

Fertilizantes

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Disciplina: Análise de Séries Temporais

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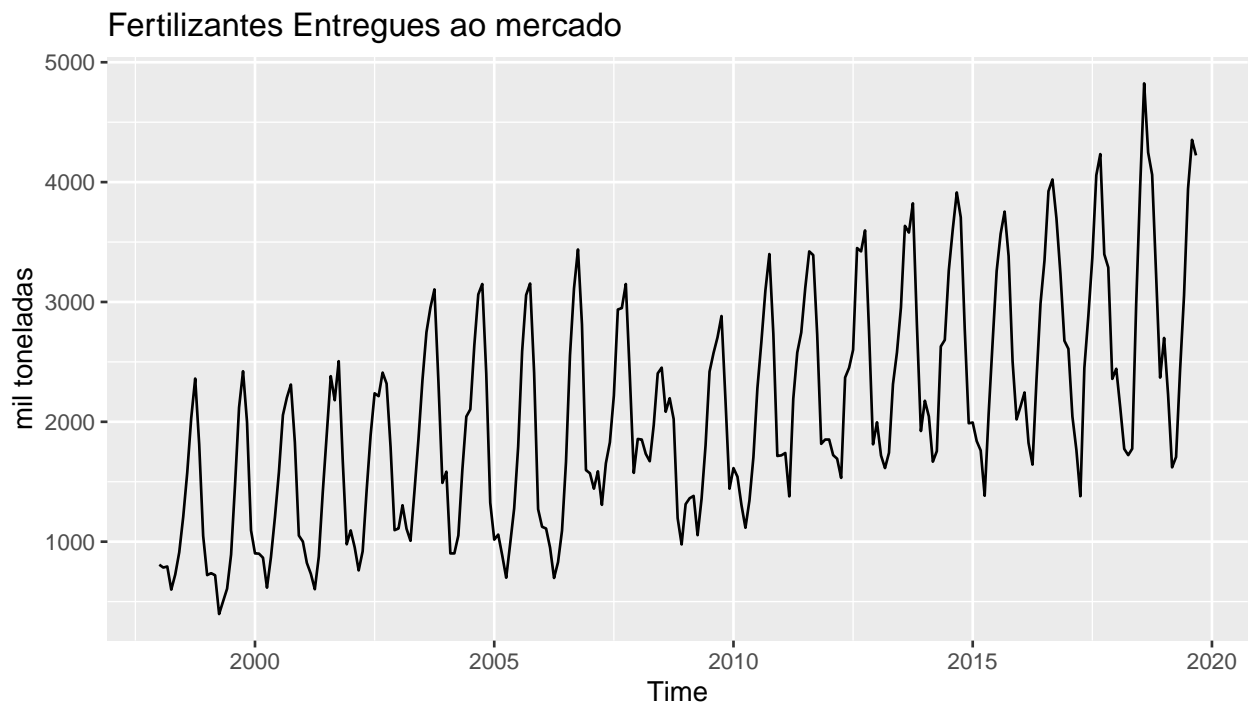
Matrícula:

Load Data

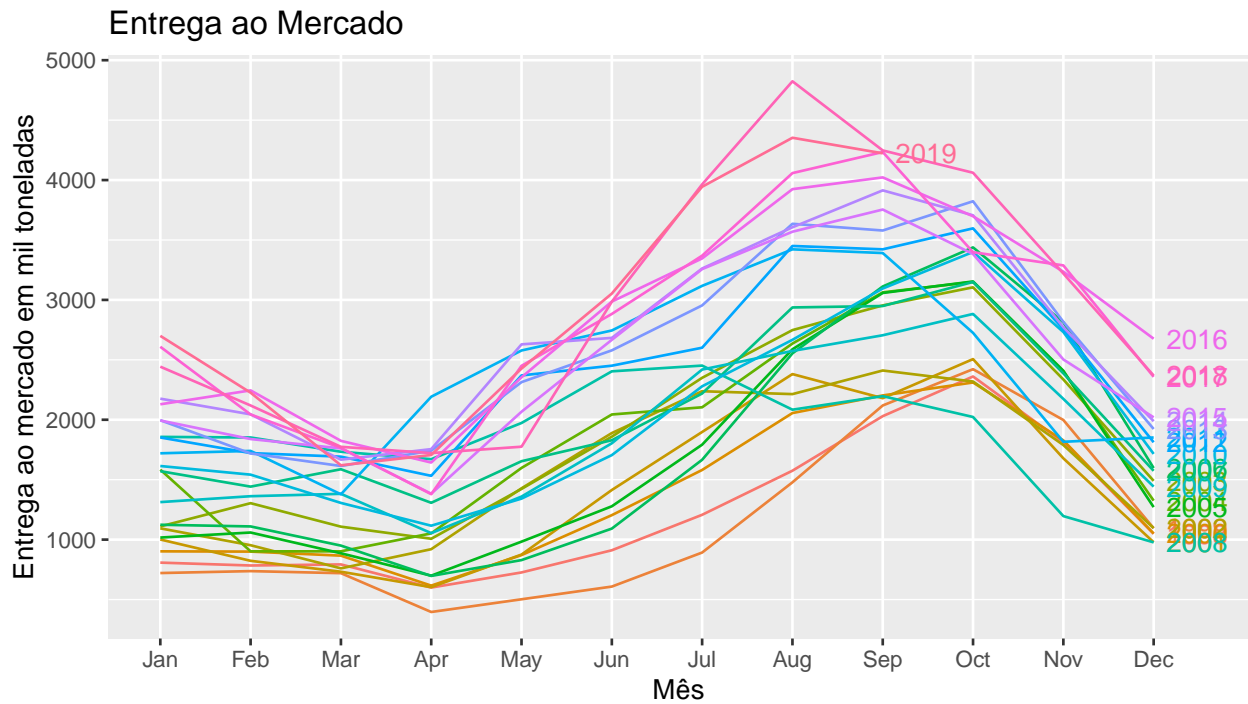
```
df = read_excel("Fertilizantes.xlsx")  
# Converter para timeseries com frequencia mensal  
ts.total = ts(df$consumo, frequency = 12, start = c(1998,1))  
  
# Separar em treino e teste  
ts.train = window(ts.total, end = c(2017,12))  
ts.test = window(ts.total, start = c(2018, 1))
```

Plot data

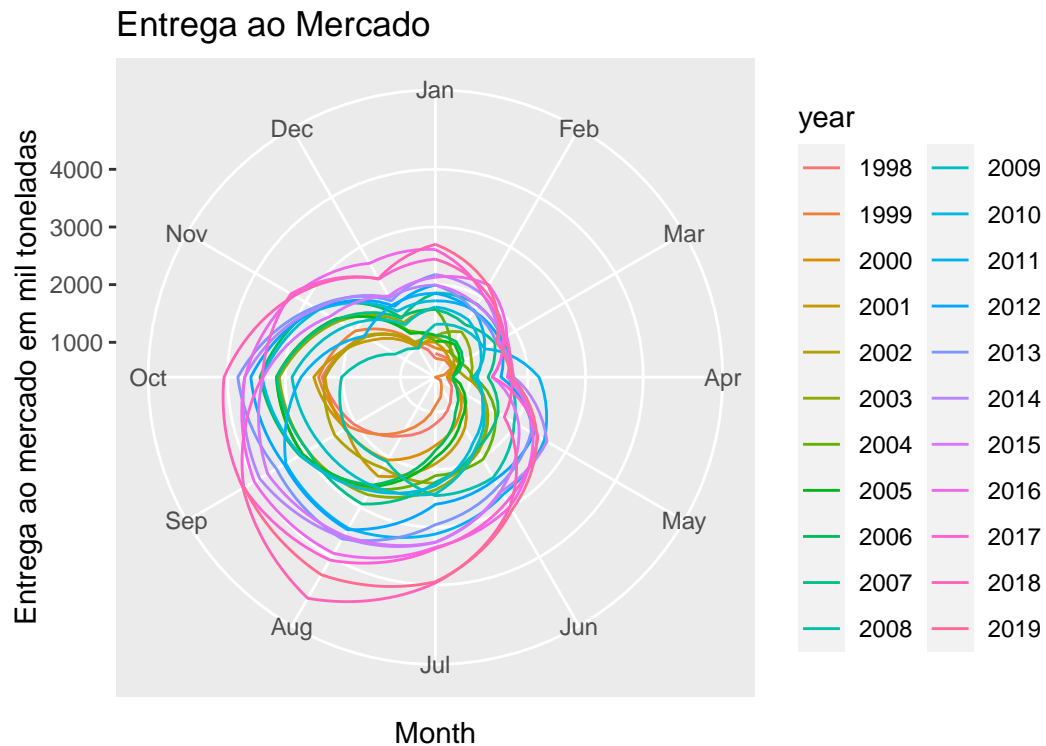
```
autoplot(ts.total) + ggtitle("Fertilizantes Entregues ao mercado") +  
  ylab("mil toneladas")
```



```
ggseasonplot(ts.total, year.labels = TRUE, year.label.left = TRUE) +
  ggtitle("Entrega ao Mercado") +
  ylab("Entrega ao mercado em mil toneladas") + xlab("Mês")
```

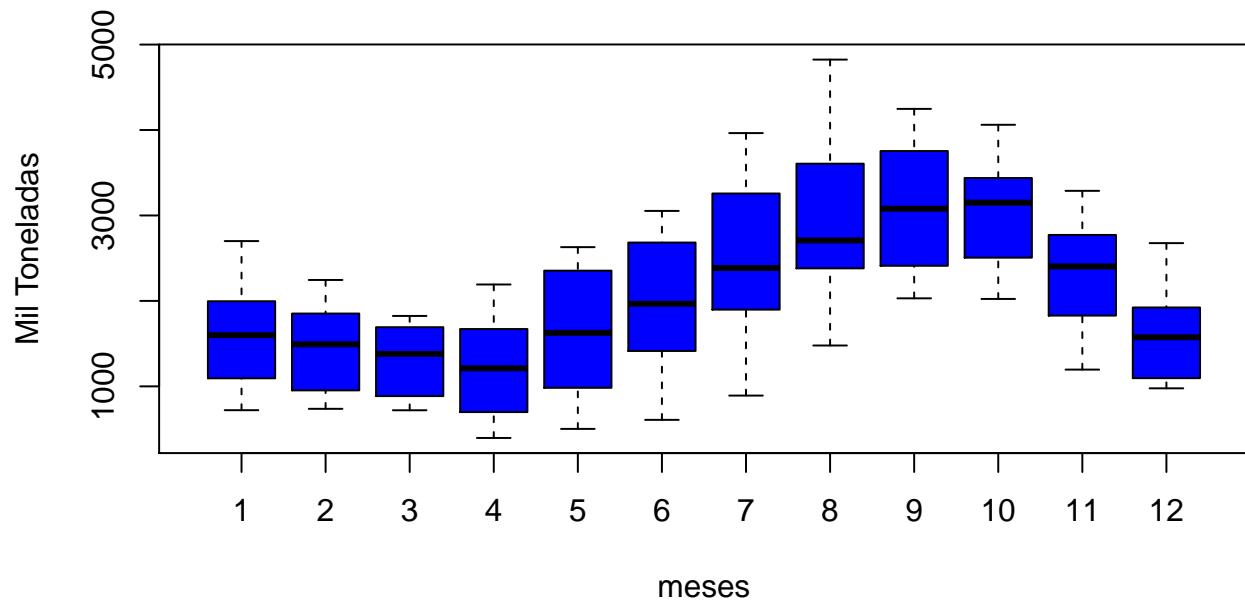


```
ggseasonplot(ts.total, polar=TRUE) +
  ylab("Entrega ao mercado em mil toneladas") +
  ggtitle("Entrega ao Mercado")
```



```
boxplot(ts.total~cycle(ts.total),xlab="meses", ylab = "Mil Toneladas" ,
        col="blue", main = "Boxplot-Entrega de Fertilizantes-BR-1998-2019")
```

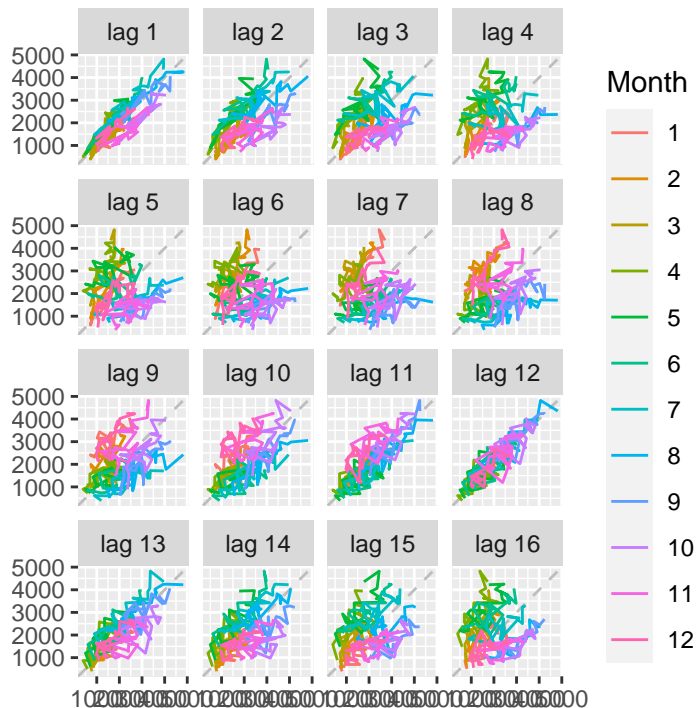
Boxplot-Entrega de Fertilizantes-BR-1998-2019



Lag Plot

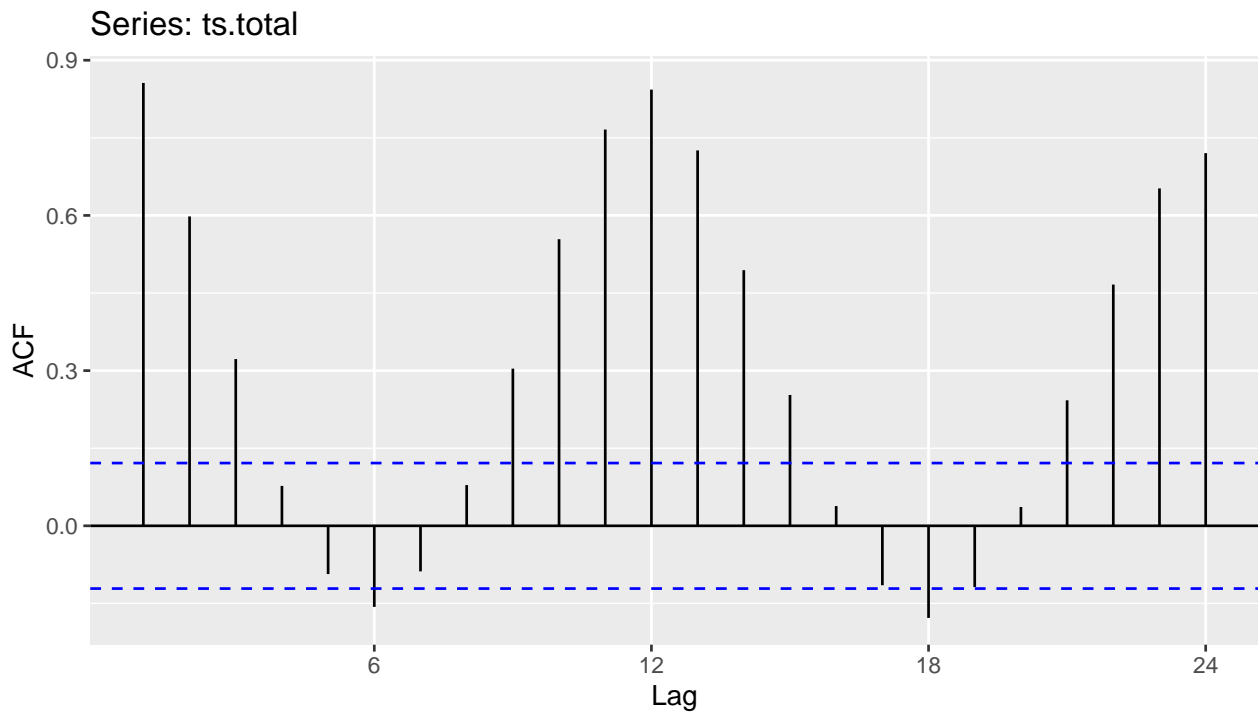
Indica a sazonalidade a cada 12 meses

```
gglagplot(ts.total)
```



Auto Correlation Function (AFC)

```
ggAcf(ts.total)
```



Decomposição

Modelos

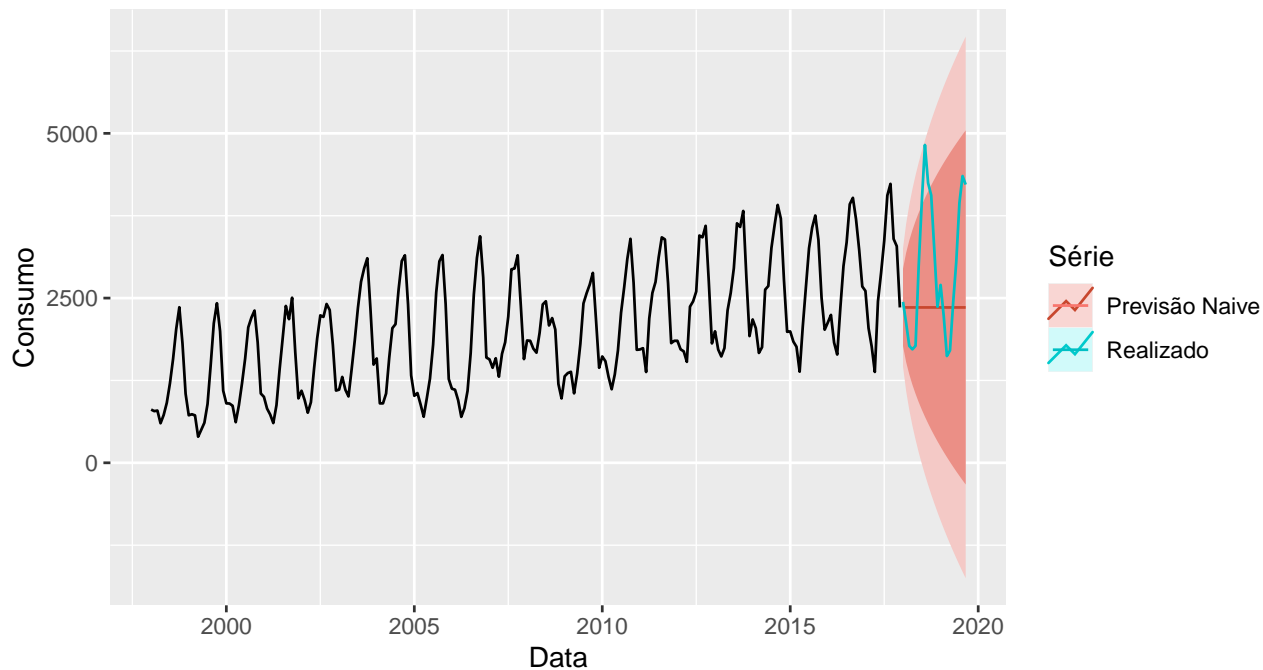
```
plot_forecast = function(modelo, nome_modelo, train_set, test_set, tslm = FALSE){  
  if (tslm){  
    modelo = fitted(modelo)  
  }  
  autoplot(train_set) +  
  autolayer(modelo, series = paste("Previsão", nome_modelo)) +  
  autolayer(test_set, series = "Realizado") +  
  xlab("Data") +  
  ylab("Consumo") +  
  ggtitle("Fertilizantes") +  
  guides(colour = guide_legend(title = "Série"))  
}
```

Transformação Box Cox

Naive

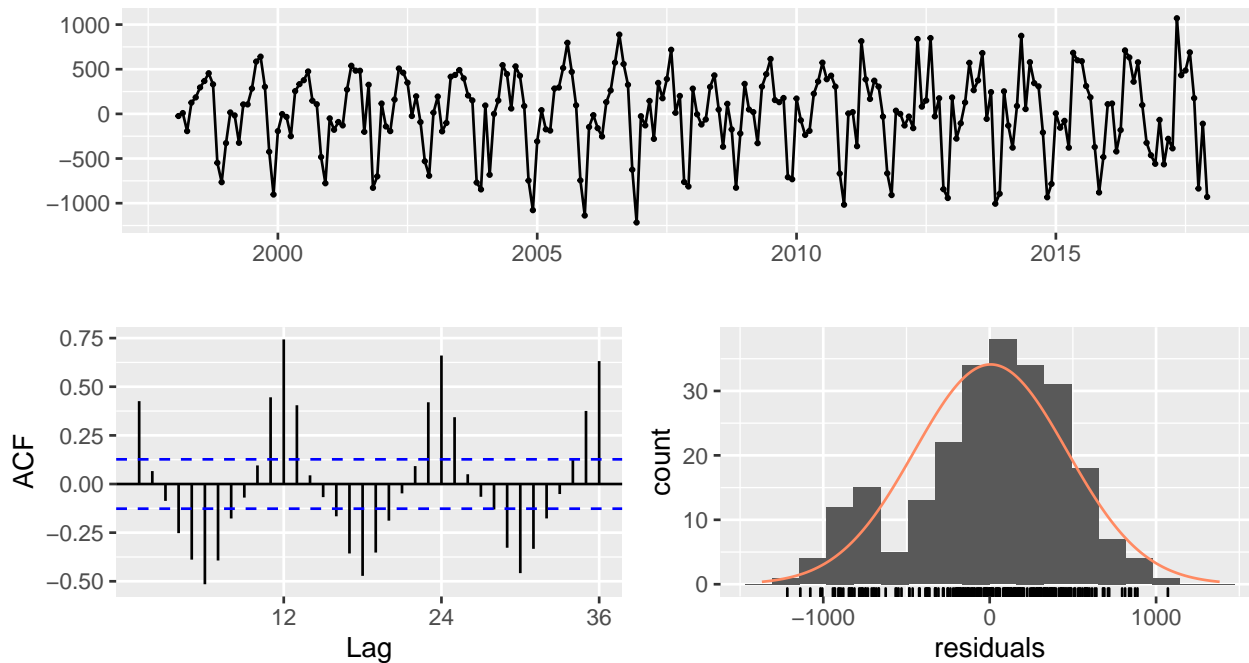
```
fit.naive = naive(ts.train, h = 21)  
  
plot_forecast(fit.naive, 'Naive', ts.train, ts.test)
```

Fertilizantes



```
checkresiduals(fit.naive)
```

Residuals from Naive method



Ljung-Box test

```
data: Residuals from Naive method
Q* = 755.72, df = 24, p-value < 2.2e-16
```

Model df: 0. Total lags used: 24

```
accuracy(fit.naive, ts.test)
```

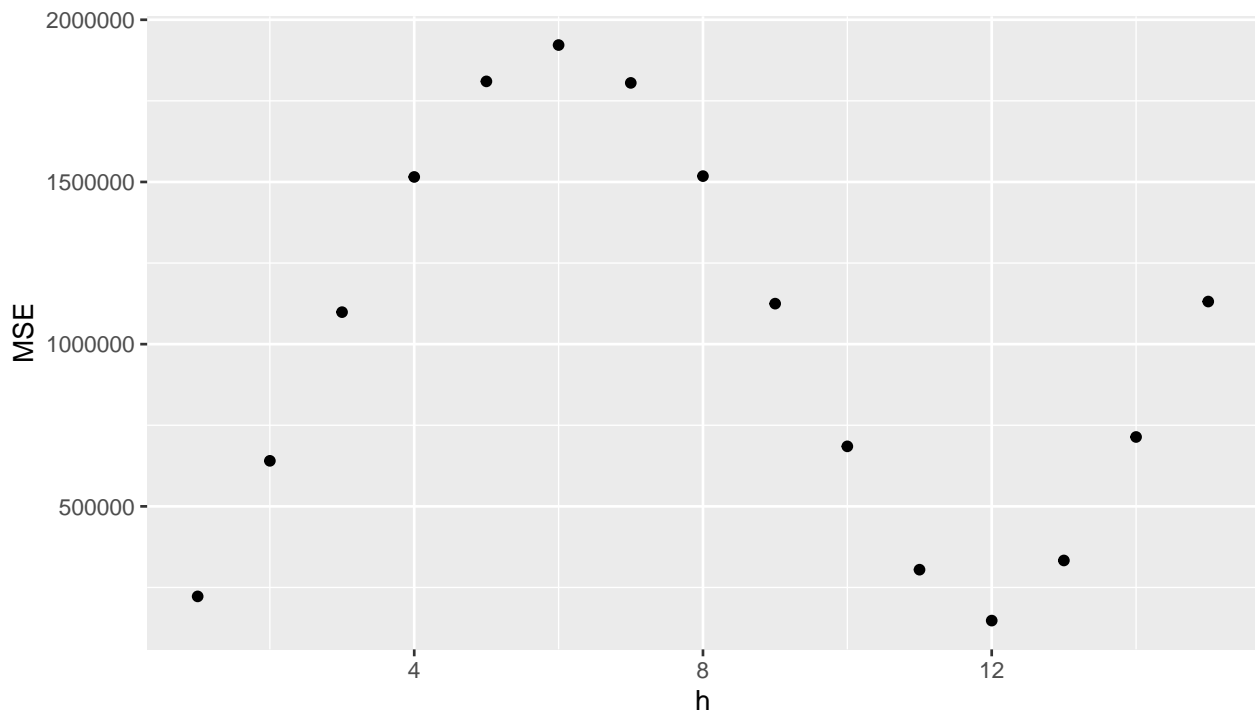
	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	6.485356	457.5677	362.7699	-2.723405	20.42512	1.271487
Test set	582.714286	1174.7456	922.1429	9.265054	28.66327	3.232057

	ACF1	Theil's U
Training set	0.4258930	NA
Test set	0.7784592	1.428229

```
ts.test %>% tsCV(forecastfunction=rwf, drift=TRUE, h=1) -> e
# RMSE
e^2 %>% mean(na.rm=TRUE) %>% sqrt()
```

[1] 676.972

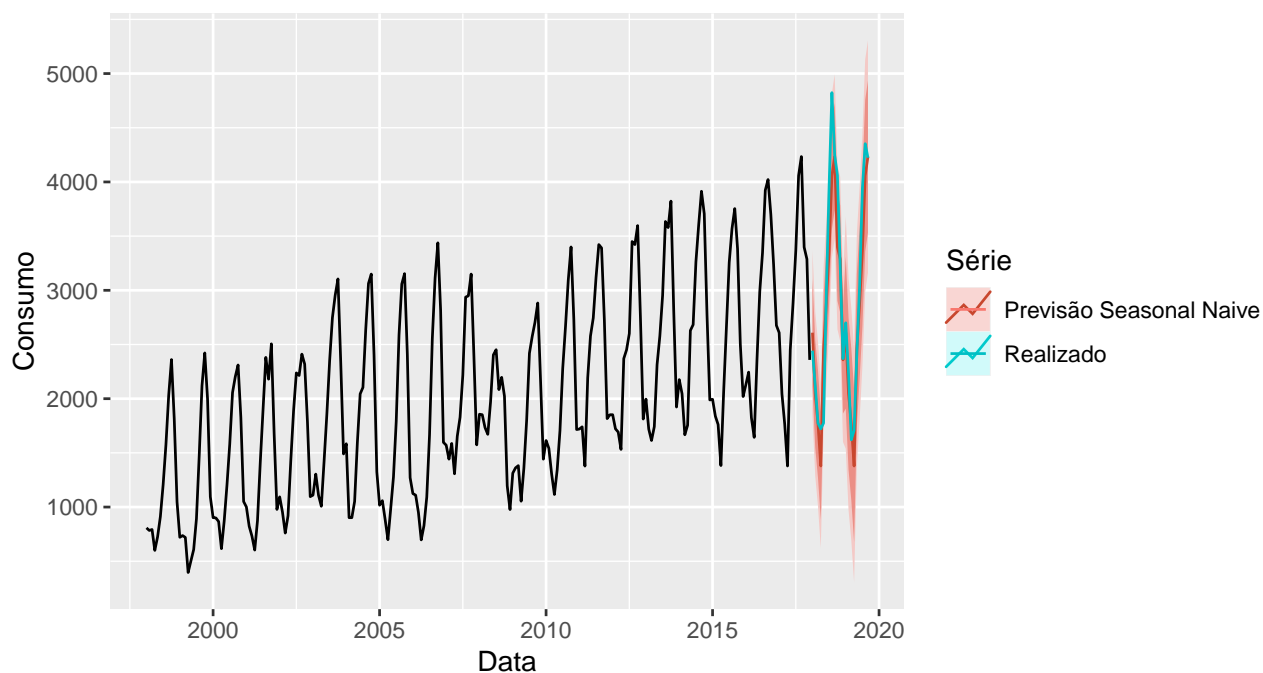
```
# Cross Validation para diferentes horizontes de previsão
e <- tsCV(ts.total, forecastfunction=naive, h=15)
# Compute the MSE values and remove missing values
mse <- colMeans(e^2, na.rm = T)
# Plot the MSE values against the forecast horizon
data.frame(h = 1:15, MSE = mse) %>%
  ggplot(aes(x = h, y = MSE)) + geom_point()
```



Seasonal Naive

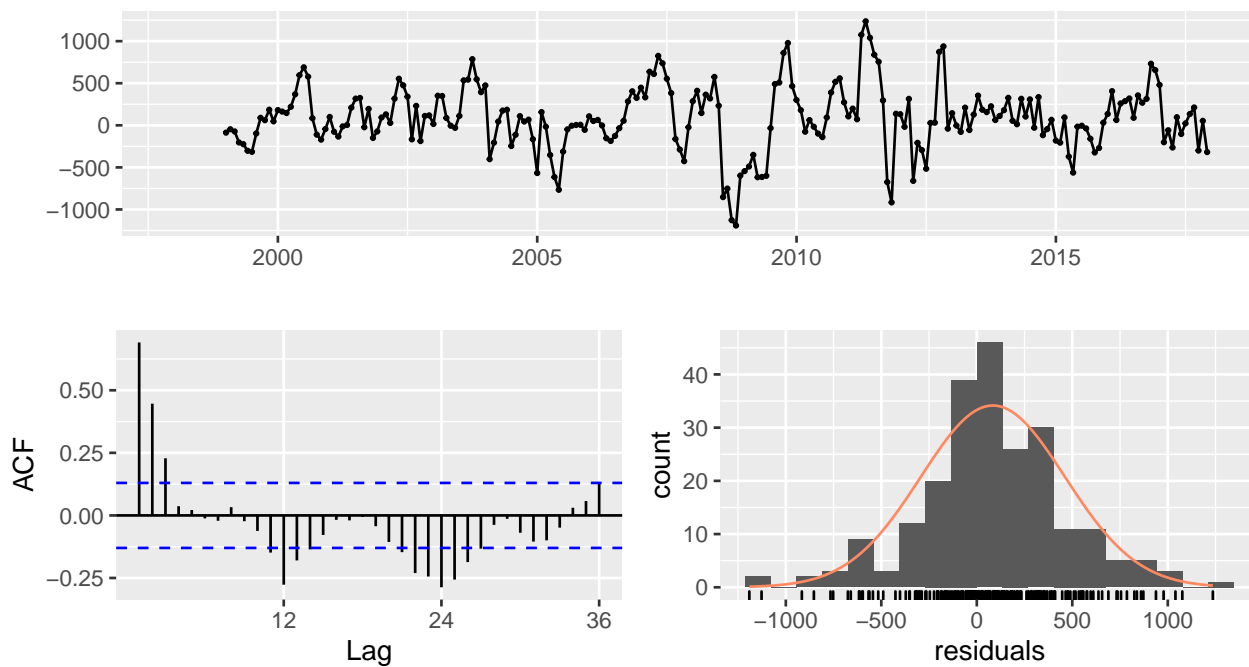
```
fit.seasonal_naive = snaive(ts.train, h = 21)
plot_forecast(fit.seasonal_naive, 'Seasonal Naive', ts.train, ts.test)
```

Fertilizantes



```
checkresiduals(fit.seasonal_naive)
```

Residuals from Seasonal naive method



Ljung-Box test

data: Residuals from Seasonal naive method
 $Q^* = 267.28$, $df = 24$, $p\text{-value} < 2.2e-16$

Model df: 0. Total lags used: 24

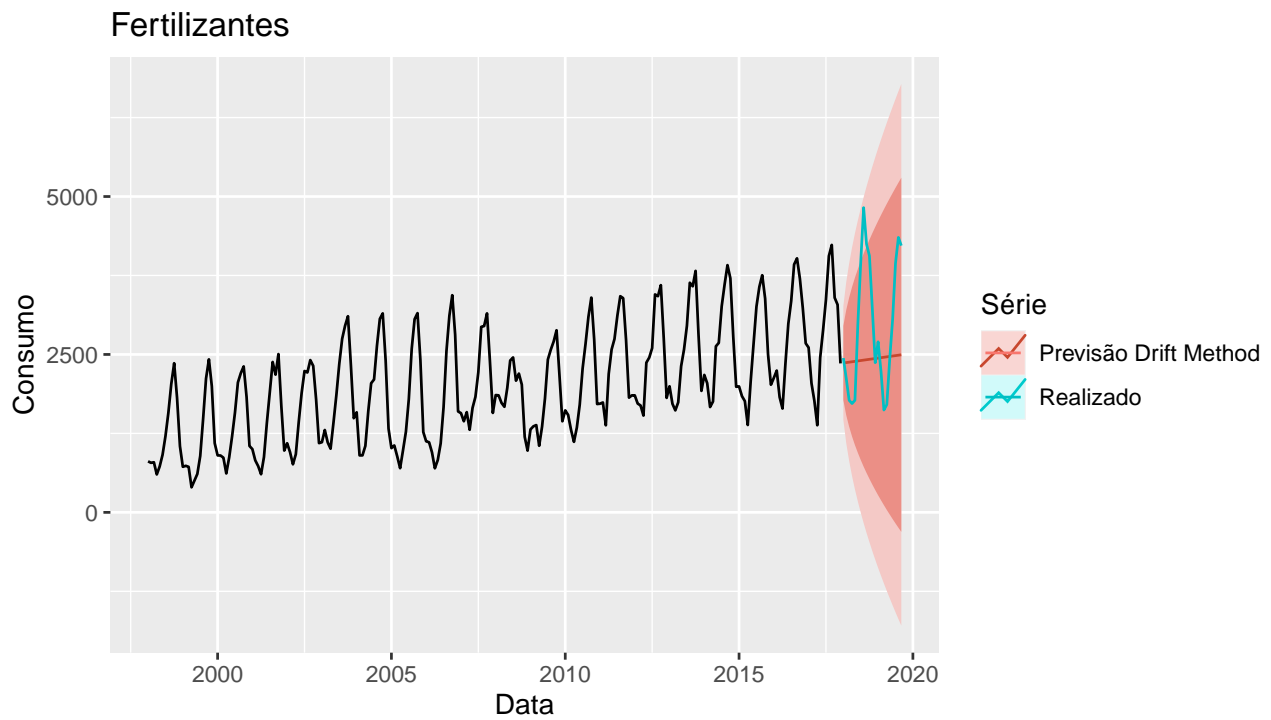
```
accuracy(fit.seasonal_naive, ts.test)
```

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	84.11842	386.4534	285.3114	2.053698	16.213822	1.0000000
Test set	149.00000	353.1331	252.6190	3.614895	9.052387	0.8854152

	ACF1	Theil's U
Training set	0.6910538	NA
Test set	-0.0642013	0.5585835

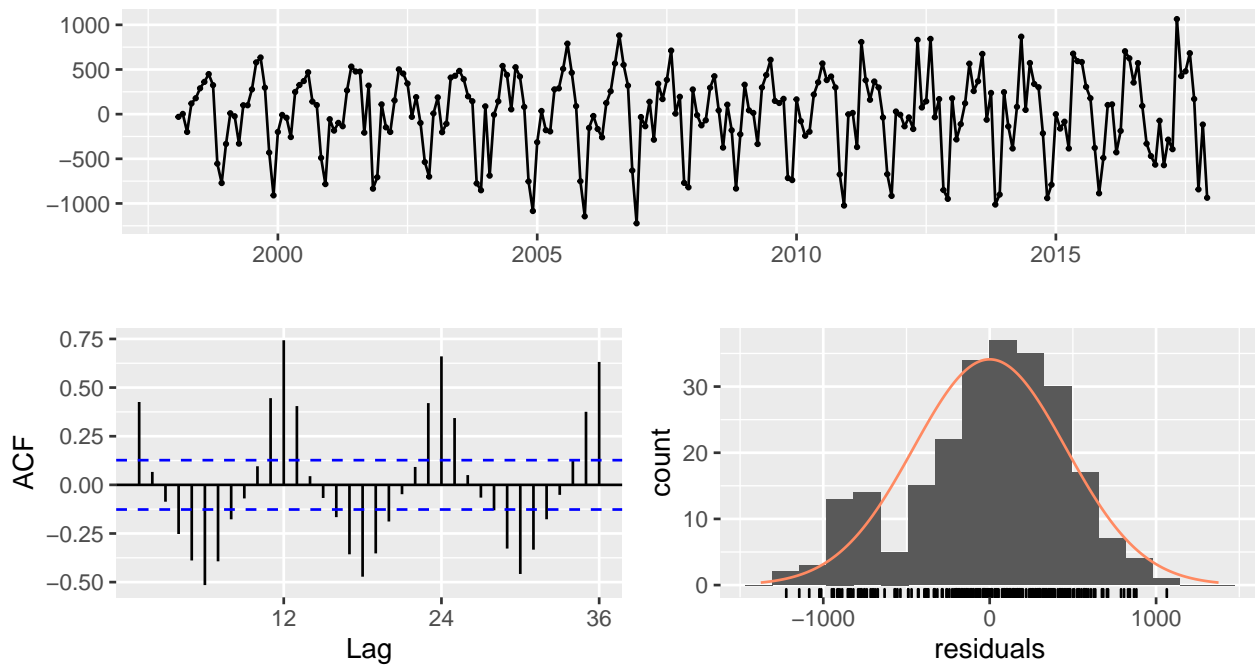
Drift Method

```
fit.drift = rwf(ts.train, h = 21, drift=TRUE)  
plot_forecast(fit.drift, 'Drift Method', ts.train, ts.test)
```



```
checkresiduals(fit.drift)
```


Residuals from Random walk with drift



Ljung-Box test

data: Residuals from Random walk with drift
 $Q^* = 755.72$, $df = 23$, $p\text{-value} < 2.2e-16$

Model df: 1. Total lags used: 24

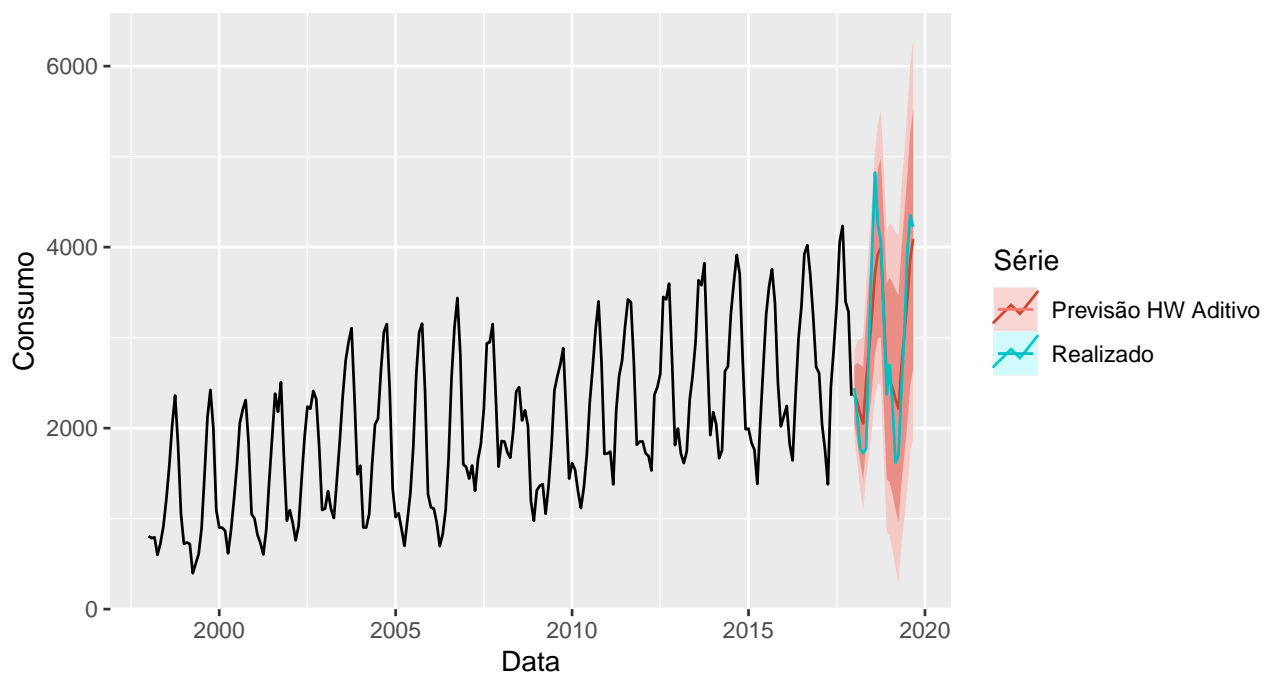
```
accuracy(fit.drift, ts.test)
```

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	8.466449e-14	457.5218	362.0537	-3.130732	20.43960	1.268977
Test set	5.113754e+02	1130.8064	897.5384	6.679907	28.52849	3.145820
	ACF1 Theil's U					
Training set	0.4258930	NA				
Test set	0.7791228	1.403644				

Holt Winther Aditivo

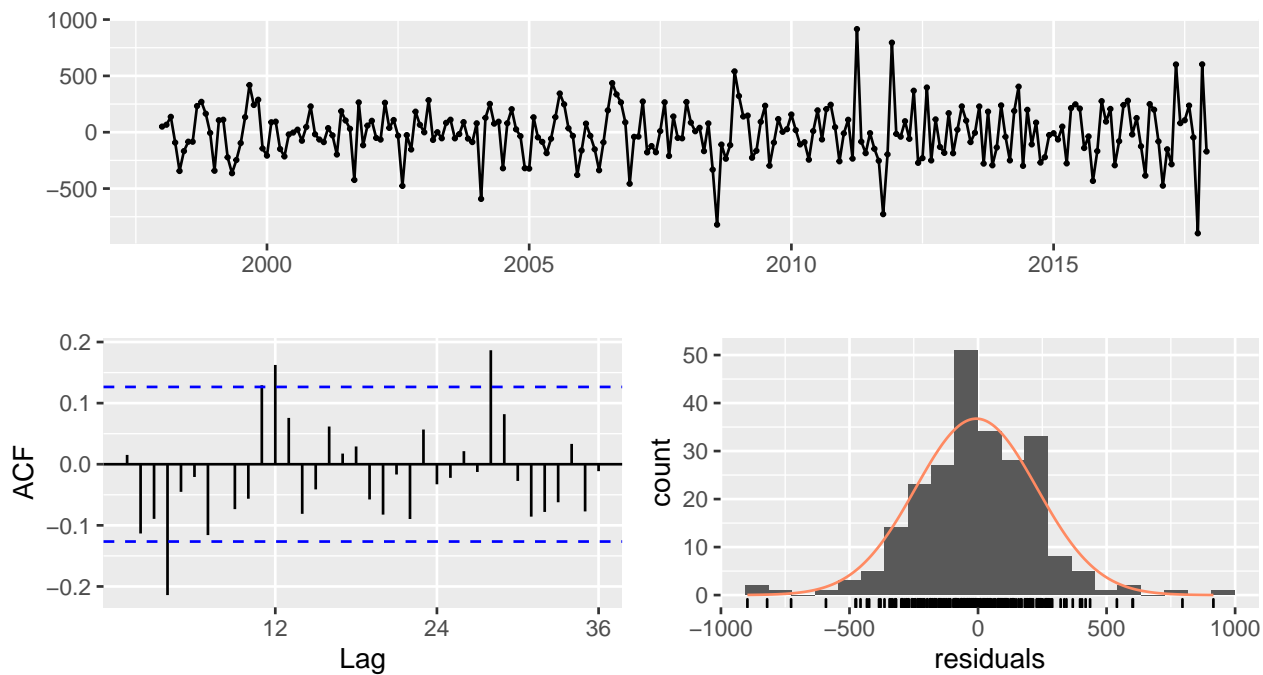
```
fit.HWA = hw(ts.train, seasonal = "additive", h = 21)
plot_forecast(fit.HWA, 'HW Aditivo', ts.train, ts.test)
```

Fertilizantes



```
checkresiduals(fit.HWA)
```

Residuals from Holt–Winters' additive method



Ljung-Box test

```
data: Residuals from Holt-Winters' additive method
Q* = 44.44, df = 8, p-value = 4.698e-07
```

```
Model df: 16. Total lags used: 24
```

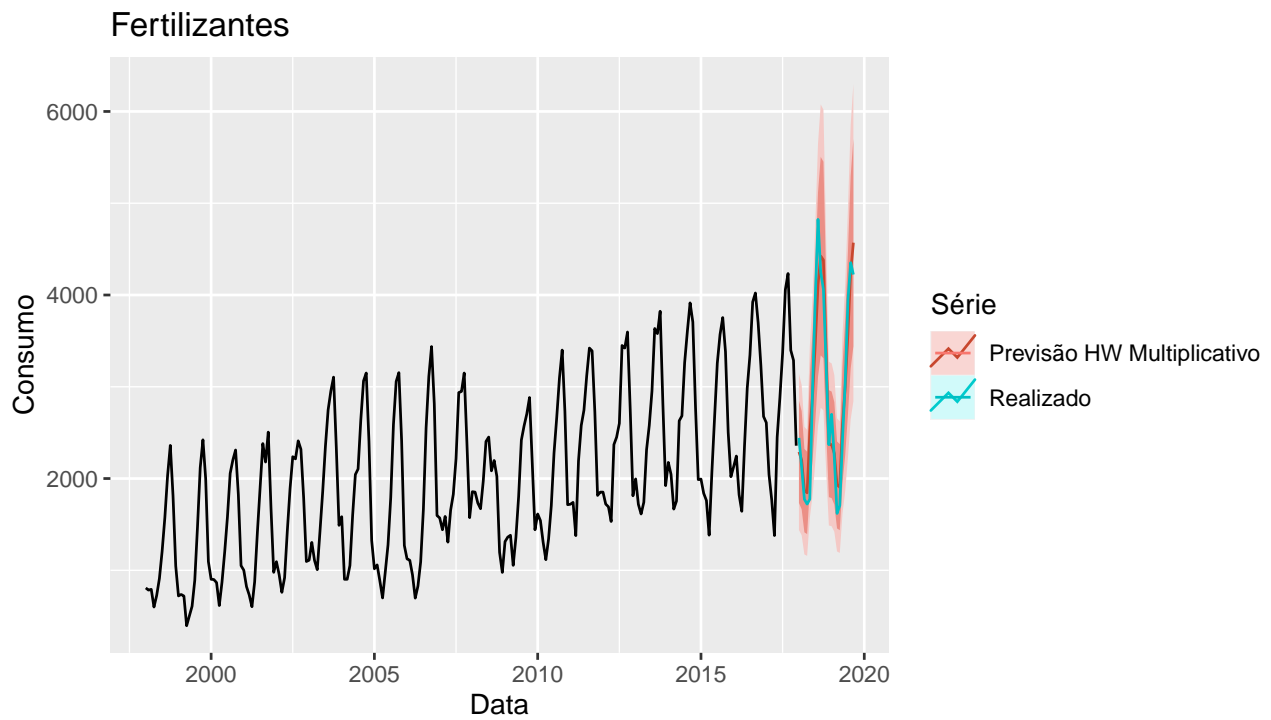
```
accuracy(fit.HWA, ts.test)
```

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	-6.732527	235.7490	177.3663	-1.845077	10.65438	0.6216586
Test set	10.773607	444.7325	344.3640	-4.764962	13.46534	1.2069759

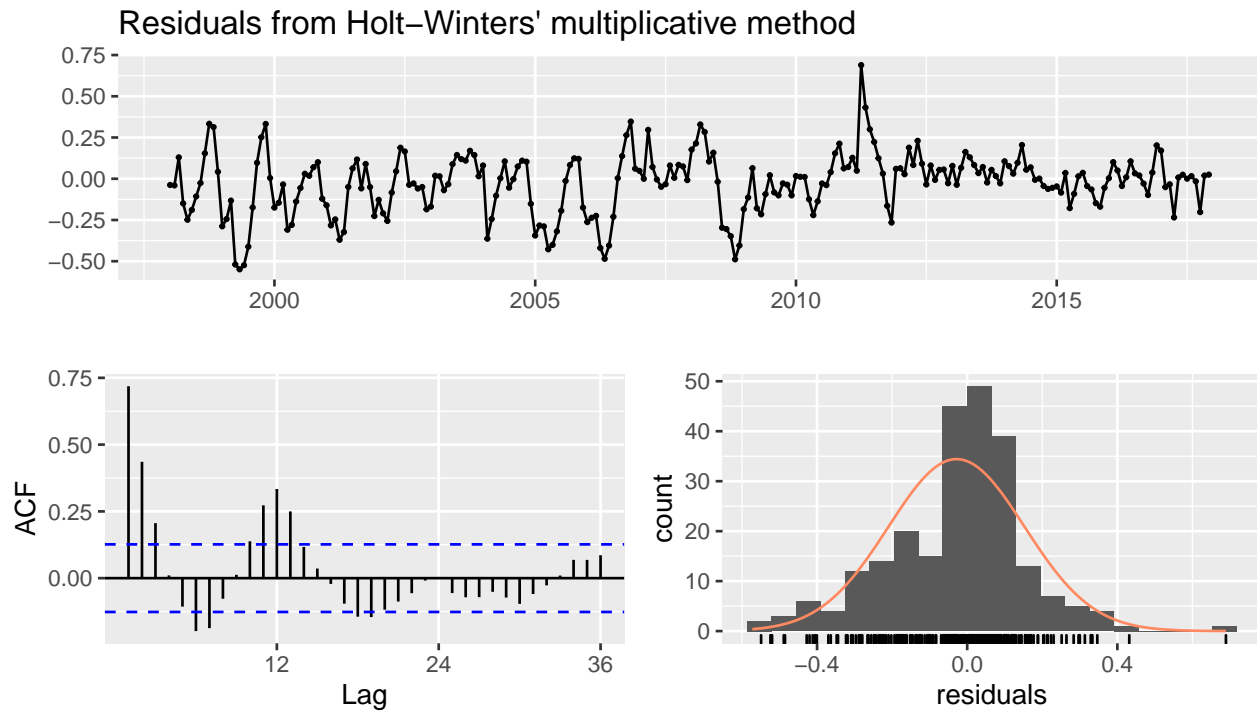
	ACF1	Theil's U
Training set	0.01524887	NA
Test set	0.60033259	0.7347298

Holt Winther Multiplicativo

```
fit.HWM <- hw(ts.train, seasonal = "multiplicative", h = 21)  
plot_forecast(fit.HWM, 'HW Multiplicativo', ts.train, ts.test)
```



```
checkresiduals(fit.HWM)
```



Ljung-Box test

data: Residuals from Holt-Winters' multiplicative method
 Q* = 296.95, df = 8, p-value < 2.2e-16

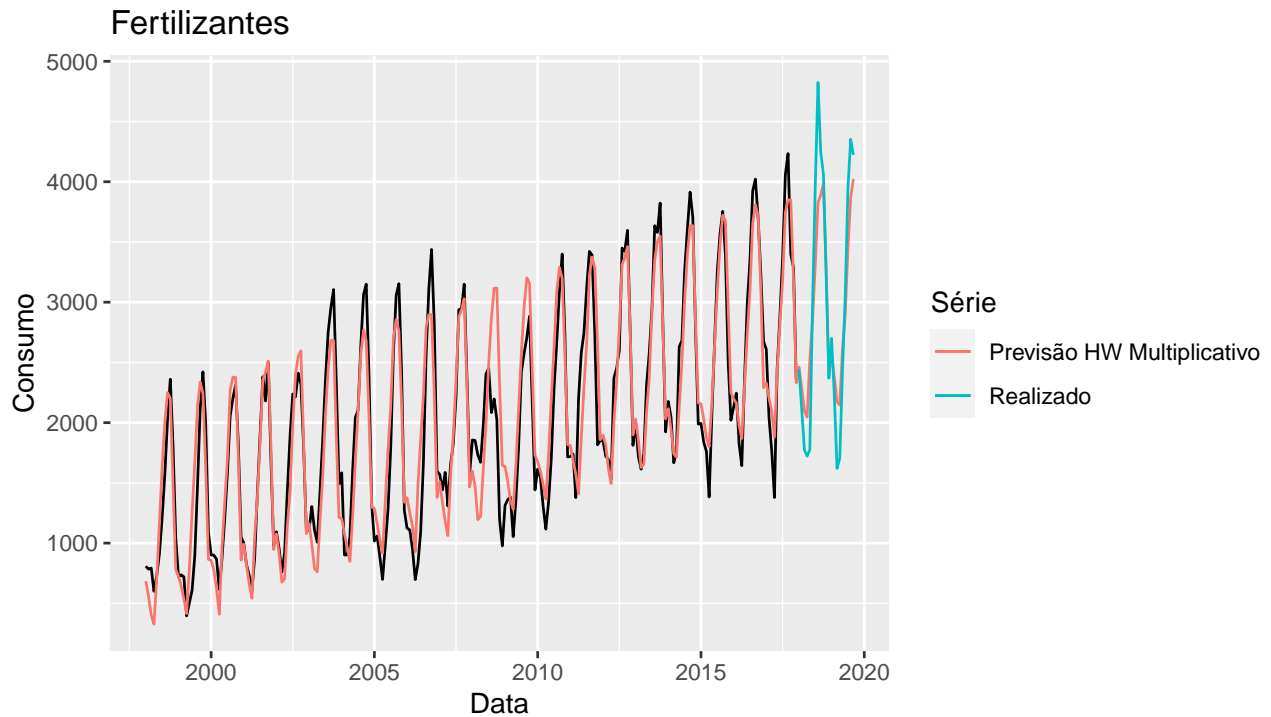
Model df: 16. Total lags used: 24

`accuracy(fit.HWM, ts.test)`

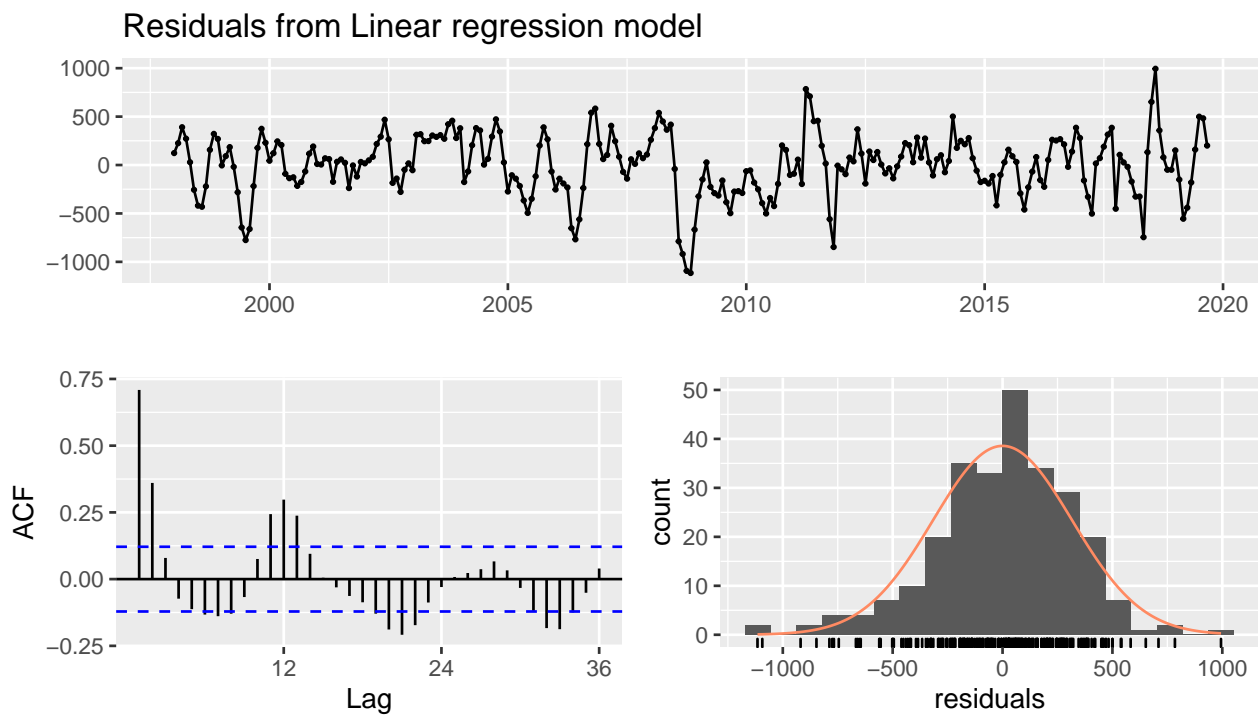
	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
Training set	-31.64425	321.7064	240.876	-7.286976	16.200865	0.8442565	0.6941948
Test set	-20.18829	311.6655	239.485	-2.836586	8.754973	0.8393811	0.2452657
Theil's U							
Training set	NA						
Test set	0.5216854						

Dummy

```
fit.dummy <- tslm(ts.total ~ trend + season + bizdays(ts.total) + easter(ts.total))
plot_forecast(fit.dummy, 'HW Multiplicativo', ts.train, ts.test, tslm = TRUE)
```



```
checkresiduals(fit.dummy)
```



Breusch-Godfrey test for serial correlation of order up to 24

```
data: Residuals from Linear regression model
LM test = 156.21, df = 24, p-value < 2.2e-16
```

```
accuracy(fitted(fit.dummy), ts.test)
```

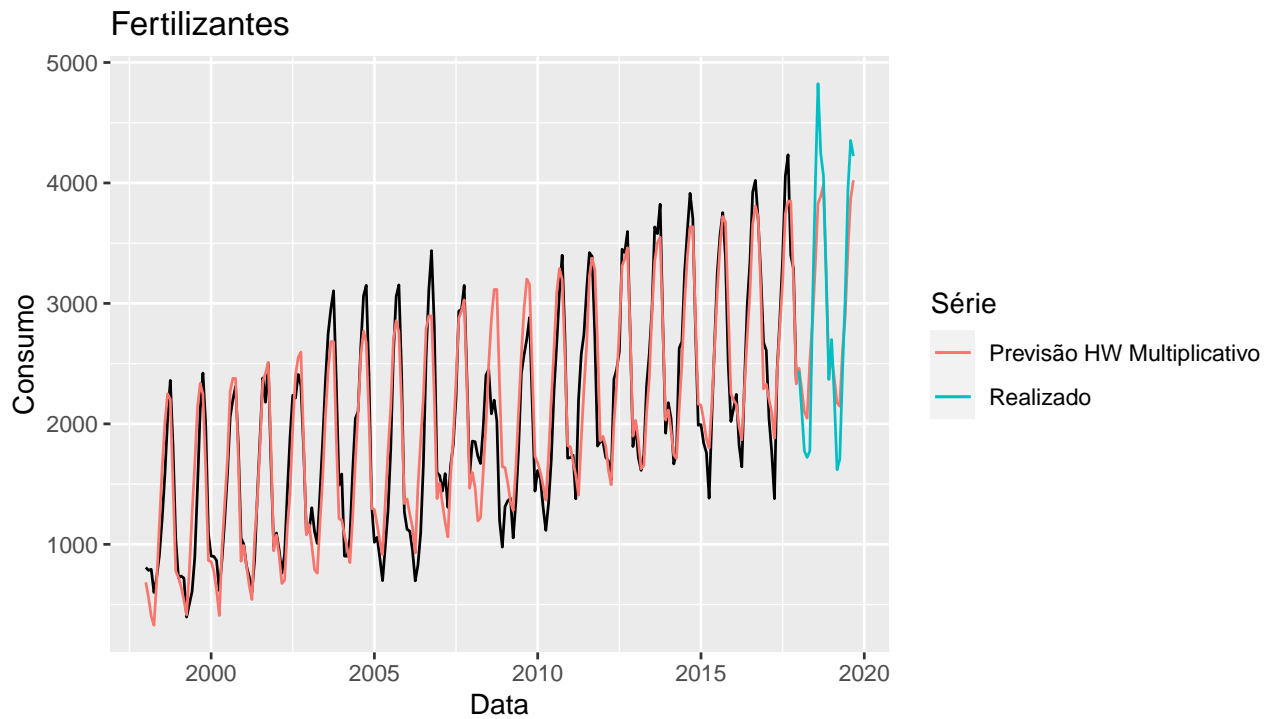
```

      ME      RMSE      MAE      MPE      MAPE      ACF1 Theil's U
Test set 33.21546 407.9278 319.9621 -3.560641 12.24497 0.6258391 0.6743043

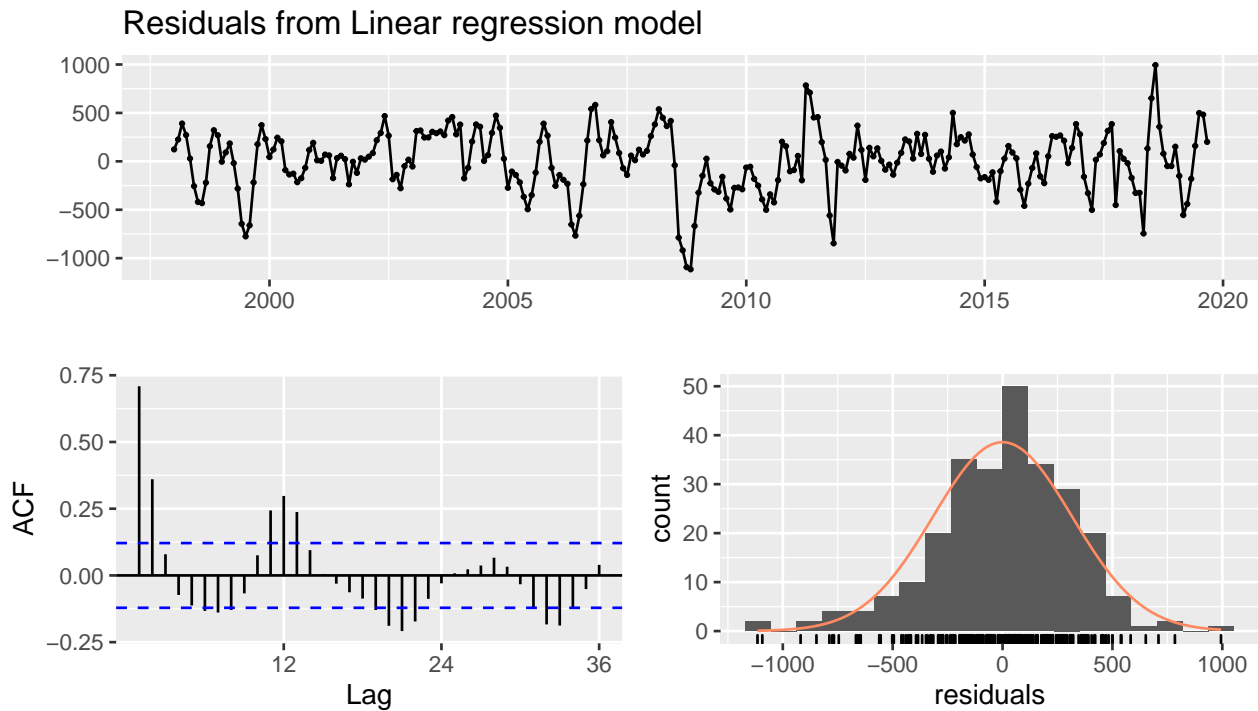
```

```
fit.fourier <- tslm(ts.total ~ trend + bizdays(ts.total) + fourier(ts.total, K = 6) + easter(ts.total))
```

```
plot_forecast(fit.fourier, 'HW Multiplicativo', ts.train, ts.test, tslm = TRUE)
```



```
checkresiduals(fit.fourier)
```



Breusch-Godfrey test for serial correlation of order up to 24

data: Residuals from Linear regression model
LM test = 156.21, df = 24, p-value < 2.2e-16

```
accuracy(fitted(fit.fourier), ts.test)
```

	ME	RMSE	MAE	MPE	MAPE	ACF1	Theil's U
Test set	33.21546	407.9278	319.9621	-3.560641	12.24497	0.6258391	0.6743043

```
arima.ts <- auto.arima(ts.train)
arima.ts
```

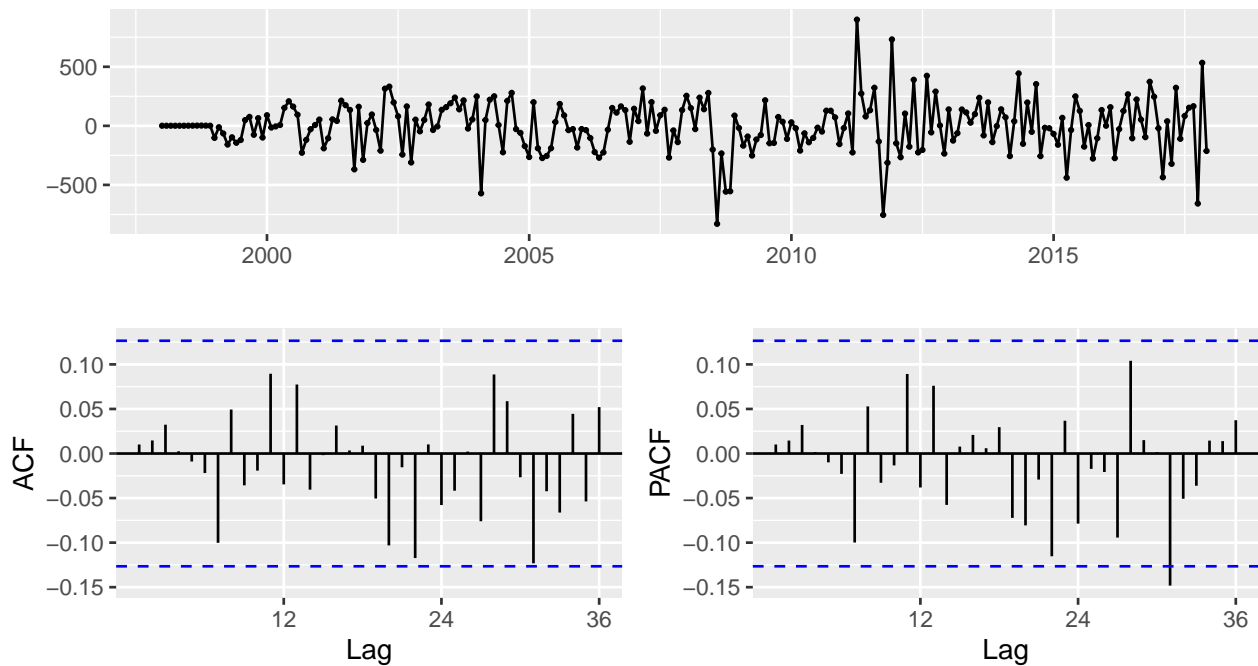
Series: ts.train
ARIMA(0,0,3)(0,1,2)[12] with drift

Coefficients:

	ma1	ma2	ma3	sma1	sma2	drift
	0.7751	0.5347	0.3254	-0.6427	-0.1657	7.1279
s.e.	0.0641	0.0738	0.0611	0.0775	0.0758	0.8615

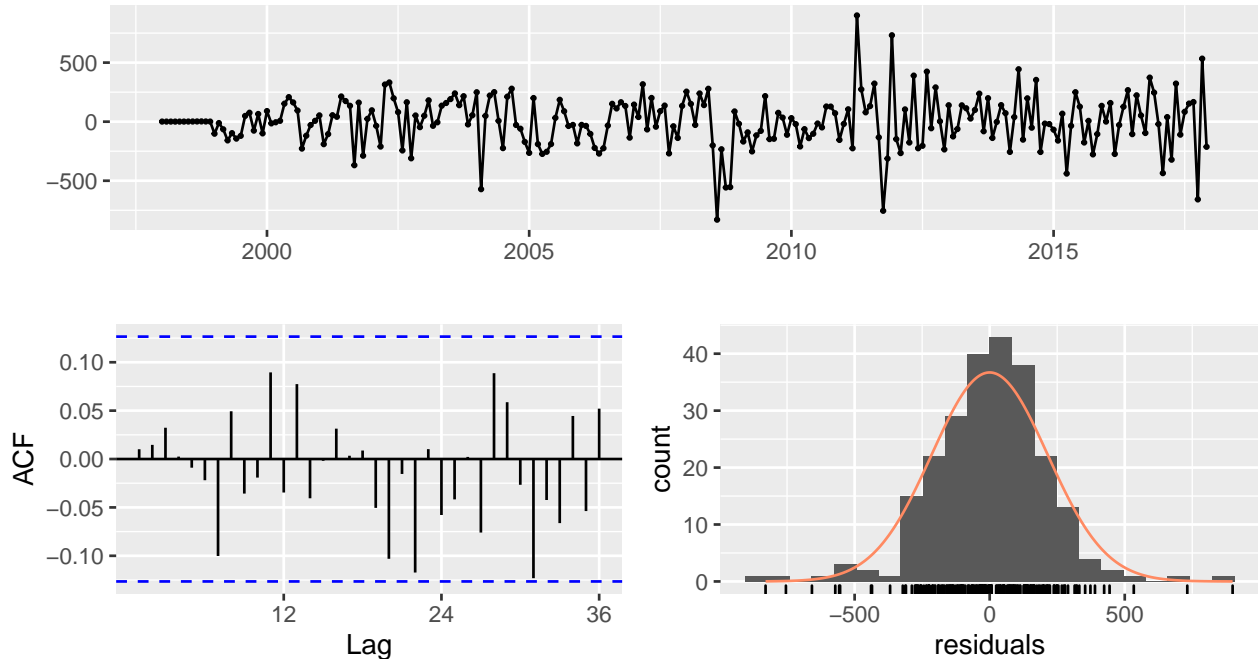
sigma² estimated as 49661: log likelihood=-1559.33
AIC=3132.65 AICc=3133.16 BIC=3156.66

```
ts.train %>%
  Arima(order=c(0,0,3), seasonal=c(0,1,2), include.drift = TRUE) %>%
  residuals() %>% ggtsdisplay()
```



```
fit.Arima <- ts.train %>%
  Arima(order=c(0,0,3), seasonal=c(0,1,2), include.drift = TRUE)
checkresiduals(fit.Arima)
```

Residuals from ARIMA(0,0,3)(0,1,2)[12] with drift



Ljung-Box test

```
data: Residuals from ARIMA(0,0,3)(0,1,2)[12] with drift
Q* = 16.705, df = 18, p-value = 0.5435
```

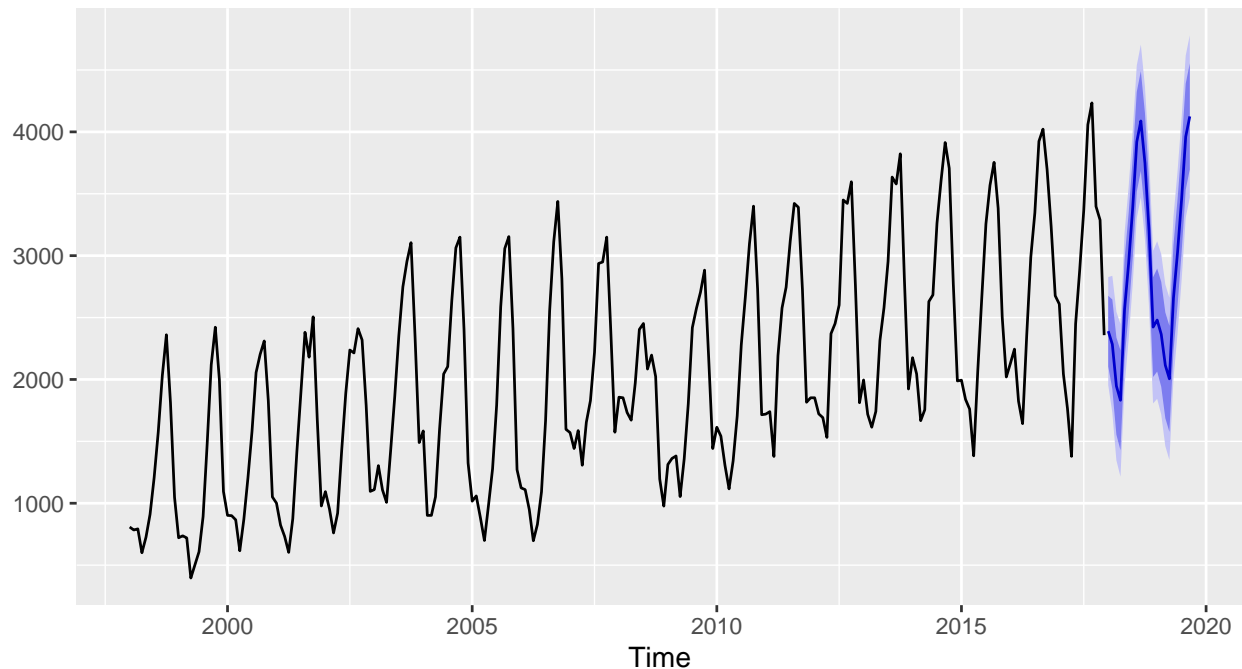

Model df: 6. Total lags used: 24

```
prev.Arima <- fit.Arima %>% forecast(h = 21)
prev.Arima
```

	Point Forecast	Lo 80	Hi 80	Lo 95	Hi 95
Jan 2018	2390.252	2104.619	2675.885	1953.414	2827.090
Feb 2018	2284.539	1923.159	2645.919	1731.855	2837.222
Mar 2018	1946.680	1554.358	2339.002	1346.675	2546.685
Apr 2018	1831.652	1428.473	2234.831	1215.044	2448.261
May 2018	2564.853	2161.675	2968.032	1948.245	3181.462
Jun 2018	2937.756	2534.577	3340.935	2321.147	3554.365
Jul 2018	3385.411	2982.233	3788.590	2768.803	4002.020
Aug 2018	3919.714	3516.535	4322.893	3303.105	4536.323
Sep 2018	4088.122	3684.943	4491.301	3471.513	4704.731
Oct 2018	3748.366	3345.188	4151.544	3131.758	4364.973
Nov 2018	3203.144	2799.968	3606.320	2586.540	3819.749
Dec 2018	2422.801	2019.630	2825.973	1806.204	3039.399
Jan 2019	2479.934	2064.037	2895.832	1843.874	3115.995
Feb 2019	2364.509	1941.146	2787.872	1717.031	3011.986
Mar 2019	2114.740	1687.871	2541.610	1461.900	2767.580
Apr 2019	2005.195	1577.035	2433.356	1350.380	2660.010
May 2019	2658.362	2230.201	3086.522	2003.547	3313.177
Jun 2019	3026.497	2598.337	3454.658	2371.682	3681.312
Jul 2019	3459.950	3031.789	3888.110	2805.135	4114.765
Aug 2019	3961.424	3533.264	4389.585	3306.609	4616.239
Sep 2019	4124.930	3696.769	4553.090	3470.115	4779.745

```
prev.Arima %>% autoplot()
```

Forecasts from ARIMA(0,0,3)(0,1,2)[12] with drift



```
accuracy(fit.naive, ts.test)
```

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	6.485356	457.5677	362.7699	-2.723405	20.42512	1.271487
Test set	582.714286	1174.7456	922.1429	9.265054	28.66327	3.232057
	ACF1 Theil's U					
Training set	0.4258930	NA				
Test set	0.7784592	1.428229				

```
accuracy(fit.seasonal_naive, ts.test)
```

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	84.11842	386.4534	285.3114	2.053698	16.213822	1.0000000
Test set	149.00000	353.1331	252.6190	3.614895	9.052387	0.8854152
	ACF1 Theil's U					
Training set	0.6910538	NA				
Test set	-0.0642013	0.5585835				

```
accuracy(fit.drift, ts.test)
```

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	8.466449e-14	457.5218	362.0537	-3.130732	20.43960	1.268977
Test set	5.113754e+02	1130.8064	897.5384	6.679907	28.52849	3.145820
	ACF1 Theil's U					
Training set	0.4258930	NA				
Test set	0.7791228	1.403644				

```
accuracy(fit.HWA, ts.test)
```

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	-6.732527	235.7490	177.3663	-1.845077	10.65438	0.6216586
Test set	10.773607	444.7325	344.3640	-4.764962	13.46534	1.2069759
	ACF1 Theil's U					
Training set	0.01524887	NA				
Test set	0.60033259	0.7347298				

```
accuracy(fit.HWM, ts.test)
```

	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
Training set	-31.64425	321.7064	240.876	-7.286976	16.200865	0.8442565	0.6941948
Test set	-20.18829	311.6655	239.485	-2.836586	8.754973	0.8393811	0.2452657
	Theil's U						
Training set	NA						
Test set	0.5216854						