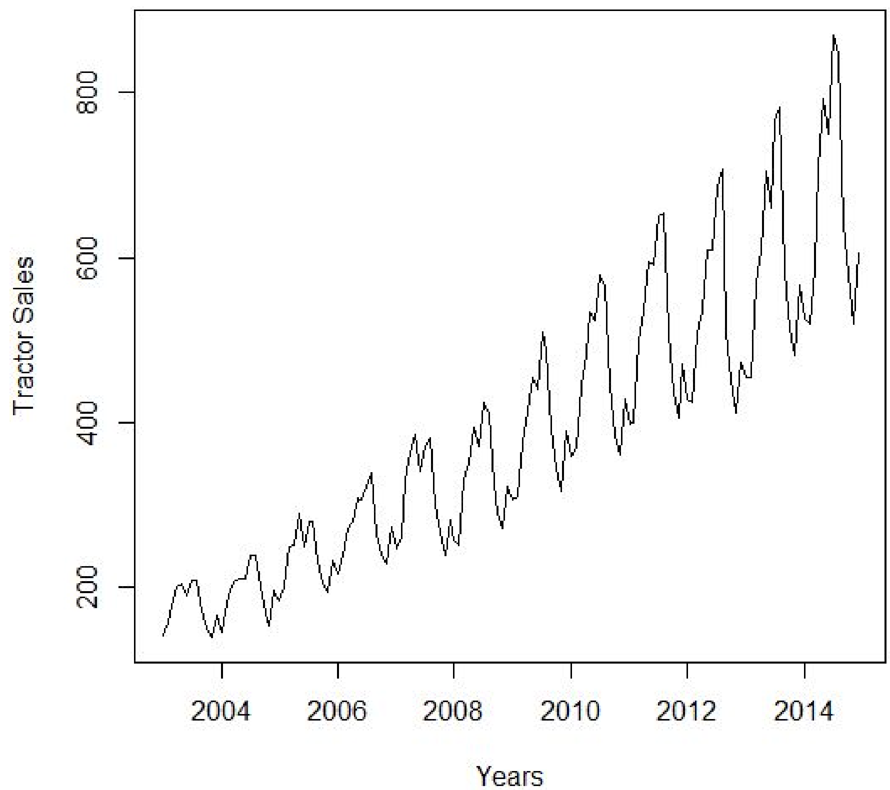
Questions:

1) After inspecting the time series:
    a) Range: Jan. 2003 - Dec. 2014.
    b) 144 Values.
    c) Monthly.

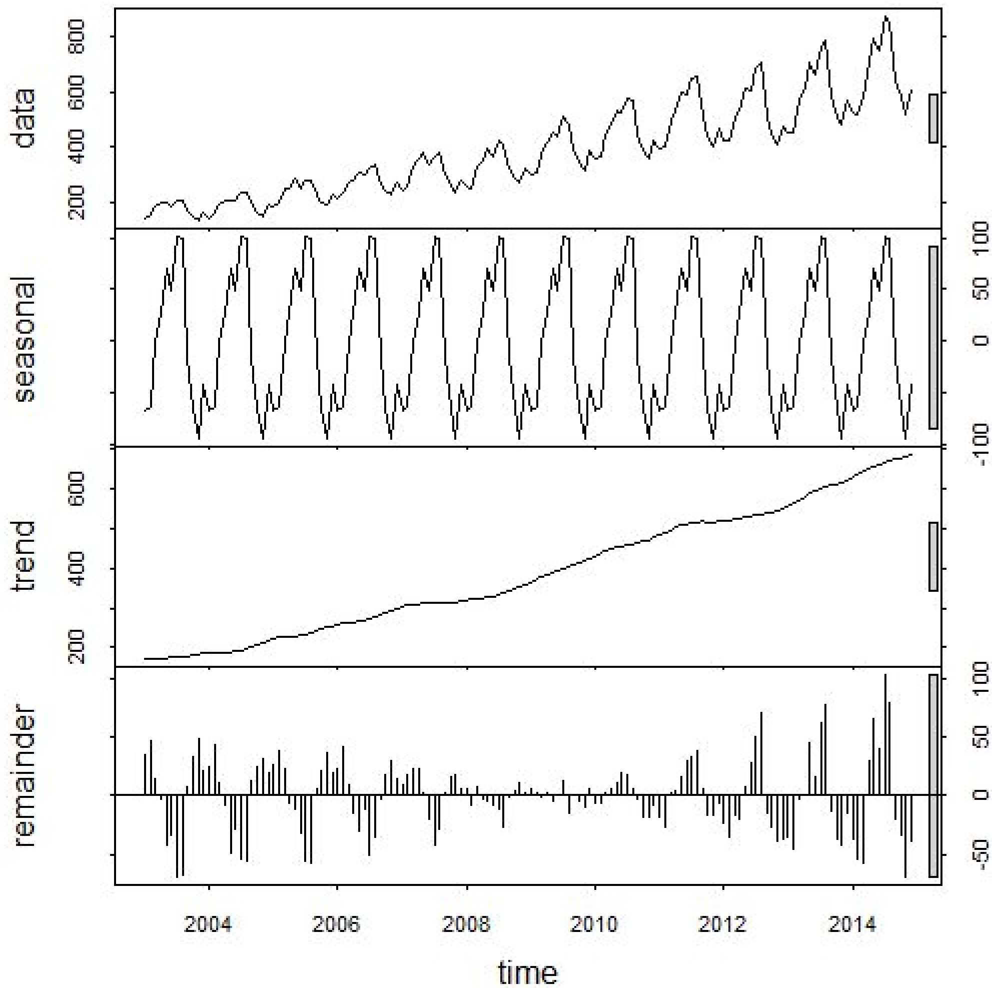
2) Frequency is the number of observations per unit of time. Since the data are sampled monthly frequency should be 12 (months) per unit time (year).

3) After visualizing the time series:
    a)



    b) Yes, linear trend.
    c) Yes, e.g. the sales start increasing in the beginning of each year and drop by the end of the year.

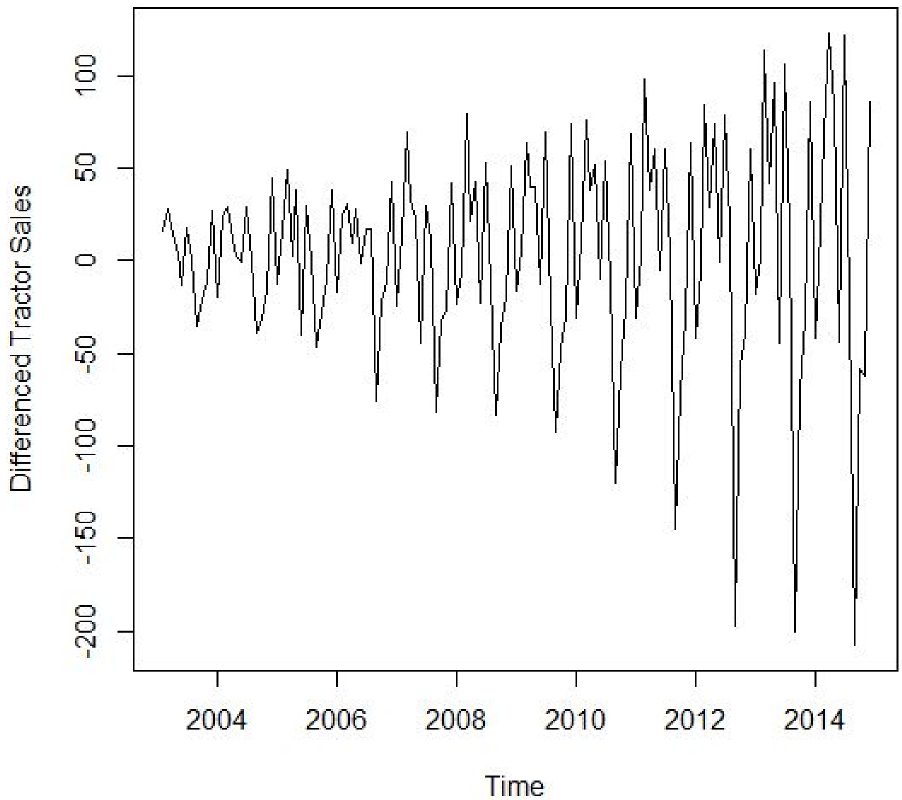
4) Stl decomposes the time series to its components (trend, seasonal, irregular/remainder)



5) Back to the original time series:
    a) Mean and Variance don't change over time.
    b) No, it isn't stationary because there is a linear trend so the mean increases over time e.g. the mean for the first 2 years is around 180 and the mean for the first 3 years is around 200. For the variance, it also increases over time since the increase in the data points (sales) is much higher than the increase in the mean.

6) After differencing the time series:

a)



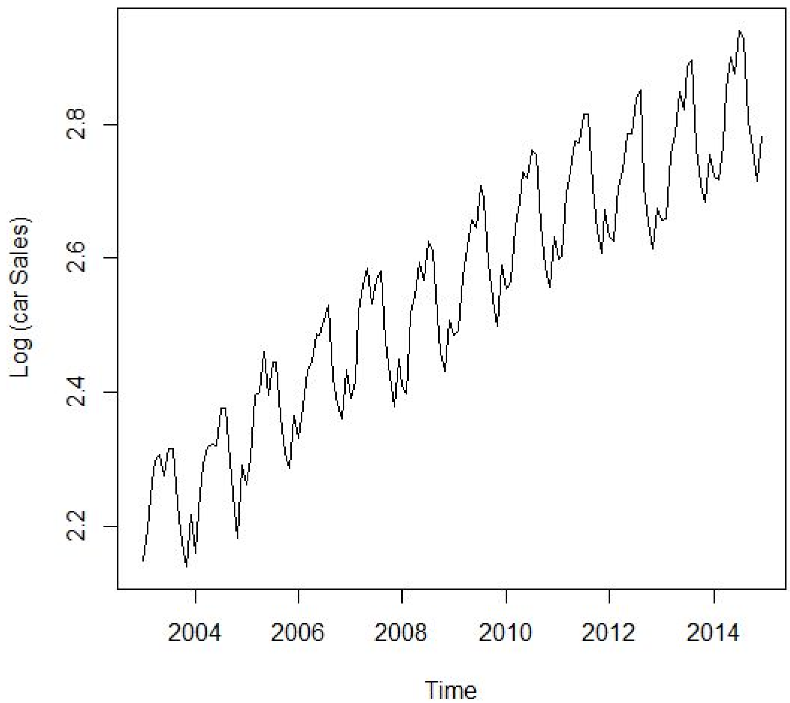
b) No not stationary, No the conditions aren’t satisfied.

c) The condition for the variance isn’t satisfied (there still exists seasonal effect)

d) By performing de-trending it makes the mean around zero (almost constant) so it doesn’t change over time.

7) After applying logarithm to the time series:

a)

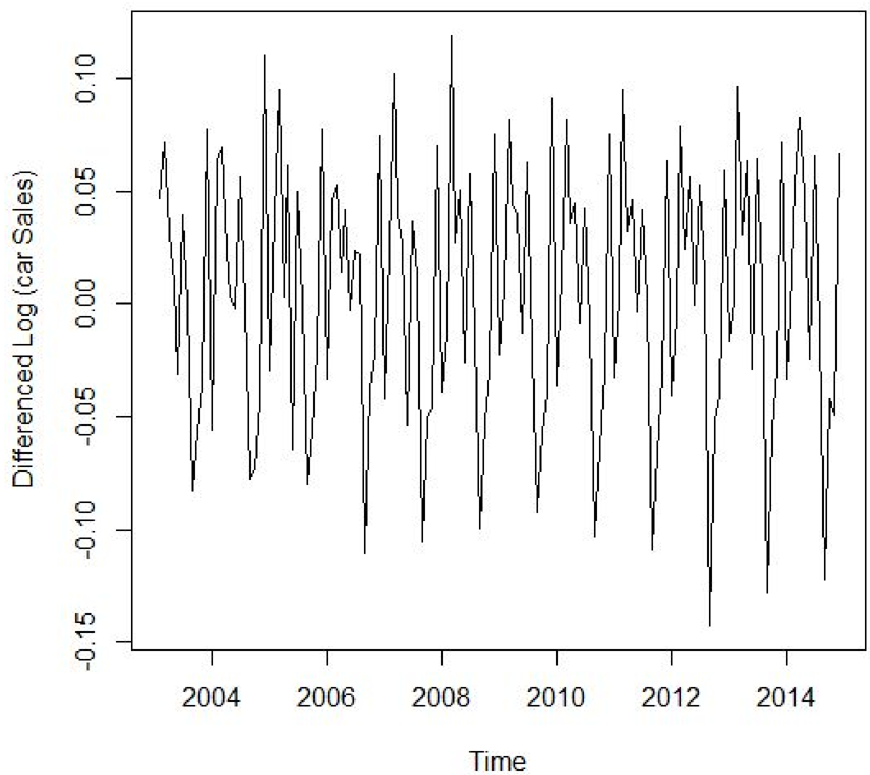


b) No not stationary. No, the conditions aren't satisfied.

c) The condition for the mean isn't satisfied.

d) I think it helps by making the variance almost constant or stable since the range of values for the data points and the mean are very close now so the variance is almost constant.

8) After applying both differencing and logarithm to the time series:
    a) Yes, it is stationary now since the plot is totally random i.e. the trend and seasonal components are removed and there is only the random/irregular component.
    b)



9) After fitting an ARIMA Model with the logarithm of the time series:
    a) Conditions:
        i) Trend's effect should be removed (to have constant mean).
        ii) Seasonal effect should be removed (to have constant variance).

    b) No, because the logarithm mostly affects the variance so it should remove only the seasonal effect. So ARIMA will handle the trend effect by differencing (de-trending) internally.

    c) The output of the ARIMA model:
        i) p → number of autoregressive terms
        ii) d → degree of usual (first) differencing.
        iii) q → number of moving average terms.
        iv) (P, D, Q) relate to seasonal ARIMA P, D, and Q are parameters same as above but here we use seasonal differencing e.g. y(t-12) for monthly data. [S] is the same as frequency (12) for monthly data which is needed for seasonal differencing.

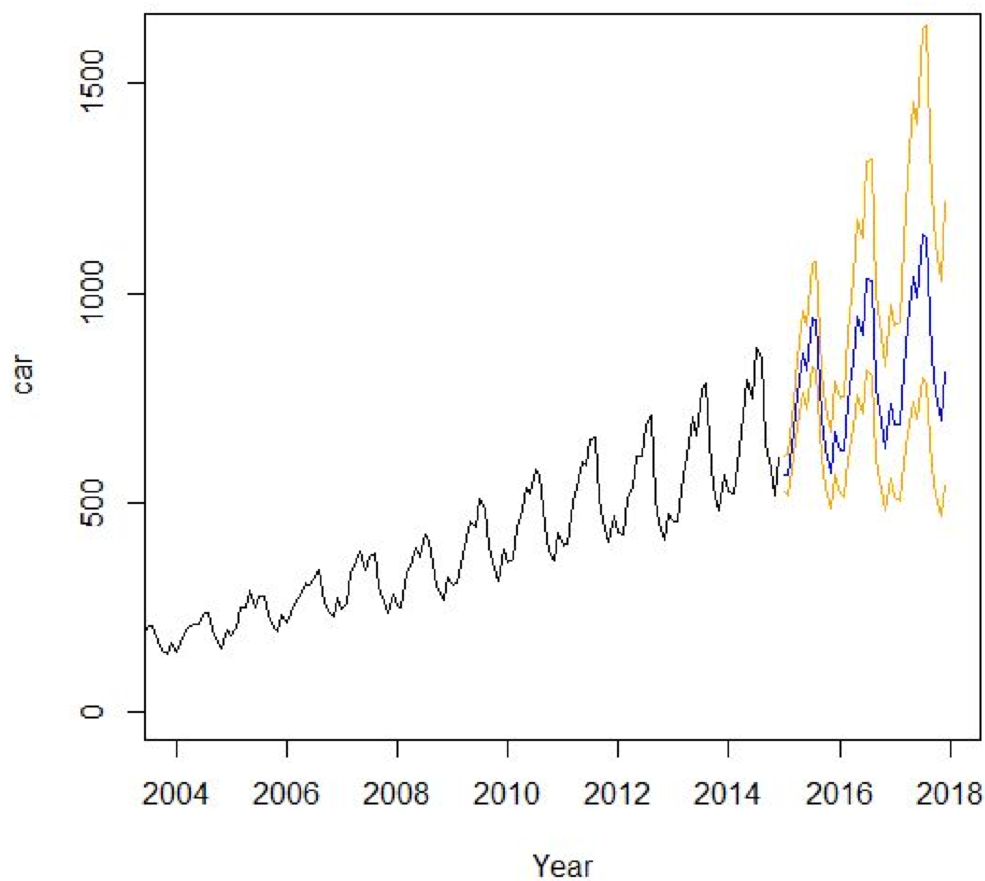
d) Yes, ARIMA handled it internally because the output is ARIMA(0,**1**,1)(0,1,1)[12]. So the best model used usual/first differencing of order 1 for de-trending. If the input was detrended then the output becomes ARIMA(0,0,1)(0,1,1)[12]

e) I think the MA model will be more suitable because the time series displays short term dependency between the data.

10) After changing trace = True:
    a) The best model is the one that has the best AICc i.e. the smallest AICc. The information criteria is AICc → Akaike information criterion with a correction.
    b) Other information criteria:
        i) AIC → Akaike information criterion.
        ii) BIC → Bayesian information criterion.
    c) The smaller the AIC or BIC, the better the fit. So we seek the minimum value.

11) n.head is the number of steps ahead for which prediction is required. So we will predict 36 ahead steps (36 months ahead).

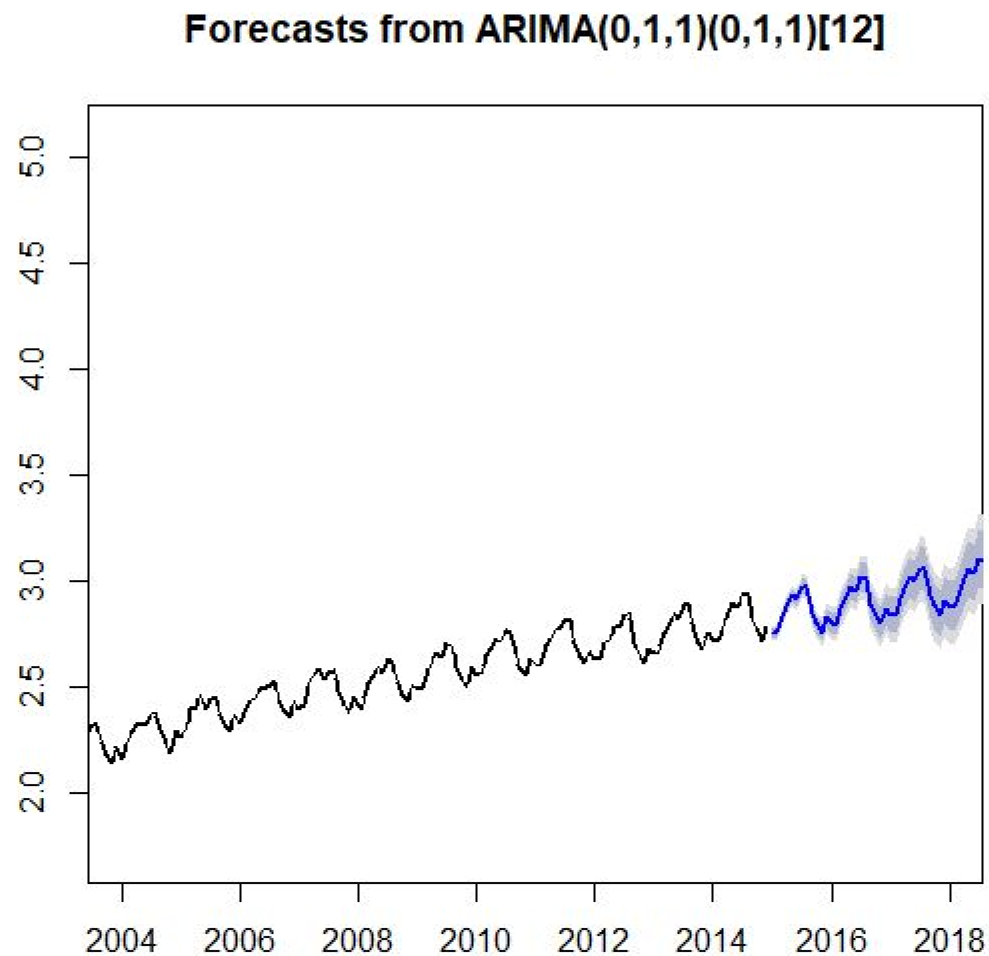
12) After forecasting and plotting the future values:
    a) I think it does work well, it follows the same trend and seasonality.
    b)



13) After using TSPred library:

   a) No, because we need to do the inverse of log10.

   b)



14) The std. Error becomes much higher. Notice that Time series is more suitable for short term predictions only.