

Amin_Baabol

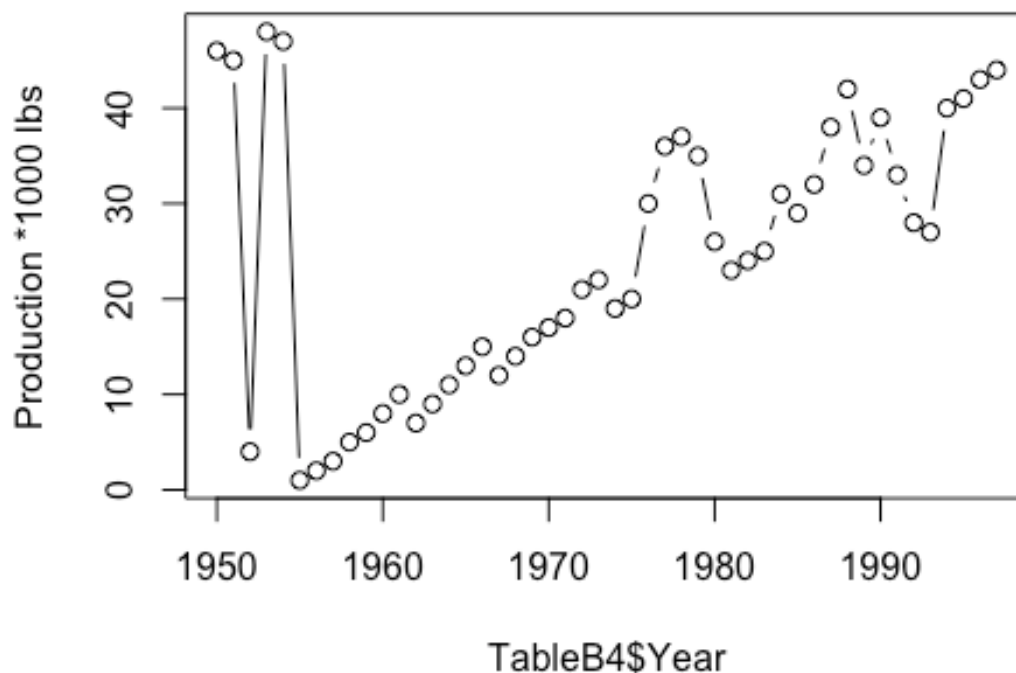
September 15,2020

2.2 Consider the data on US production of blue and gorgonzola cheeses in Table B.4.

- b. Take the first difference of the time series, then find the sample autocorrelation function and the variogram. What conclusions can you draw about the structure and behavior of the time series?

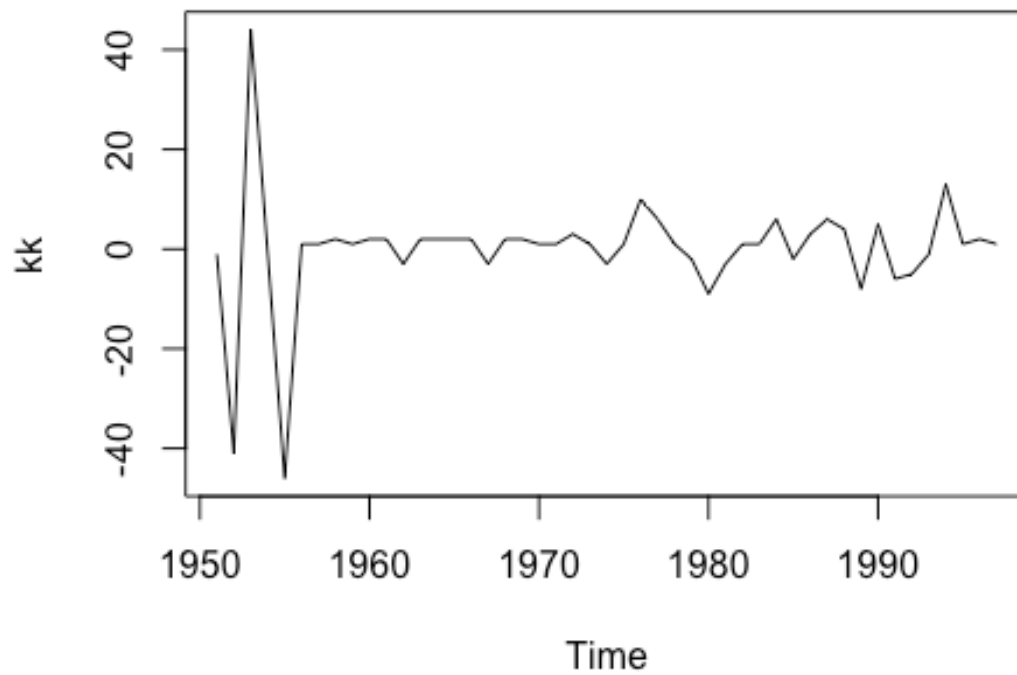
```
#install.packages("pastecs")  
library(pastecs)  
#importing table B.4 from the appendix  
TableB4 <- read.csv("~/Desktop/GradSchool/Fall/STAT-560/Content/TableB4.csv")  
  
plot(x=TableB4$Year,y=TableB4$Production.lbs, main="US production of blue and  
gorgonzola cheese",ylab="Production *1000 lbs", type="b")
```

US production of blue and gorgonzola cheese



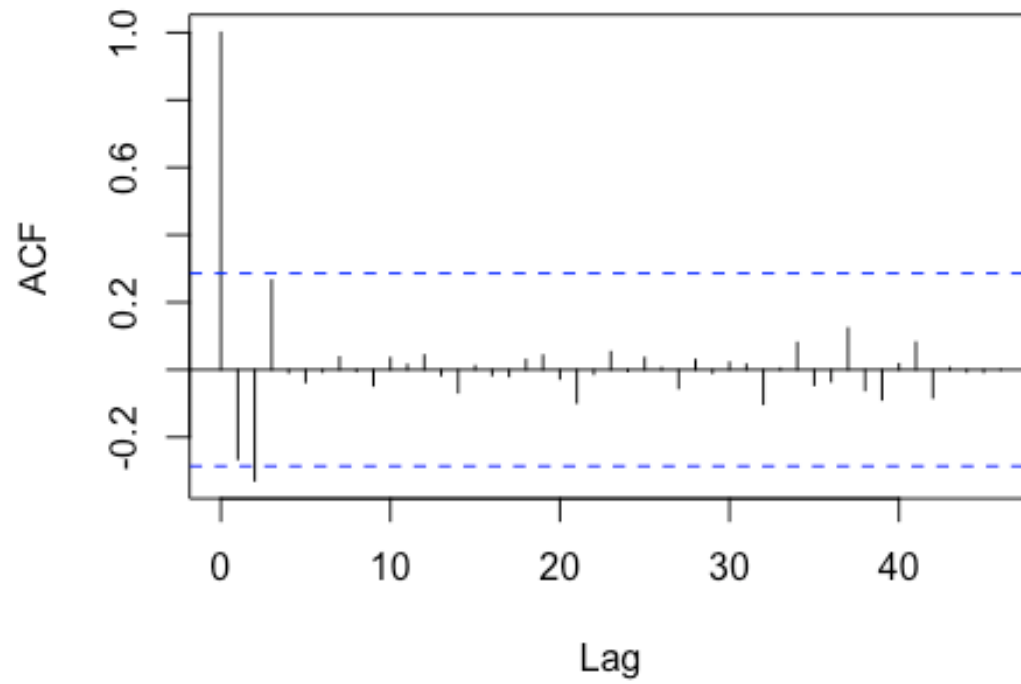
```
#time series  
time.series=ts(TableB4$Production.lbs,start=1950,end=1997,frequency=1)
```

```
#part b  
#first difference of the time series  
kk <- diff(time.series)  
plot(kk)
```



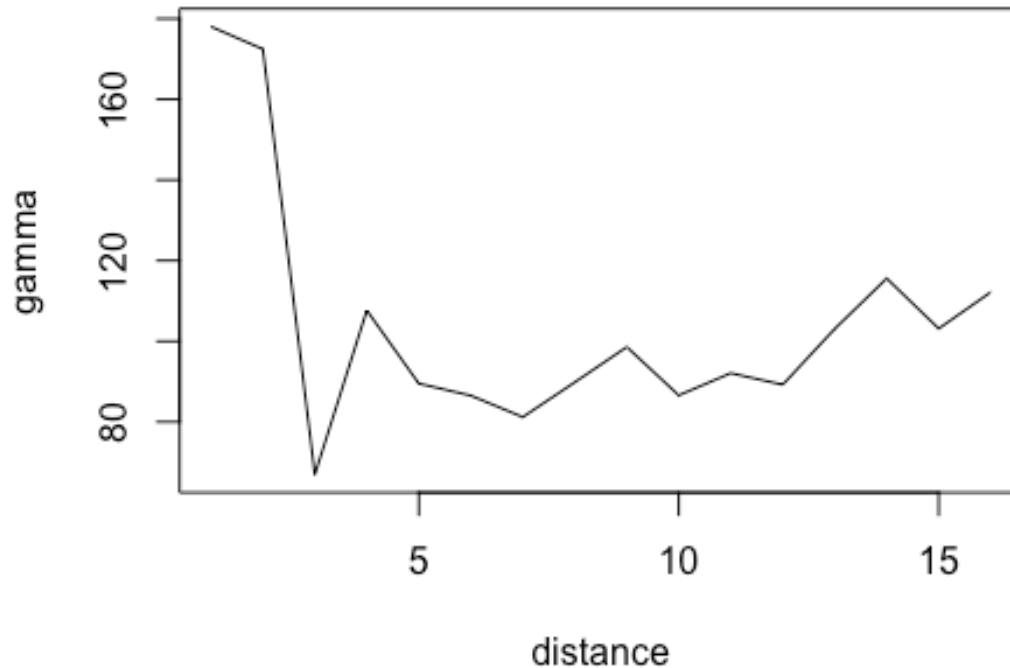
```
#Sample autocorrelation function  
acf(kk, lag.max = 100)
```

Series kk



`vario(kk)`

Semi-variogram for: kk



```
## distance semivario
## 1      1 178.04348
## 2      2 172.45556
## 3      3  66.93182
## 4      4 107.65116
## 5      5  89.51190
## 6      6  86.52439
## 7      7  81.20000
## 8      8  89.83333
## 9      9  98.57895
## 10     10  86.59459
## 11     11  92.08333
## 12     12  89.22857
## 13     13 103.08824
## 14     14 115.57576
## 15     15 103.14062
## 16     16 112.16129
```

Conclusion: Looking at the ACF bounds and the time series plot we can't be confidently classified the data as non-stationary as its plot doesn't adequately indicate an increasing trend, hence it's safe to say that when we difference the first order data it strongly indicates a stationary behavior and sample autocorrelation function within significant range.

2.11 Reconsider the data on the number of airline miles flown in the United Kingdom from Exercise 2.10. Take the natural logarithm of the data and plot this new time series. a. What impact has the log transformation had on the time series? b. Find the autocorrelation function for this time series. c. Interpret the sample autocorrelation function.

```
TableB10 <- read.csv("~/Desktop/GradSchool/Fall/STAT-560/Content/TableB10.csv")
```

```
#part a
```

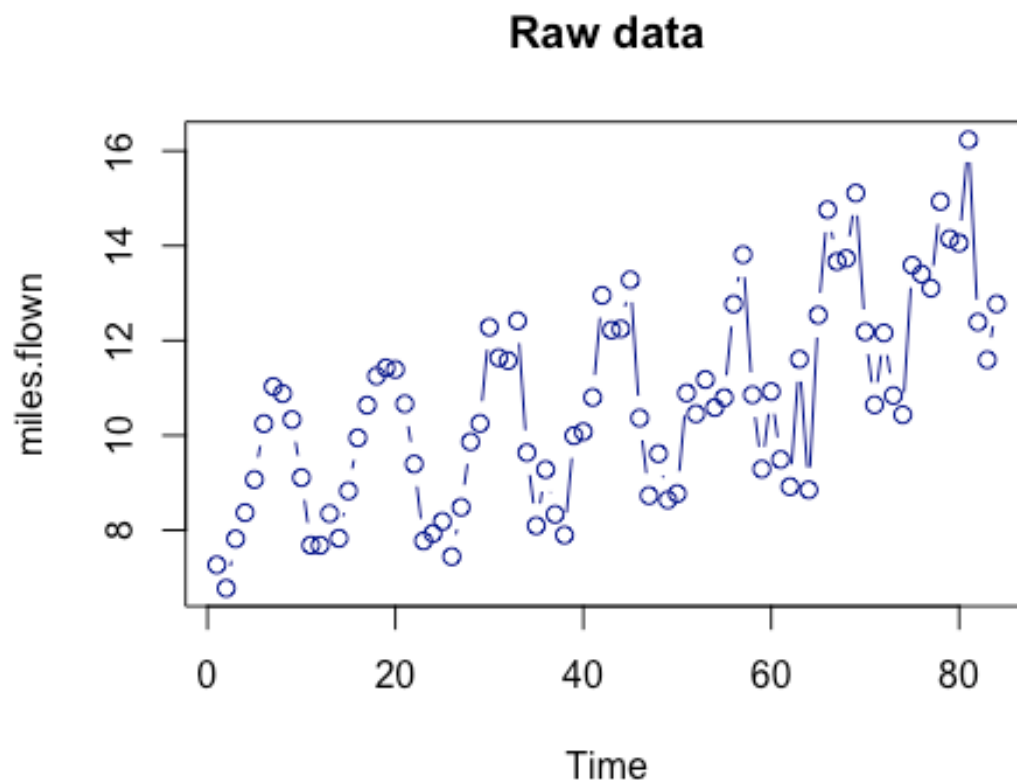
```
#plotting before we take the natural log
```

```
miles.flown <- ts(TableB10$Miles.mil.)
```

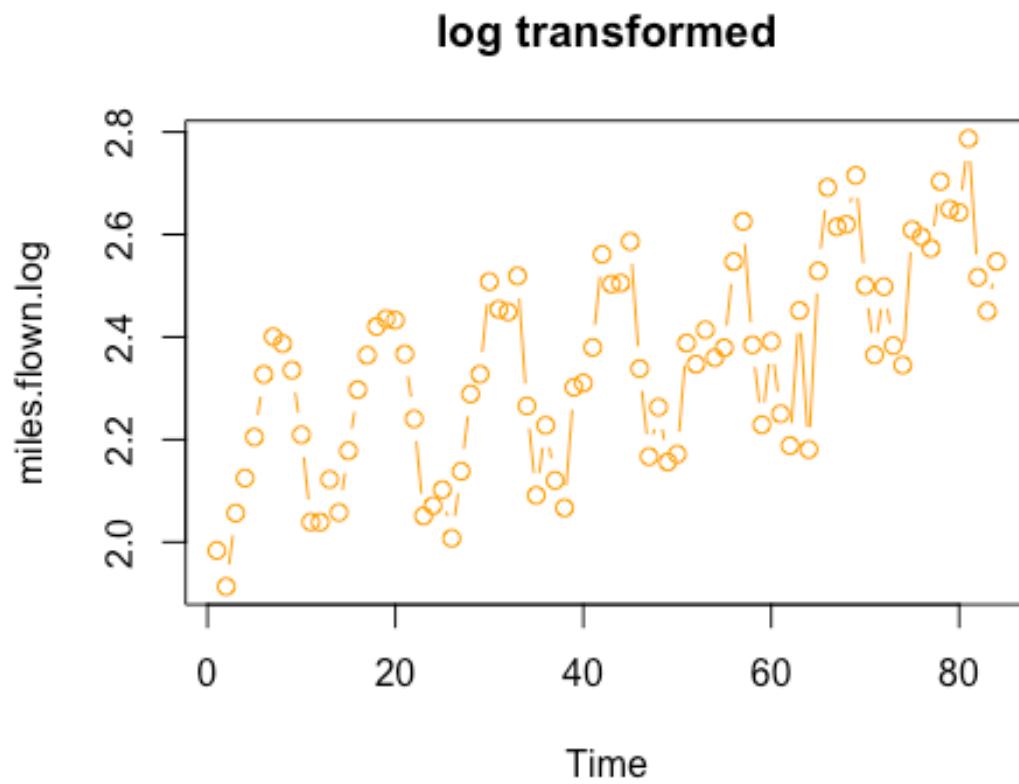
```
#Taking the natural log of the data
```

```
miles.flown.log <- log(miles.flown)
```

```
plot(miles.flown,main="Raw data",type="b",col="darkblue")
```

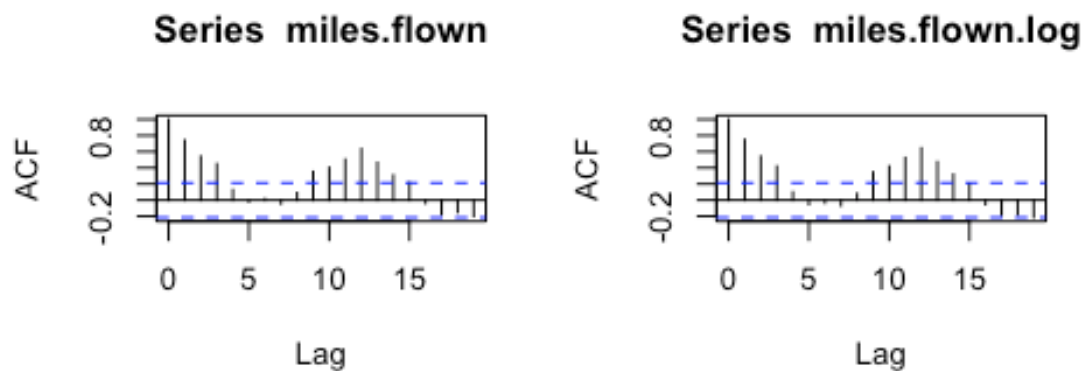


```
plot(miles.flown.log,main="log transformed", type="b",col="orange")
```



```
#part b
par(mfrow=c(2, 2))
#ACF of raw data
acf(miles.flown,plot=T)
#ACF of Log-transformed data
acf(miles.flown.log,plot=T)

#part c
```



conclusion:

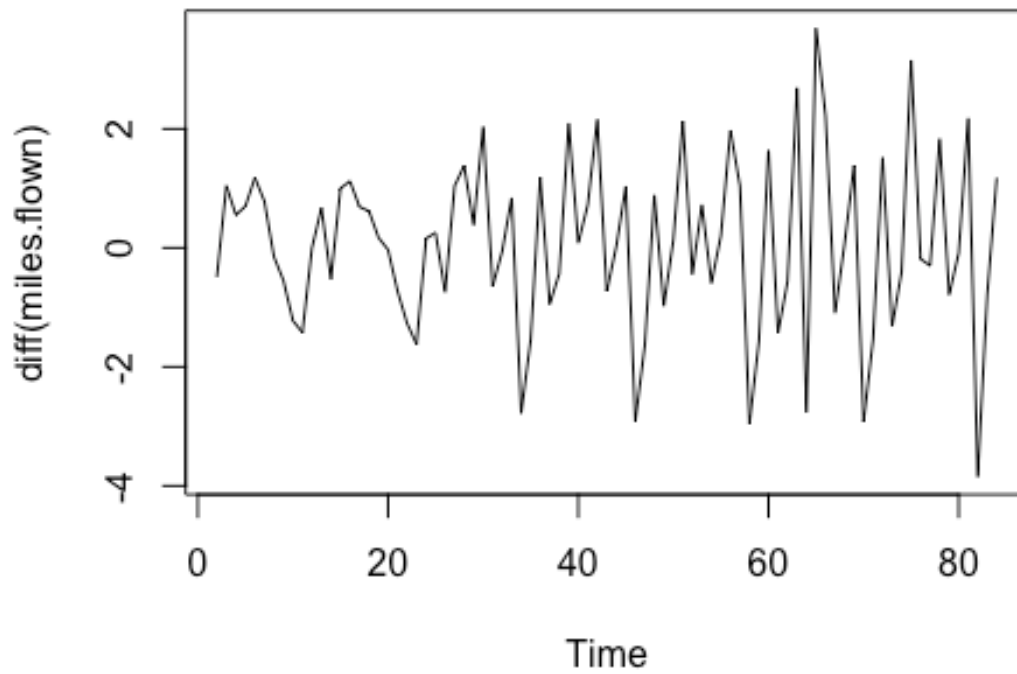
- a) The log transformation seem to have rescaled the time series plot but didn't greatly influence the trend or the miles flown by the airlines. However, taking the natural log brought down the variability as the data points became closer to each other.
- b) The sample autocorrelation function of the miles flown by the airlines indicates there are a local or seasonal trends. Beyond those seasonal or local trends the acf value drops from nearly 0.9 to close to 0 which perhaps is revealing its stationarity.

2.12 Reconsider the data on the number of airline miles flown in the United Kingdom from Exercises 2.10 and 2.11. Take the first difference of the natural logarithm of the data and plot this new time series. a. What impact has the log transformation had on the time series? b. Find the autocorrelation function for this time series. c. Interpret the sample autocorrelation function.

#First difference of raw data time series

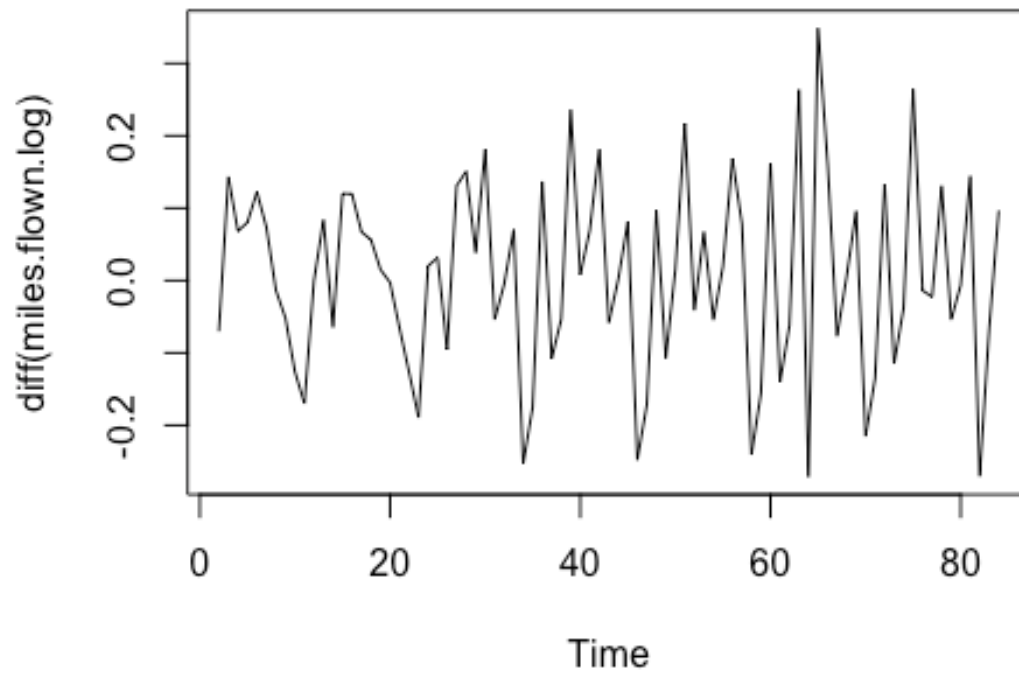
```
plot(diff(miles.flown),main="1st diff of the raw data time seires")
```

1st diff of the raw data time seires

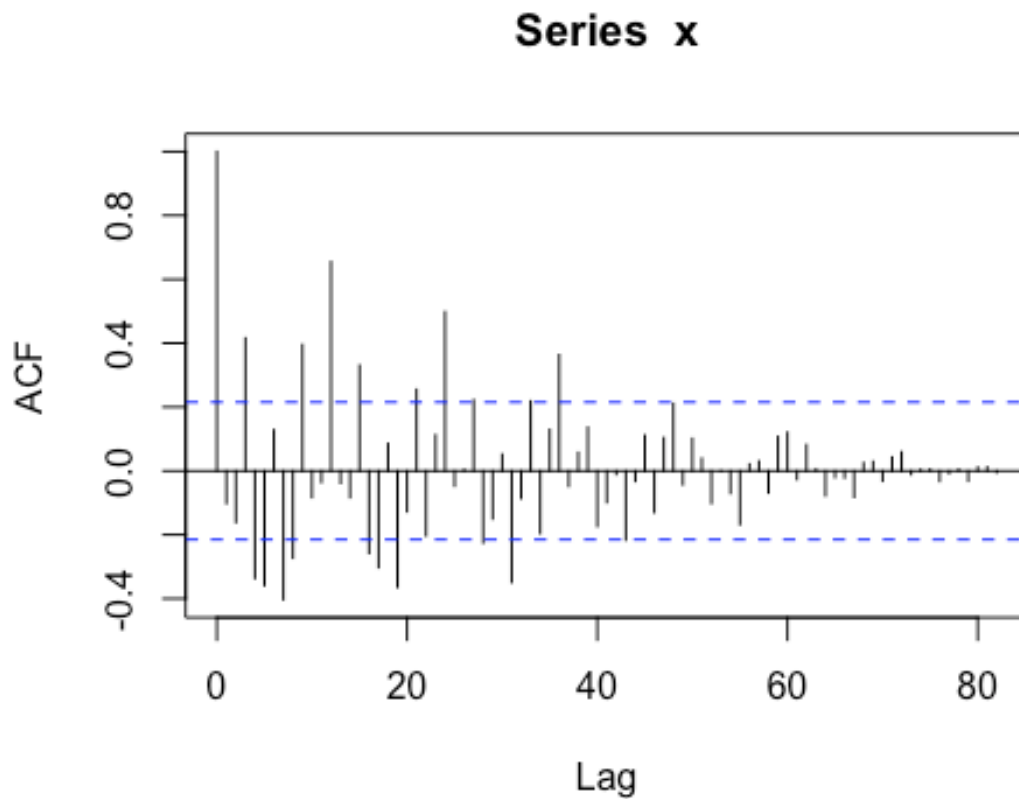


```
#First difference of log transformed data time series  
plot(diff(miles.flown.log),main="1st diff of the log data time series")
```


1st diff of the log data time series



```
#part b  
x <- diff(miles.flown.log)  
acf(x, lag.max = 100)
```



Conclusion:

- a) Taking the natural log of the data and then implementing the first order difference greatly reduced the trends which essentially limited the variability in the data, thus lower variance.
- b) The sample autocorrelation oscillates at a decreasing rate as the lag picks up and increases. This gradual decrease is a behavior typical to stationary time series.