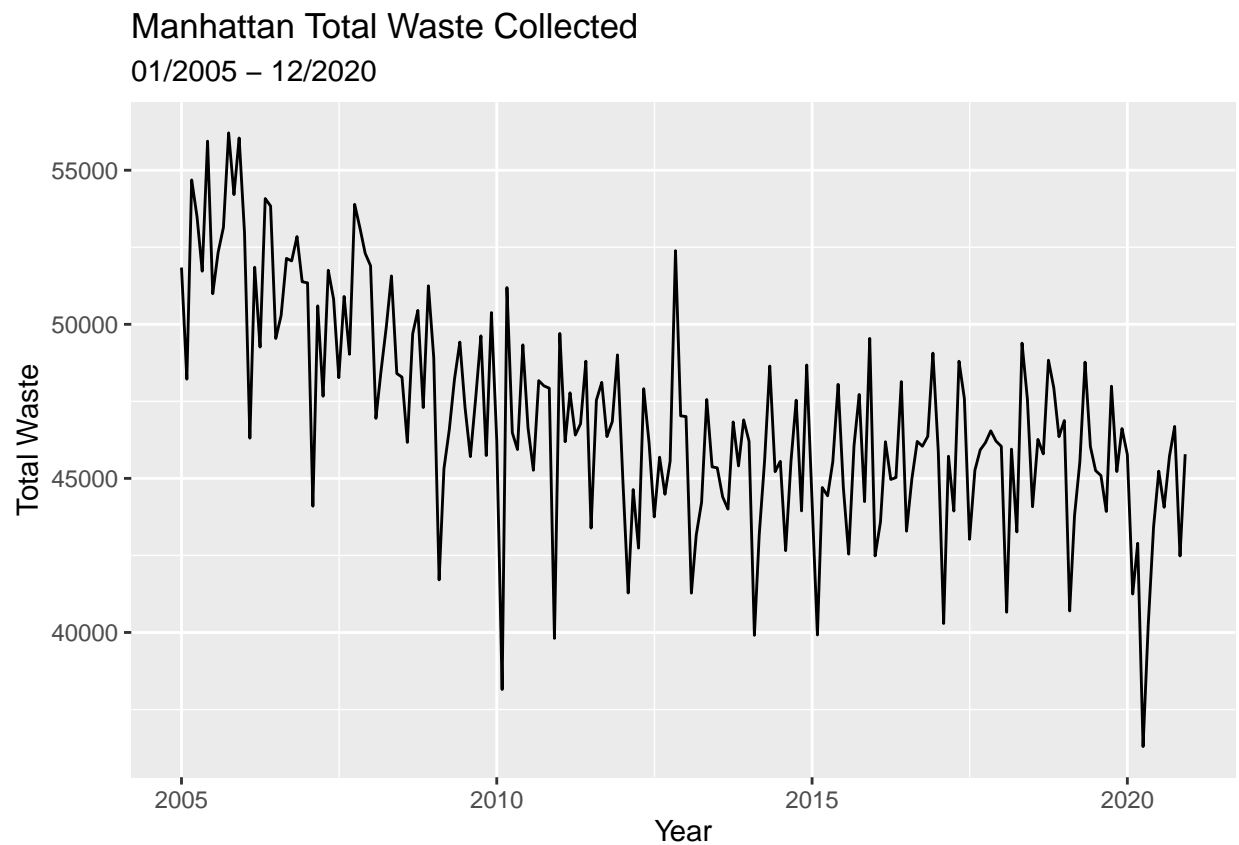# MN_ts.Rmd

Daniel L.

5/3/2022

```
man_ts %>%
  ggplot(mapping = aes(x = (month),
                       y = total_waste)) +
  geom_line() +
  labs(x = "Year",
       y = "Total Waste",
       title = "Manhattan Total Waste Collected",
       subtitle = "01/2005 - 12/2020")
```

Manhattan Total Waste Collected
01/2005 – 12/2020

I should investigate the average tonnage collected in MN from 2005 through 2010.

```
DSNY_third_manhattan %>%
  group_by("Year" = year(month)) %>%
```

```
    summarise(.,
              "Average Total Waste" = mean(total_waste))
```

```
## # A tibble: 16 x 2
##     Year `Average Total Waste`
##    <dbl>                 <dbl>
##  1  2005                53237.
##  2  2006                51380.
##  3  2007                50315.
##  4  2008                49194.
##  5  2009                47211.
##  6  2010                46094.
##  7  2011                47242.
##  8  2012                45549.
##  9  2013                45123.
## 10  2014                45221.
## 11  2015                45143.
## 12  2016                45528.
## 13  2017                45445.
## 14  2018                46012.
## 15  2019                45485.
## 16  2020                43321.
```

We do see a decrease in average waste collected by 7,000 tons in 2010, when compared to 2005. And a decrease in average waste collected by 4,000 tons in 2020, when compared to 2011.

KPSS Test for 'total_waste'

H_0 : The time series is trend stationary vs H_a : The time series is not trend stationary

If the p-value of the test is less than some significance level (e.g. $\alpha = .05$) then we reject the null hypothesis and conclude that the time series is not trend stationary.

```
#total waste values
man_ts %>% features(total_waste, unitroot_kpss)
```

```
## # A tibble: 1 x 2
##   kpss_stat kpss_pvalue
##       <dbl>       <dbl>
## 1      2.66        0.01
```

```
#differenced values
man_ts %>% features(diff1, unitroot_kpss)
```
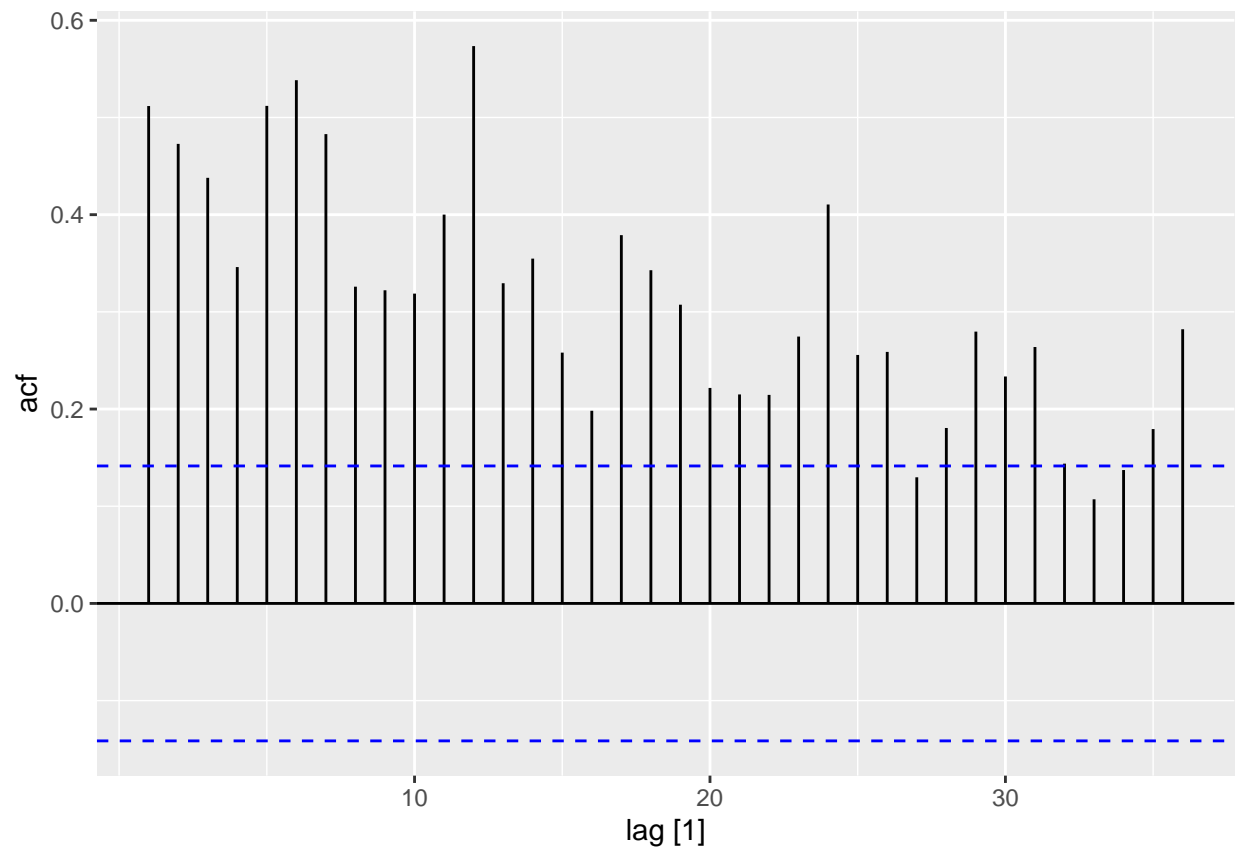
```
## # A tibble: 1 x 2
##   kpss_stat kpss_pvalue
##       <dbl>       <dbl>
## 1    0.0259         0.1
```
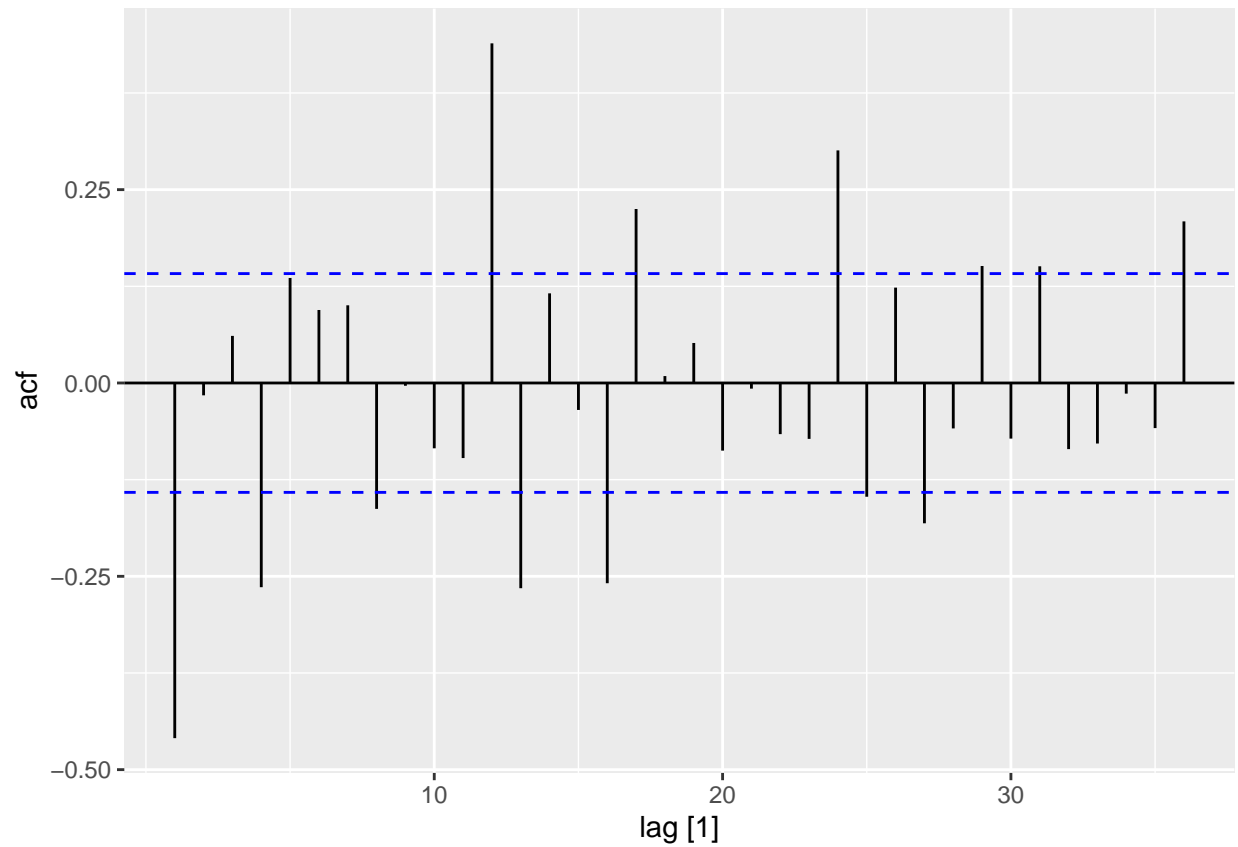
According to the results of the KPSS test, we reject the H_0 when evaluating the total_waste values. We fail to reject the H_0 when evaluating the differenced values

Begin by looking at ACF and PACF of the total_waste and differenced values

```
man_ts3 %>%
  ACF(total_waste, lag_max = 36) %>%
  autoplot()
```
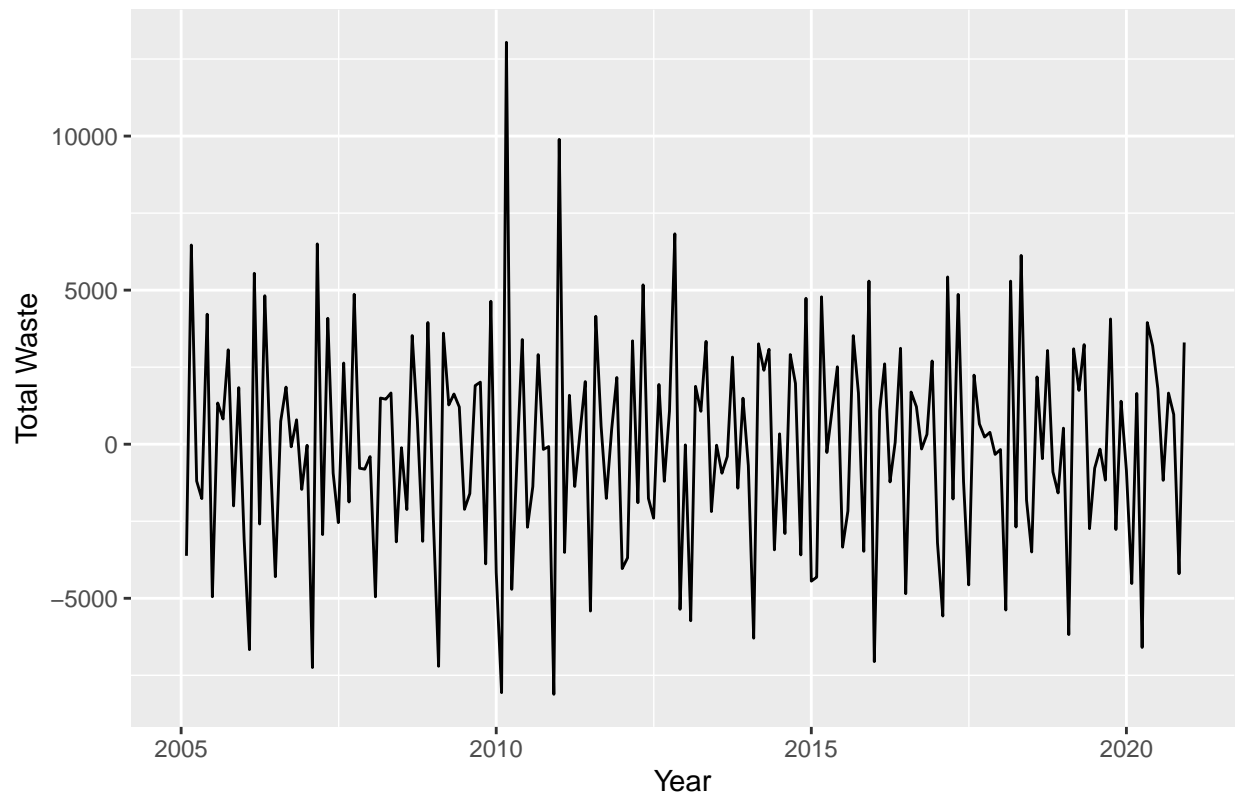


```
#acf of the differenced values
man_ts3 %>%
  ACF(diff1, lag_max = 36) %>%
  autoplot()
```

```
man_ts3 %>%
  ggplot(mapping = aes(x = month, y = diff1)) + geom_line() +
  labs(x = "Year",
       y = "Total Waste",
       title = "Differenced Values: Manhattan Total Waste Collected")
```
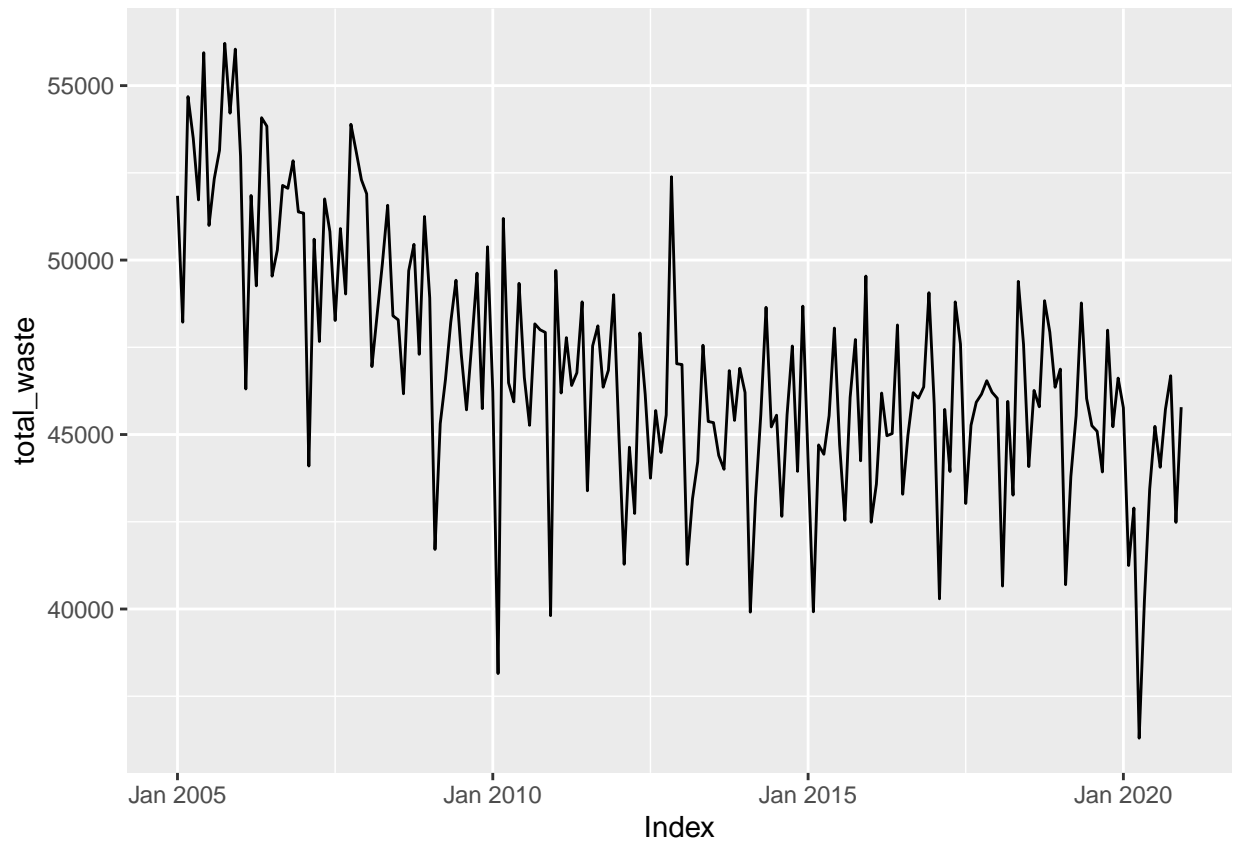
Warning: Removed 1 row(s) containing missing values (geom_path).

4

Differenced Values: Manhattan Total Waste Collected

Creating models with zoo() and the arima package from stats()

```
DSNY_MN_zoo_ts <- ts(DSNY_third_manhattan[,2],
    start = as.yearmon(DSNY_third_manhattan$month)[1],
    frequency = 12)

autoplot(as.zoo(DSNY_MN_zoo_ts))
```
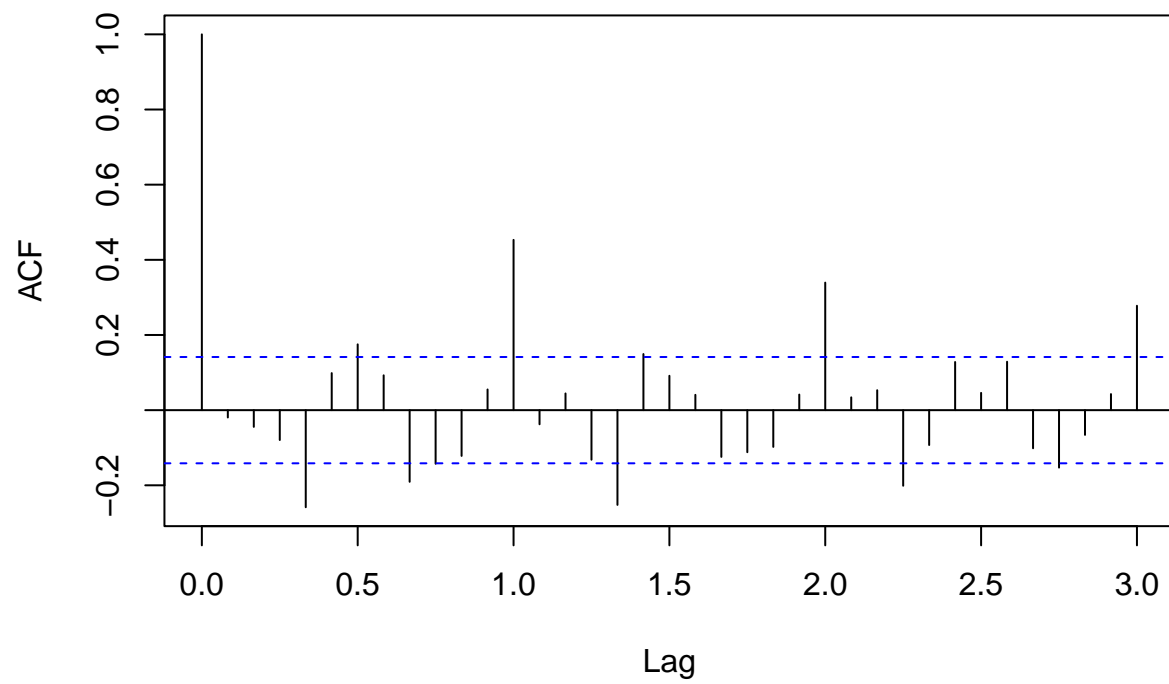
ARIMA(0,0,0) with constant
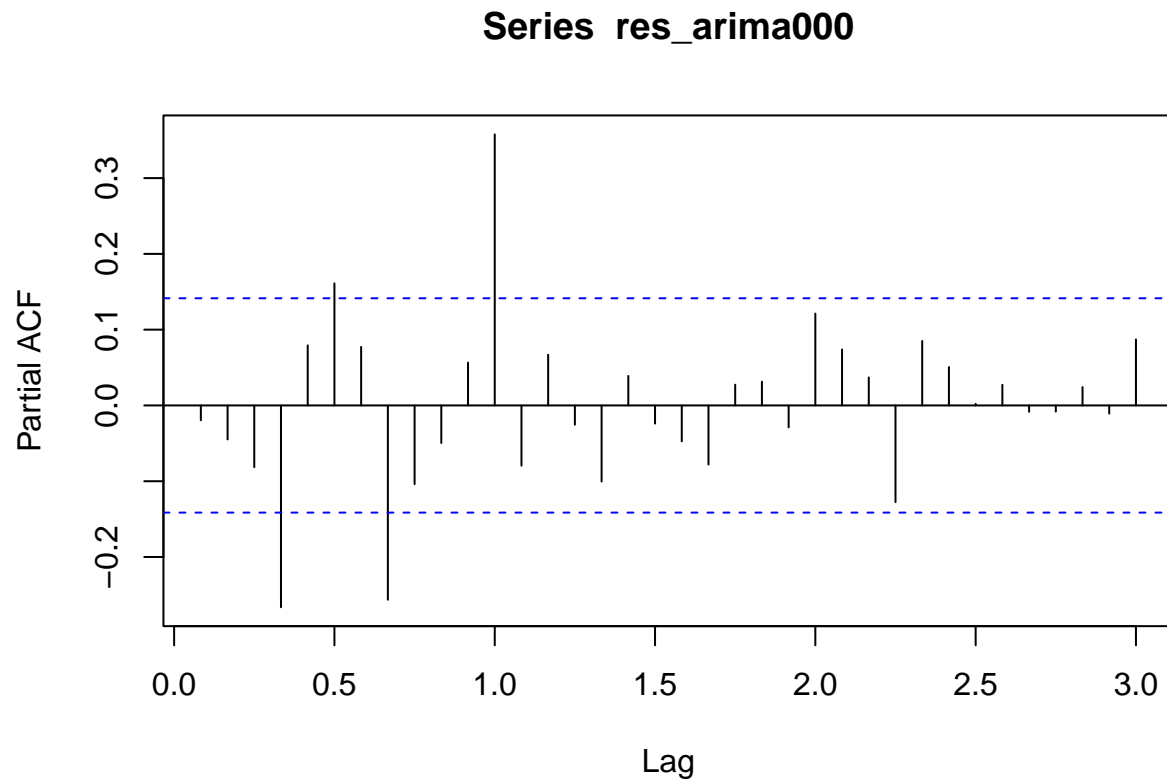
ARIMA(0, 0, 0)

```
man_arima000_fit_cons <- man_ts3 %>%
  model(arima000_constant = ARIMA(total_waste ~ 1 + pdq(0,0,0)))

zoo_arima000_fit <- arima(DSNY_MN_zoo_ts, order = 1 + c(0,0,0))
res_arima000 <- zoo_arima000_fit$residuals
acf(res_arima000, lag.max = 36)
```

Series res_arima000


```
pacf(res_arima000, lag.max = 36)
```

Series res_arima000


```
accuracy(man_arima000_fit_cons)[4]
```

```
## # A tibble: 1 x 1
##     RMSE
##    <dbl>
## 1 3502.
```

RMSE = 3501. The first significant lag in the ACF plot is lag 4. The first significant lag in the PACF plot is also lag 4. Both these lags are negative, which indicate the use of an MA() argument. The seasonal lags are once again present in both plots. In the PACF() plot, lag 6 is positive and significant.

With out working with the differenced values yet, I will add the MA() or seasonal MA paramters first.

ARIMA(0,0,0)(1,0,0) with constant and seasonal parameter

$ARIMA(0,0,0)(1,0,0)$

```
man_arima000_fit_seasonal_cons <- man_ts3 %>%
  model(arima000_constant_seasonal = ARIMA(total_waste ~ 1 +
                                     pdq(0,0,0) +
                                     PDQ(1,0,0, period = 12)))

zoo_arima000_seasonal_fit <- arima(DSNY_MN_zoo_ts,
                          order = 1 + c(0,0,0),
```
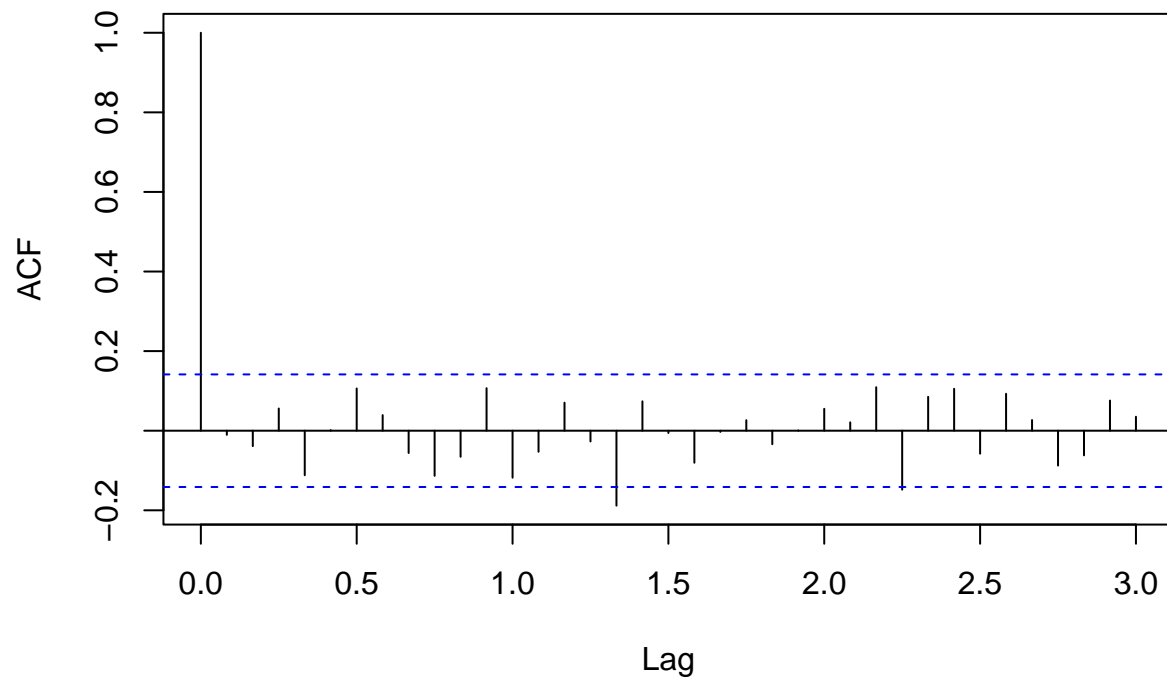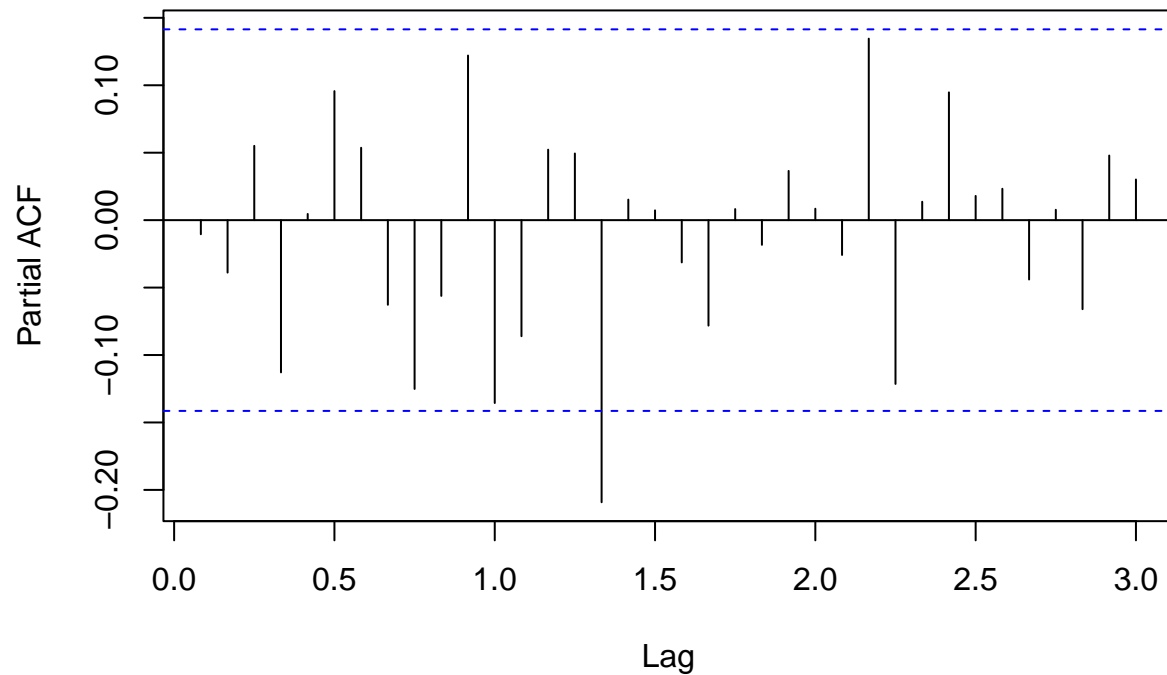
```
                                 seasonal = list(order = c(1,0L,0L), period = 12))
#names(zoo_arima000_fit)
res_arima000_seasonal <- zoo_arima000_seasonal_fit$residuals
acf(res_arima000_seasonal, lag.max = 36)
```

Series res_arima000_seasonal


```
pacf(res_arima000_seasonal, lag.max = 36)
```

Series res_arima000_seasonal


```
accuracy(man_arima000_fit_seasonal_cons)[4]
```

```
## # A tibble: 1 x 1
##     RMSE
##    <dbl>
## 1 2499.
```

RMSE = 2499.473. The majority of the lags in the ACF plot are contained within bounds. Along with the lags of the PACF plot. Only lag = 14 is significant and positive. The values are bounded b/w (-0.20, 0.15).

Let's work with an MA(4) model before we are confident in the previous model

ARIMA(0,0,4) with constant

$ARIMA(0,0,4)$

```
man_arima004_fit_cons <- man_ts3 %>%
  model(arima004_constant = ARIMA(total_waste ~ 1 +
                                   pdq(0,0,4)))

zoo_arima004_fit <- arima(DSNY_MN_zoo_ts,
                          order = 1 + c(0,0,4))
#names(zoo_arima000_fit)
res_arima004 <- zoo_arima004_fit$residuals
acf(res_arima004, lag.max = 36)
```

Series res_arima004
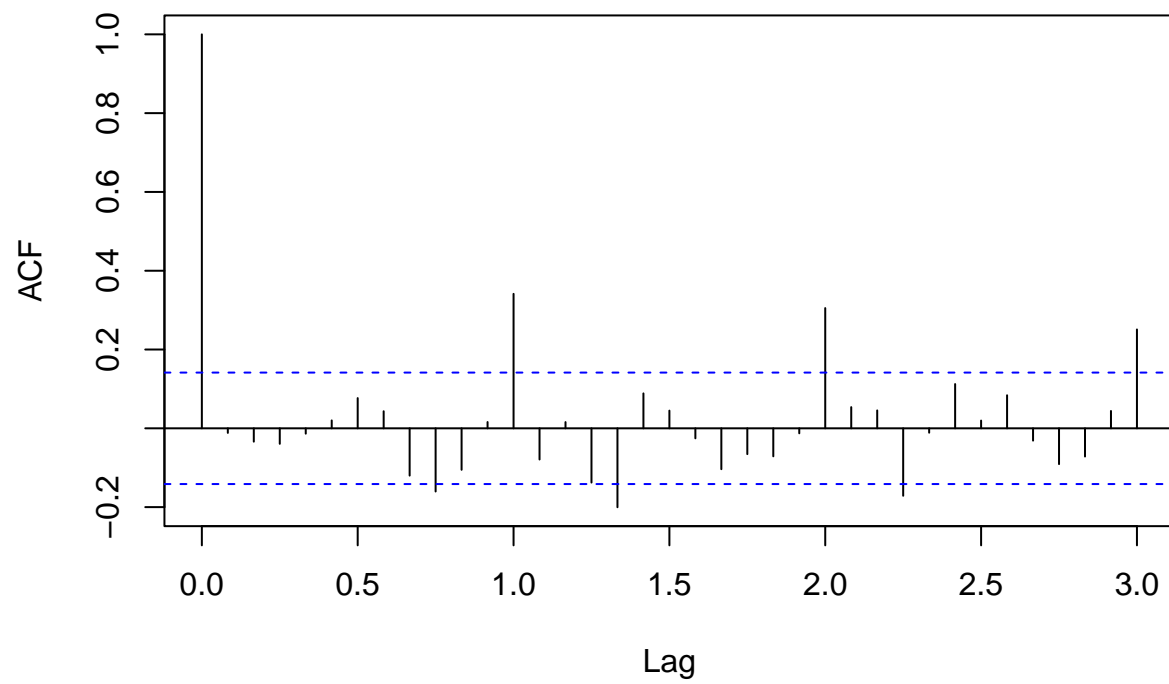

```
pacf(res_arima004, lag.max = 36)
```

11

Series res_arima004
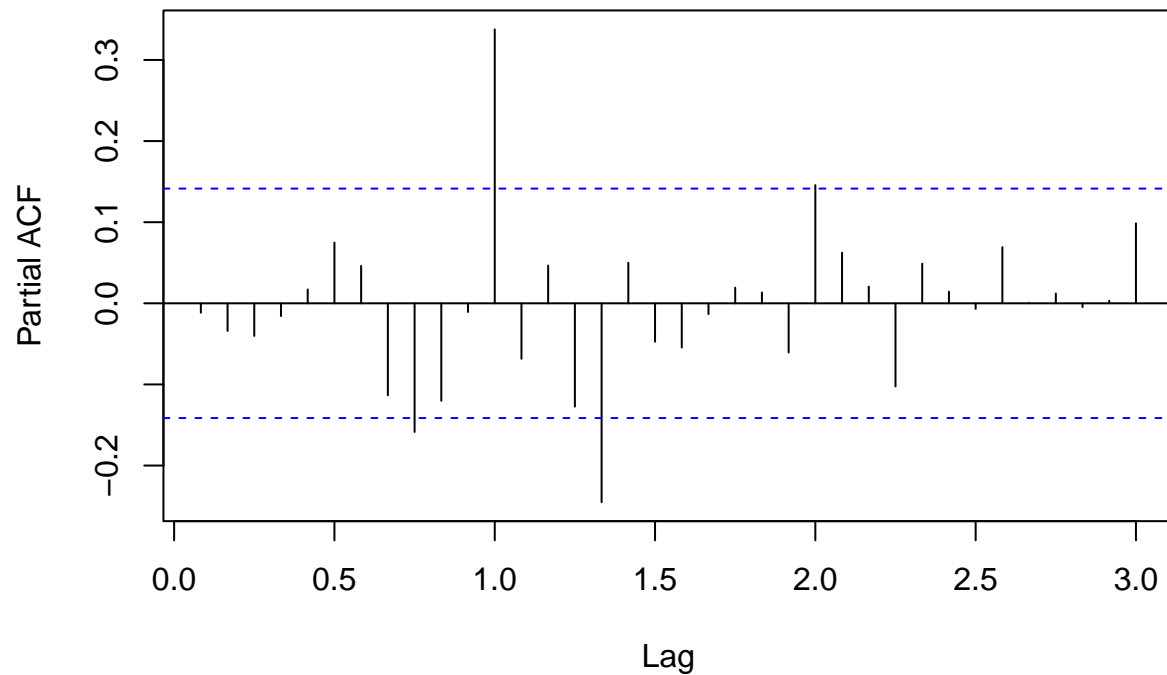

```
accuracy(man_arima004_fit_cons)[4]
```

```
## # A tibble: 1 x 1
##    RMSE
##   <dbl>
## 1 2862.
```

The RMSE = 2826.278. We do see a decrease in the RMSE when compared to the first ARIMA(0,0,0).The seasonal lags are significant in both plots. In the PACF plot, lags 1-12 are not significant and contained within the bounds.

Lets work with this model and add a seasonal argument.

ARIMA(0,0,4)(1,0,0) with constant and seasonal

$ARIMA(0,0,4)(1,0,0)_{12}$

```
man_arima004_100_seasonal_fit_cons <- man_ts3 %>%
  model(arima004_constant = ARIMA(total_waste ~ 1 +
                            pdq(0,0,4) +
                            PDQ(1,0,0,
                                period = 12)))

zoo_arima004_100_seasonalfit <- arima(DSNY_MN_zoo_ts,
```
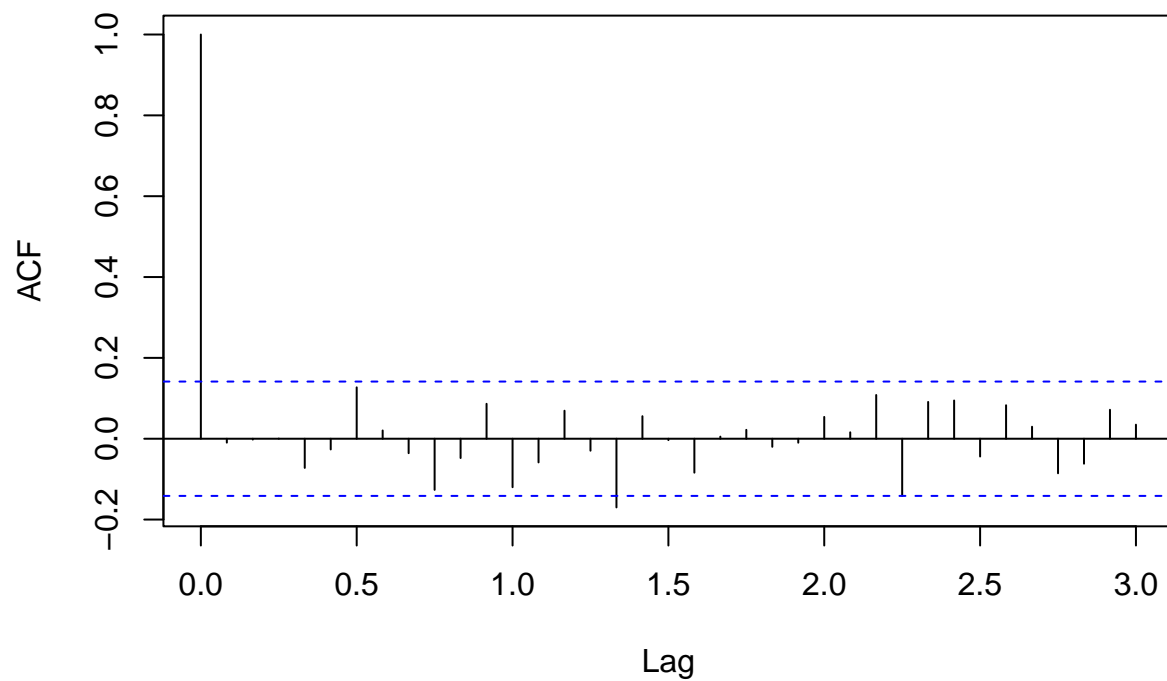
```
                        order = 1 + c(0,0,4),
                        seasonal = list(order = c(1, 0L, 0L),
                                        period = 12))
#names(zoo_arima000_fit)
res_arima004_100 <- zoo_arima004_100_seasonalfit$residuals
acf(res_arima004_100, lag.max = 36)
```
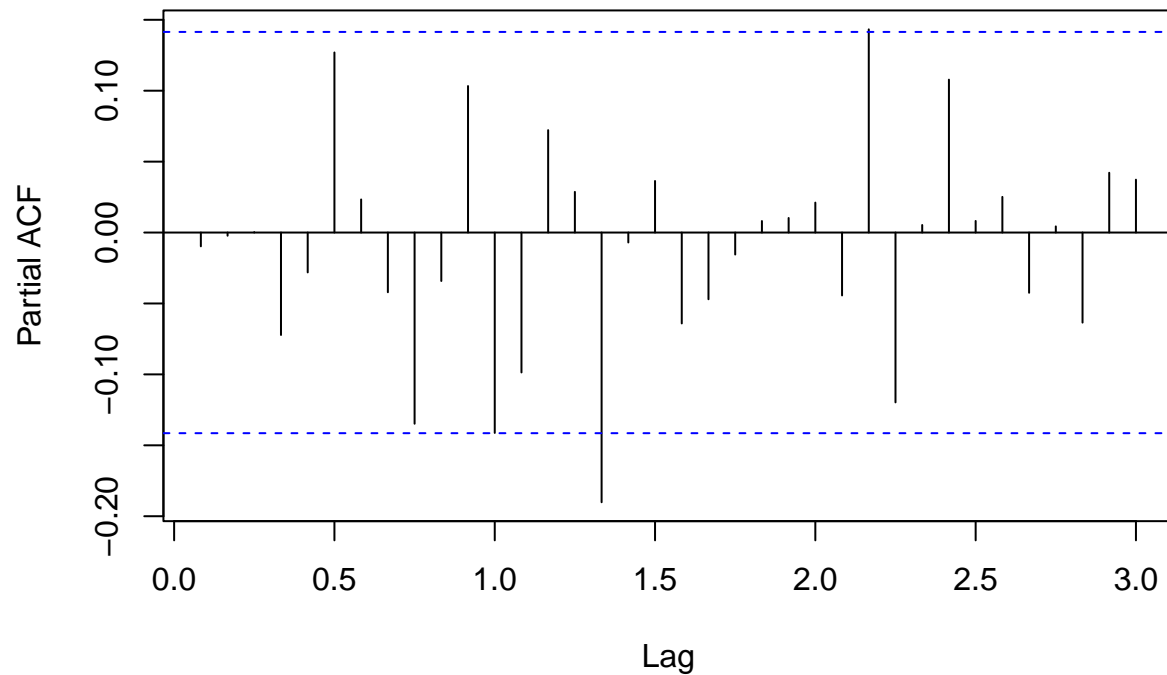
Series res_arima004_100


```
pacf(res_arima004_100, lag.max = 36)
```

Series res_arima004_100


```
accuracy(man_arima004_100_seasonal_fit_cons)[4]
```

```
## # A tibble: 1 x 1
##     RMSE
##    <dbl>
## 1 2386.
```

RMSE = 2386.418. In both plots, all first 15 lags are not significant. It is hard to explain why lag = 16 in the PACF plot is significant. This model is a strong contender.

Since we can also work with the differenced values, we will create some models with them

ARIMA(0,1,0) with constant
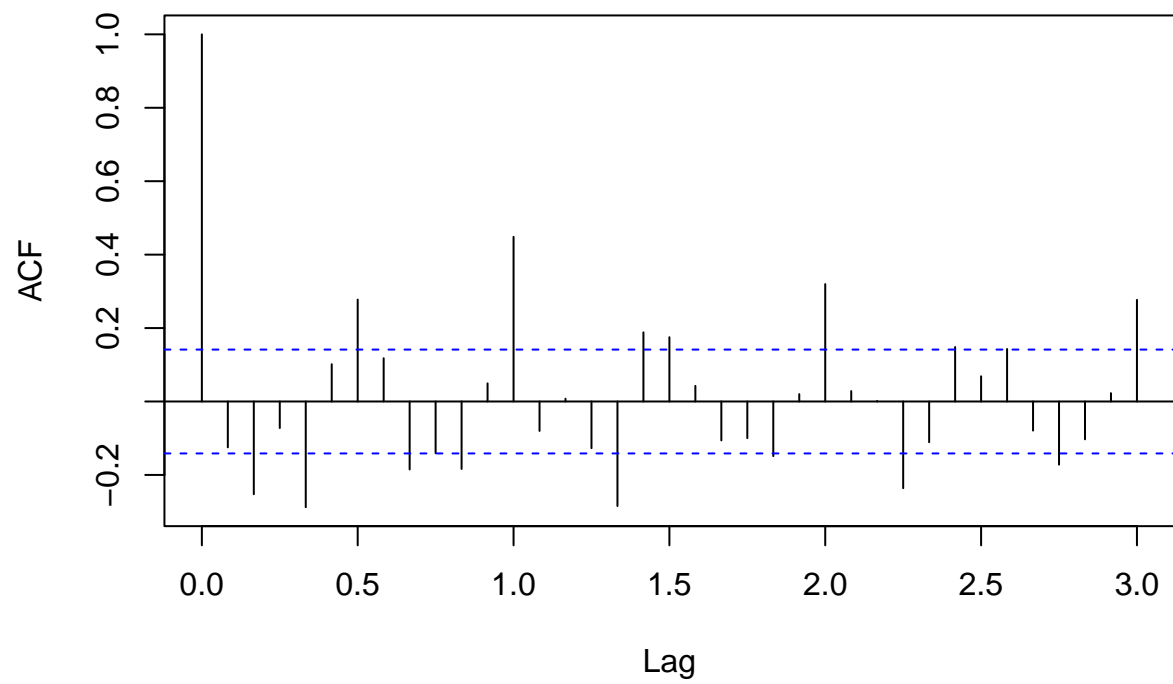
$ARIMA(0,1,0)$

```
man_arima010_fit_cons <- man_ts3 %>%
  model(arima010_constant = ARIMA(total_waste ~ 1 + pdq(0,1,0)))

zoo_arima010_fit <- arima(DSNY_MN_zoo_ts,
                          order = 1 + c(0,1,0))

res_arima010 <- zoo_arima010_fit$residuals
acf(res_arima010, lag.max = 36)
```

Series res_arima010


```
pacf(res_arima010, lag.max = 36)
```

Series res_arima010


```
accuracy(man_arima010_fit_cons)[4]
```

```
## # A tibble: 1 x 1
##    RMSE
##   <dbl>
## 1 3441.
```

RMSE = 3441.309. Try an MA(2) or MA(4) model and address the seasonality later.

ARIMA(0,1,2) with constant

$ARIMA(0, 1, 2)$

```
man_arima012_fit_cons <- man_ts3 %>%
  model(arima012_constant = ARIMA(total_waste ~ 1 + pdq(0,1,2)))

zoo_arima012_fit <- arima(DSNY_MN_zoo_ts, order = 1 + c(0,1,2))
res_arima012 <- zoo_arima012_fit$residuals
acf(res_arima012, lag.max = 36)
```
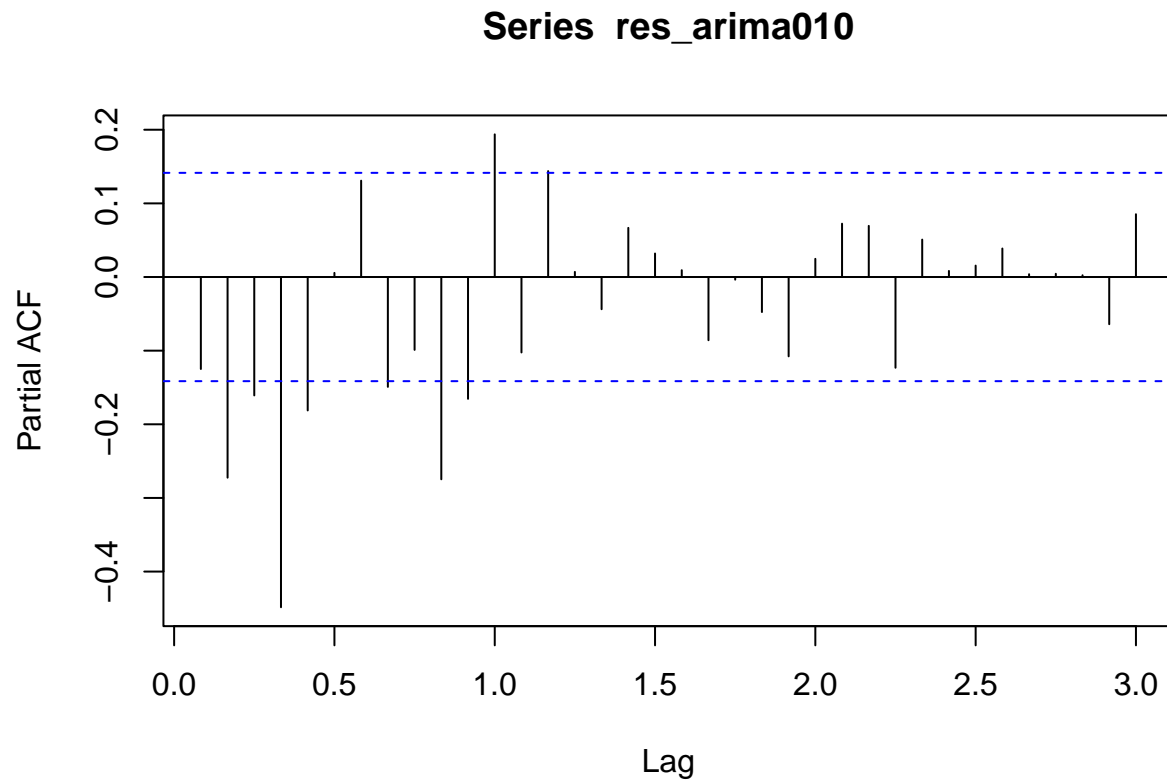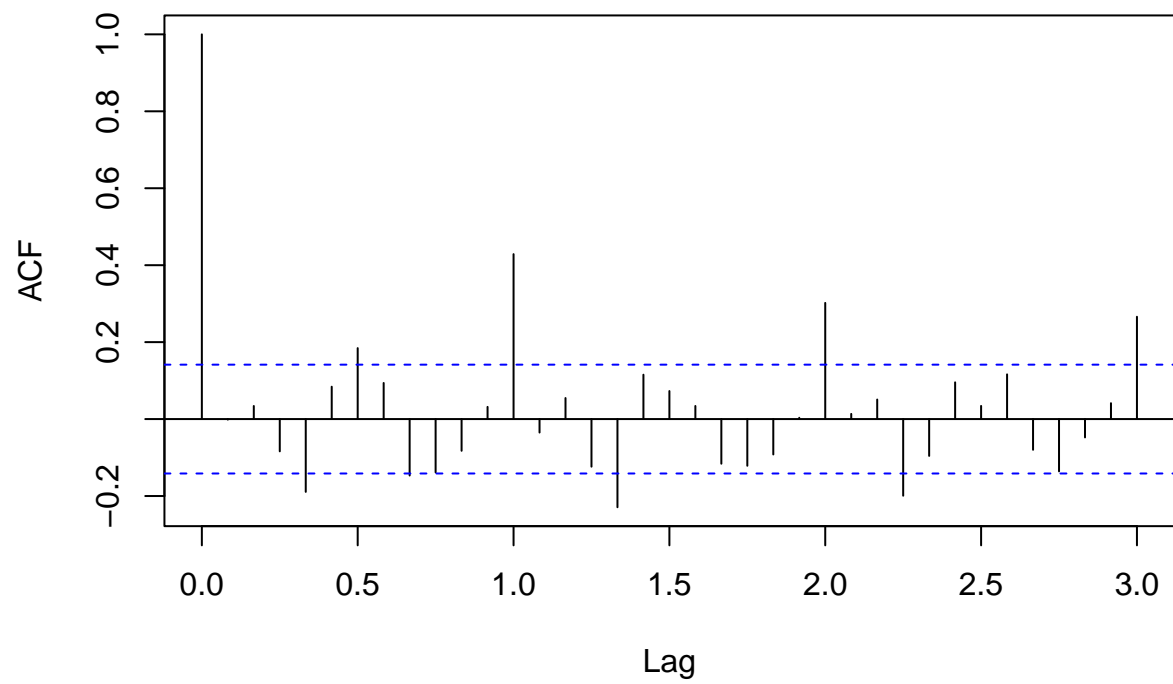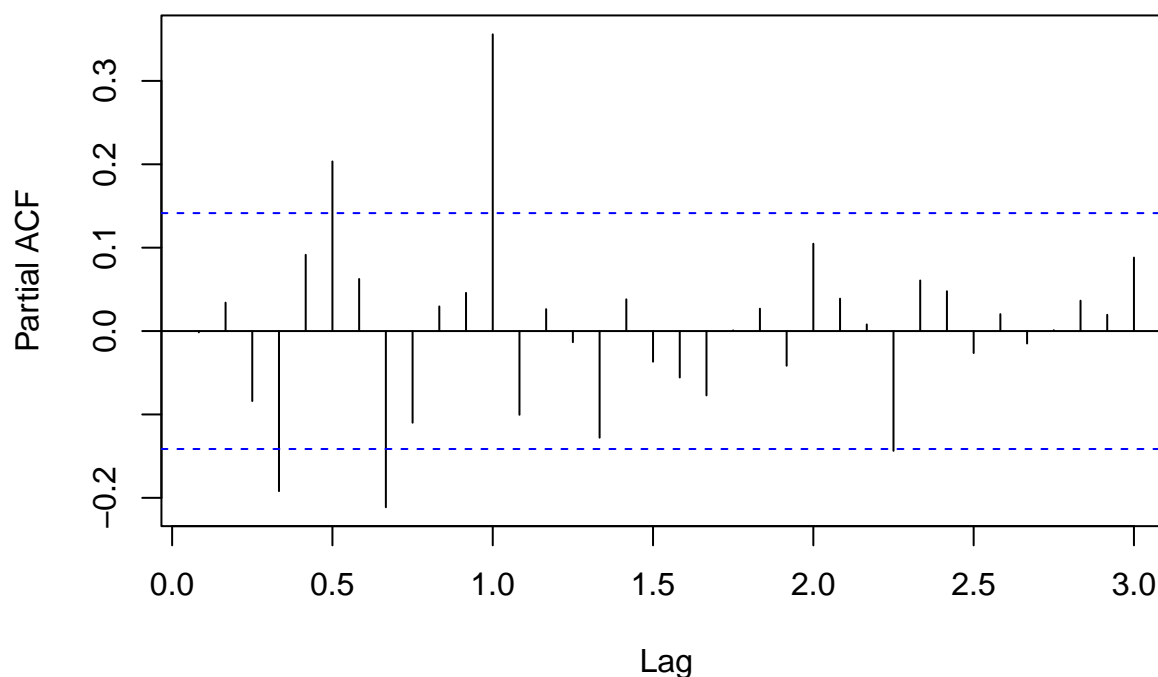
Series res_arima012


```
pacf(res_arima012, lag.max = 36)
```

Series res_arima012


```
accuracy(man_arima012_fit_cons)[4]
```

```
## # A tibble: 1 x 1
##    RMSE
##   <dbl>
## 1 2586.
```

RMSE = 2586.395. We continue to see the RMSE decrease. Lag 4 in both the ACF and PACF plot is significant. We could try an ARIMA(0,1,4), but let us first address the seasonality on the current model.

ARIMA(0,1,2)(1,0,0) with constant and seasonality

$ARIMA(0, 1, 2)(1, 0, 0)[12]$

```
man_arima012_100_fit_cons <- man_ts3 %>%
  model(arima012_100_constant = ARIMA(total_waste ~ 1 +
                                   pdq(0,1,2) +
                                   PDQ(1,0,0,
                                       period = 12)))

zoo_arima012_100_fit <- arima(DSNY_MN_zoo_ts,
                              order = 1 + c(0,1,2),
                              seasonal = list(order = c(1,0L,0L),
                                              period = 12))
```

```
res_arima012_100 <- zoo_arima012_100_fit$residuals
acf(res_arima012_100, lag.max = 36)
```

Series res_arima012_100


```
pacf(res_arima012_100, lag.max = 36)
```

Series res_arima012_100
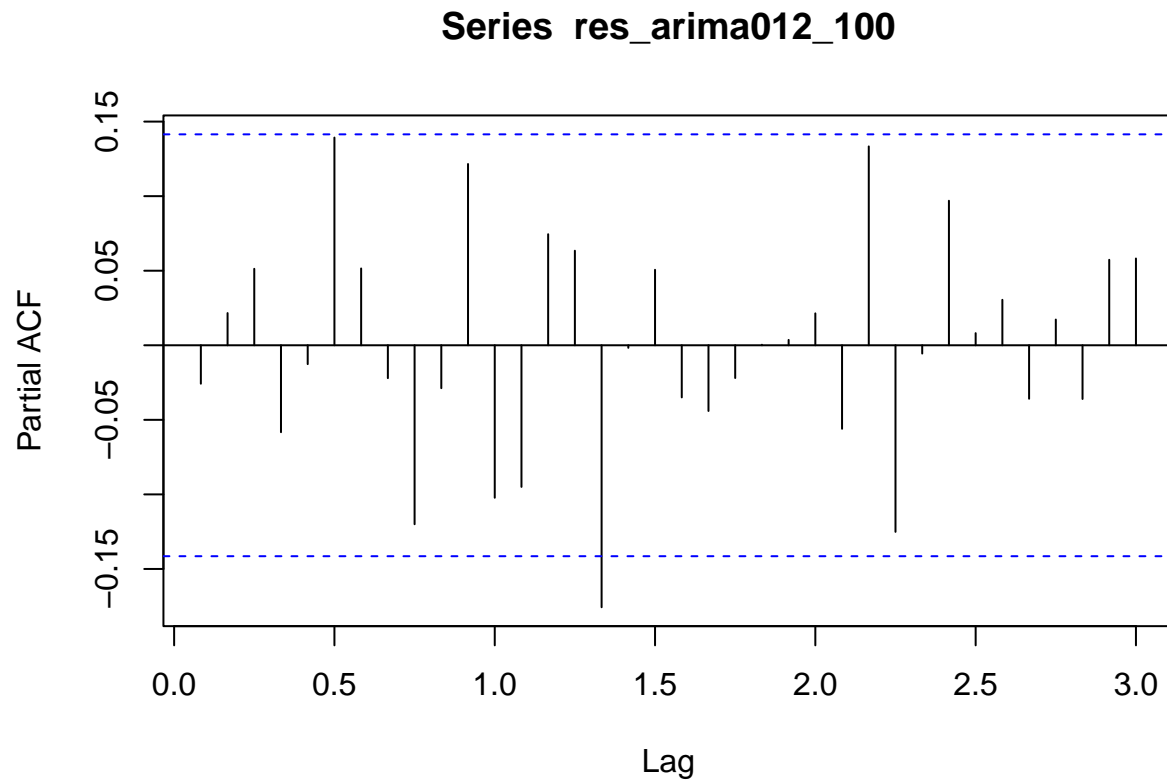

```
accuracy(man_arima012_100_fit_cons)[4]
```

```
## # A tibble: 1 x 1
##     RMSE
##    <dbl>
## 1 2215.
```

RMSE = 2215.12. The majority of the ACF and PACF lag values are contained within bounds. However, lag 16 in both plots are significant. Being bounded b/w (-0.15, 0.15). There wouldn't be a direct way to address this lag without adding a high MA argument and potentialy overfitting this model.

Before turning to the auto arima model, lets work on a $ARIMA(0,1,4)(1,0,0)[12]$ model.

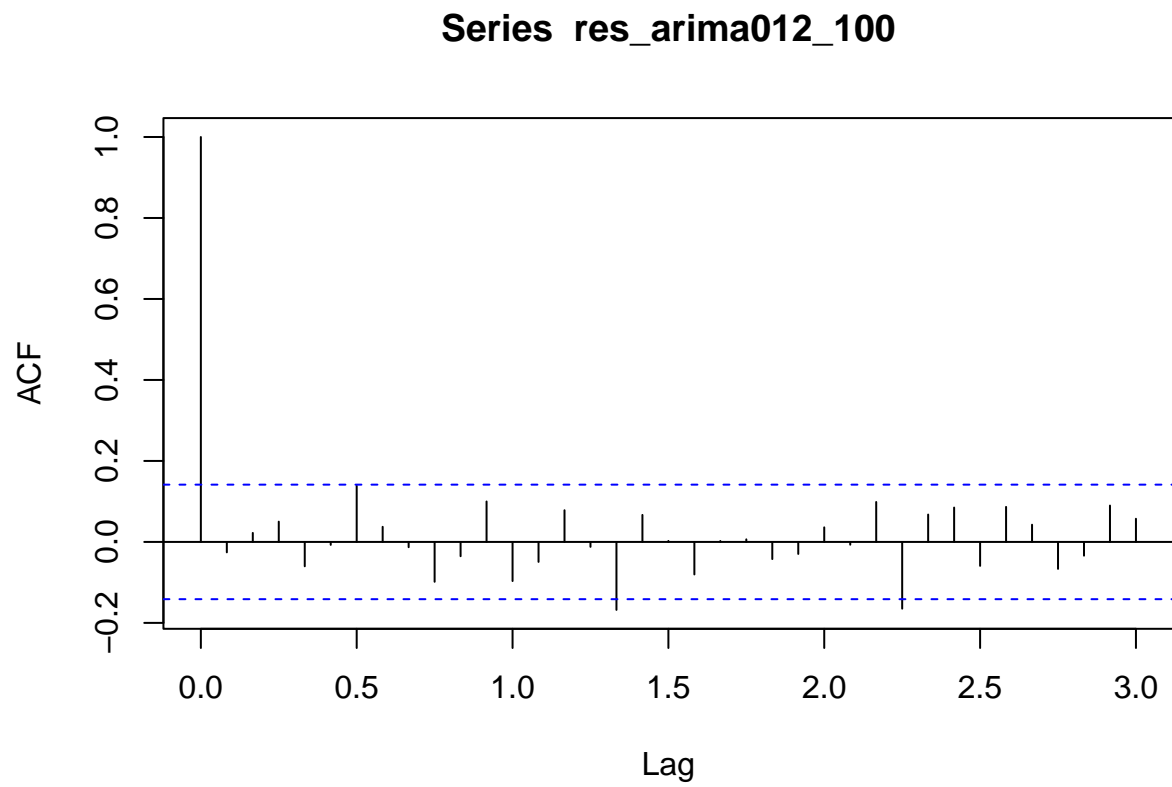## ARIMA(0,1,4)(1,0,0) with constant and seasonality

$ARIMA(0,1,4)(1,0,0)[12]$

```
man_arima014_100_fit_cons <- man_ts3 %>%
  model(arima014_100_constant = ARIMA(total_waste ~ 1 +
                                        pdq(0,1,4) +
                                        PDQ(1,0,0,
                                            period = 12)))

zoo_arima014_100_fit <- arima(DSNY_MN_zoo_ts,
```

```
                            order = 1 + c(0,1,4),
                            seasonal = list(order = c(1,0L,0L),
                                            period = 12))
res_arima014_100 <- zoo_arima014_100_fit$residuals
acf(res_arima014_100, lag.max = 36)
```

Series res_arima014_100


```
pacf(res_arima014_100, lag.max = 36)
```
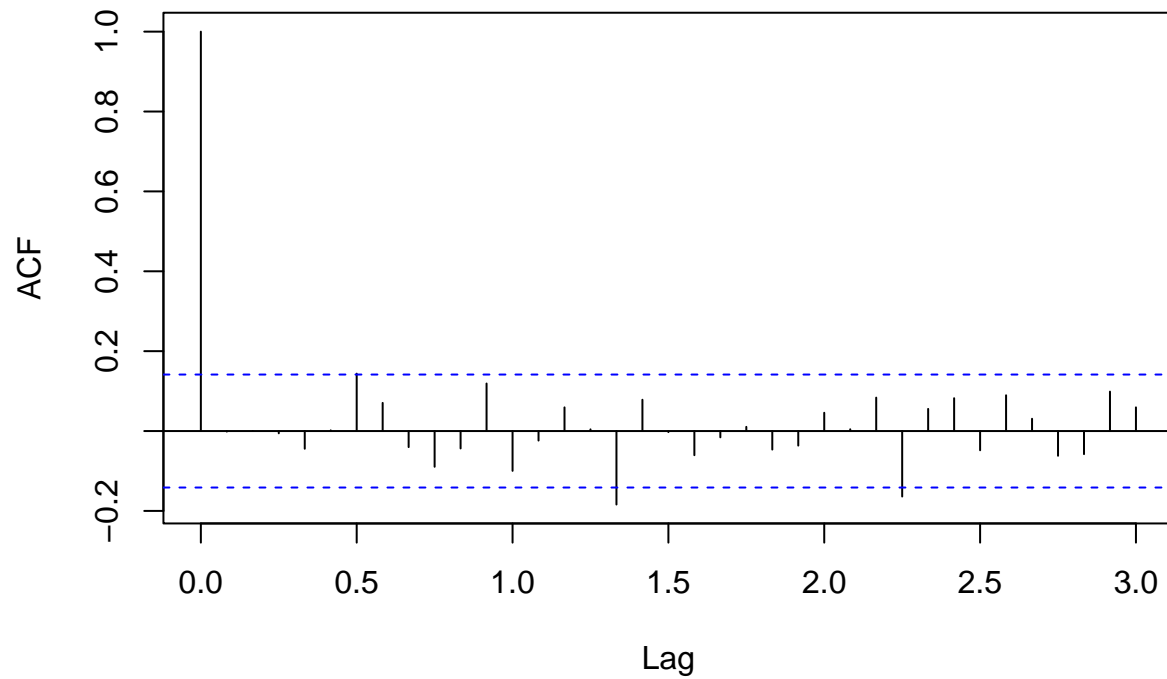
Series res_arima014_100


```
accuracy(man_arima014_100_fit_cons)[4]
```

```
## # A tibble: 1 x 1
##     RMSE
##    <dbl>
## 1 2208.
```

RMSE $= 2208.185$. Which is a decrease when compared to $ARIMA(0,1,2)(1,0,0)[12]$. Again, the majority of the lags are contained within the bounds. However we are not able to make the lag 16 insignificant in both plots.

Auto-arima

For our final model, we will look and compare the results of an auto-arima model from the feasts package.
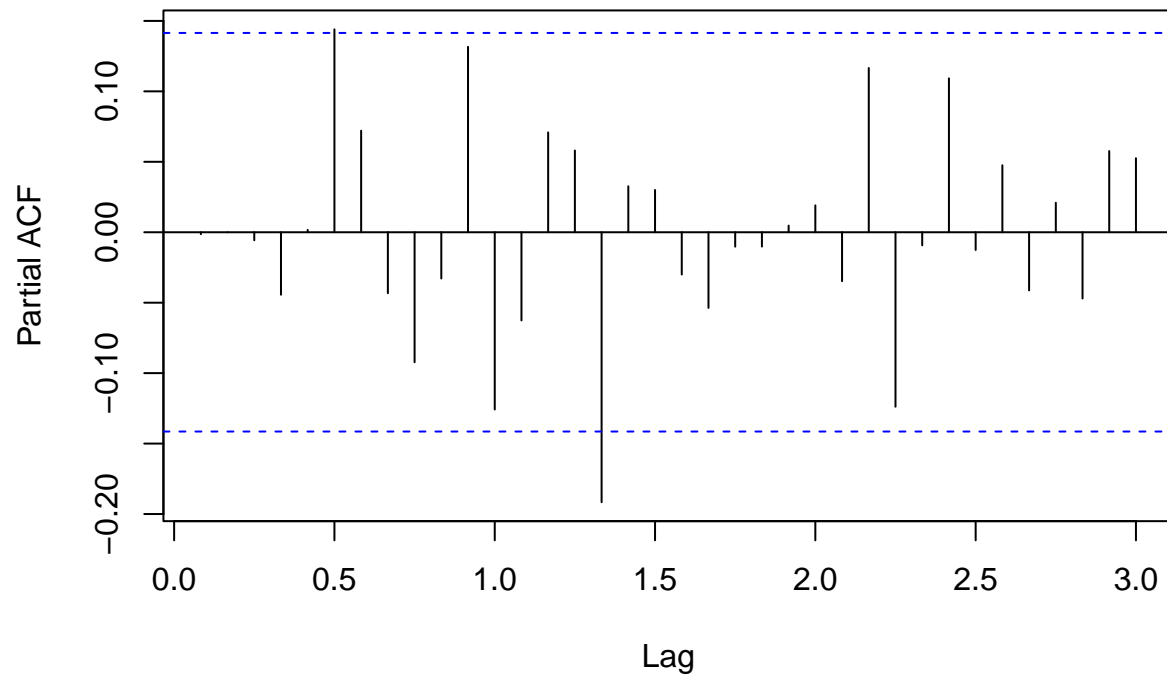
```
man_auto_arima_fit_cons <- man_ts3 %>%
  model(stepwise = ARIMA(total_waste),
        search = ARIMA(total_waste,
                       stepwise = FALSE,
                       approximation = FALSE))

# zoo_arima014_100_fit <- arima(DSNY_MN_zoo_ts,
#                               order = 1 + c(0,1,4),
#                               seasonal = list(order = c(1,0L,0L),
```

```
#                                        period = 12))
# res_arima014_100 <- zoo_arima014_100_fit$residuals
# acf(res_arima014_100, lag.max = 36)
# pacf(res_arima014_100, lag.max = 36)
accuracy(man_auto_arima_fit_cons)[1:4]
```

```
## # A tibble: 2 x 4
##   .model   .type       ME  RMSE
##   <chr>    <chr>     <dbl> <dbl>
## 1 stepwise Training  17.4 2589.
## 2 search   Training  38.8 2450.
```

```
#man_auto_arima_fit_cons %>% accuracy()
```

The stepwise model has RMSE = 2588.702, while the search model has RMSE = 2449.647. We will take a look at the ACF and PACF plots of the search model

Return the coefficients of the models above

```
man_auto_arima_fit_cons %>% select(.model = stepwise) %>% report()
```

```
## Series: total_waste
## Model: ARIMA(0,1,1) w/ drift
##
## Coefficients:
##           ma1  constant
##       -0.9140  -45.1428
## s.e.   0.0247   17.1493
##
## sigma^2 estimated as 6807750:  log likelihood=-1773.47
## AIC=3552.94   AICc=3553.07   BIC=3562.7
```

```
print("--------------")
```

```
## [1] "--------------"
```

```
man_auto_arima_fit_cons %>% select(.model = search) %>% report()
```

```
## Series: total_waste
## Model: ARIMA(0,1,5) w/ drift
##
## Coefficients:
##           ma1     ma2      ma3      ma4     ma5  constant
##       -0.9074  0.0146  -0.0520  -0.2763  0.3286  -50.0732
## s.e.   0.0688  0.0935   0.0834   0.0919  0.0648   19.6900
##
## sigma^2 estimated as 6227826:  log likelihood=-1763.23
## AIC=3540.47   AICc=3541.08   BIC=3563.23
```

23

ARIMA(0,1,5) with constant from auto-arima

$ARIMA(0, 1, 5)$

```
man_arima015_fit_cons <- man_ts3 %>%
  model(arima015_constant = ARIMA(total_waste ~ 1 +
                                    pdq(0,1,5)))

zoo_arima015_fit <- arima(DSNY_MN_zoo_ts,
                          order = 1 + c(0,1,5))

res_arima015 <- zoo_arima015_fit$residuals
acf(res_arima015, lag.max = 36)
```

Series res_arima015
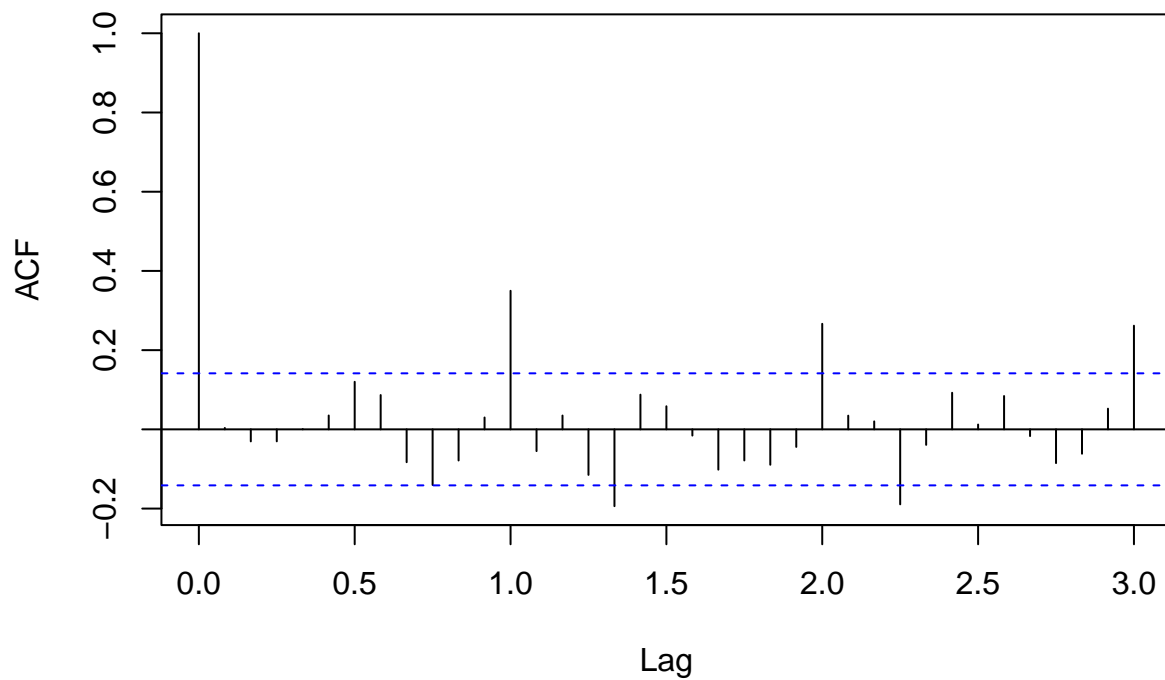

```
pacf(res_arima015, lag.max = 36)
```

Series res_arima015
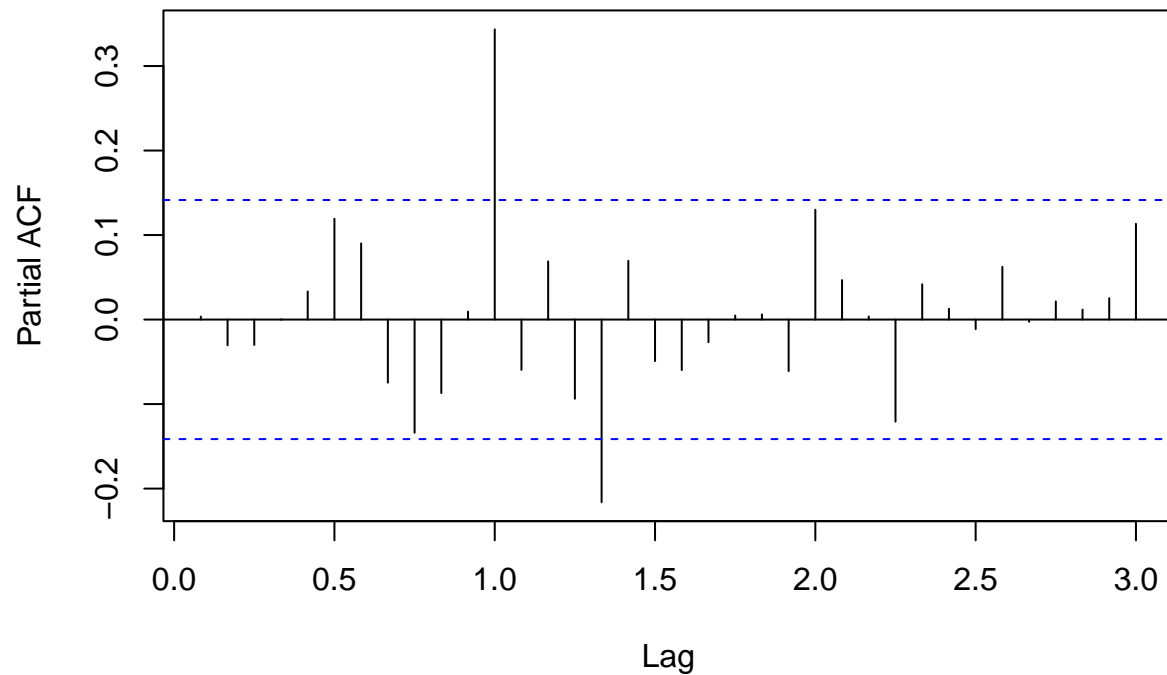

```
accuracy(man_arima015_fit_cons)[4]
```

```
## # A tibble: 1 x 1
##    RMSE
##   <dbl>
## 1 2450.
```

Yeah this model was going to have significant lags without adressing the seasonality.

Summary of Models

$ARIMA(0,0,4)(1,0,0)[12]$ has RMSE = 2386.46
$ARIMA(0,1,4)(1,0,0)[12]$ has RMSE = 2208.185
$ARIMA(0,1,2)(1,0,0)[12]$ has RMSE = 2215.12
$ARIMA(0,1,5)$ is the search model and has RMSE = 2449.647

Plots and Visualizations

The fable package automatically produces forecast means (by back-transforming and adjusting the transformed forecasts). The forecast medians can be obtained via the forecast intervals when level=0. (https://fable.tidyverts.org/articles/transformations.html)

Preliminary forecast of $ARIMA(0,0,4)(1,0,0)_{12}$

```
man_arima004_100_seasonal_fit_cons %>%
  forecast(h = 4) %>%
  autoplot(man_ts3)
```
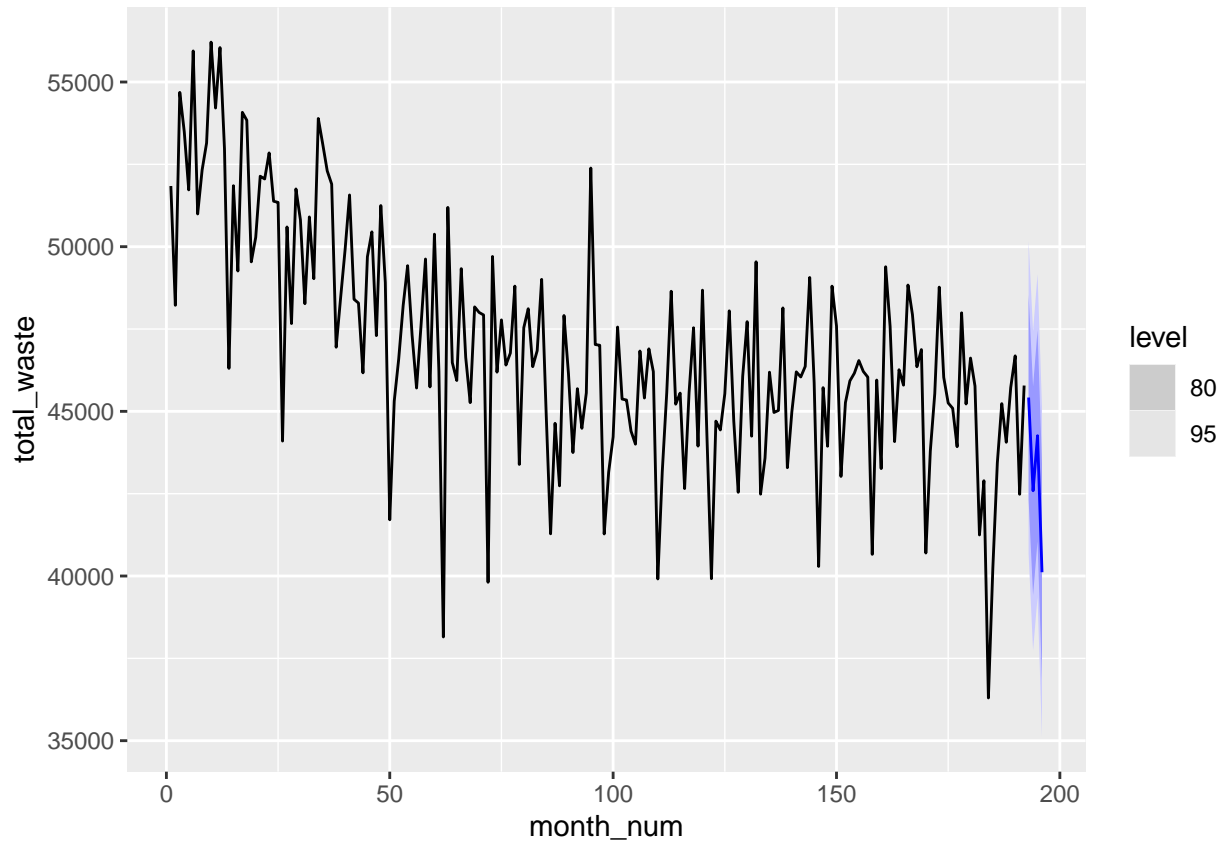


```
man_arima004_100_seasonal_fit_cons %>%
  forecast(h = 4,
           point_forecast = list(.mean = mean)) %>%
  hilo(level=95) %>%
  unpack_hilo('95%')
```

```
## # A tsibble: 4 x 6 [1]
## # Key:       .model [1]
##   .model           month_num      total_waste  .mean `95%_lower` `95%_upper`
##   <chr>                <dbl>           <dist> <dbl>       <dbl>       <dbl>
## 1 arima004_constant      193 N(45419, 5878700) 45419.      40667.      50172.
## 2 arima004_constant      194 N(42589, 6102615) 42589.      37747.      47431.
## 3 arima004_constant      195 N(44260, 6249915) 44260.      39360.      49160.
## 4 arima004_constant      196 N(40115, 6510563) 40115.      35114.      45116.
```

```
man_arima004_100_seasonal_fit_cons %>% glance()
```

```
## # A tibble: 1 x 8
##   .model            sigma2 log_lik   AIC  AICc   BIC ar_roots   ma_roots
##   <chr>              <dbl>   <dbl> <dbl> <dbl> <dbl> <list>     <list>
## 1 arima004_constant 5878700.  -1769. 3552. 3553. 3575. <cpl [12]> <cpl [4]>
```

Preliminary forecast of $ARIMA(0,1,4)(1,0,0)[12]$

```
man_arima014_100_fit_cons %>%
  forecast(h = 8) %>%
  autoplot(man_ts3) + labs(x = "Month Number",
                           y = "Total Waste",
                           title = "Forecasted Values",
                           subtitle = "01/2005 - 08/2021")
```



```
man_arima014_100_fit_cons %>%
  forecast(h = 8, point_forecast = list(.median = median)) %>%
  hilo(level=95) %>%
  unpack_hilo('95%')
```
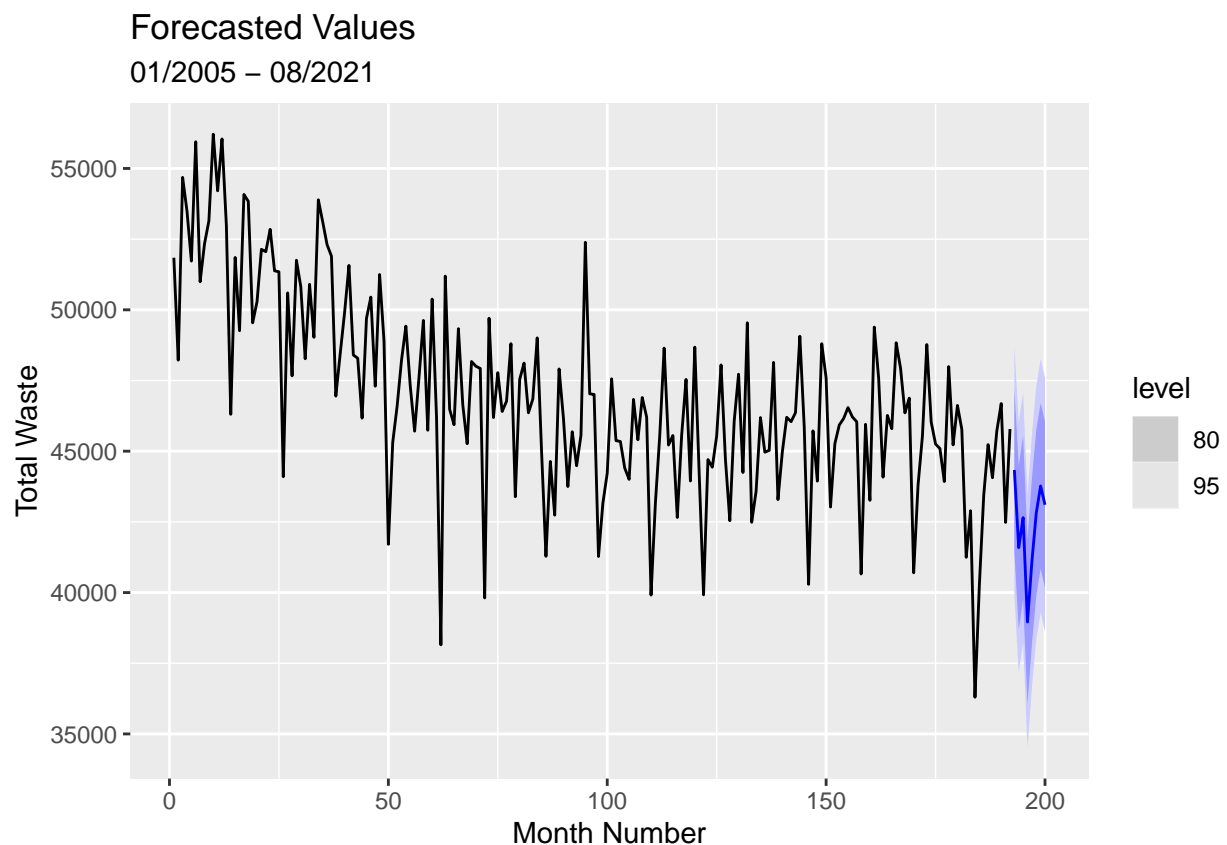
```
## # A tsibble: 8 x 6 [1]
## # Key:       .model [1]
##   .model          month_num      total_waste .median `95%_lower` `95%_upper`
##   <chr>                <dbl>           <dist>   <dbl>       <dbl>       <dbl>
```
```

```
## 1 arima014_100_cons~         193 N(44335, 5060580)  44335.       39926.        48744.
## 2 arima014_100_cons~         194 N(41590, 5085400)  41590.       37170.        46010.
## 3 arima014_100_cons~         195 N(42650, 5089155)  42650.       38229.        47072.
## 4 arima014_100_cons~         196 N(38961, 5166604)  38961.       34506.        43416.
## 5 arima014_100_cons~         197 N(41093, 5187860)  41093.       36629.        45557.
## 6 arima014_100_cons~         198 N(42812, 5209116)  42812.       38338.        47285.
## 7 arima014_100_cons~         199 N(43770, 5230372)  43770.       39287.        48252.
## 8 arima014_100_cons~         200 N(43105, 5251627)  43105.       38613.        47596.
```

```r
man_arima014_100_fit_cons %>%
  forecast(h = 8, point_forecast = list(.mean = mean)) %>%
  hilo(level=95) %>%
  unpack_hilo('95%')
```

```
## # A tsibble: 8 x 6 [1]
## # Key:       .model [1]
##   .model            month_num     total_waste  .mean `95%_lower` `95%_upper`
##   <chr>                 <dbl>          <dist> <dbl>      <dbl>        <dbl>
## 1 arima014_100_const~     193 N(44335, 5060580) 44335.      39926.       48744.
## 2 arima014_100_const~     194 N(41590, 5085400) 41590.      37170.       46010.
## 3 arima014_100_const~     195 N(42650, 5089155) 42650.      38229.       47072.
## 4 arima014_100_const~     196 N(38961, 5166604) 38961.      34506.       43416.
## 5 arima014_100_const~     197 N(41093, 5187860) 41093.      36629.       45557.
## 6 arima014_100_const~     198 N(42812, 5209116) 42812.      38338.       47285.
## 7 arima014_100_const~     199 N(43770, 5230372) 43770.      39287.       48252.
## 8 arima014_100_const~     200 N(43105, 5251627) 43105.      38613.       47596.
```

```r
man_arima014_100_fit_cons %>%
  forecast(h = 8, point_forecast = list(.max = max)) %>%
  hilo(level=95) %>%
  unpack_hilo('95%')
```

```
## # A tsibble: 8 x 6 [1]
## # Key:       .model [1]
##   .model  month_num      total_waste              .max `95%_lower` `95%_upper`
##   <chr>       <dbl>           <dist>            <dist>      <dbl>        <dbl>
## 1 arima01~      193 N(44335, 5060580) N(43105, 5251627)     39926.       48744.
## 2 arima01~      194 N(41590, 5085400) N(43105, 5251627)     37170.       46010.
## 3 arima01~      195 N(42650, 5089155) N(43105, 5251627)     38229.       47072.
## 4 arima01~      196 N(38961, 5166604) N(43105, 5251627)     34506.       43416.
## 5 arima01~      197 N(41093, 5187860) N(43105, 5251627)     36629.       45557.
## 6 arima01~      198 N(42812, 5209116) N(43105, 5251627)     38338.       47285.
## 7 arima01~      199 N(43770, 5230372) N(43105, 5251627)     39287.       48252.
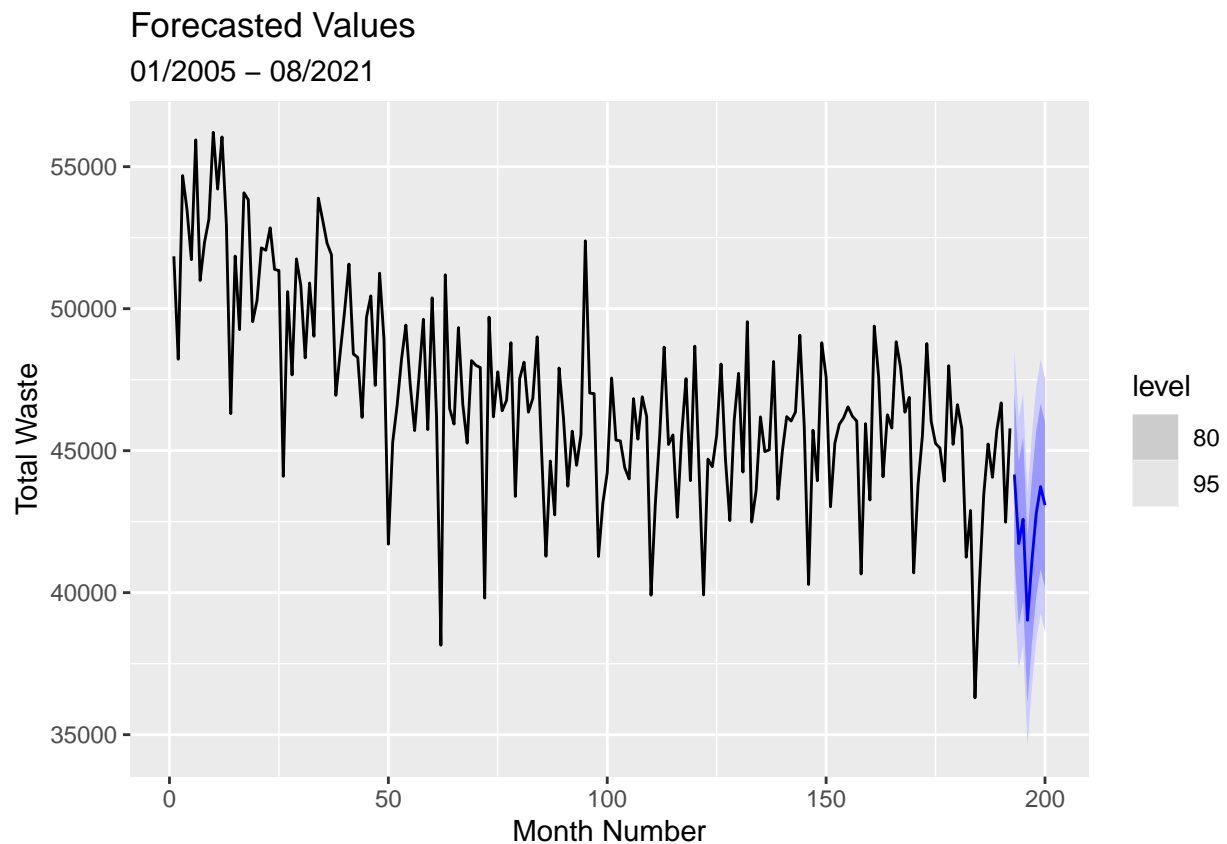## 8 arima01~      200 N(43105, 5251627) N(43105, 5251627)     38613.       47596.
```

```r
man_arima014_100_forecasts <- man_arima014_100_fit_cons %>%
  forecast(h = 8)

man_arima014_100_forecasts %>%
  hilo(level=95) %>%
  unpack_hilo('95%')
```

```
## # A tsibble: 8 x 6 [1]
## # Key:       .model [1]
##   .model             month_num   total_waste  .mean `95%_lower` `95%_upper`
##   <chr>                   <dbl>        <dist>  <dbl>       <dbl>       <dbl>
## 1 arima014_100_const~       193 N(44335, 5060580) 44335.      39926.      48744.
## 2 arima014_100_const~       194 N(41590, 5085400) 41590.      37170.      46010.
## 3 arima014_100_const~       195 N(42650, 5089155) 42650.      38229.      47072.
## 4 arima014_100_const~       196 N(38961, 5166604) 38961.      34506.      43416.
## 5 arima014_100_const~       197 N(41093, 5187860) 41093.      36629.      45557.
## 6 arima014_100_const~       198 N(42812, 5209116) 42812.      38338.      47285.
## 7 arima014_100_const~       199 N(43770, 5230372) 43770.      39287.      48252.
## 8 arima014_100_const~       200 N(43105, 5251627) 43105.      38613.      47596.
```

Preliminary forecast of $ARIMA(0,1,2)(1,0,0)[12]$

```
man_arima012_100_fit_cons %>%
  forecast(h = 8) %>%
  autoplot(man_ts3) + labs(x = "Month Number",
                    y = "Total Waste",
                    title = "Forecasted Values",
                    subtitle = "01/2005 - 08/2021")
```

```
man_arima012_100_fit_cons %>%
  forecast(h = 8, point_forecast = list(.median = median)) %>%
  hilo(level=95) %>%
  unpack_hilo('95%')
```

```
## # A tsibble: 8 x 6 [1]
## # Key:        .model [1]
##   .model            month_num      total_waste .median `95%_lower` `95%_upper`
##   <chr>                 <dbl>           <dist>   <dbl>       <dbl>       <dbl>
## 1 arima012_100_cons~      193   N(44161, 5e+06)  44161.      39761.      48560.
## 2 arima012_100_cons~      194 N(41728, 5054881)  41728.      37321.      46135.
## 3 arima012_100_cons~      195 N(42583, 5077518)  42583.      38167.      47000.
## 4 arima012_100_cons~      196 N(39030, 5100155)  39030.      34604.      43457.
## 5 arima012_100_cons~      197 N(41116, 5122791)  41116.      36680.      45553.
## 6 arima012_100_cons~      198 N(42798, 5145428)  42798.      38352.      47244.
## 7 arima012_100_cons~      199 N(43735, 5168065)  43735.      39279.      48190.
## 8 arima012_100_cons~      200 N(43082, 5190701)  43082.      38617.      47548.
```

```
man_arima012_100_fit_cons %>%
  forecast(h = 8, point_forecast = list(.mean = mean)) %>%
  hilo(level=95) %>%
  unpack_hilo('95%')
```

```
## # A tsibble: 8 x 6 [1]
## # Key:        .model [1]
##   .model             month_num      total_waste .mean `95%_lower` `95%_upper`
##   <chr>                  <dbl>           <dist> <dbl>       <dbl>       <dbl>
## 1 arima012_100_const~      193   N(44161, 5e+06) 44161.      39761.      48560.
## 2 arima012_100_const~      194 N(41728, 5054881) 41728.      37321.      46135.
## 3 arima012_100_const~      195 N(42583, 5077518) 42583.      38167.      47000.
## 4 arima012_100_const~      196 N(39030, 5100155) 39030.      34604.      43457.
## 5 arima012_100_const~      197 N(41116, 5122791) 41116.      36680.      45553.
## 6 arima012_100_const~      198 N(42798, 5145428) 42798.      38352.      47244.
## 7 arima012_100_const~      199 N(43735, 5168065) 43735.      39279.      48190.
## 8 arima012_100_const~      200 N(43082, 5190701) 43082.      38617.      47548.
```

```
man_arima012_100_fit_cons %>%
  forecast(h = 8, point_forecast = list(.max = max)) %>%
  hilo(level=95) %>%
  unpack_hilo('95%')
```

```
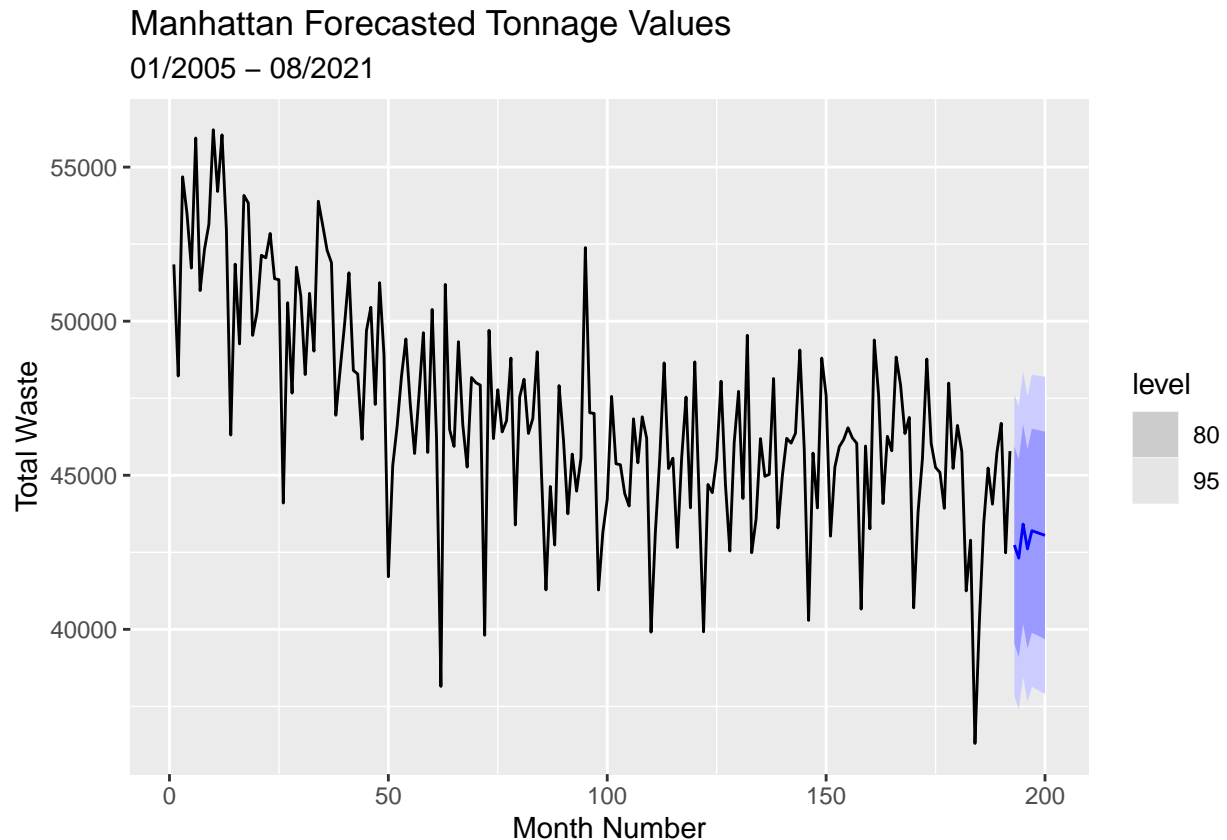## # A tsibble: 8 x 6 [1]
## # Key:        .model [1]
##   .model   month_num      total_waste             .max `95%_lower` `95%_upper`
##   <chr>        <dbl>           <dist>           <dist>       <dbl>       <dbl>
## 1 arima01~       193   N(44161, 5e+06) N(43082, 5190701)      39761.      48560.
## 2 arima01~       194 N(41728, 5054881) N(43082, 5190701)      37321.      46135.
## 3 arima01~       195 N(42583, 5077518) N(43082, 5190701)      38167.      47000.
## 4 arima01~       196 N(39030, 5100155) N(43082, 5190701)      34604.      43457.
## 5 arima01~       197 N(41116, 5122791) N(43082, 5190701)      36680.      45553.
## 6 arima01~       198 N(42798, 5145428) N(43082, 5190701)      38352.      47244.
## 7 arima01~       199 N(43735, 5168065) N(43082, 5190701)      39279.      48190.
## 8 arima01~       200 N(43082, 5190701) N(43082, 5190701)      38617.      47548.
```

Preliminary forecast of $ARIMA(0,1,5)$

```
man_arima015_fit_cons %>%
  forecast(h = 8) %>%
  autoplot(man_ts3) + labs(x = "Month Number",
                           y = "Total Waste",
                           title = "Manhattan Forecasted Tonnage Values",
                           subtitle = "01/2005 - 08/2021")
```



```
man_arima015_fit_cons %>%
  forecast(h = 8, point_forecast = list(.median = median)) %>%
  hilo(level=95) %>%
  unpack_hilo('95%')
```

```
## # A tsibble: 8 x 6 [1]
## # Key:        .model [1]
##   .model            month_num      total_waste .median `95%_lower` `95%_upper`
##   <chr>                 <dbl>           <dist>   <dbl>       <dbl>       <dbl>
## 1 arima015_constant       193 N(42736, 6227826)  42736.     37845.      47627.
## 2 arima015_constant       194 N(42311, 6281216)  42311.     37399.      47223.
## 3 arima015_constant       195 N(43417, 6352737)  43417.     38477.      48357.
## 4 arima015_constant       196 N(42612, 6371662)  42612.     37664.      47559.
## 5 arima015_constant       197 N(43201, 6676240)  43201.     38137.      48265.
## 6 arima015_constant       198 N(43151, 6748179)  43151.     38059.      48242.
```

```
## 7 arima015_constant      199 N(43101, 6820118)  43101.        37982.        48219.
## 8 arima015_constant      200 N(43051, 6892057)  43051.        37905.        48196.
```

```
man_arima015_fit_cons %>%
  forecast(h = 8, point_forecast = list(.mean = mean)) %>%
  hilo(level=95) %>%
  unpack_hilo('95%')
```

```
## # A tsibble: 8 x 6 [1]
## # Key:       .model [1]
##   .model            month_num      total_waste  .mean `95%_lower` `95%_upper`
##   <chr>                   <dbl>          <dist> <dbl>       <dbl>       <dbl>
## 1 arima015_constant         193 N(42736, 6227826) 42736.      37845.      47627.
## 2 arima015_constant         194 N(42311, 6281216) 42311.      37399.      47223.
## 3 arima015_constant         195 N(43417, 6352737) 43417.      38477.      48357.
## 4 arima015_constant         196 N(42612, 6371662) 42612.      37664.      47559.
## 5 arima015_constant         197 N(43201, 6676240) 43201.      38137.      48265.
## 6 arima015_constant         198 N(43151, 6748179) 43151.      38059.      48242.
## 7 arima015_constant         199 N(43101, 6820118) 43101.      37982.      48219.
## 8 arima015_constant         200 N(43051, 6892057) 43051.      37905.      48196.
```

```
man_arima015_fit_cons %>%
  forecast(h = 8, point_forecast = list(.max = max)) %>%
  hilo(level=95) %>%
  unpack_hilo('95%')
```

```
## # A tsibble: 8 x 6 [1]
## # Key:       .model [1]
##   .model   month_num      total_waste              .max `95%_lower` `95%_upper`
##   <chr>         <dbl>          <dist>            <dist>       <dbl>       <dbl>
## 1 arima01~        193 N(42736, 6227826) N(43051, 6892057)      37845.      47627.
## 2 arima01~        194 N(42311, 6281216) N(43051, 6892057)      37399.      47223.
## 3 arima01~        195 N(43417, 6352737) N(43051, 6892057)      38477.      48357.
## 4 arima01~        196 N(42612, 6371662) N(43051, 6892057)      37664.      47559.
## 5 arima01~        197 N(43201, 6676240) N(43051, 6892057)      38137.      48265.
## 6 arima01~        198 N(43151, 6748179) N(43051, 6892057)      38059.      48242.
## 7 arima01~        199 N(43101, 6820118) N(43051, 6892057)      37982.      48219.
## 8 arima01~        200 N(43051, 6892057) N(43051, 6892057)      37905.      48196.
```