q* = 42.8, df = 21, p-value = 0.003333
##
## Model df: 3.   Total lags used: 24
```

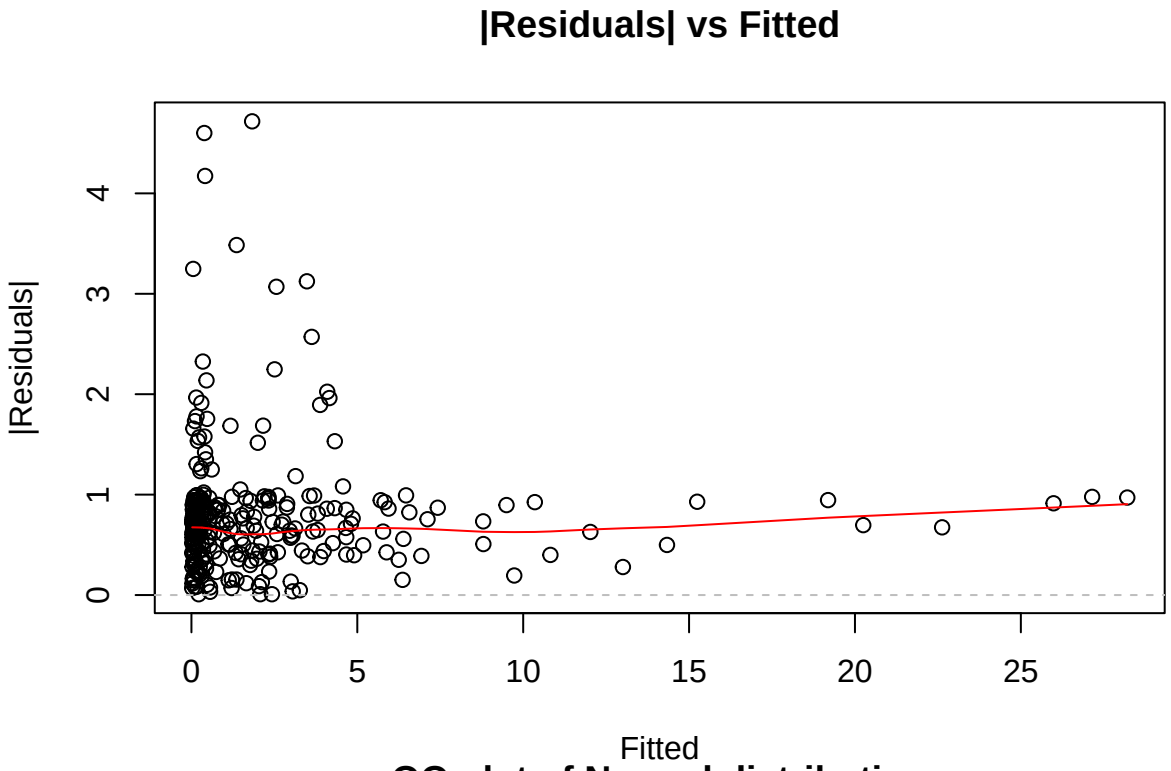
```
#Generating forecasts
#remember auto.arima does not call the forecast() internally so we need one more step
SARIMA_for <- forecast(SARIMA_autofit,h=12)
plot(SARIMA_for)
```

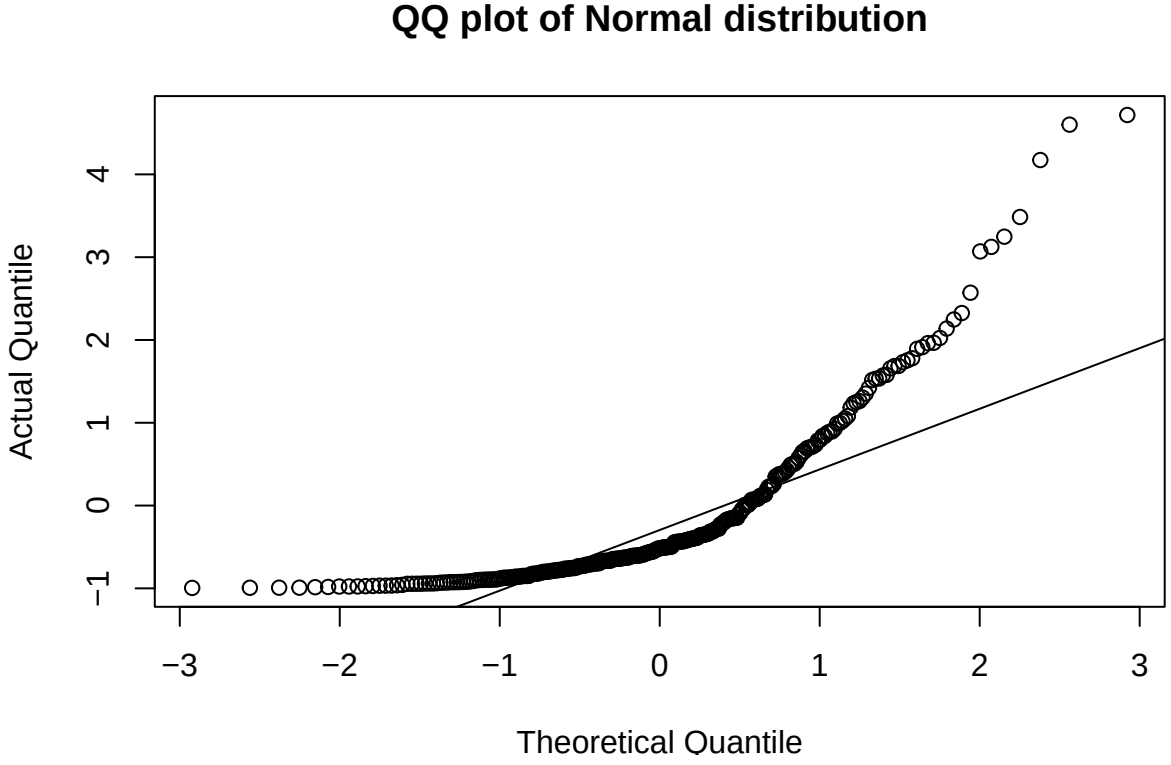



```
# Model 4: SS Exponential smoothing
SSES_seas <- es(ts_biomass,model="ZZZ",h=12,holdout=FALSE)
plot(SSES_seas)
```


Actuals vs Fitted
Actuals
Fitted
0
5
10
15
20
25

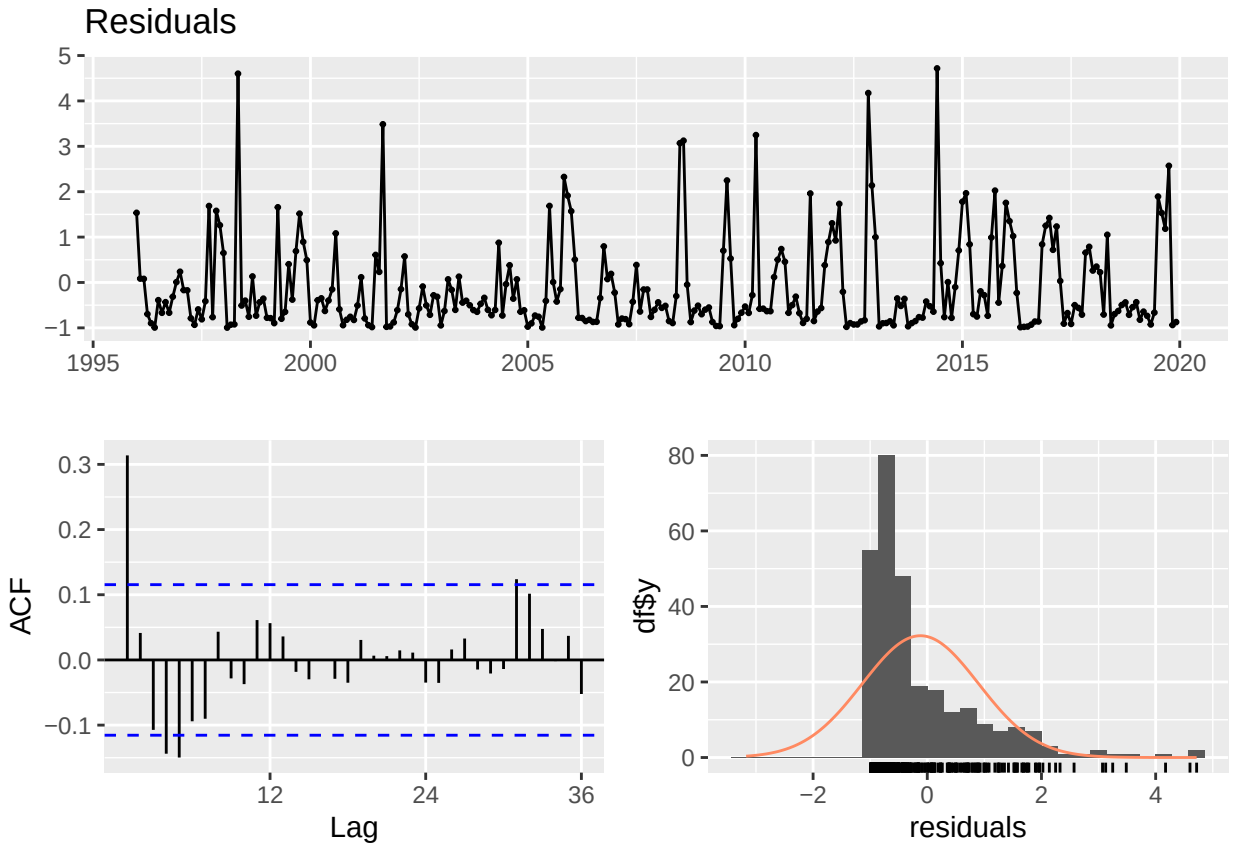

Standardised Residuals vs Fitted
Standardised Residuals
Fitted
−2
0
2
4
0
5
10
15
20
25
29
222
203
69
172
151
152
119
164





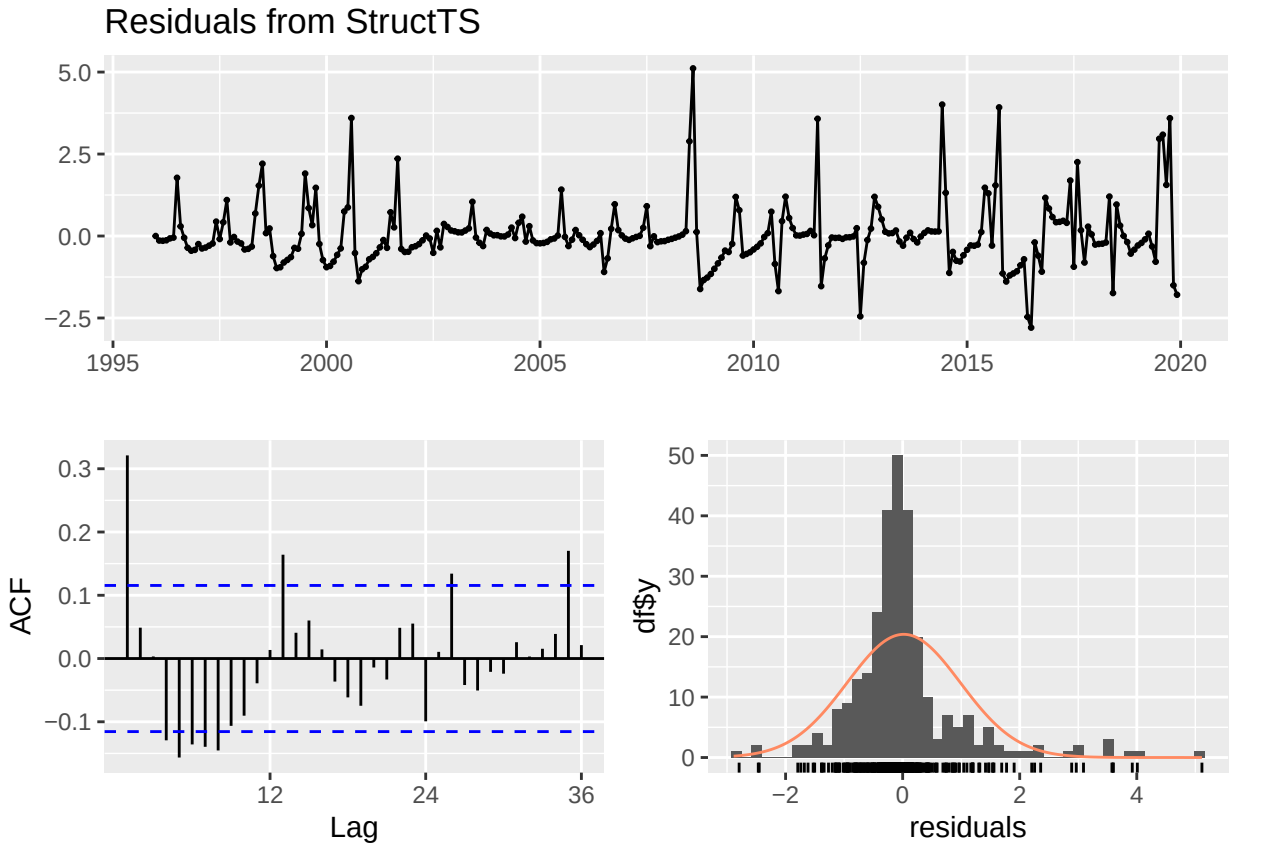

```
checkresiduals(SSES_seas)
```

```
## Warning in modeldf.default(object): Could not find appropriate degrees of
## freedom for this model.
```




```
# Model 5: SS with StructTS()

SS_seas <- StructTS(ts_biomass,
                    type="BSM",fixed=c(0,0.001,0.3,NA))   #this function has convergence issues
checkresiduals(SS_seas)
```

```
## Warning in modeldf.default(object): Could not find appropriate degrees of
## freedom for this model.
```




```
#Generating forecasts
# StructTS() does not call the forecast() internally so we need one more step
SS_for <- forecast(SS_seas,h=12)
plot(SS_for)
```

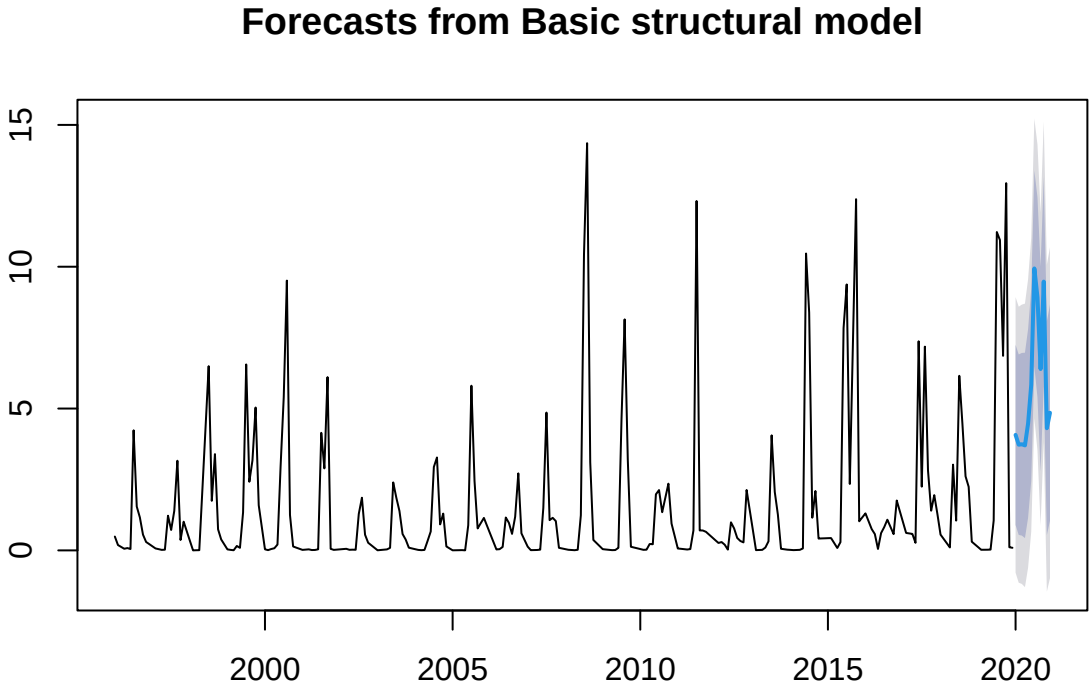


Table 1: Forecast Accuracy for Seasonal Data

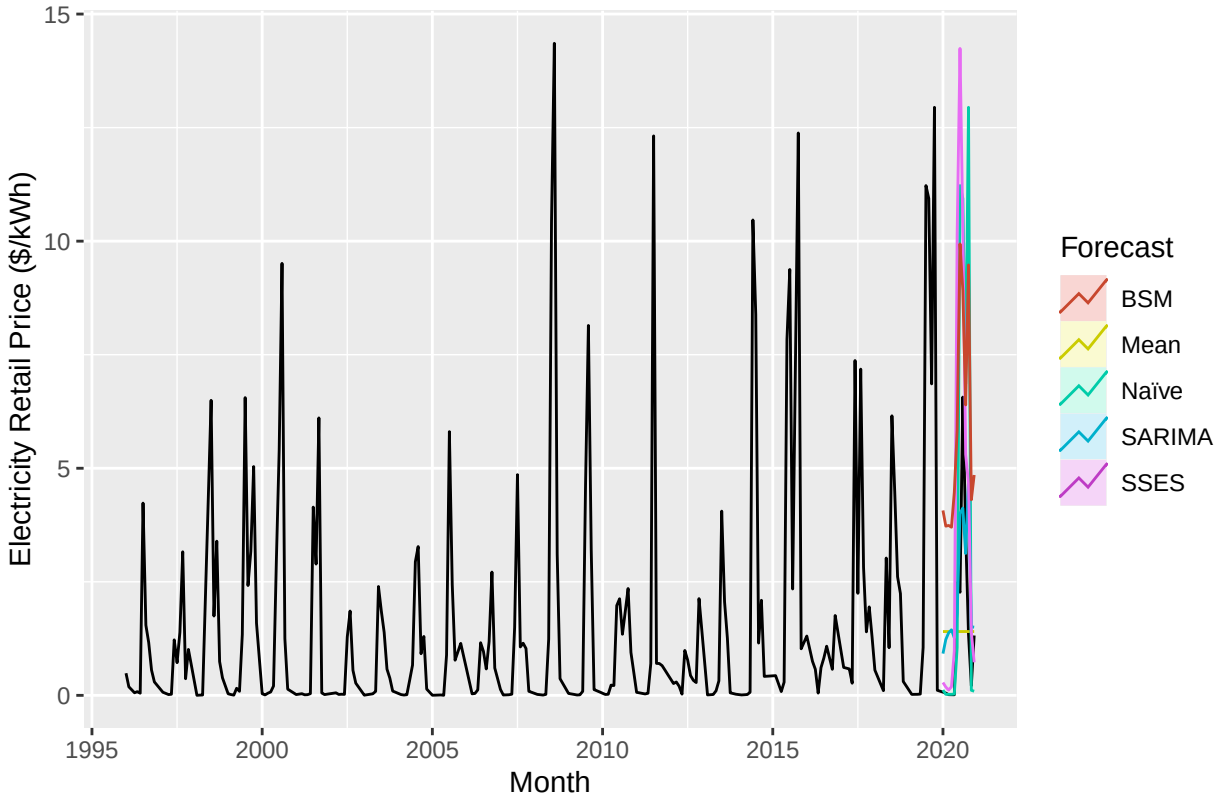
	ME	RMSE	MAE	MPE	MAPE
MEAN	0.09077	1.91972	1.45817	-2993.9993	3030.8195
SNAIVE	-2.12360	4.54636	2.58677	-122.4177	164.9659
SARIMA	-0.75532	1.58841	1.35418	-2867.0051	2879.9488
SSES	-2.55079	4.40694	2.64893	-998.5011	1005.9502
BSM	-4.29032	4.61610	4.29032	-8743.8441	8743.8441

```
#Model 1: Arithmetic mean
MEAN_scores <- accuracy(MEAN_seas$mean,last_obs)  #store the performance metrics

#Model 2: Seasonal naive
SNAIVE_scores <- accuracy(SNAIVE_seas$mean,last_obs)

# Model 3:  SARIMA
SARIMA_scores <- accuracy(SARIMA_for$mean,last_obs)

# Model 4:  SSES
SSES_scores <- accuracy(SSES_seas$forecast,last_obs)

# Model 5:  BSM
SS_scores <- accuracy(SS_for$mean,last_obs)


#create data frame
seas_scores <- as.data.frame(rbind(MEAN_scores, SNAIVE_scores, SARIMA_scores,SSES_scores,SS_scores))
row.names(seas_scores) <- c("MEAN", "SNAIVE","SARIMA","SSES","BSM")

#choose model with lowest RMSE
best_model_index <- which.min(seas_scores[,"RMSE"])
cat("The best model by RMSE is:", row.names(seas_scores[best_model_index,]))
```

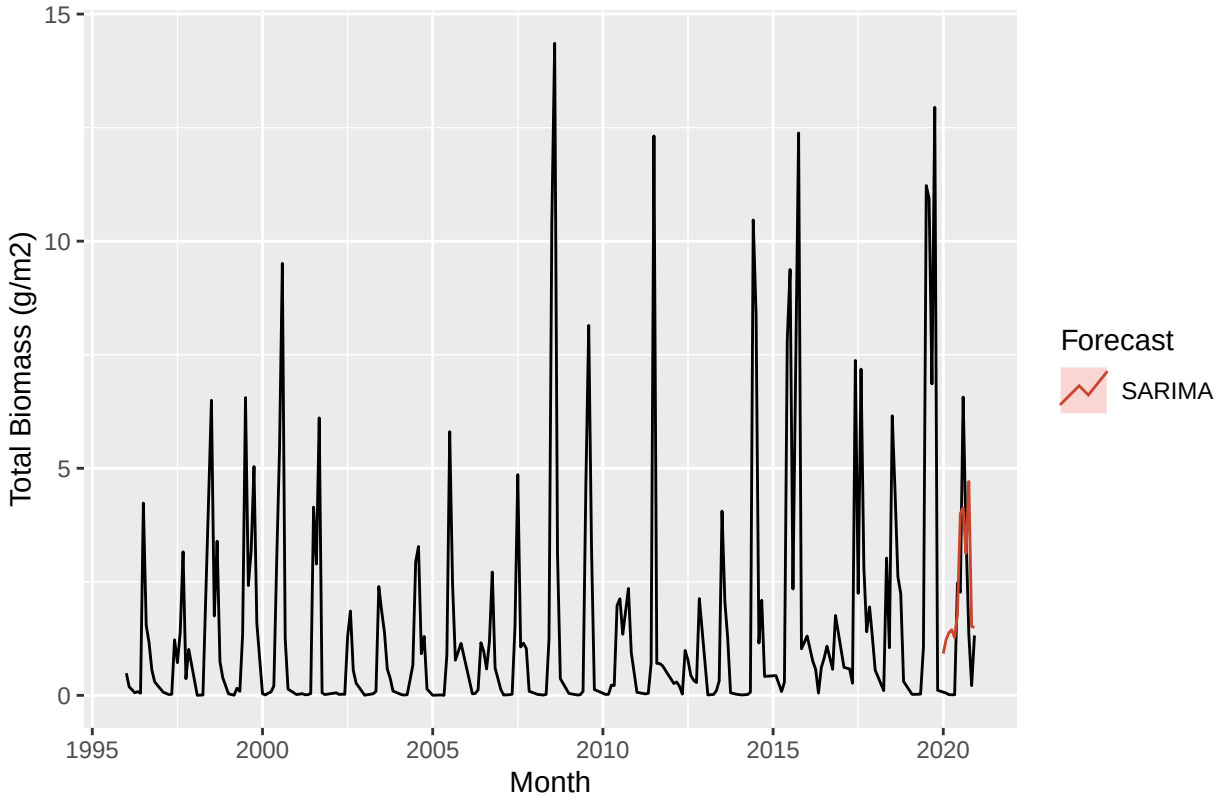
```
## The best model by RMSE is: SARIMA
```

```
kbl(seas_scores,
      caption = "Forecast Accuracy for Seasonal Data",
      digits = array(5,ncol(seas_scores))) %>%
  kable_styling(full_width = FALSE, position = "center") %>%
  #highlight model with lowest RMSE
  kable_styling(latex_options="striped", stripe_index = which.min(seas_scores[,"RMSE"]))
```

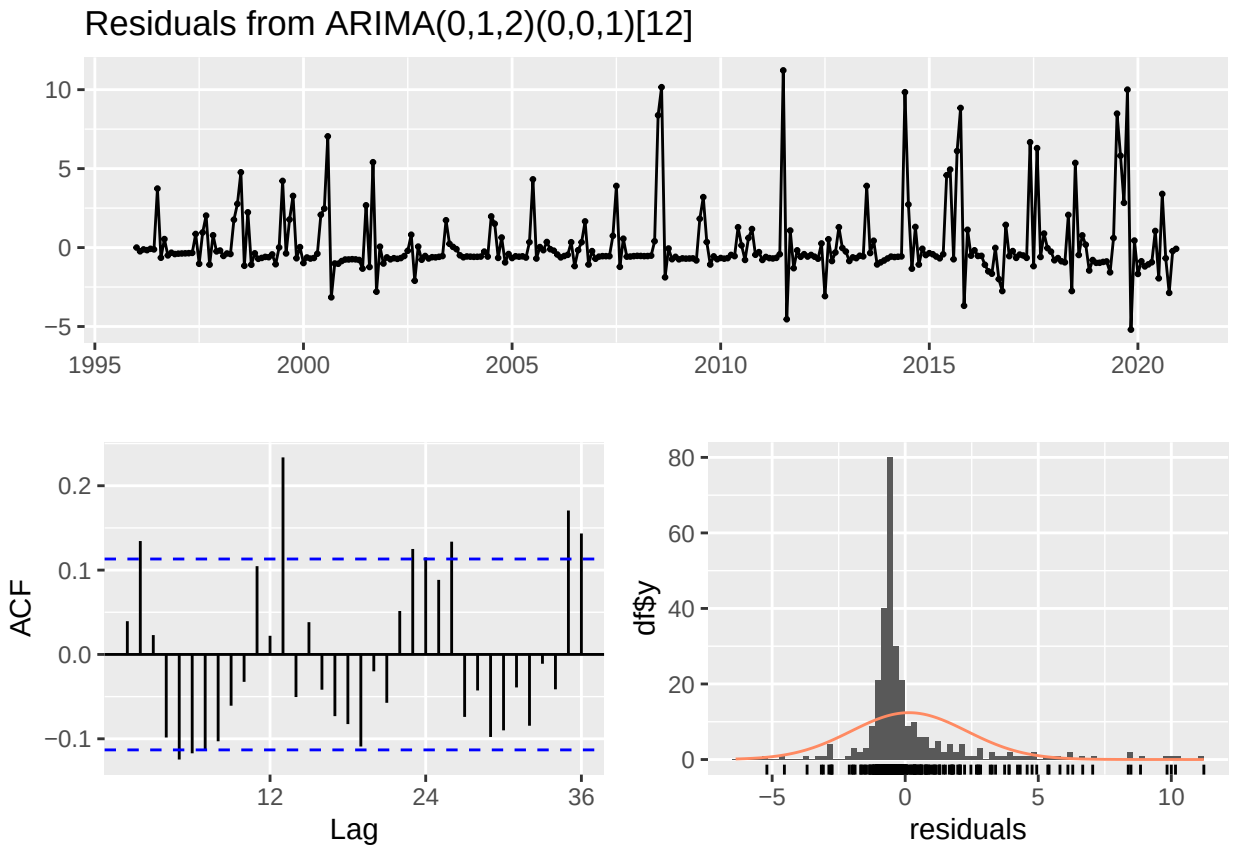
```
autoplot(ts_biomass_data) +
  autolayer(MEAN_seas, PI=FALSE, series="Mean") +
  autolayer(SNAIVE_seas, PI=FALSE, series="Naïve") +
  autolayer(SARIMA_for,PI=FALSE, series="SARIMA") +
  autolayer(SSES_seas$forecast, series="SSES") +
  autolayer(SS_for,PI=FALSE,series="BSM") +
  xlab("Month") + ylab("Electricity Retail Price ($/kWh)") +
  guides(colour=guide_legend(title="Forecast"))
```




```
autoplot(ts_biomass_data) +

autolayer(SARIMA_for,PI=FALSE, series="SARIMA") +
  xlab("Month") + ylab("Total Biomass (g/m2)") +
  guides(colour=guide_legend(title="Forecast"))
```

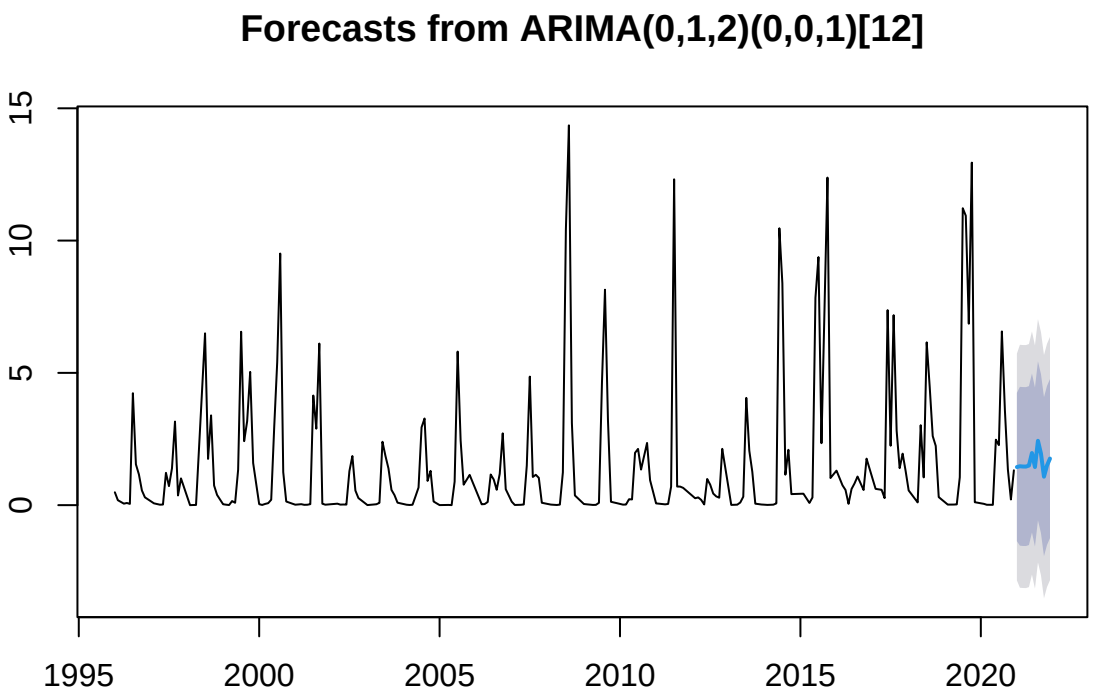



```
# Forecast

SARIMA_autofit_new <- auto.arima(ts_biomass_data)
checkresiduals(SARIMA_autofit_new)
```




```
##
##  Ljung-Box test
##
## data:  Residuals from ARIMA(0,1,2)(0,0,1)[12]
## Q* = 68.766, df = 21, p-value = 5.534e-07
##
## Model df: 3.   Total lags used: 24
```

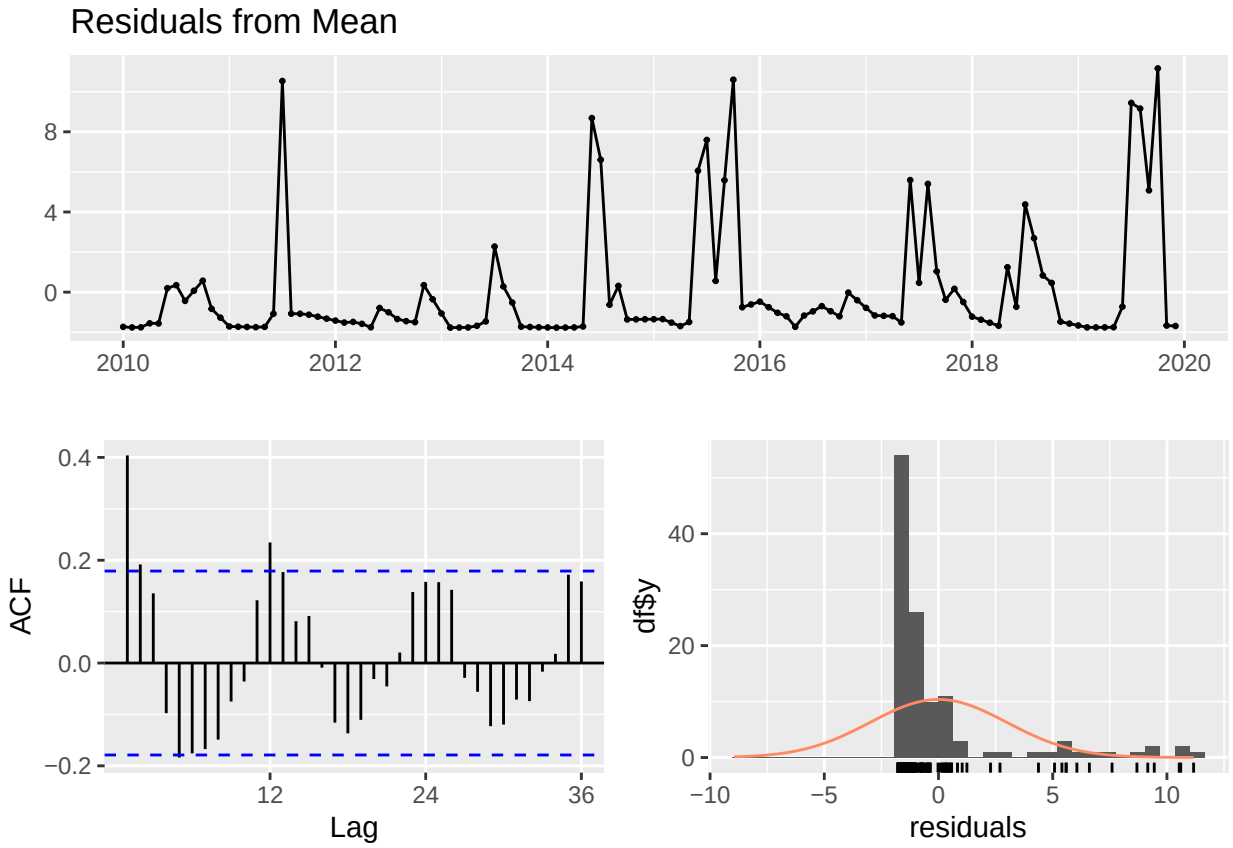
```
SARIMA_for_new <- forecast(SARIMA_autofit_new,h=12)
plot(SARIMA_for_new)
```



Use recent ten-year data to forcast

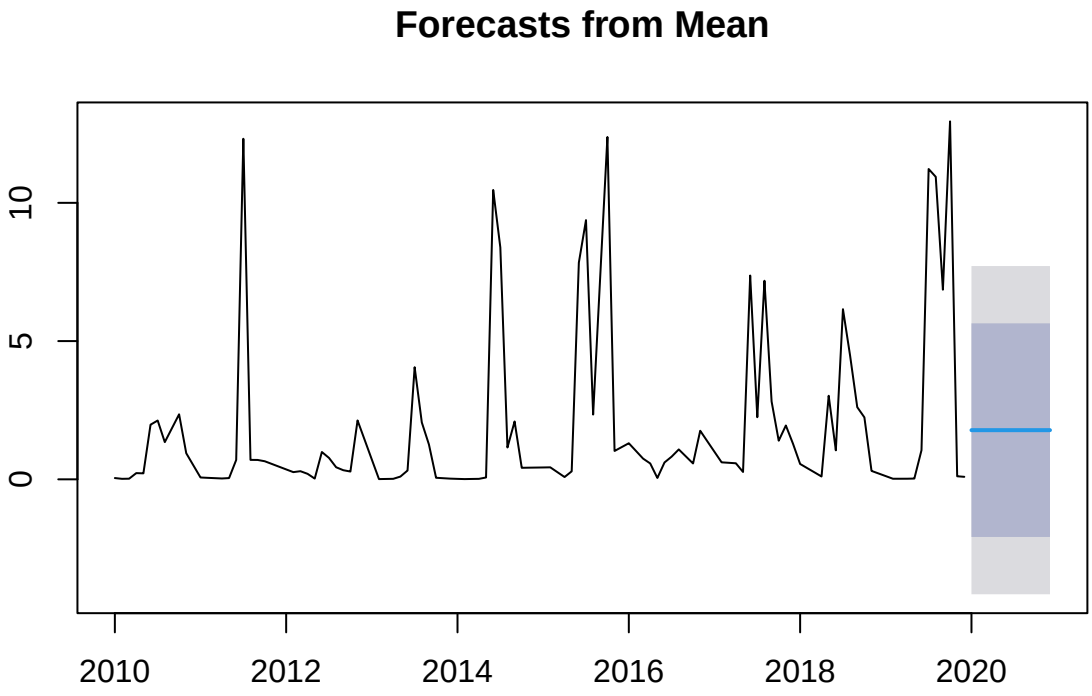
```
# Change the time span

# Transform to time series format

ts_biomass_data <- ts(
  biomass_data_frame[169:300,2],
  start=c(year(biomass_data_frame$Month[169]),month(biomass_data_frame$Month[169])),
  frequency=12)

ts_biomass <- ts(
  biomass_data_frame[169:288,2],
  start=c(year(biomass_data_frame$Month[169]),month(biomass_data_frame$Month[169])),
  frequency=12)


last_obs <- ts_biomass_data[121:132]
```

```
# Model 1: Arithmetic mean
# The meanf() has no holdout option
MEAN_seas <- meanf(y = ts_biomass, h = 12)
checkresiduals(MEAN_seas)
```

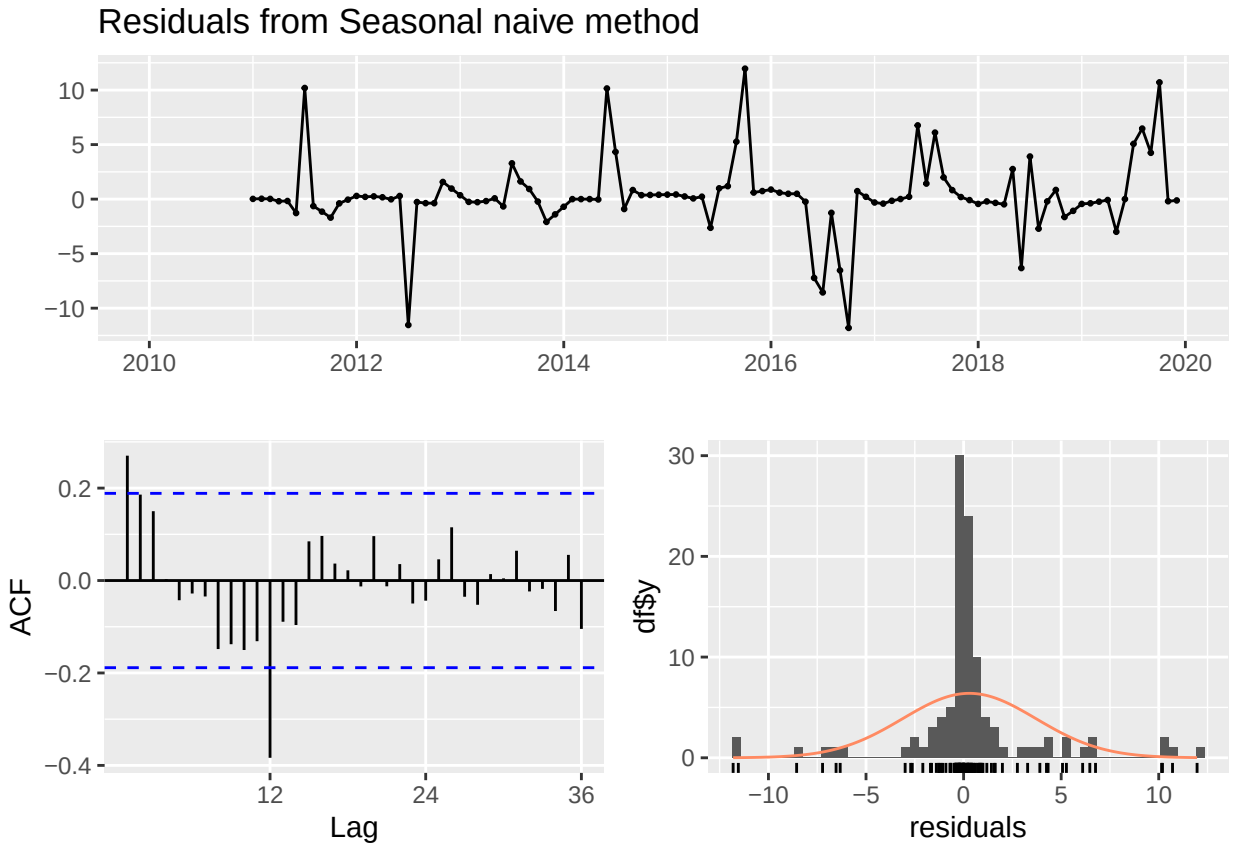



```
##
##  Ljung-Box test
##
## data:  Residuals from Mean
## Q* = 73.247, df = 23, p-value = 3.795e-07
##
## Model df: 1.   Total lags used: 24
```

```
plot(MEAN_seas)
```



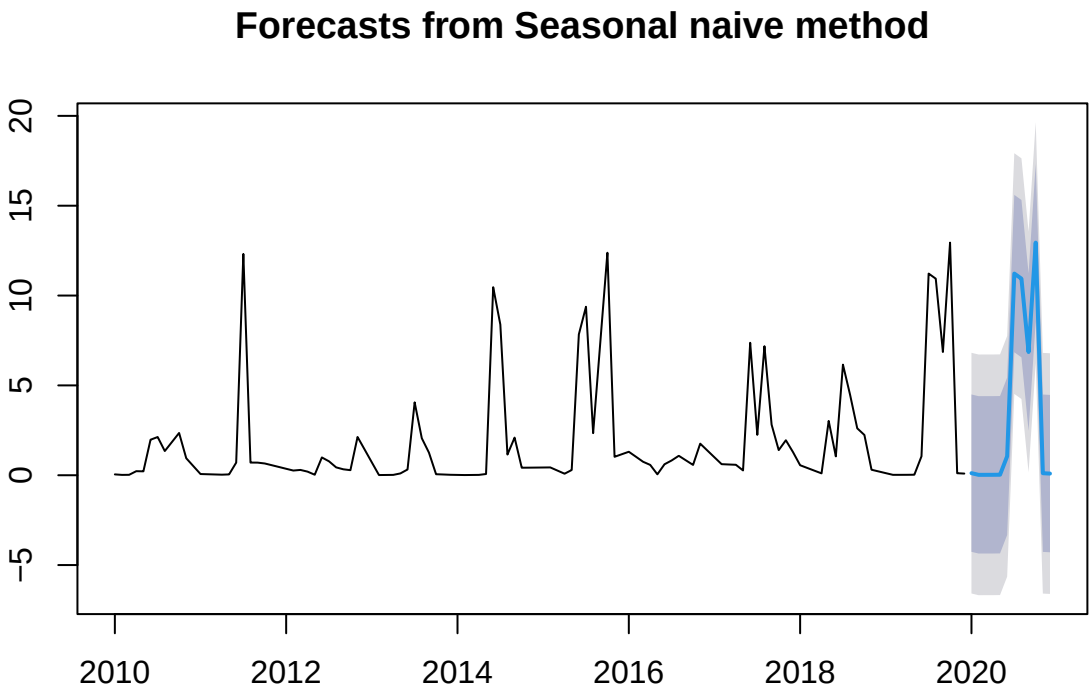

```
# Model 2: Seasonal naive
SNAIVE_seas <- snaive(ts_biomass, h=12, holdout=FALSE)
checkresiduals(SNAIVE_seas)
```



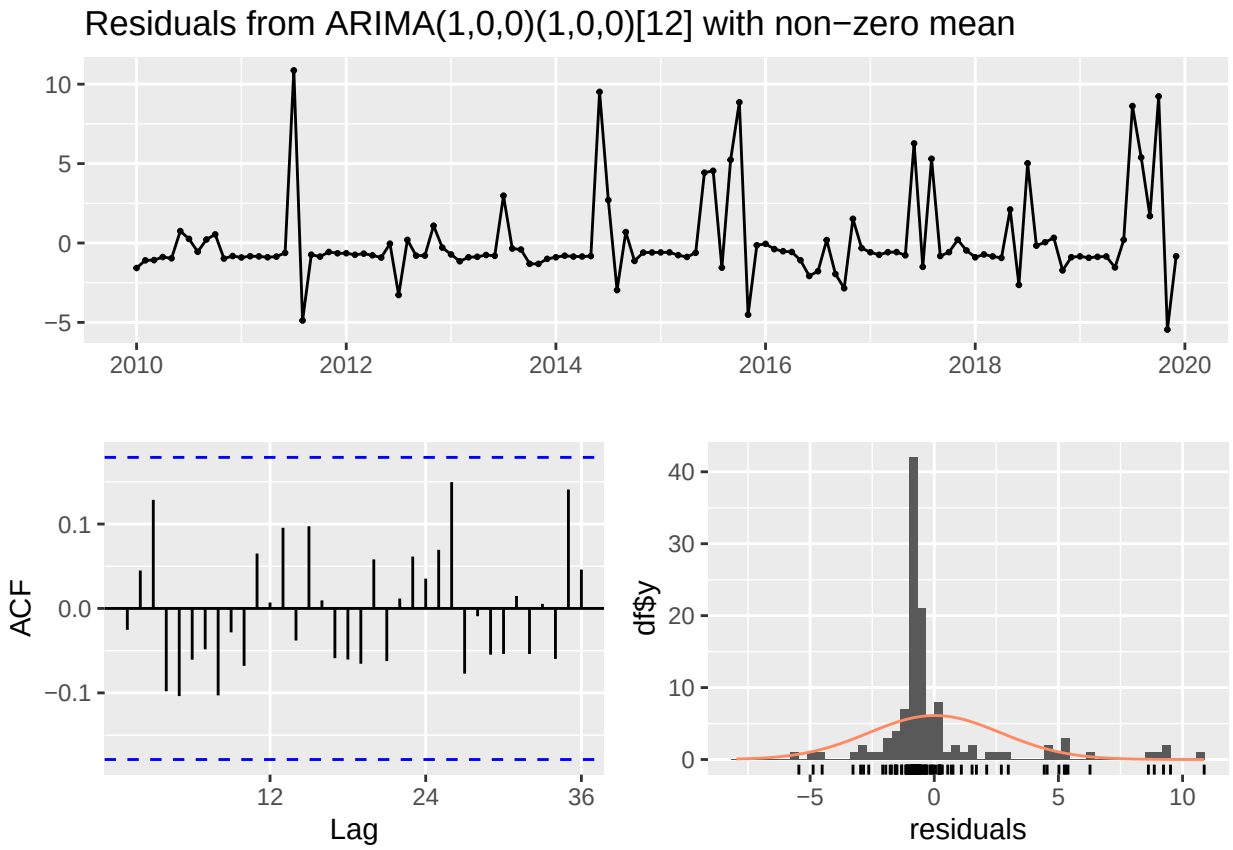

```
##
##  Ljung-Box test
```

```
##
## data:  Residuals from Seasonal naive method
## Q* = 49.511, df = 24, p-value = 0.001633
##
## Model df: 0.   Total lags used: 24
```

```
plot(SNAIVE_seas)
```

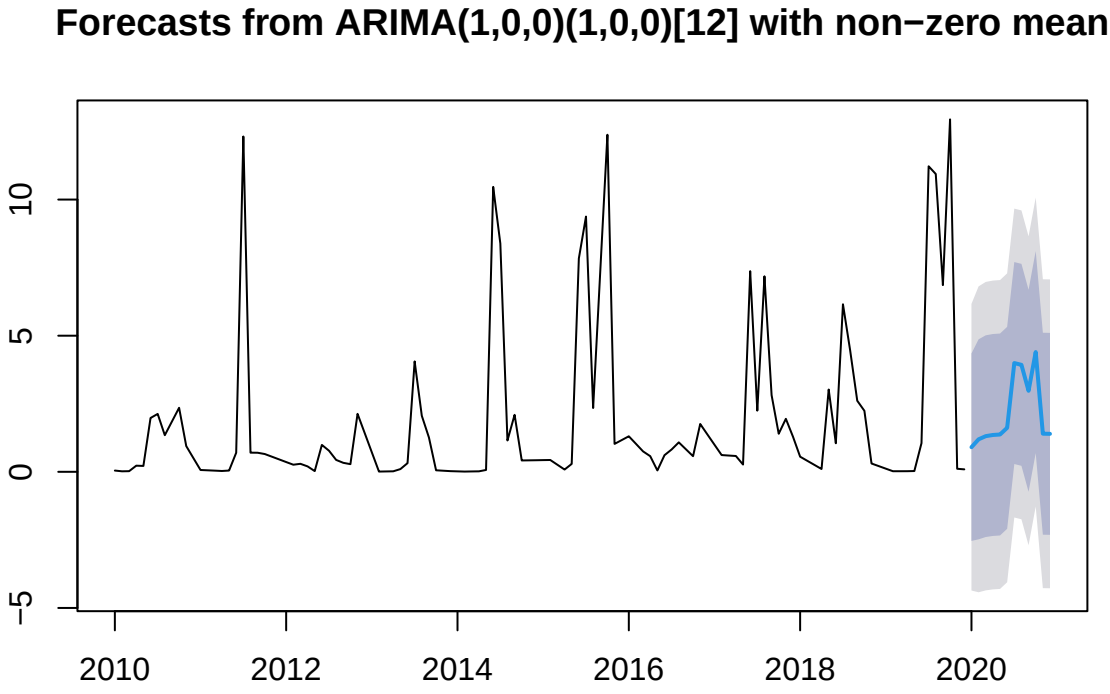



```
# Model 3: SARIMA

SARIMA_autofit <- auto.arima(ts_biomass)
checkresiduals(SARIMA_autofit)
```

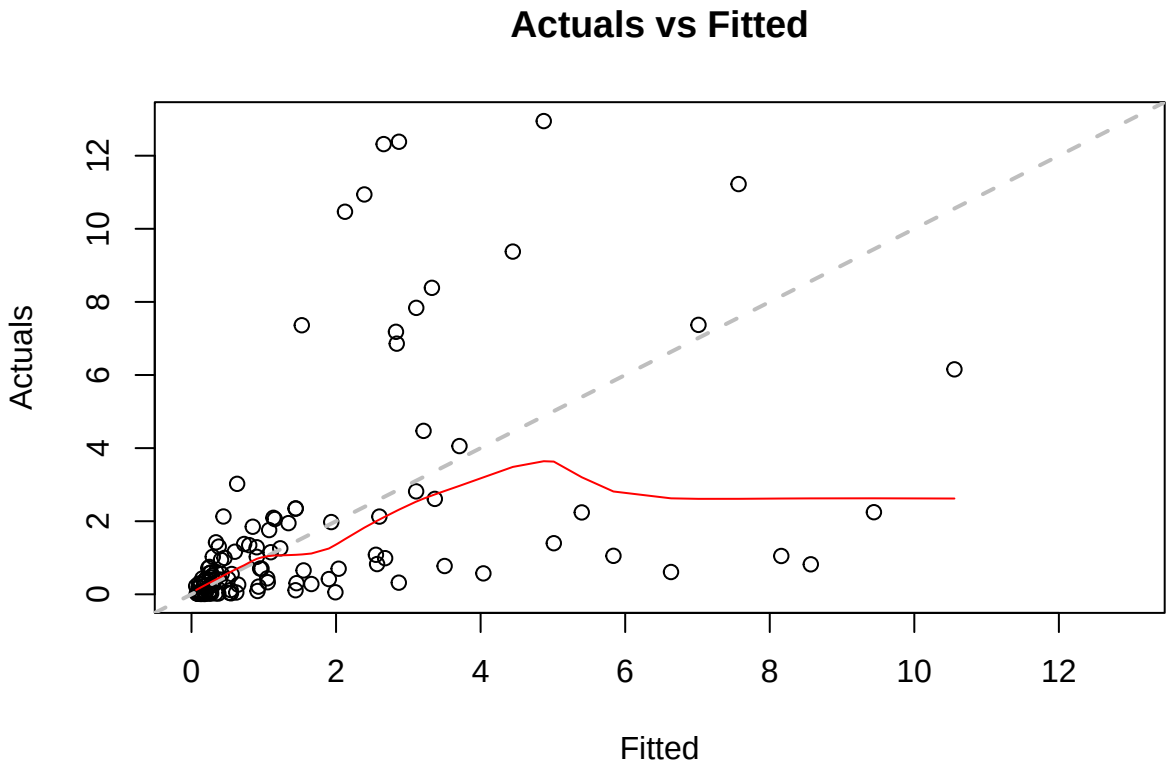


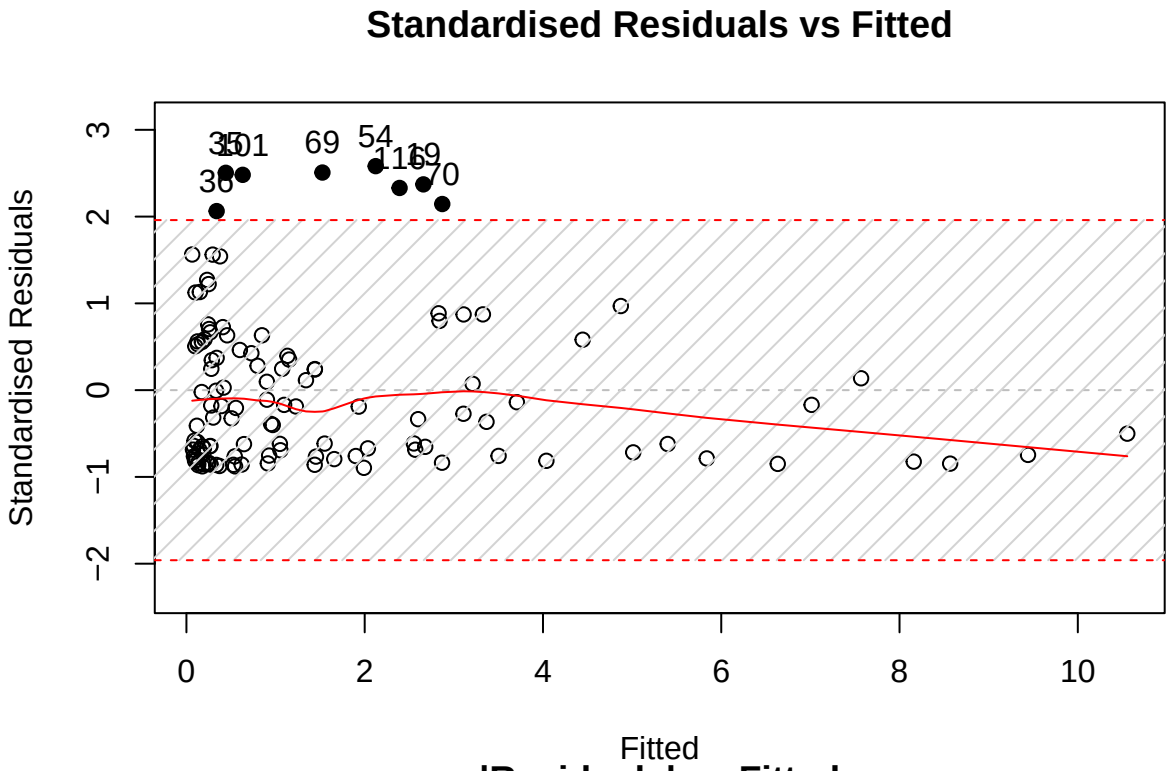

```
##
##  Ljung-Box test
##
## data:  Residuals from ARIMA(1,0,0)(1,0,0)[12] with non-zero mean
## Q* = 14.711, df = 22, p-value = 0.8743
##
## Model df: 2.   Total lags used: 24
```

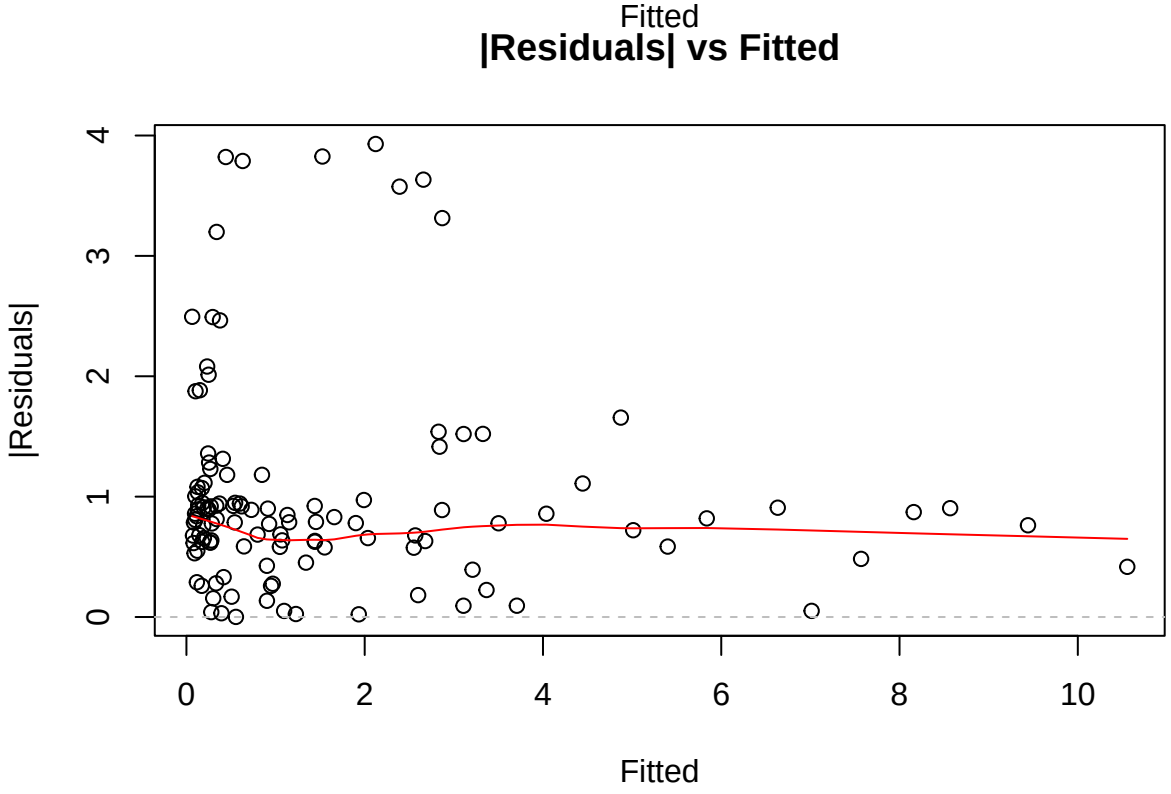
```
#Generating forecasts
#remember auto.arima does not call the forecast() internally so we need one more step
SARIMA_for <- forecast(SARIMA_autofit,h=12)
plot(SARIMA_for)
```

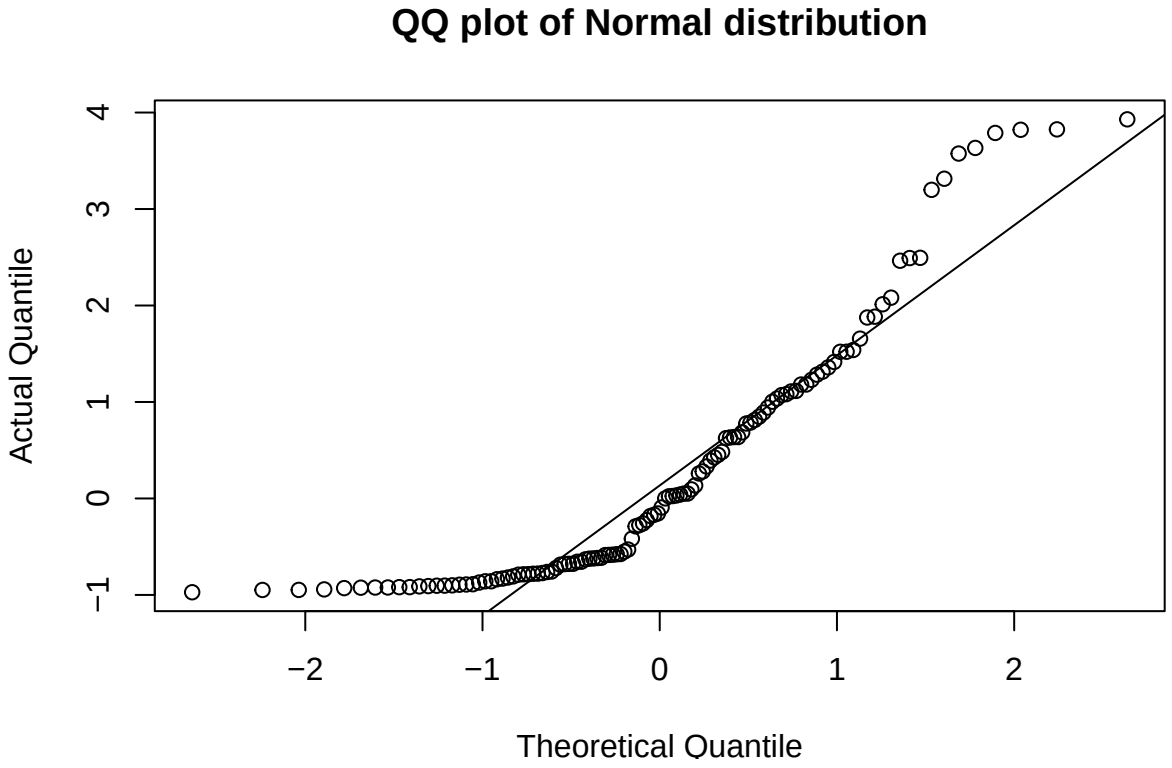



```
# Model 4: SS Exponential smoothing
SSES_seas <- es(ts_biomass,model="ZZZ",h=12,holdout=FALSE)
plot(SSES_seas)
```



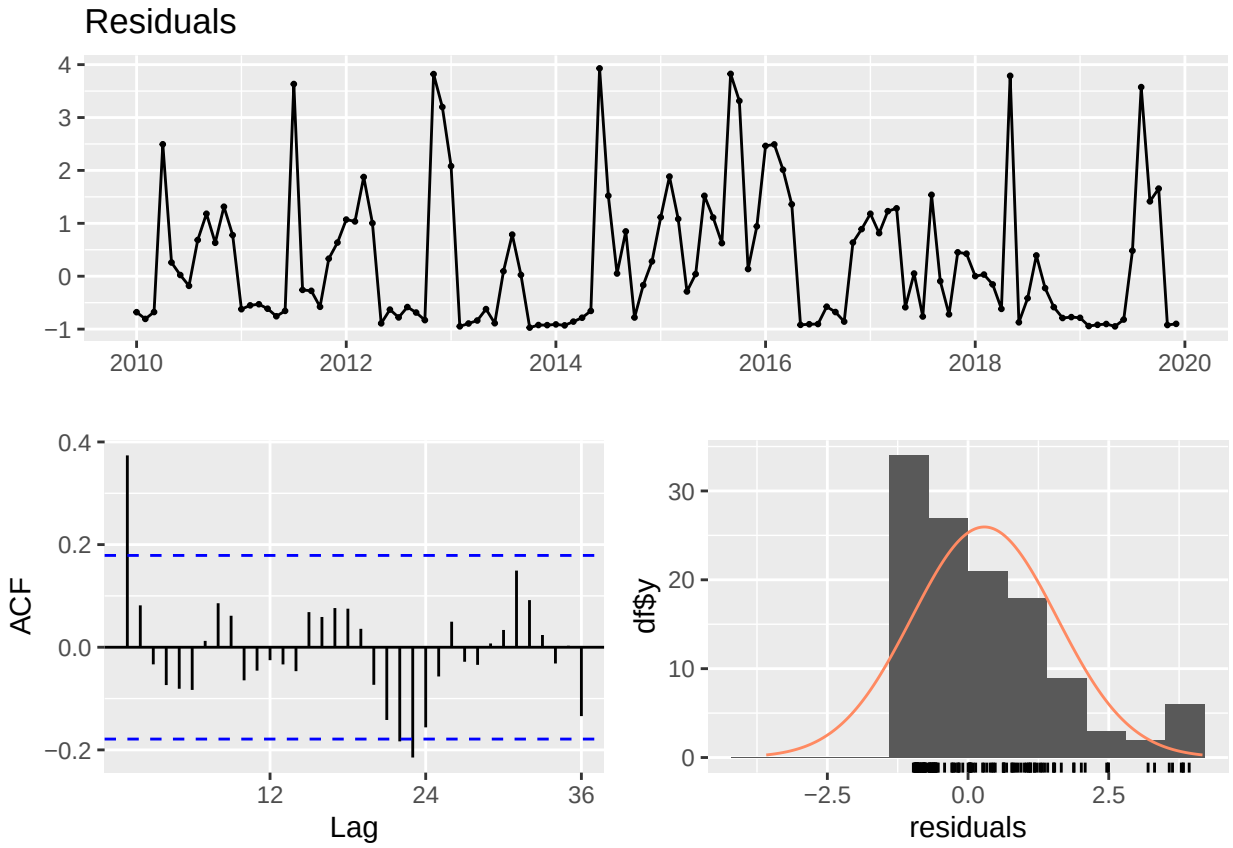

Standardised Residuals vs Fitted
Standardised Residuals
Fitted
35
101
69
54
116
69
70
36
3
2
1
0
−1
−2
0
2
4
6
8
10


|Residuals| vs Fitted
|Residuals|
Fitted
4
3
2
1
0
0
2
4
6
8
10



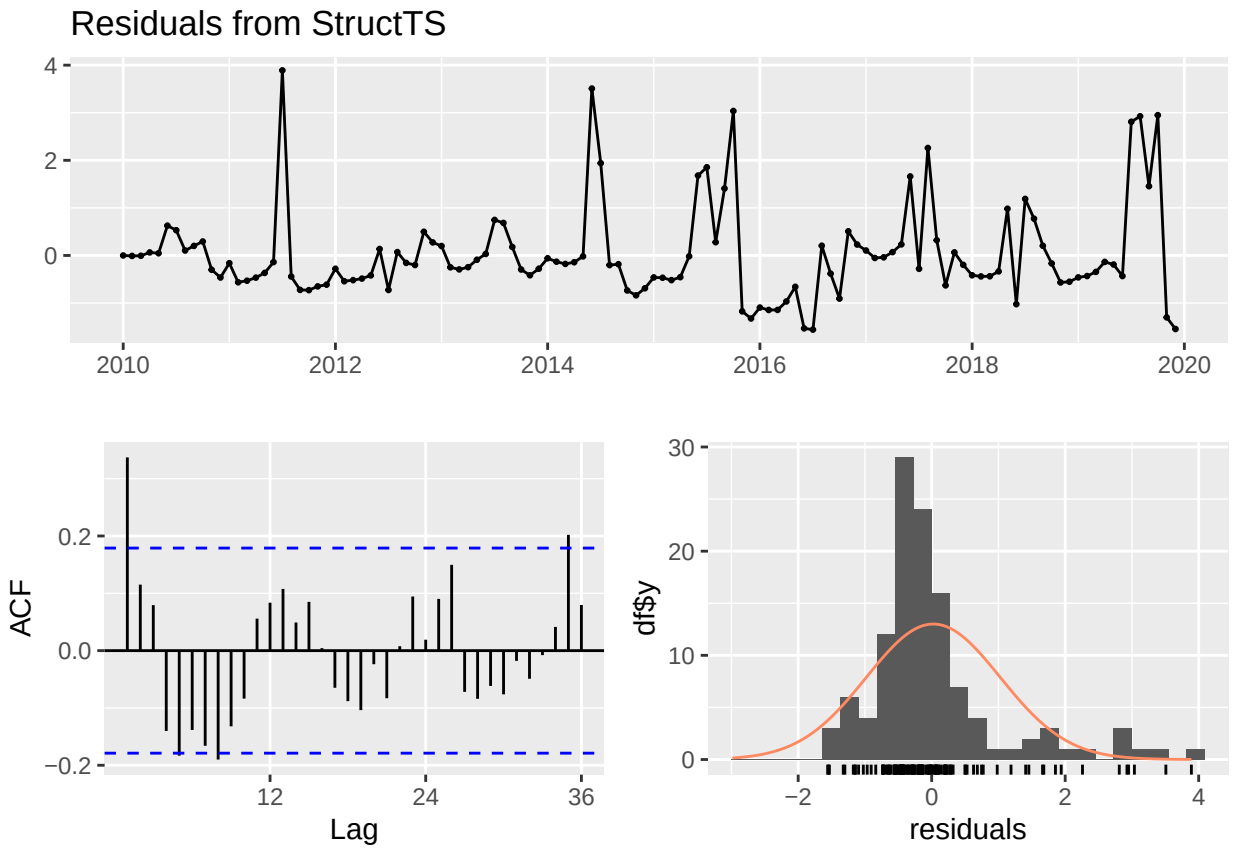

```
checkresiduals(SSES_seas)
```

```
## Warning in modeldf.default(object): Could not find appropriate degrees of
## freedom for this model.
```




```
# Model 5: SS with StructTS()

SS_seas <- StructTS(ts_biomass,
                    type="BSM",fixed=c(0,0.001,0.3,NA))   #this function has convergence issues
checkresiduals(SS_seas)
```

```
## Warning in modeldf.default(object): Could not find appropriate degrees of
## freedom for this model.
```




```
#Generating forecasts
# StructTS() does not call the forecast() internally so we need one more step
SS_for <- forecast(SS_seas,h=12)
plot(SS_for)
```

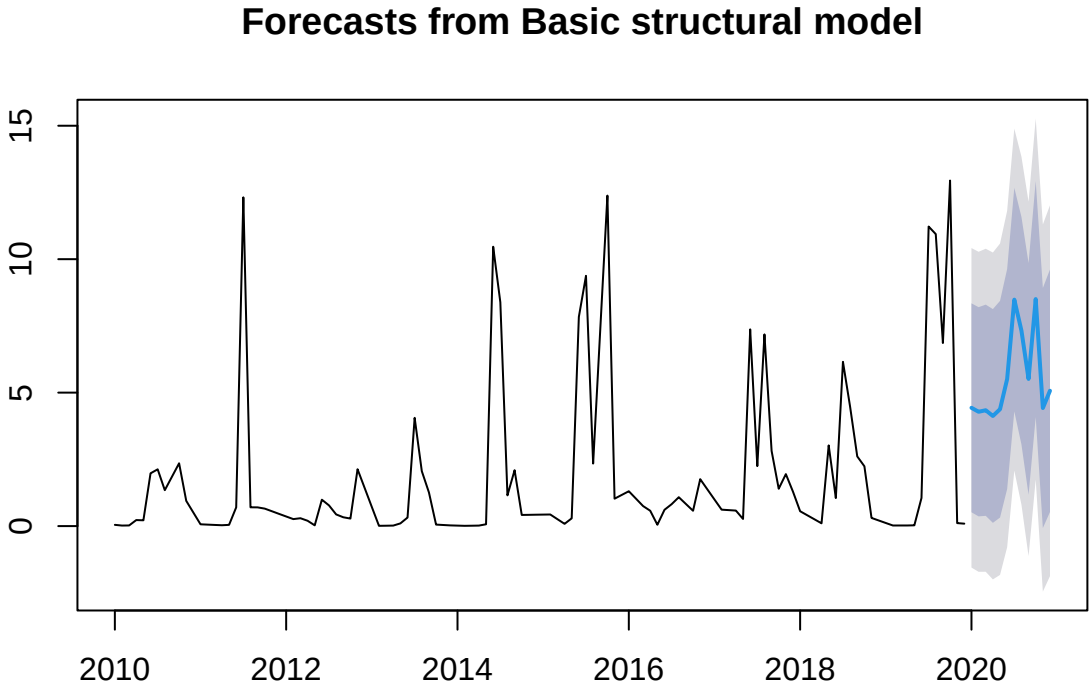


Table 2: Forecast Accuracy for Seasonal Data

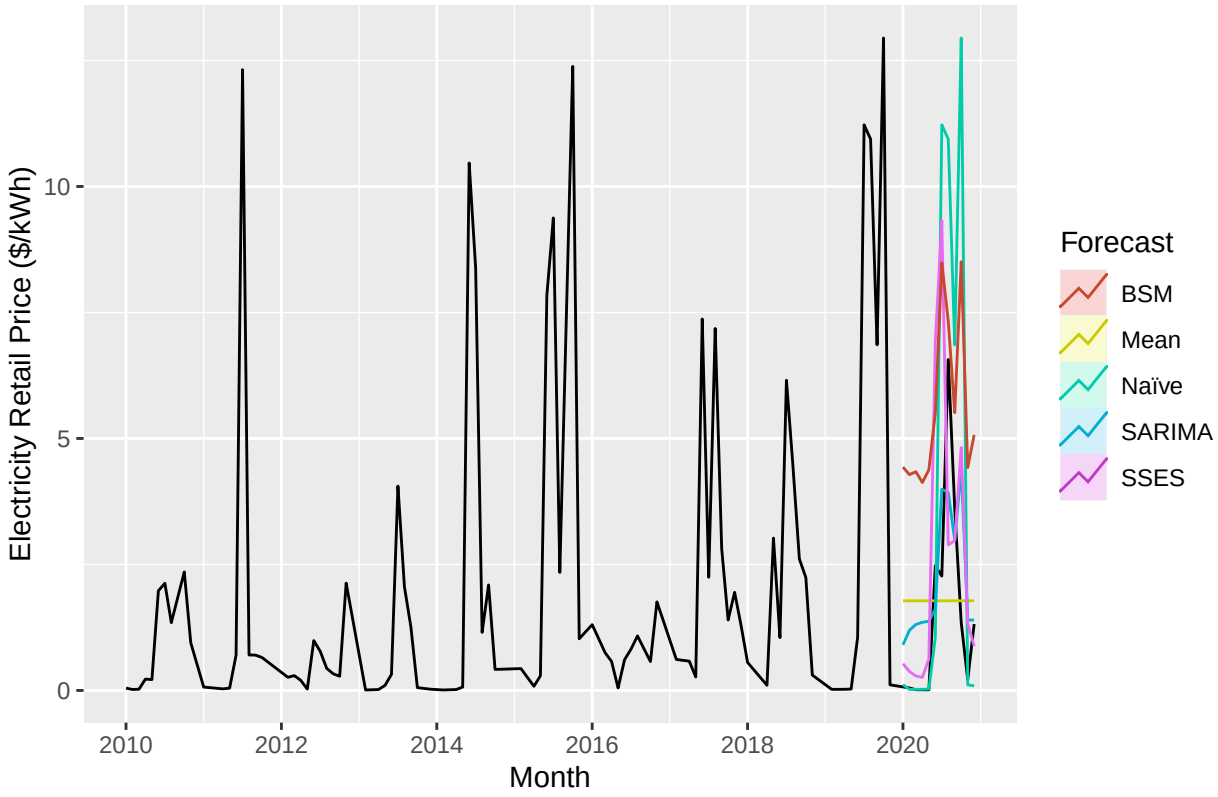
	ME	RMSE	MAE	MPE	MAPE
MEAN	-0.28323	1.93838	1.58284	-3817.5199	3846.3960
SNAIVE	-2.12360	4.54636	2.58677	-122.4177	164.9659
SARIMA	-0.65751	1.55783	1.34461	-2824.6163	2839.9915
SSES	-1.10662	2.85708	1.89745	-919.7008	937.4871
BSM	-4.03626	4.34690	4.03626	-9410.6202	9410.6202

```
#Model 1: Arithmetic mean
MEAN_scores <- accuracy(MEAN_seas$mean,last_obs)  #store the performance metrics

#Model 2: Seasonal naive
SNAIVE_scores <- accuracy(SNAIVE_seas$mean,last_obs)

# Model 3:  SARIMA
SARIMA_scores <- accuracy(SARIMA_for$mean,last_obs)

# Model 4:  SSES
SSES_scores <- accuracy(SSES_seas$forecast,last_obs)

# Model 5:  BSM
SS_scores <- accuracy(SS_for$mean,last_obs)


#create data frame
seas_scores <- as.data.frame(rbind(MEAN_scores, SNAIVE_scores, SARIMA_scores,SSES_scores,SS_scores))
row.names(seas_scores) <- c("MEAN", "SNAIVE","SARIMA","SSES","BSM")

#choose model with lowest RMSE
best_model_index <- which.min(seas_scores[,"RMSE"])
cat("The best model by RMSE is:", row.names(seas_scores[best_model_index,]))
```

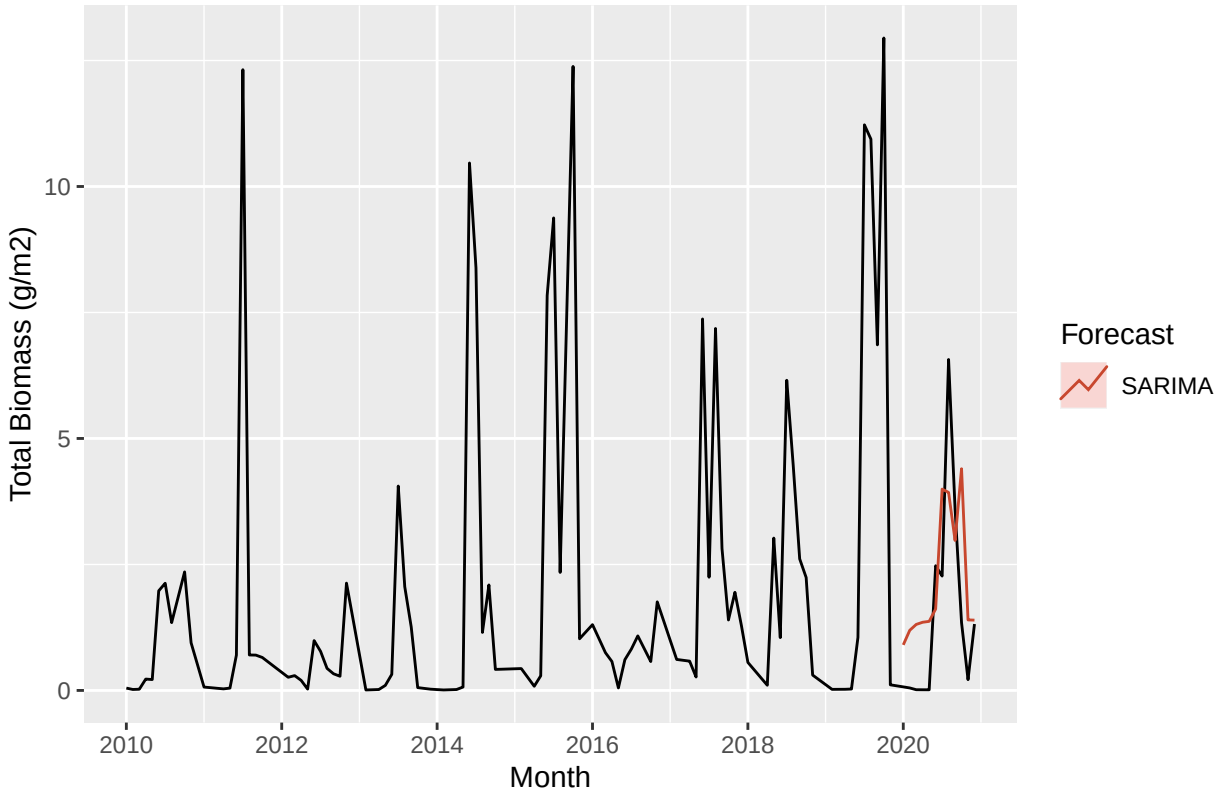
```
## The best model by RMSE is: SARIMA
```

```
kbl(seas_scores,
      caption = "Forecast Accuracy for Seasonal Data",
      digits = array(5,ncol(seas_scores))) %>%
  kable_styling(full_width = FALSE, position = "center") %>%
  #highlight model with lowest RMSE
  kable_styling(latex_options="striped", stripe_index = which.min(seas_scores[,"RMSE"]))
```

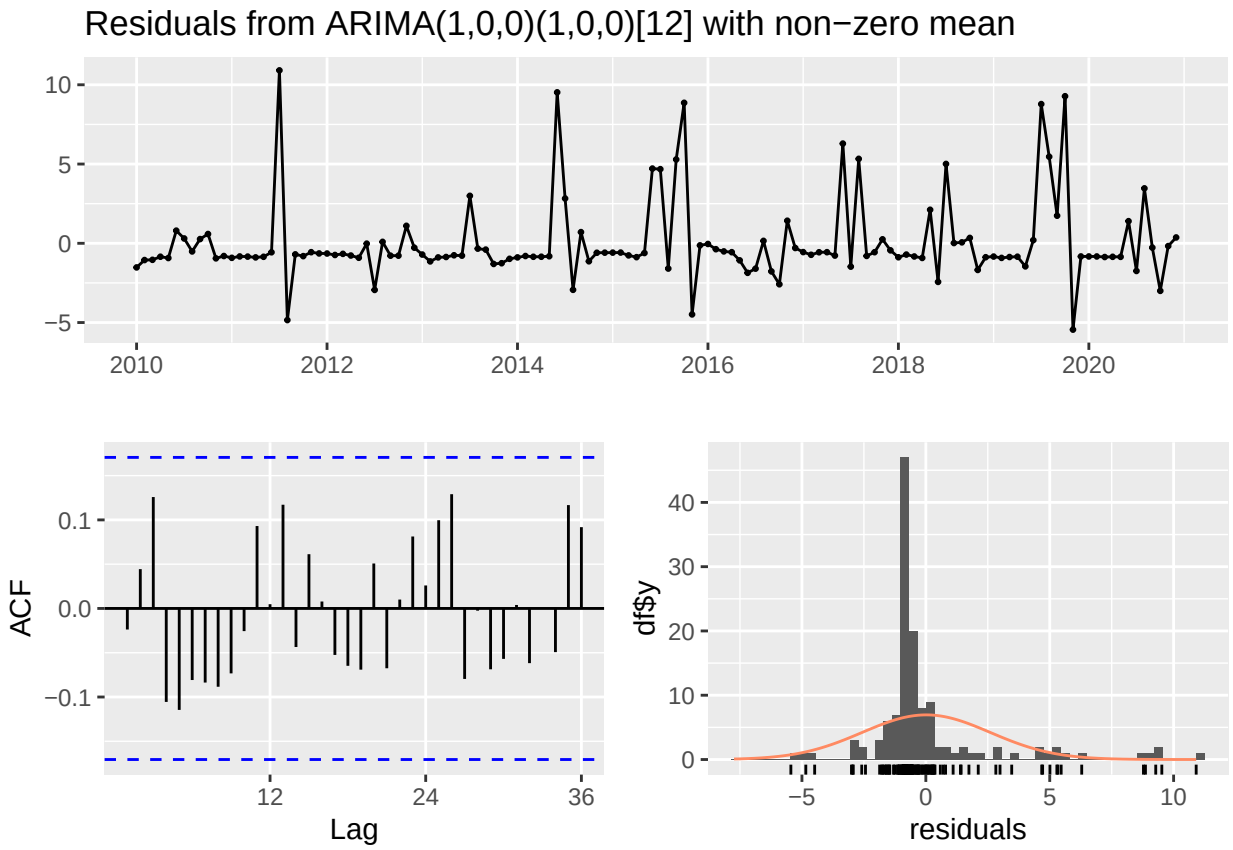
```
autoplot(ts_biomass_data) +
  autolayer(MEAN_seas, PI=FALSE, series="Mean") +
  autolayer(SNAIVE_seas, PI=FALSE, series="Naïve") +
  autolayer(SARIMA_for,PI=FALSE, series="SARIMA") +
  autolayer(SSES_seas$forecast, series="SSES") +
  autolayer(SS_for,PI=FALSE,series="BSM") +
  xlab("Month") + ylab("Electricity Retail Price ($/kWh)") +
  guides(colour=guide_legend(title="Forecast"))
```




```
autoplot(ts_biomass_data) +

autolayer(SARIMA_for,PI=FALSE, series="SARIMA") +
  xlab("Month") + ylab("Total Biomass (g/m2)") +
  guides(colour=guide_legend(title="Forecast"))
```

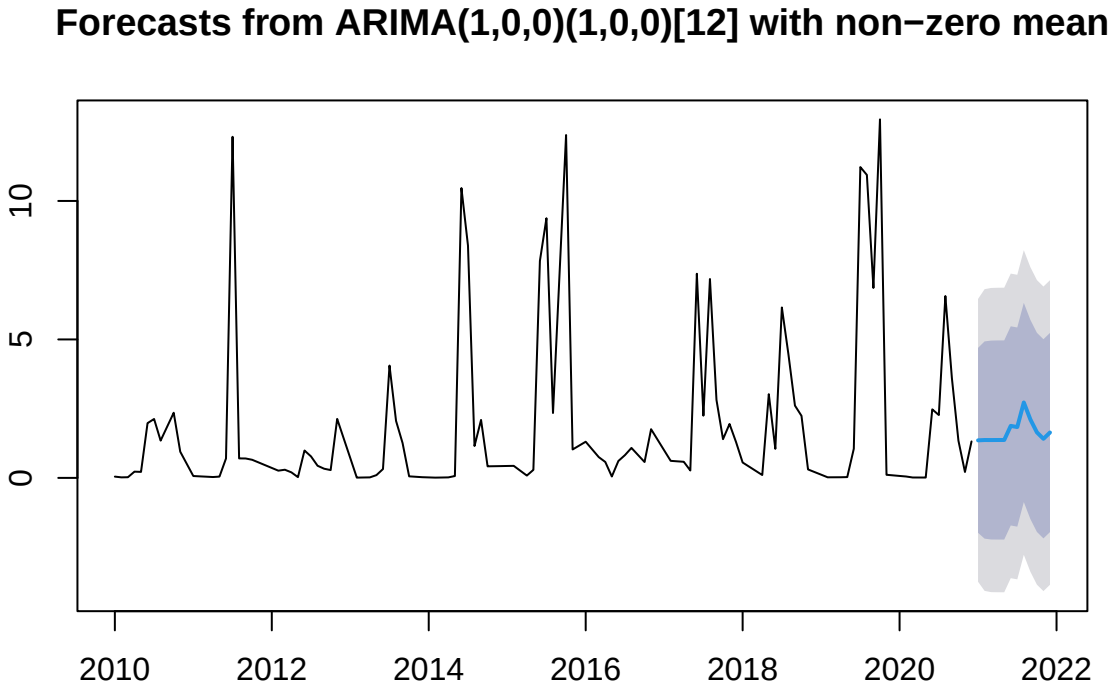



```
# Forecast

SARIMA_autofit_new <- auto.arima(ts_biomass_data)
checkresiduals(SARIMA_autofit_new)
```




```
##
##  Ljung-Box test
##
## data:  Residuals from ARIMA(1,0,0)(1,0,0)[12] with non-zero mean
## Q* = 18.099, df = 22, p-value = 0.7001
##
## Model df: 2.   Total lags used: 24
```

```
SARIMA_for_new <- forecast(SARIMA_autofit_new,h=12)
plot(SARIMA_for_new)
```



Note that the `echo = FALSE` parameter was added to the code chunk to prevent printing of the R code that generated the plot.