MATH 545 Intro to Time Series Final Project

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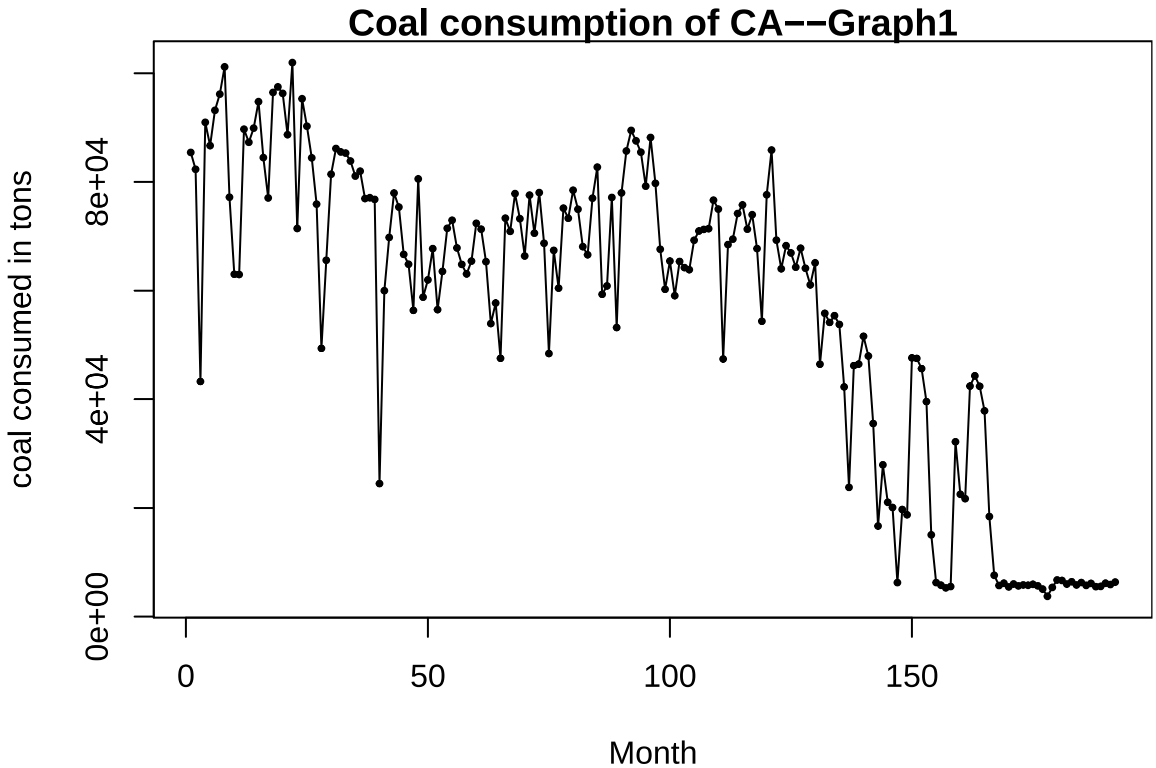
Background

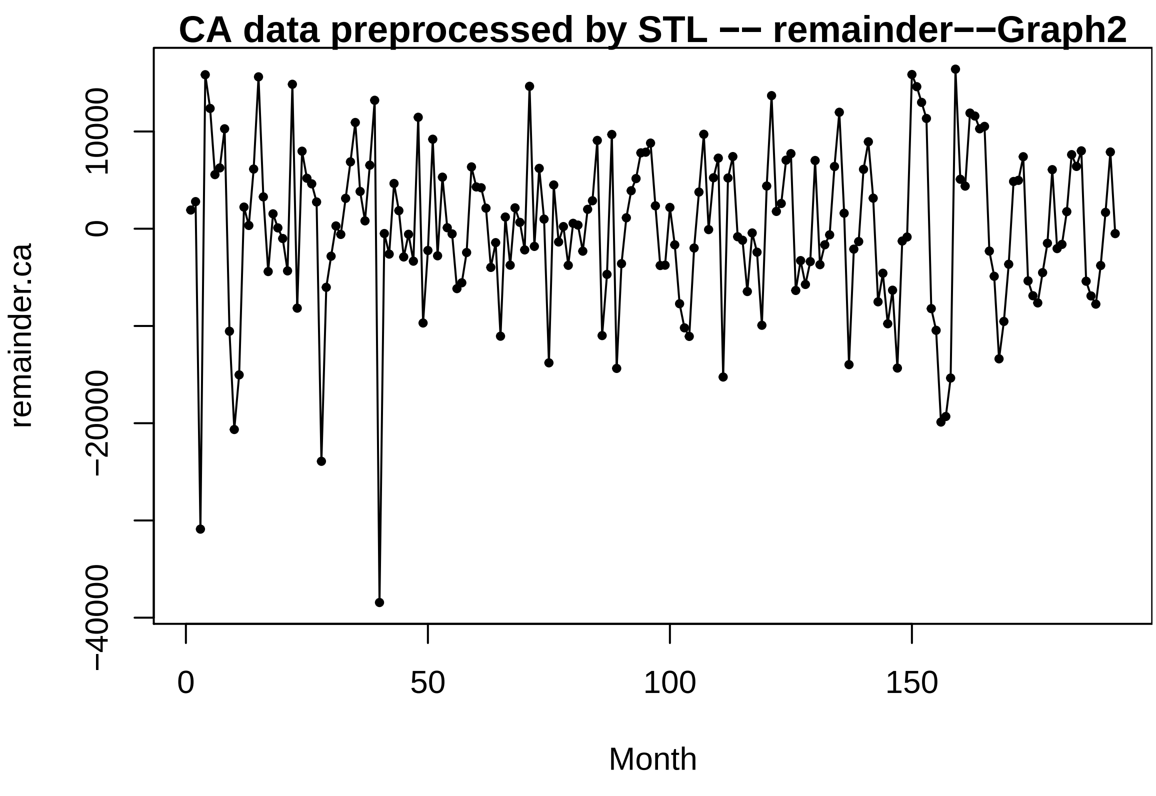
The data in the file USCoal-2016.csv contains monthly observations from January 2001 to December 2016 (192 observations) of the amount (in tons) of coal consumed in energy production in each of five US states (California, Florida, Illinois, North Carolina and Pennsylvania). Write a report on the analysis of these data sets, commenting on the following aspects:

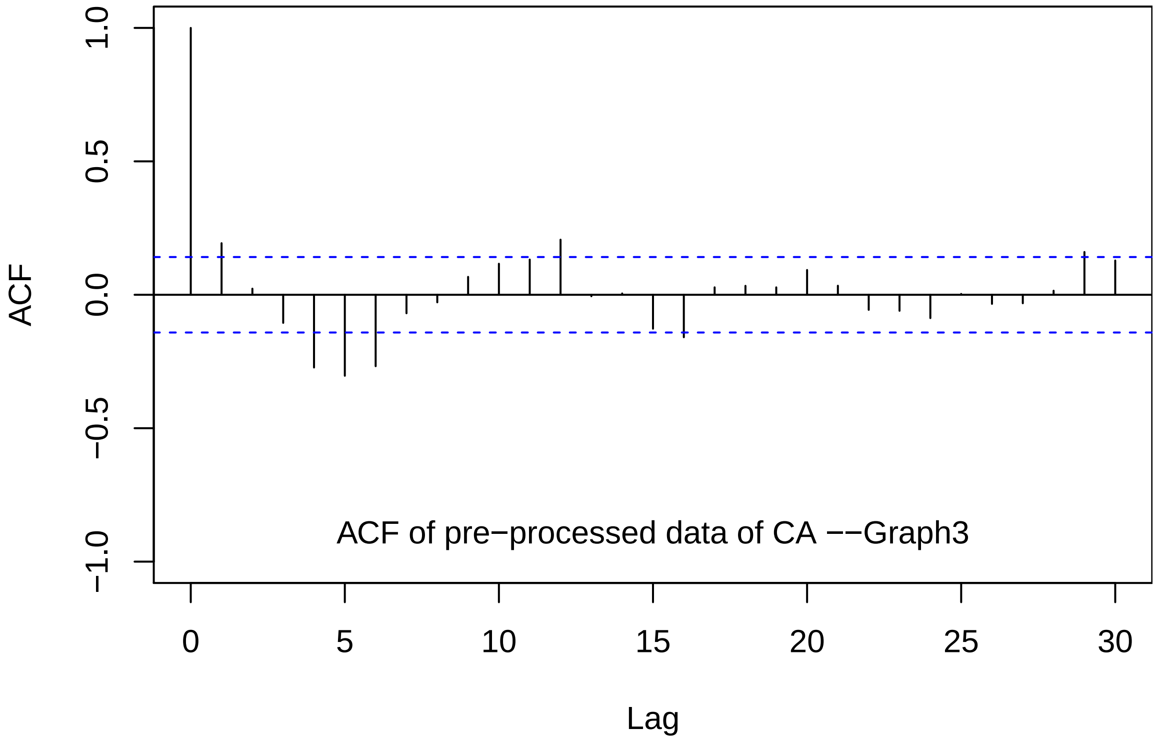
- the deterministic and stochastic time series components for each state;
- similarities and differences, in the data and proposed models, between states;
- constructed monthly forecasts for years 2017;

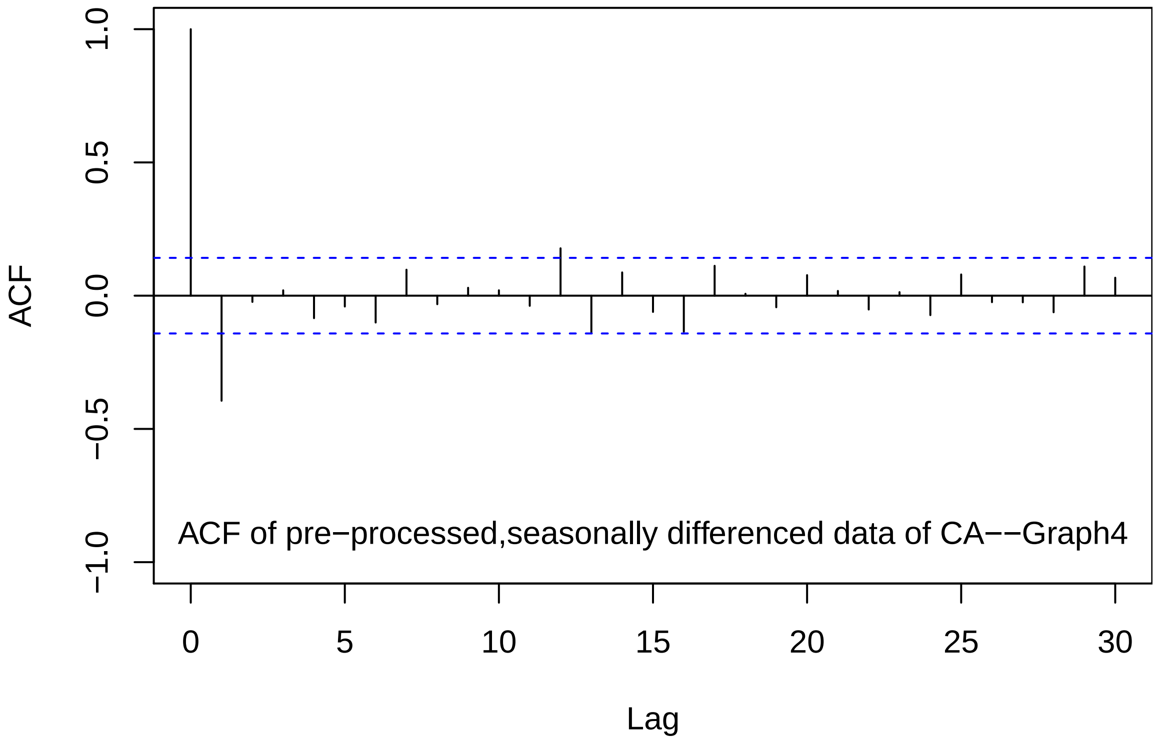
California

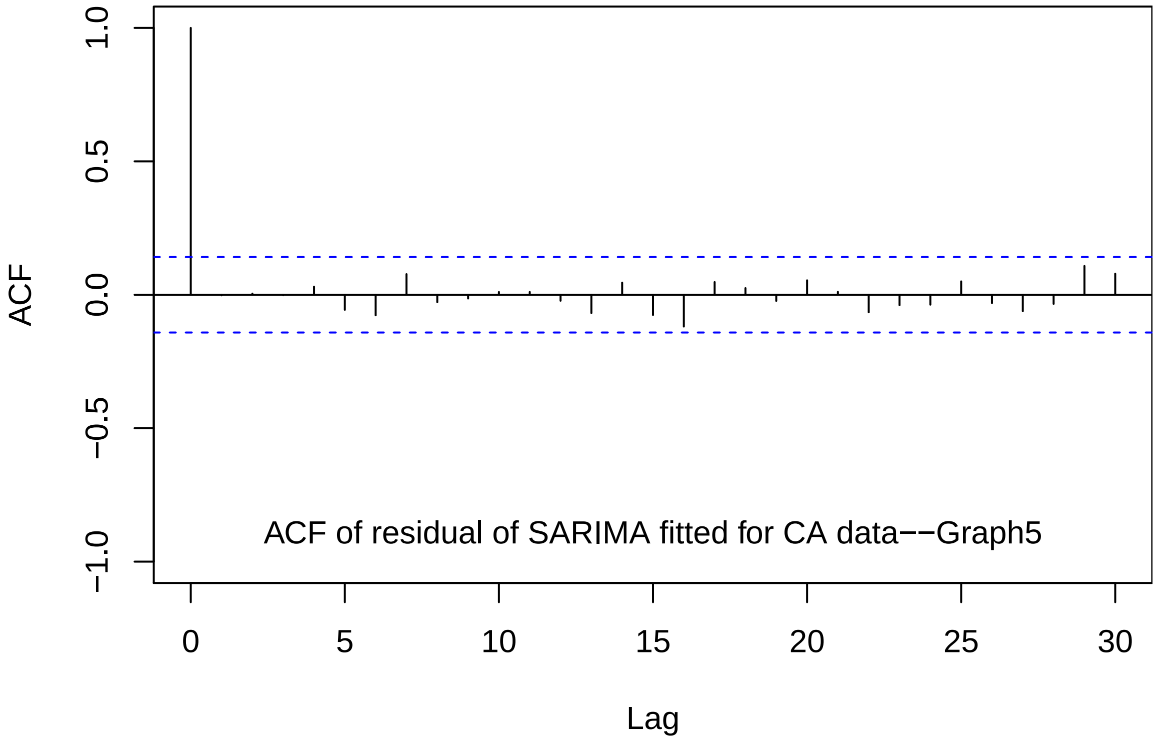
We try to analyze these data state by state. First we inspect the plot of the raw data(Graph1). We find that there is stochasticly seasonal behaviour as well as a decreasing trend. Next we do the STL decomposition to remove the determisnitic trend and seasonality. The remainder is shown in (Graph2). (Graph3) shows the ACF of the remainder series. We still see some seasonal component in the ACF plot (Graph3) thus we try differencing, with d=1 and produce (Graph4). The ACF of seasonally differenced data suggests that we can try a SARIMA model, namely with s=12, d=1, Q=1,(we see a spike at lag=12) D=0, P=0. We fitted different p,q from 0:7, 0:7 respectively, We found that p,q=(4,2). has the lowest AIC value. So, the final model we use is SARIMA$(4, 1, 2) \times (0, 0, 1)_{12}$ Then we inspect the residual of the fitted model. The ACF of the residuals is shown in Graph(5). We see that the model fits quite well as the residuals do seem like a white noise process. Finally, we plot the data along with the 12-month ahead predictions in (Graph 6).The predicted results is graphed in red, note that we have made an adjustment since some of the predicted value is below 0, which does not make sense in the current context, we therefore set those value to 0. Also note that we forecast the STL components seperately. let$Y_t = M_t + S_t + X_t$ where M_t is the trend series, S_t is the seasonal series and X_t is the remainder series. We forecast $\hat{X}_t$ with the SARIMA model and add it with $\hat{M}_t$ and $\hat{S}_t$.

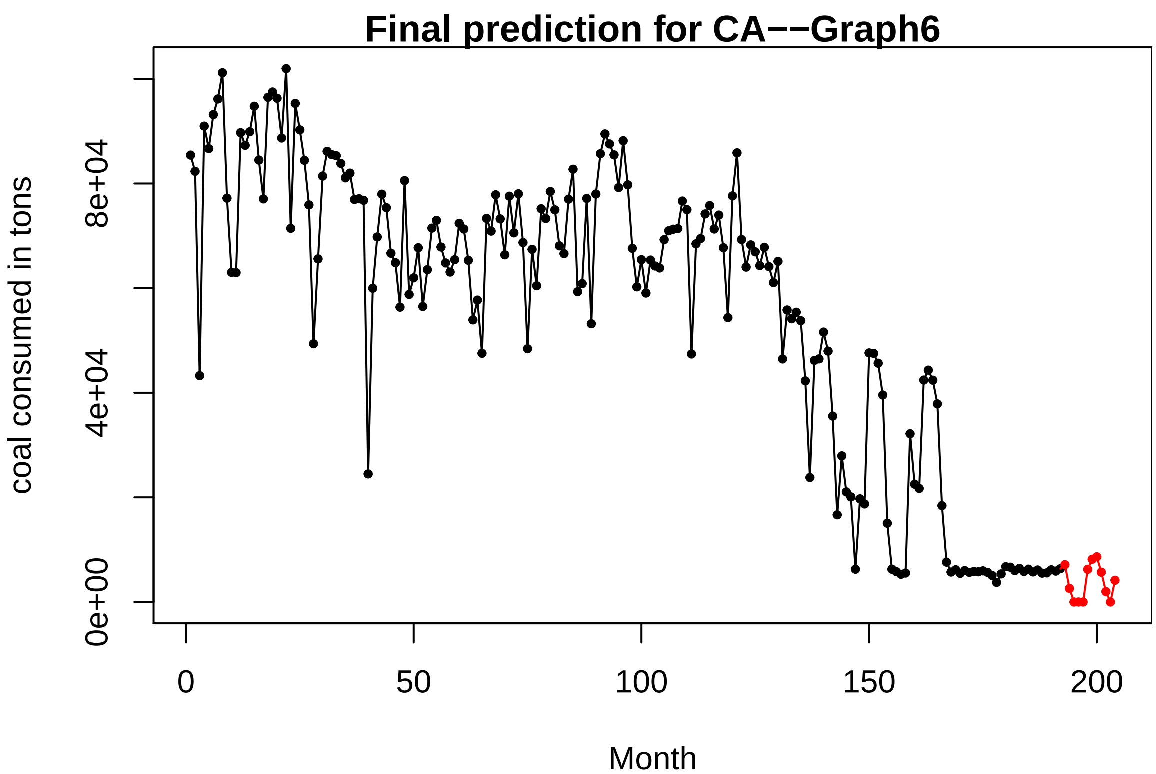

Coal consumption of CA−−Graph1
coal consumed in tons
0e+00
4e+04
8e+04
0
50
100
150
Month


CA data preprocessed by STL −− remainder−−Graph2
remainder.ca
−40000
−20000
0
10000
0
50
100
150
Month


ACF
1.0
0.5
0.0
−0.5
−1.0
0
5
10
15
20
25
30
Lag
ACF of pre−processed data of CA −−Graph3


ACF
1.0
0.5
0.0
−0.5
−1.0
0
5
10
15
20
25
30
Lag
ACF of pre−processed,seasonally differenced data of CA−−Graph4

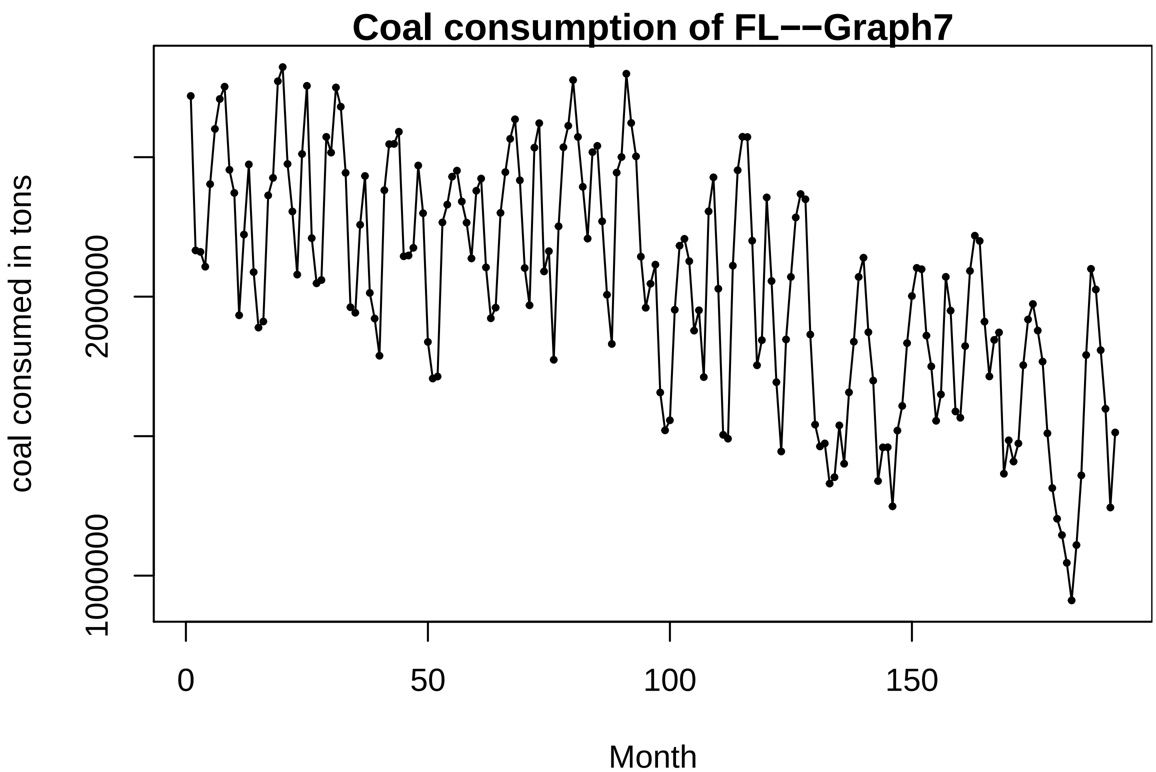


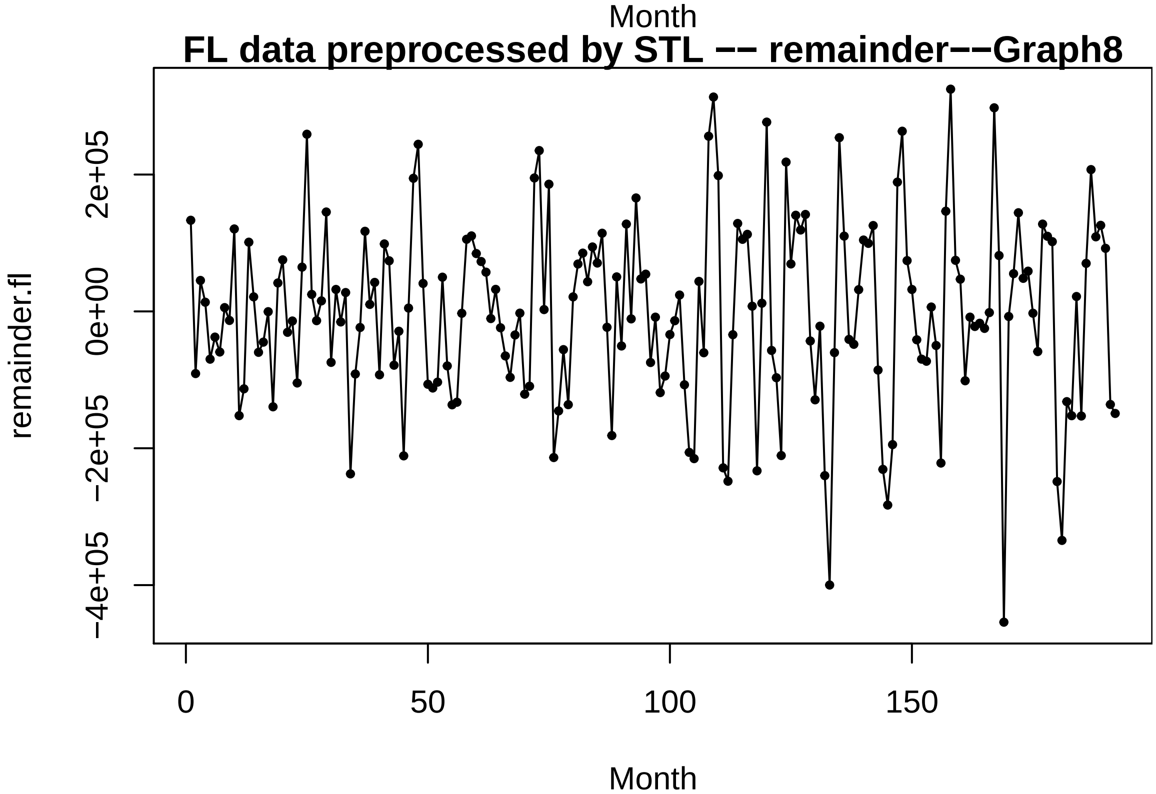


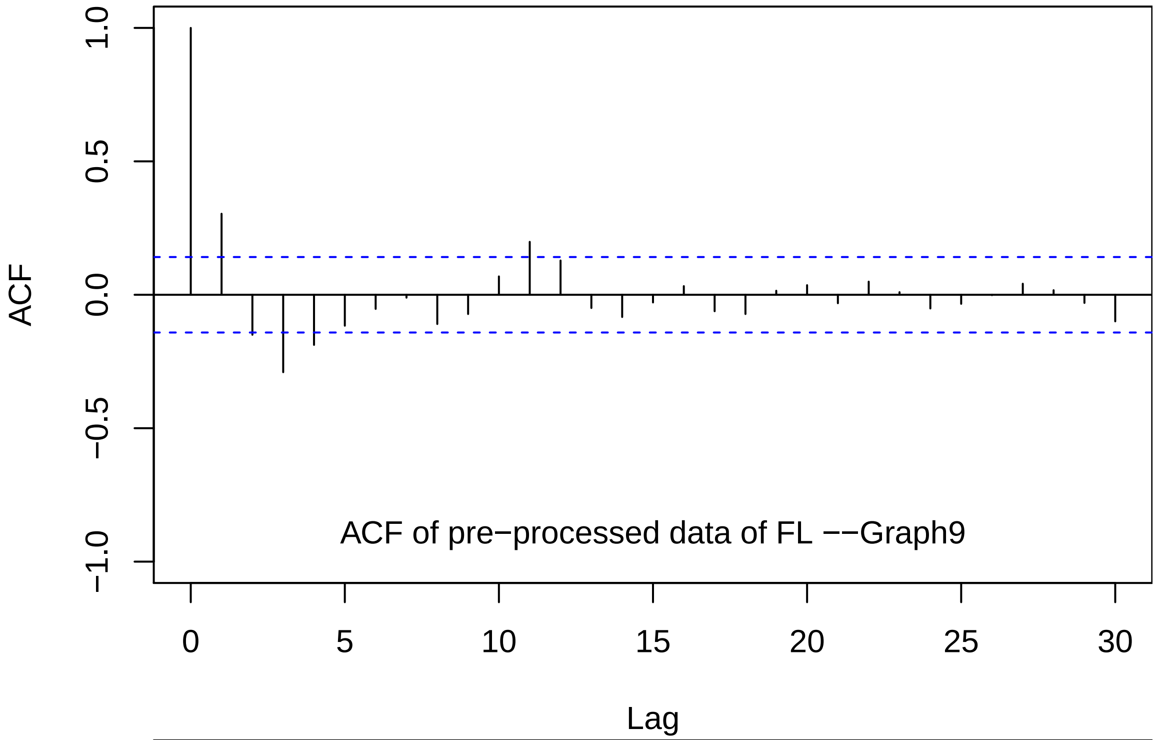
Florida

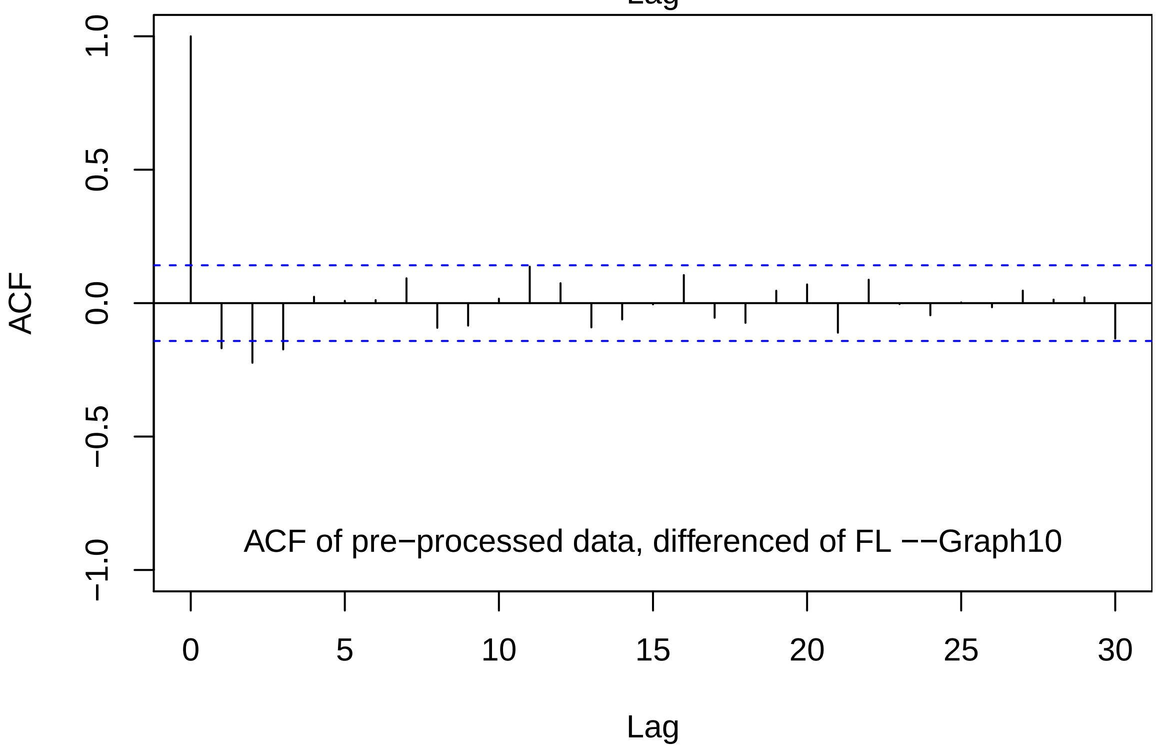
We follow a similar procedure. First we inspect Florida's raw data(Graph7). We find a decreasing trend as well as some seasonal behavior, we will need to check some ACF plots to determine whether there is stochastic seasonality or not. Next we use STL to do decomposition and plot the remainder series (Graph8) and the

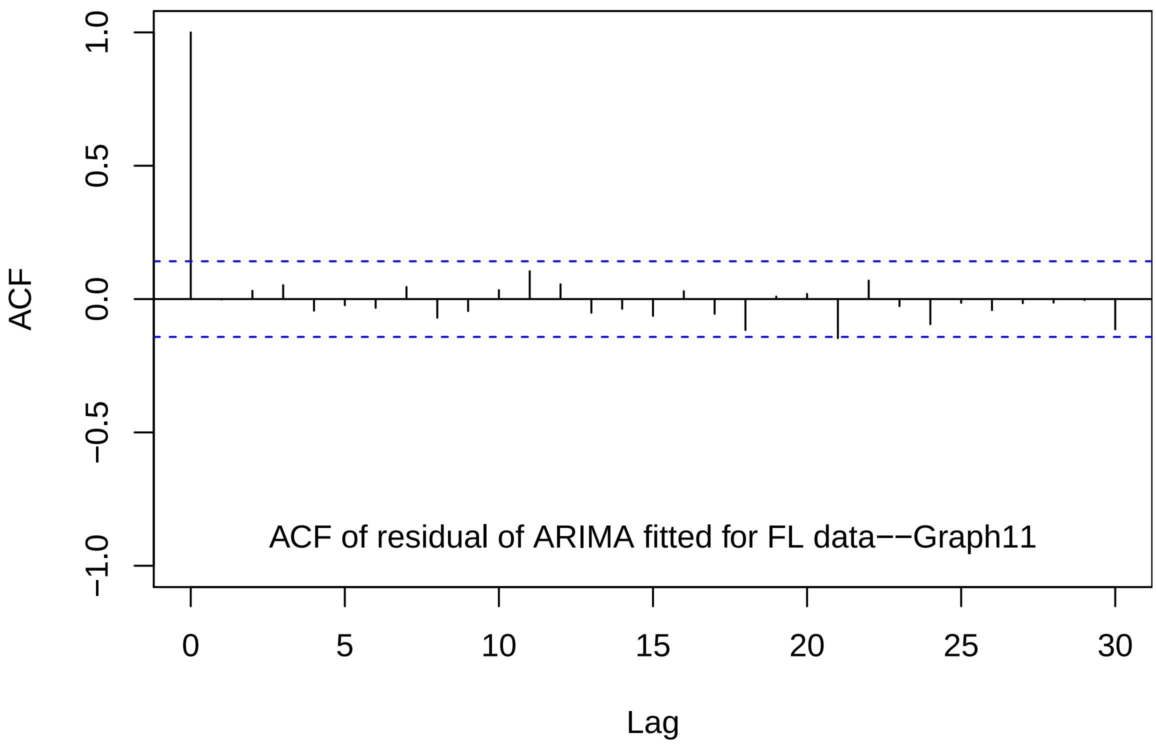
ACF of the remainder series(Graph9). We see that there seems to be an increase in variance which indicates non-stationarity, We try to difference the remainder series with d=1 and plot the ACF of the differenced data(Graph10). We don't see any spike at lag=12. So we believe that stochastic seasonality is removed by differencing and thus an ARIMA model will suffice. We try different (p,q) vaules from 0:7 and 0:7 and find that (1,5) has the lowest AIC. We proceed to fit the model with ARIMA$(1, 1, 5)$. We checked the ACF of the residuals(Graph 11). It looks like a white noise process. Finally we produce the 2017 Forecast for FL in (Graph 12), using the same method as we did for CA.

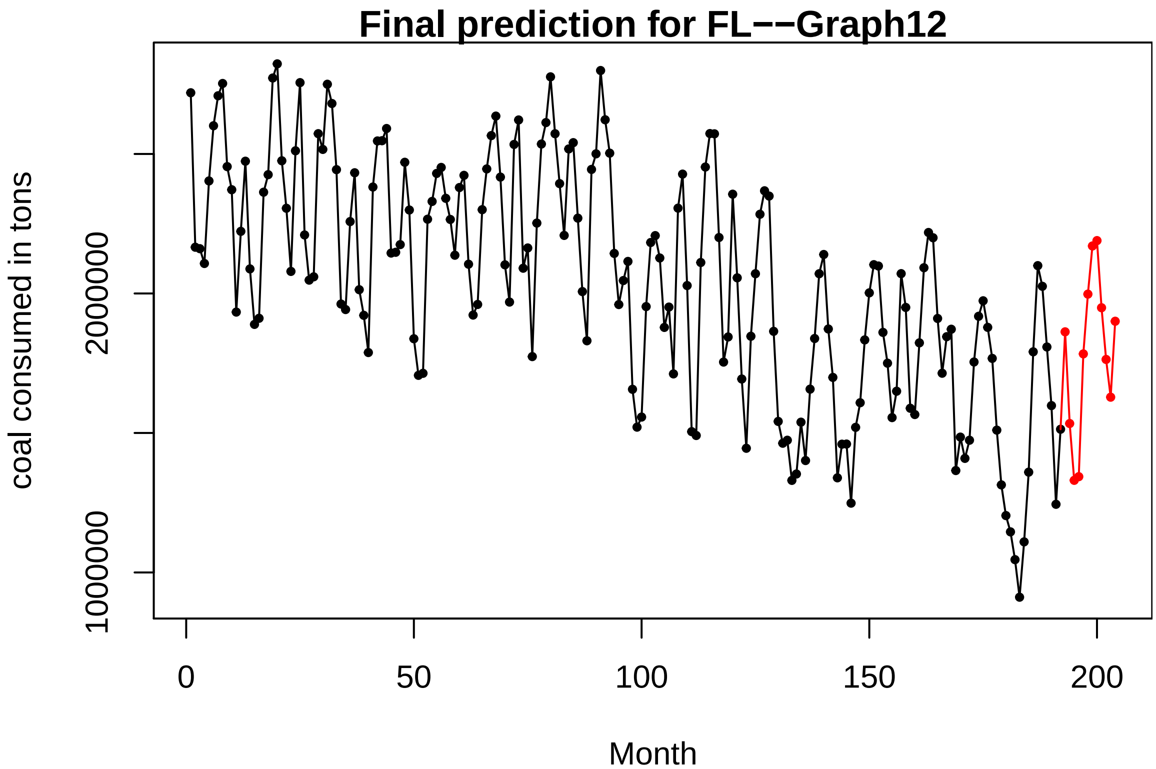

Coal consumption of FL−−Graph7
coal consumed in tons
1000000
2000000
0
50
100
150
Month


FL data preprocessed by STL −− remainder−−Graph8
remainder.fl
−4e+05
−2e+05
0e+00
2e+05
0
50
100
150
Month


ACF
1.0
0.5
0.0
−0.5
−1.0
ACF of pre−processed data of FL −−Graph9
0
5
10
15
20
25
30
Lag

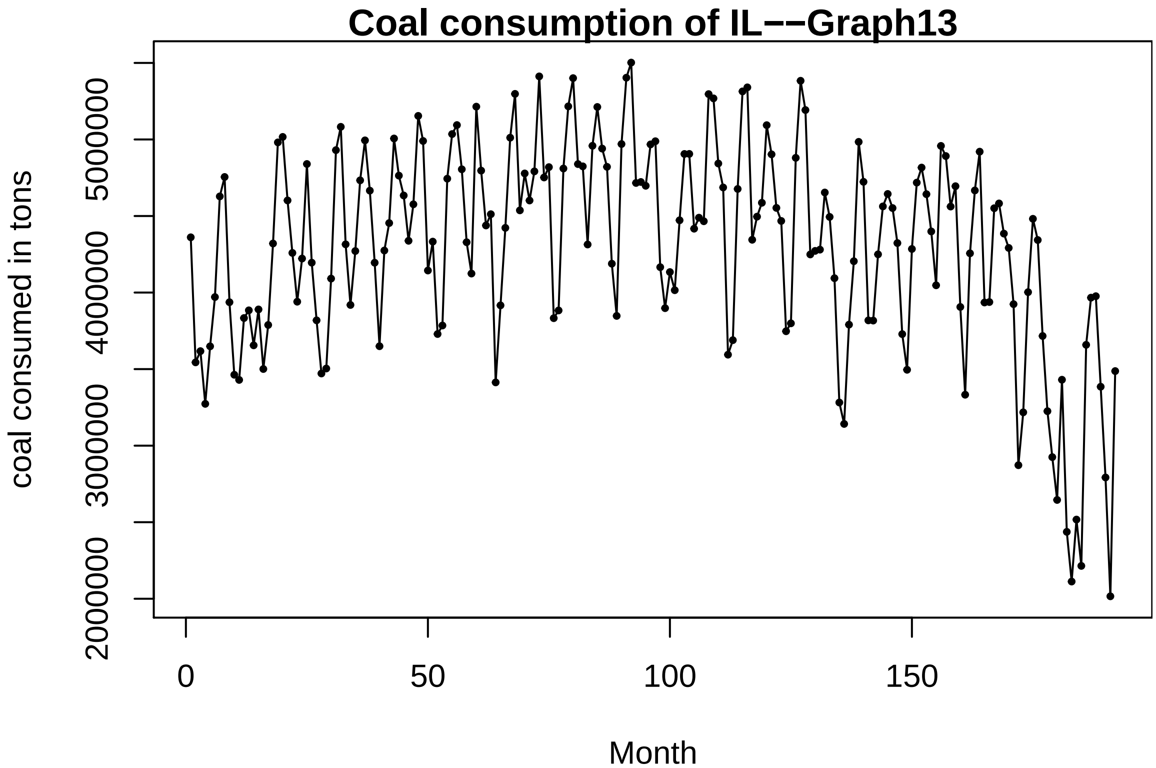

ACF
1.0
0.5
0.0
−0.5
−1.0
ACF of pre−processed data, differenced of FL −−Graph10
0
5
10
15
20
25
30
Lag

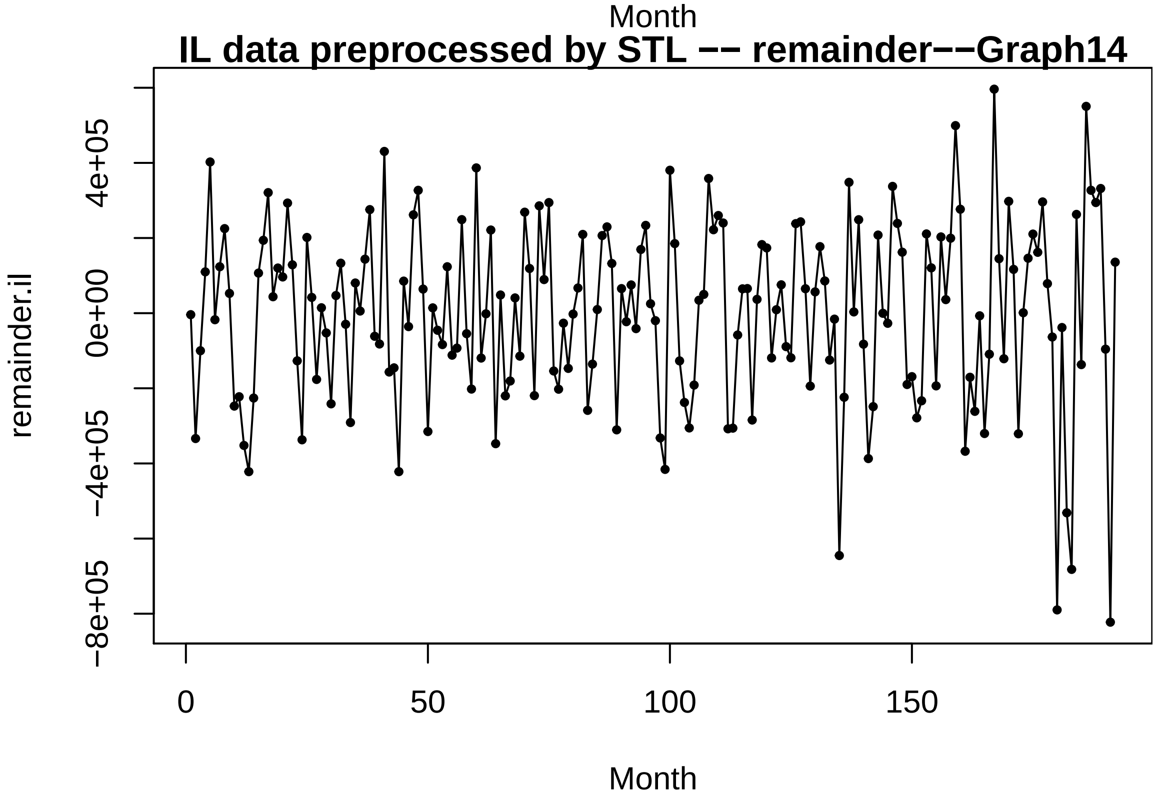


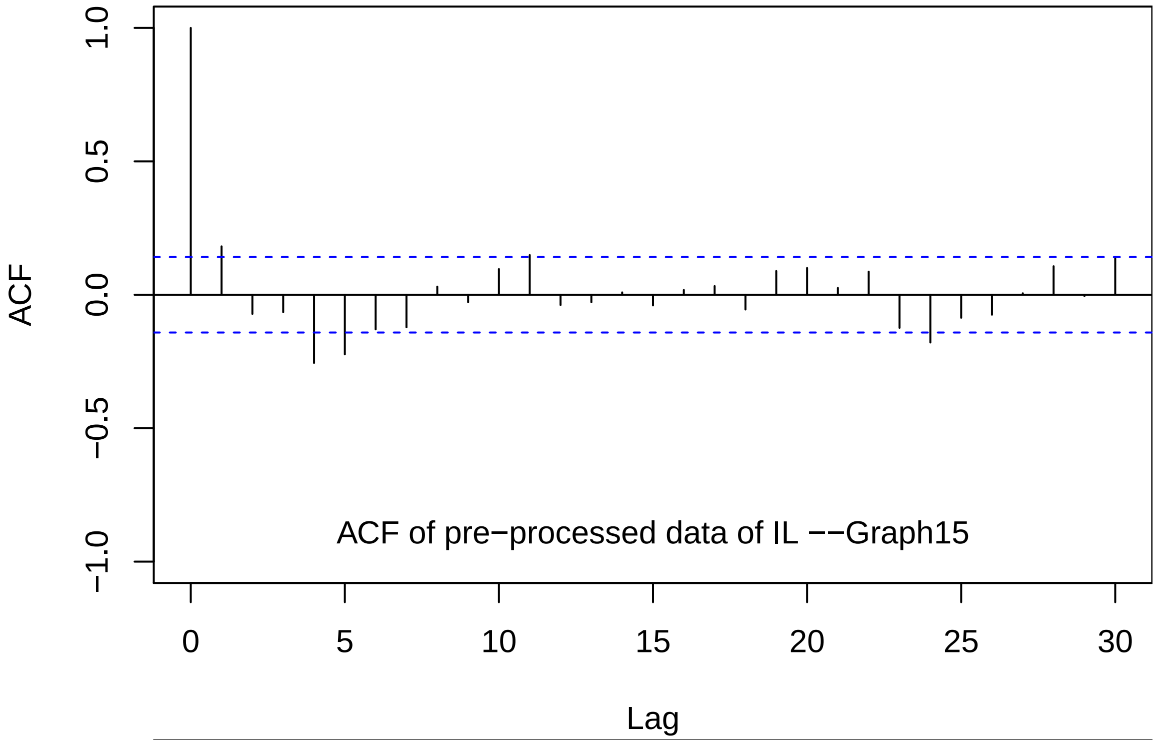


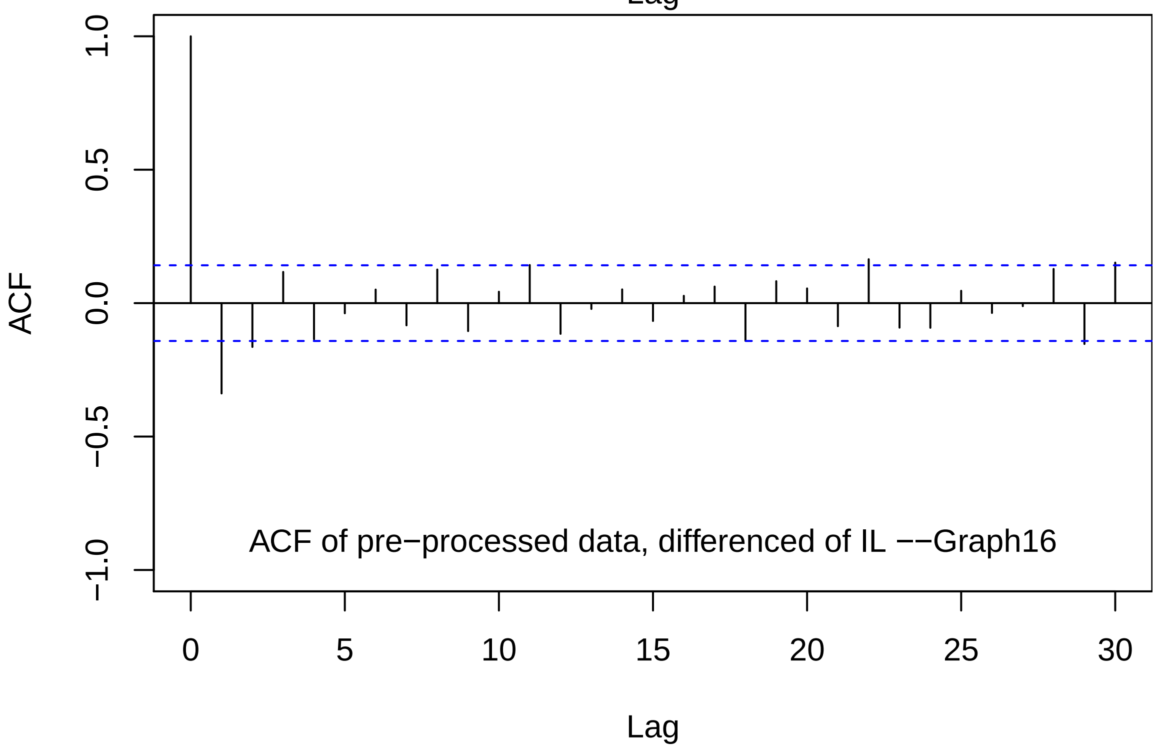
Illinois

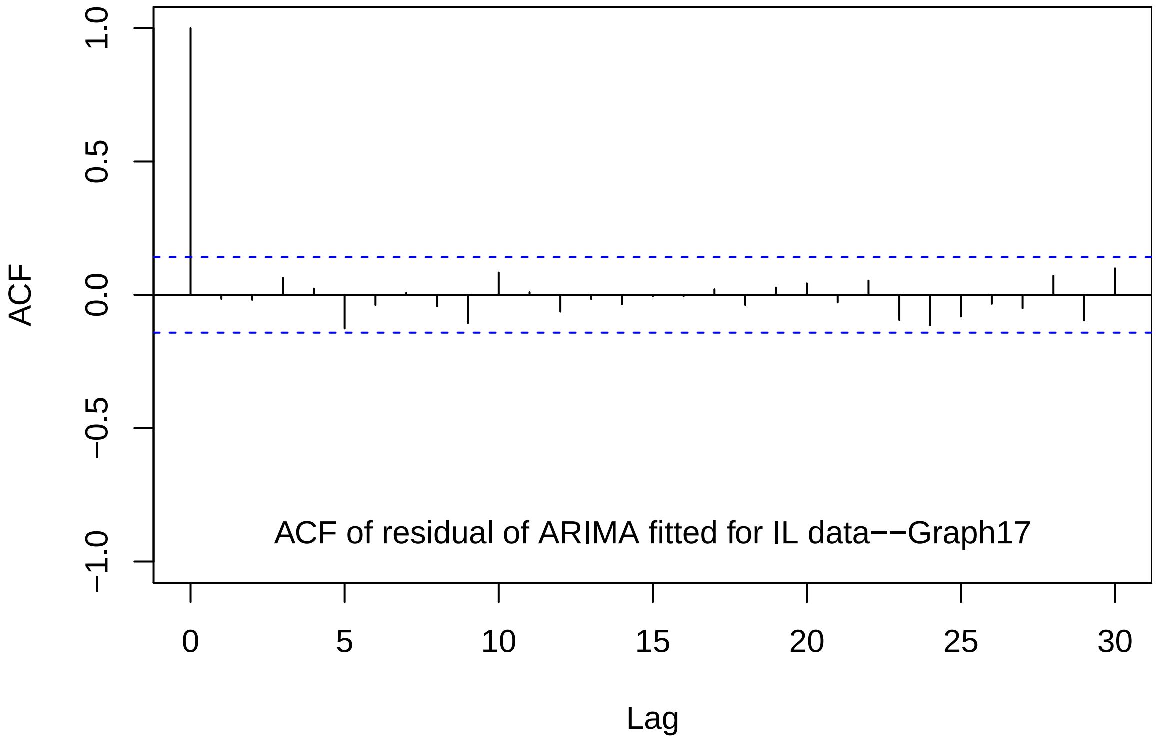
First we inspect Illinois's raw data(Graph13). We find a decreasing trend as well as some seasonal behavior, we will need to check some ACF plots to determine whether there is stochastic seasonality or not. Next we use STL to do decomposition and plot the remainder series (Graph14) and the ACF of the remainder series(Graph15). The data does not seem to have constant variance, thus we try to difference the remainder series with d=1, and plot the ACF of the differenced data(Graph16). After differencing, we see the stochastic seasonality seems to be removed. We decide to fit the Illinois data with an ARIMA model starting with d=1. We try different (p,q) vaules from 0:7 and 0:7 and find that (4,5) has the lowest AIC. We proceed to fit the model with ARIMA$(4, 1, 5)$. We check the ACF of the residuals(Graph 17). It looks like a white noise process. Finally we produce the 2017 Forecast for IL in (Graph 18), using the same method as we did for CA.

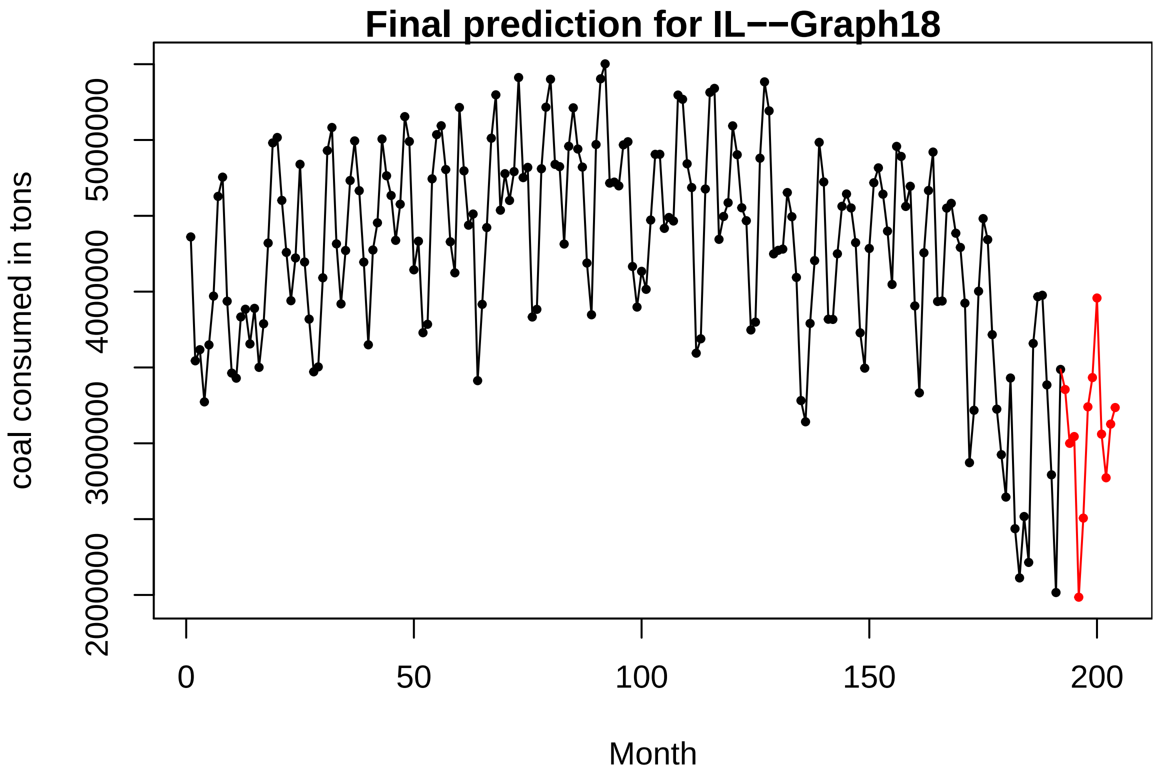

Coal consumption of IL−−Graph13
coal consumed in tons
2000000
3000000
4000000
5000000
0
50
100
150
Month


IL data preprocessed by STL −− remainder−−Graph14
remainder.il
−8e+05
−4e+05
0e+00
4e+05
0
50
100
150
Month


ACF of pre−processed data of IL −−Graph15
ACF
1.0
0.5
0.0
−0.5
−1.0
0
5
10
15
20
25
30
Lag

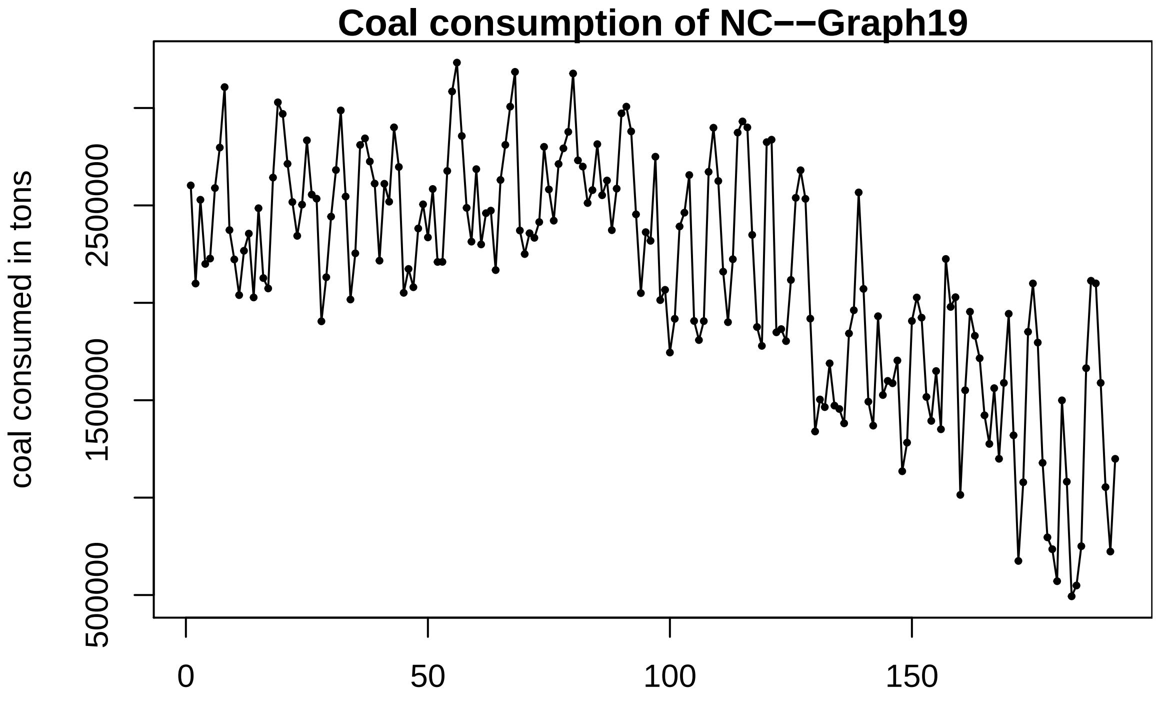

ACF of pre−processed data, differenced of IL −−Graph16
ACF
1.0
0.5
0.0
−0.5
−1.0
0
5
10
15
20
25
30
Lag

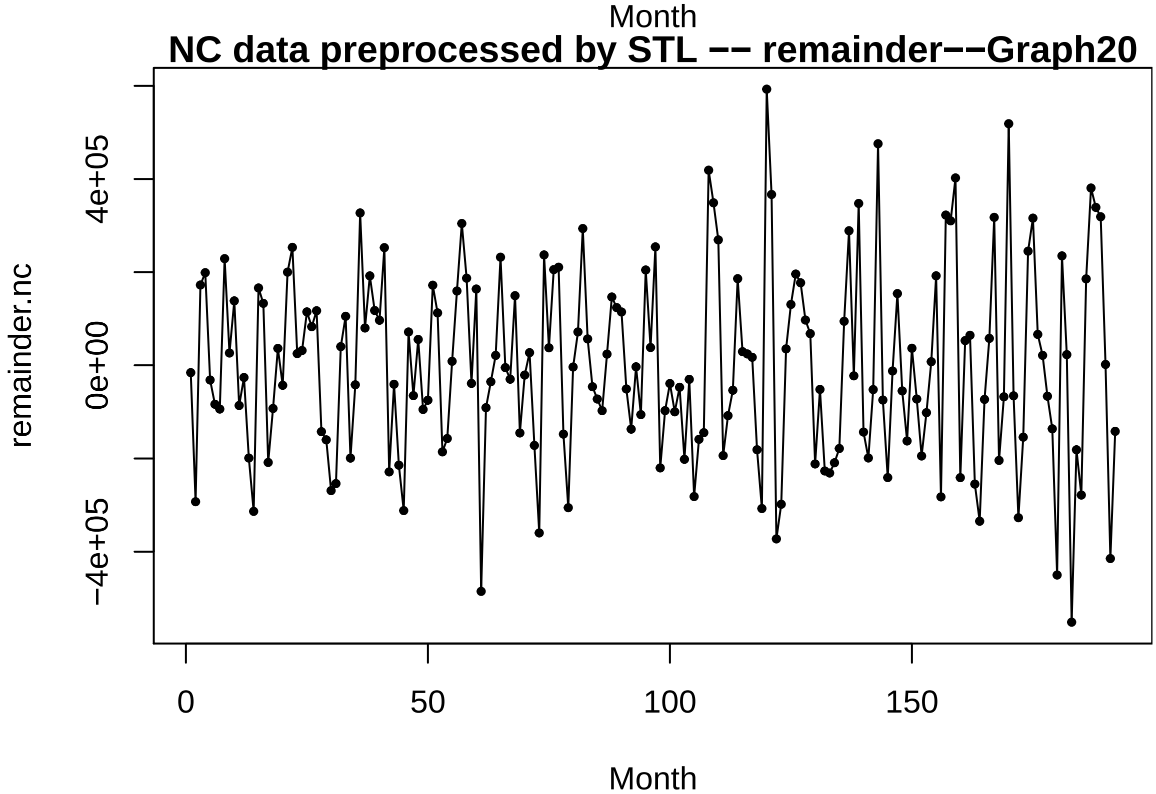


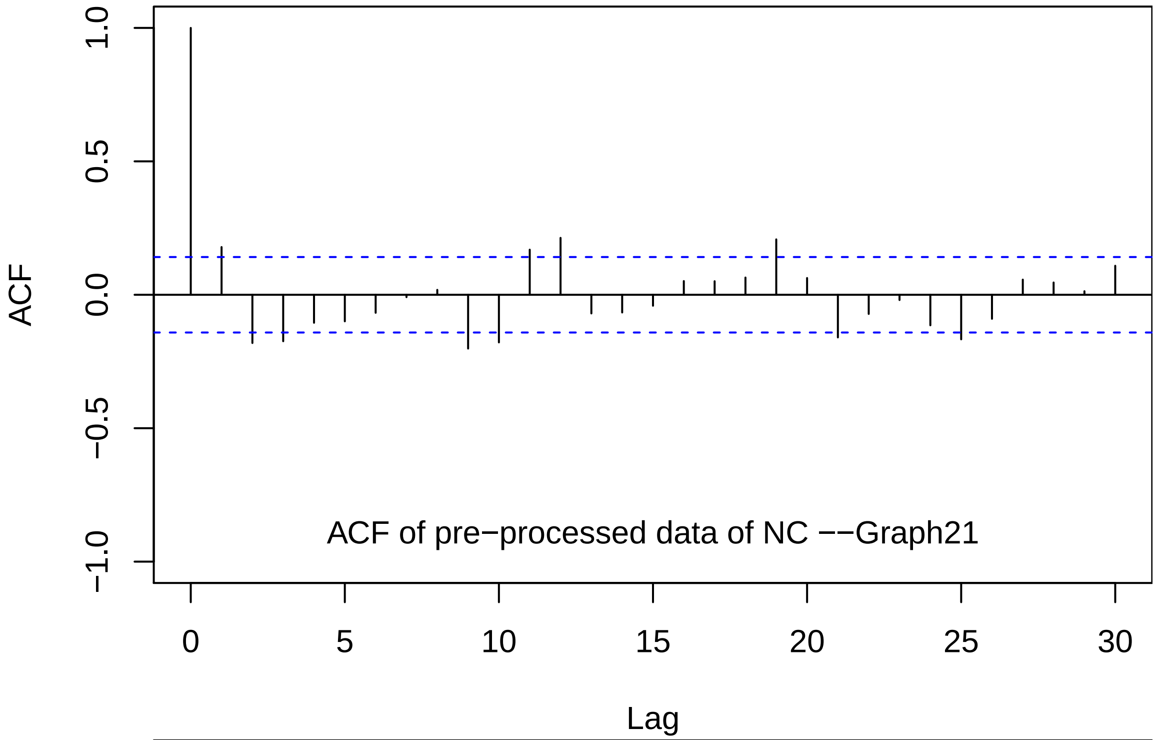


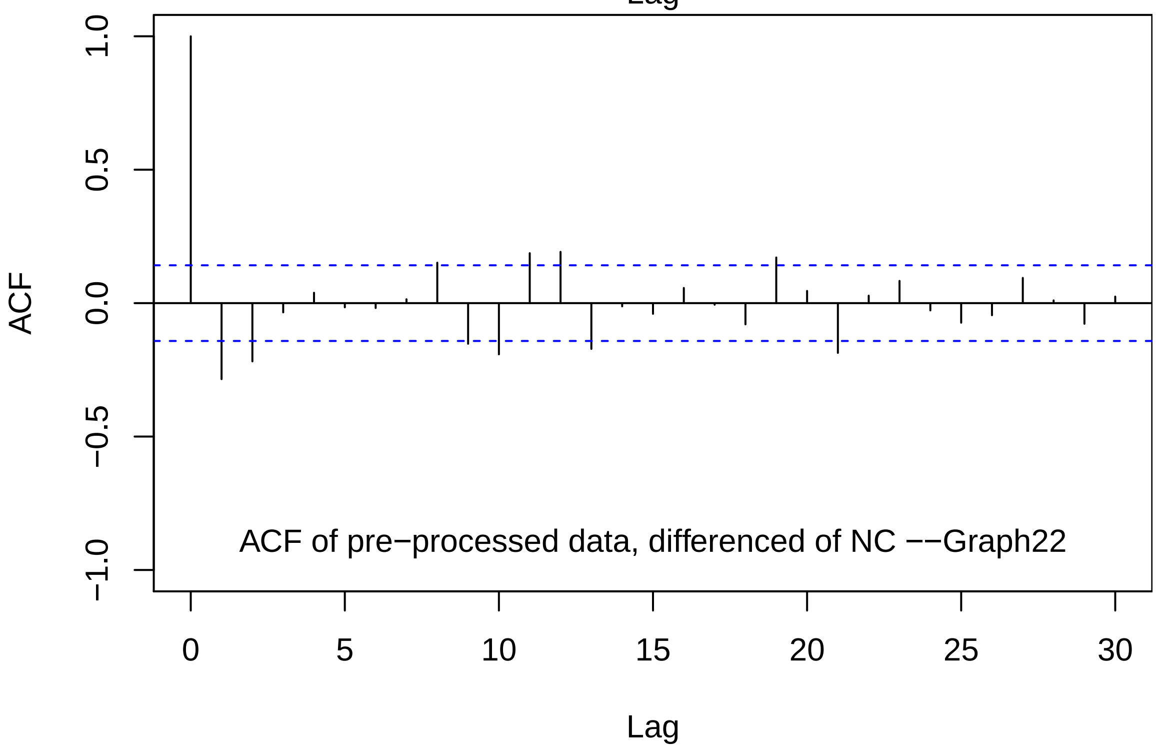
North Carolina

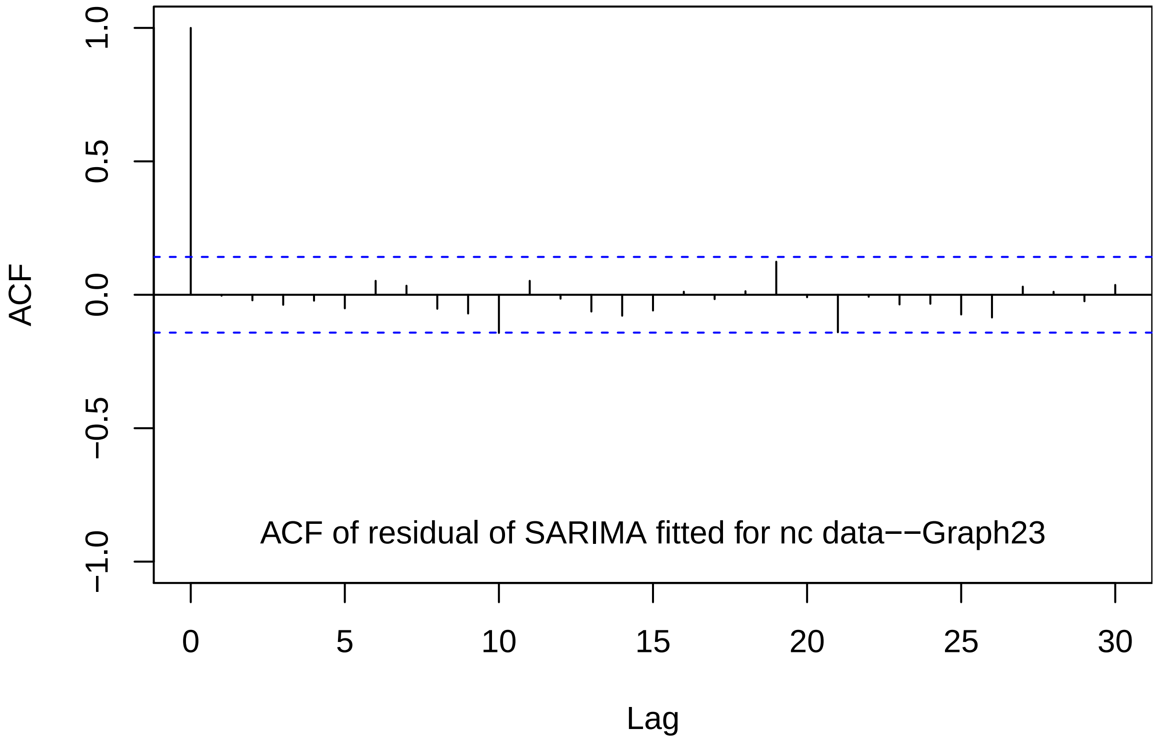
First we inspect North Carolina's raw data(Graph19). We find a decreasing trend as well as some seasonal behavior, we will need to check some ACF plots to determine whether there is stochastic seasonality or not. Next we use STL to do decomposition and plot the remainder series (Graph20) and the ACF of the remainder series(Graph21). The data does not seem to have constant variance, thus we try to difference the remainder series with d=1 and plot the ACF of the differenced data(Graph22). The stochastic seasonality seems to be removed. The plot has a spike at lag=12, suggesting a SARIMA model with s=12,P=0,Q=1,d=0,D=0,d=1. We try different (p,q) vaules from 0:7 and 0:7 and find that (7,6) has the lowest AIC. We proceed to fit the model with SARIMA$(7, 1, 6) \times (0, 0, 1)_{12}$. We check the ACF of the residuals(Graph 23). It looks like a white noise process. Finally we produce the 2017 Forecast for NC in (Graph 24), using the same method as we did for CA.

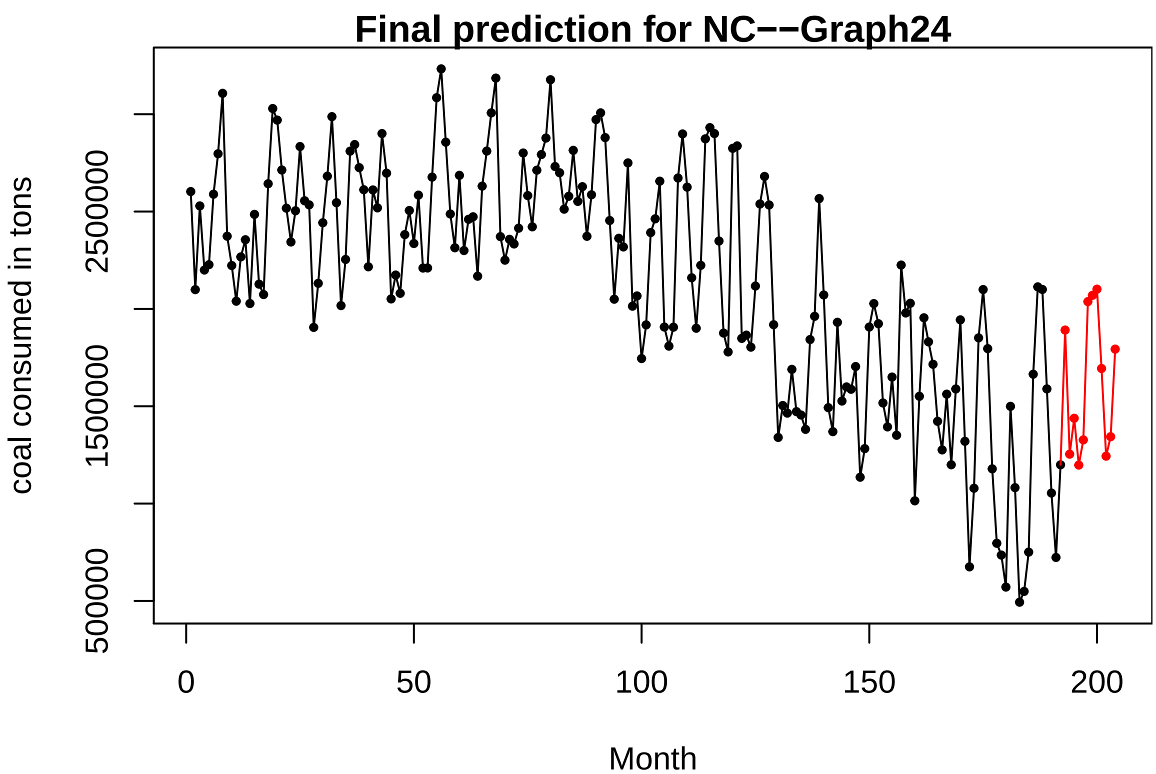

Coal consumption of NC−−Graph19
coal consumed in tons
500000
1500000
2500000
0
50
100
150
Month


NC data preprocessed by STL −− remainder−−Graph20
remainder.nc
−4e+05
0e+00
4e+05
0
50
100
150
Month


ACF of pre−processed data of NC −−Graph21
ACF
Lag
1.0
0.5
0.0
−0.5
−1.0
0
5
10
15
20
25
30

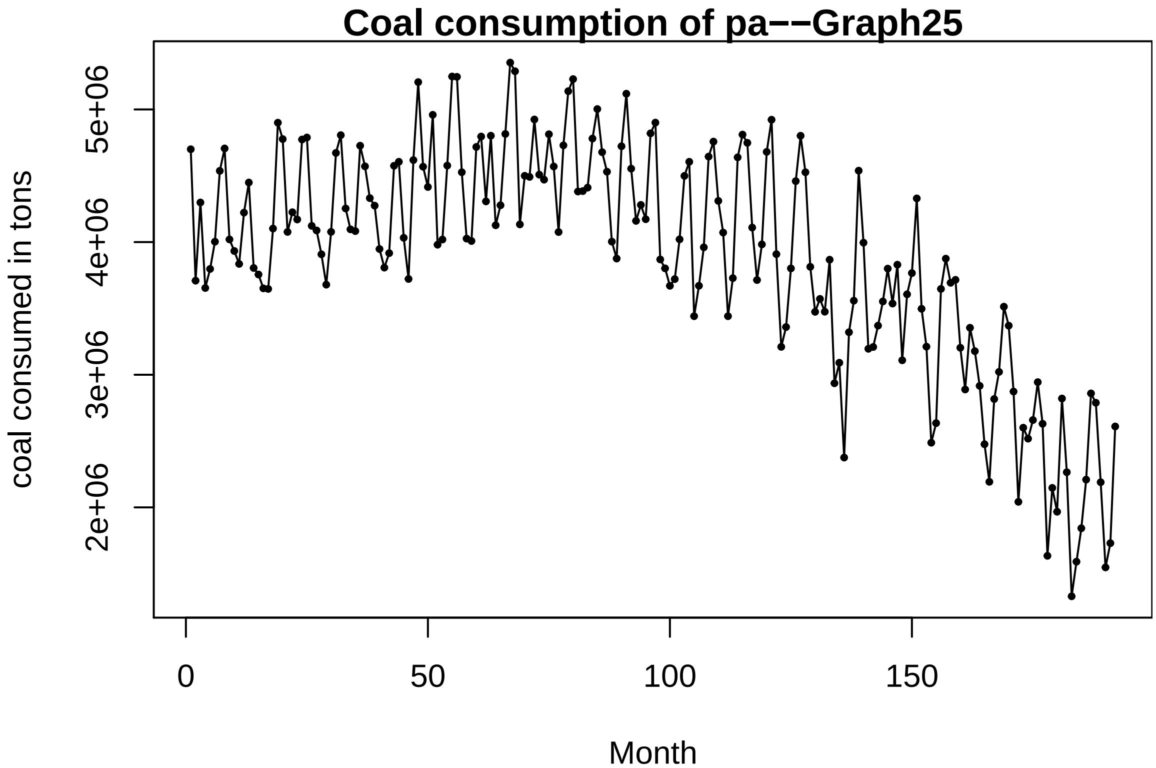

ACF of pre−processed data, differenced of NC −−Graph22
ACF
Lag
1.0
0.5
0.0
−0.5
−1.0
0
5
10
15
20
25
30

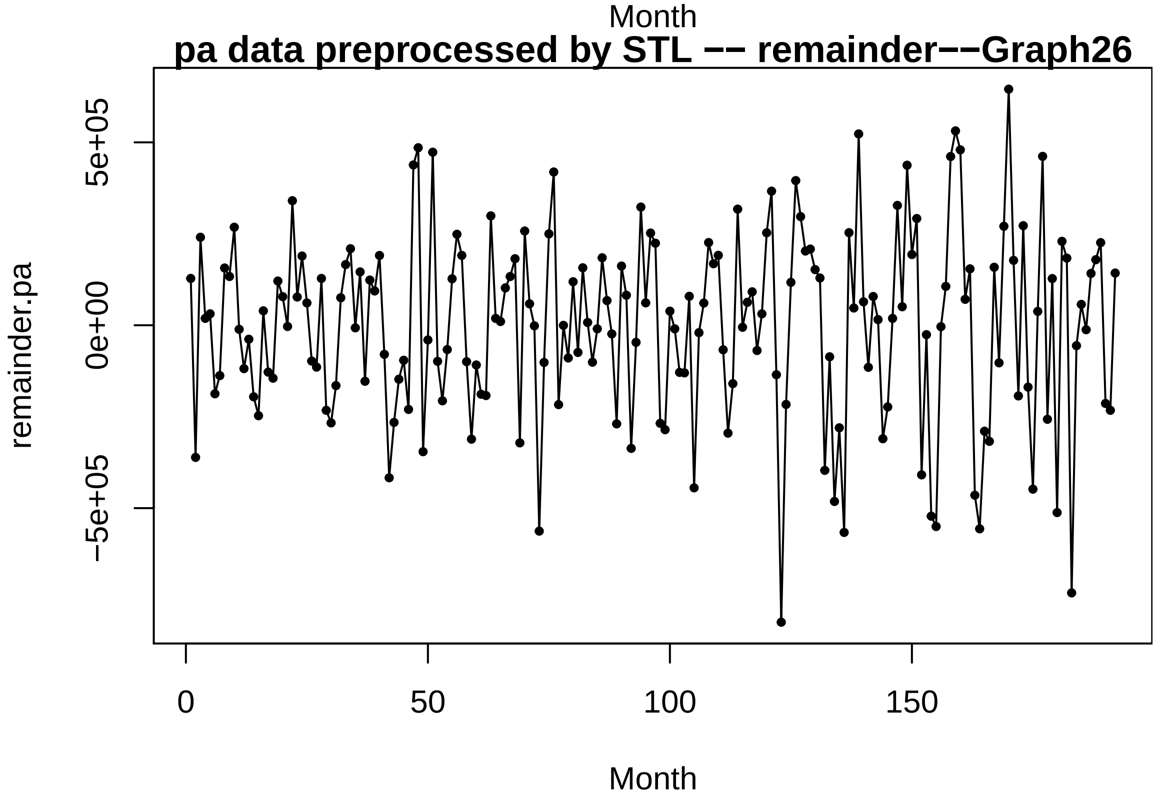


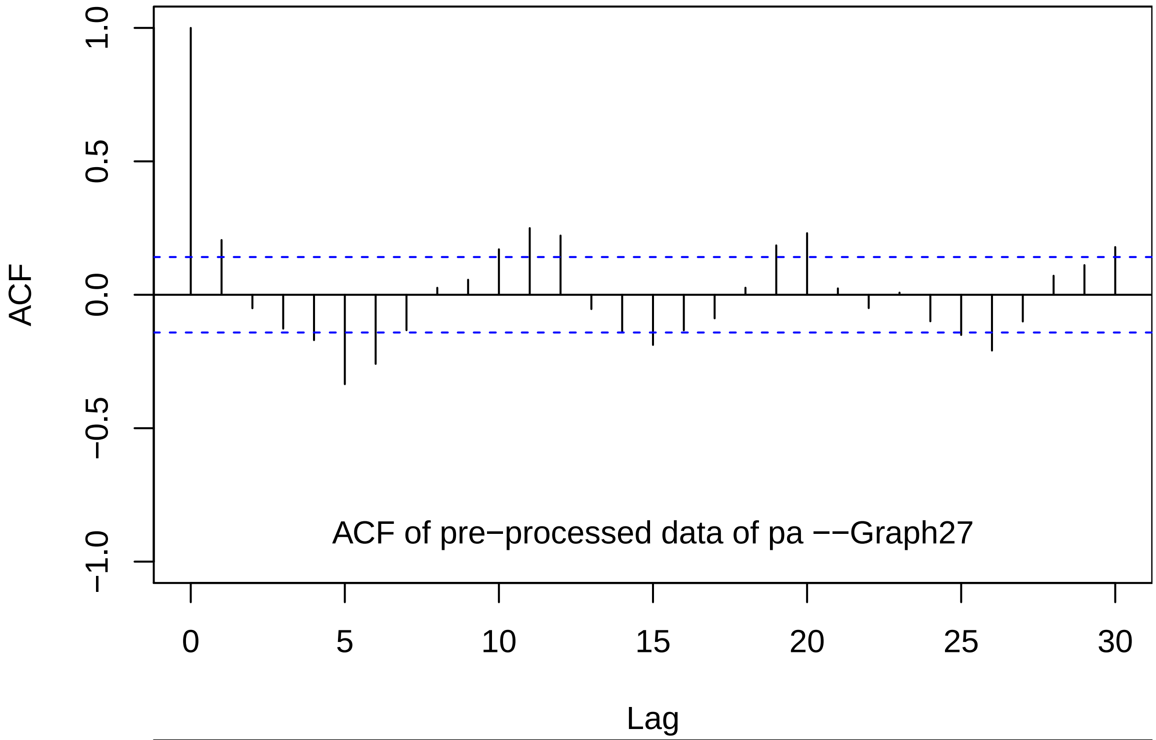


Pennsylvania

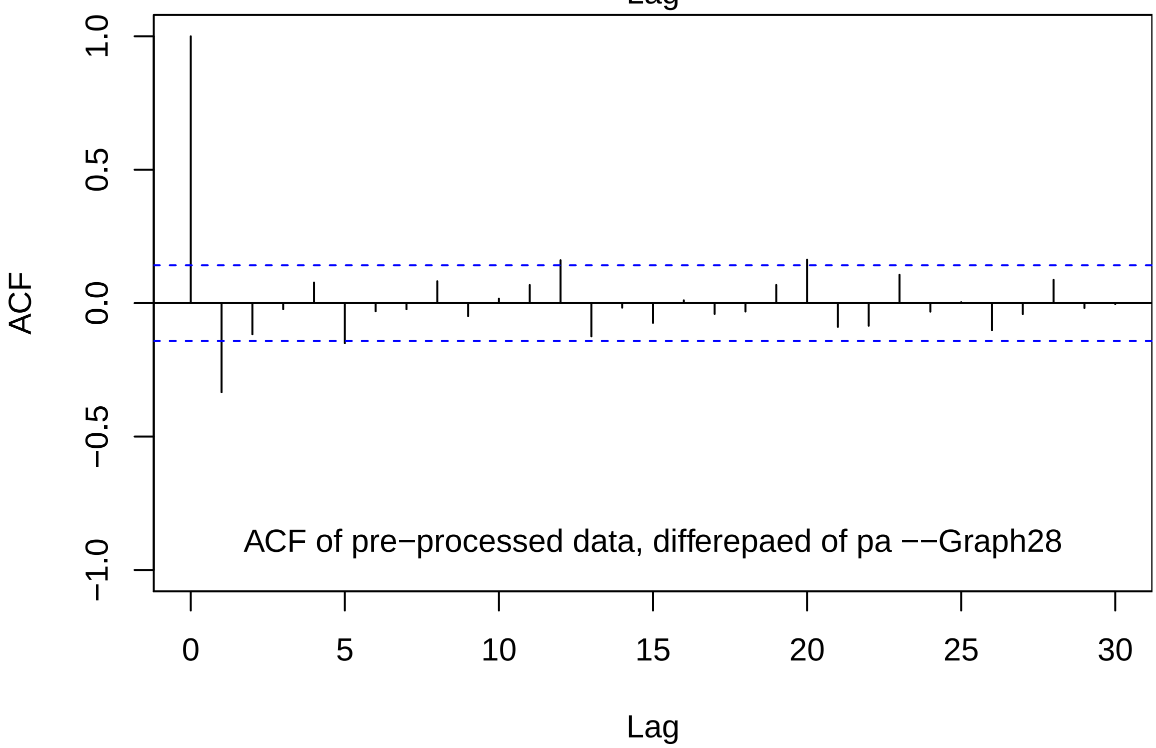
First we inspect Pennsylvania's raw data(Graph25). We find a decreasing trend as well as some seasonal behavior, we will need to check some ACF plots to determine whether there is stochastic seasonality or not. Next we use STL to do decomposition and plot the remainder series (Graph26) and the ACF of the remainder series(Graph27). The data does not seem to have constant variance, thus we try to difference the remainder series with d=1 and plot the ACF of the differenced data(Graph28). The stochastic seasonality seems to be removed. The plot does not have a spike at lag=12,thus we think an ARIMA model with d=1 should suffice. We try different (p,q) vaules from 0:7 and 0:7 and find that (5,4) has the lowest AIC. We proceed to fit the model with ARIMA$(5, 1, 4)$. We check the ACF of the residuals(Graph 29). It looks like a white noise process. Finally we produce the 2017 Forecast for PA in (Graph 30), using the same method as we did for CA.


Coal consumption of pa−−Graph25
coal consumed in tons
2e+06
3e+06
4e+06
5e+06
0
50
100
150
Month

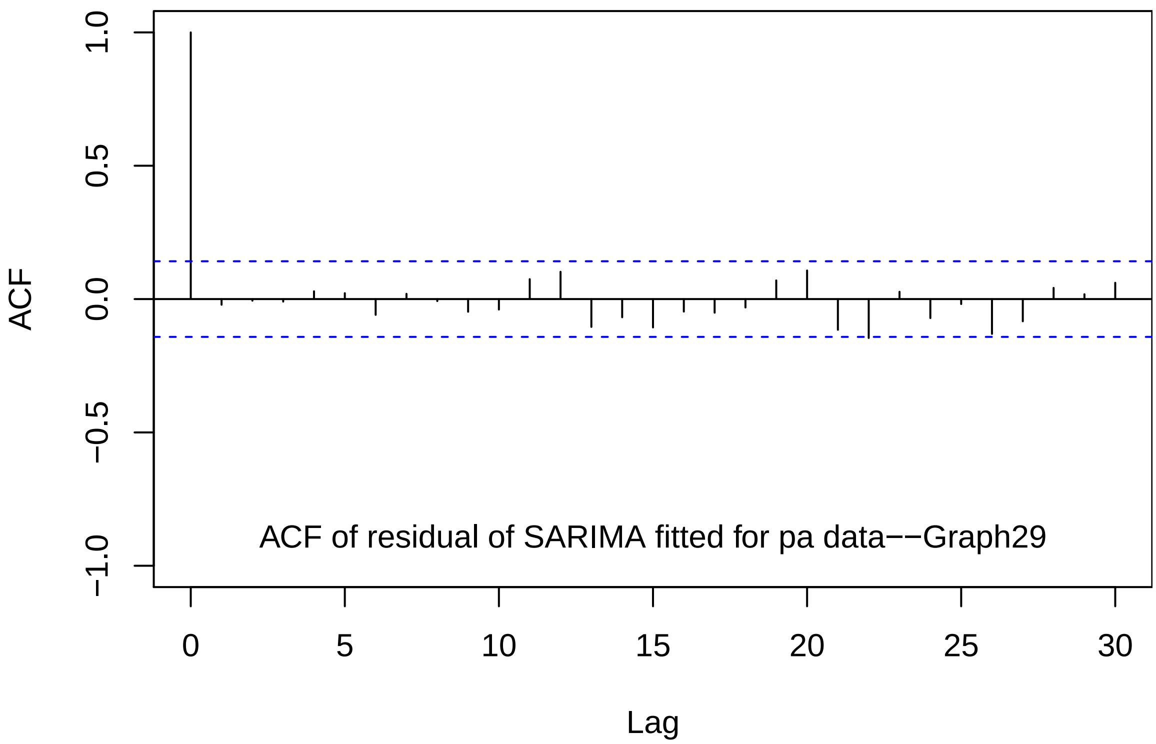

pa data preprocessed by STL −− remainder−−Graph26
remainder.pa
−5e+05
0e+00
5e+05
0
50
100
150
Month

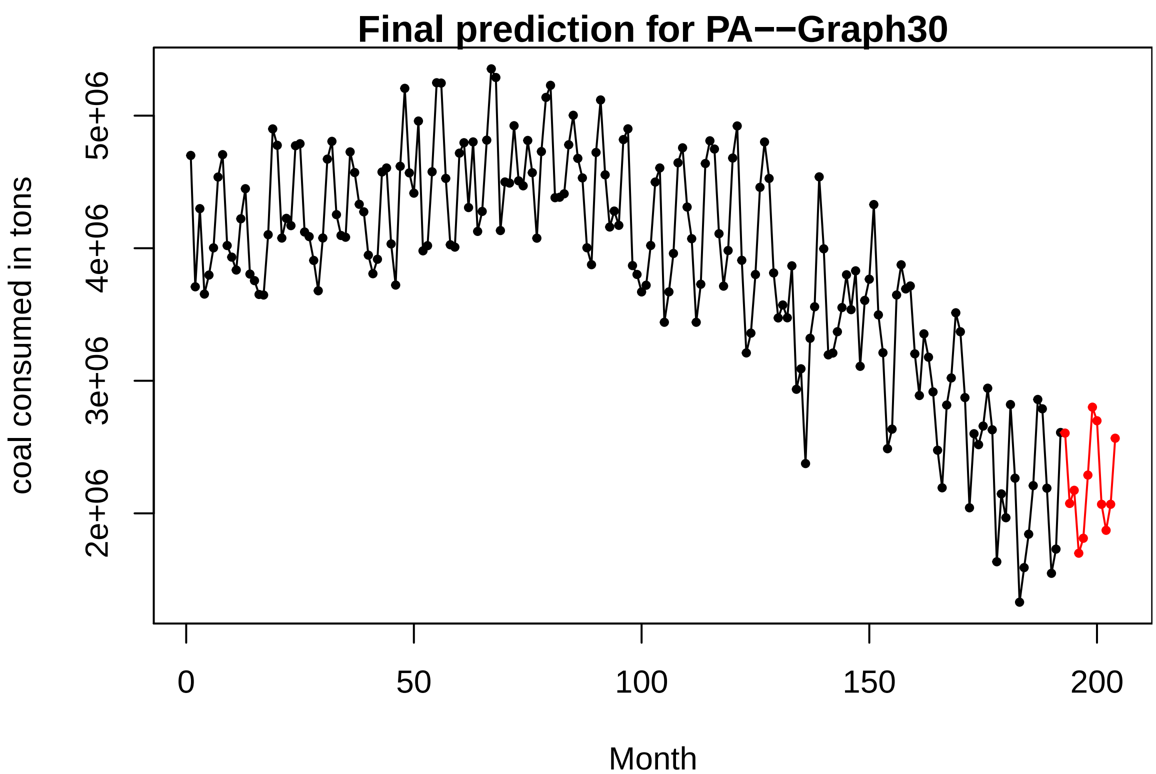


ACF of pre−processed data of pa −−Graph27
ACF
Lag



ACF of pre−processed data, differepaed of pa −−Graph28
ACF
Lag





In conclusion we have

CA: SARIMA$(4, 1, 2) \times (0, 0, 1)_{12}$ FL: ARIMA$(1, 1, 5)$ IL: ARIMA$(4, 1, 5)$

NC:SARIMA$(7, 1, 6) \times (0, 0, 1)_{12}$ PA: ARIMA$(5, 1, 4)$

We see that all the models have integrated component d=1, that is all the stochastic seasonality can be roughly accounted by differencing once at lag 1. In addition, we see all the data from 5 states can be modelled by relative small order of (p,q) of ARIMA/SARIMA models. However, in California and North Carolina, the coal consumption are more heavily affected by the stochastic seasonal component, thus we need to use SMA to account it. Moreover, we observe that all the data have decreasing trends. We inspected the STL graphs (not ploted in the final pdf) and find out the deterministic periodicity are quite similar among all the states. The assumption is that the coal consumption relates closely to the weather/seasons. For the trend component, we observe that California has the sharpest decreasing slope. We think this observation corresponds the fact that they have abundant solar energy in California and their advancement in solar panel technology helps them greatly to reduce the coal consumption.

APPENDIX

```
par(mar=c(4,4,1,0))
X.ca<-as.numeric(Y.ca)
plot(X.ca,pch=19,cex=0.4,xlab='Month',ylab="coal consumed in tons");lines(X.ca);title('Coal consumption
```

```
STL.ca<-stl(Y.ca,s.window = "periodic")
remainder.ca<-as.vector(STL.ca$time.series[,"remainder"])
trend.ca<-STL.ca$time.series[,"trend"]
seasonal.ca<-STL.ca$time.series[,"seasonal"]
par(mar=c(4,4,1,0))
plot(remainder.ca,pch=19,cex=.5,xlab="Month");lines(remainder.ca);title("CA data preprocessed by STL --
#plot(trend.ca,pch=19,cex=.5,xlab="Month");lines(trend.ca);title("Calinfornia graph preprocessed by STL
```

```
par(mar=c(4,4,1,0))
acf(remainder.ca,lag.max=30,ylim=range(-1,1),main='')
text(15,-0.9,'ACF of pre-processed data of CA --Graph3')
```

```
par(mar=c(4,4,1,0))
diffed.ca<-diff(remainder.ca,lag=1)
#diffed.ca<-diff(diffed.ca,lag=12)
#par(mar=c(1,1,1,1))
acf(diffed.ca,lag.max=30,ylim=range(-1,1),main='')
text(15,-0.9,'ACF of pre-processed,seasonally differenced data of CA--Graph4')
```

```
#AIC.mat<-BIC.mat<-matrix(0,8,8)
#for(p in 0:7){
#for(q in 0:7){
#fit.ca<-arima(remainder.ca,order=c(p,1,q),seasonal=list(order=c(0,0,1),period=12),
#include.mean=FALSE,method='ML',optim.control=list(maxit=1000))
#AIC.mat[p+1,q+1]<-AIC(fit.ca)
#BIC.mat[p+1,q+1]<-BIC(fit.ca)
#}
#}
#rownames(AIC.mat)<-paste("p=",c(0:7),sep="");colnames(AIC.mat)<-paste("q=",c(0:7),sep="")
#round(AIC.mat-min(AIC.mat),3)
fit.ca<-arima(remainder.ca,order=c(4,1,2),seasonal=list(order=c(0,0,1),period=12),
include.mean=FALSE,method='ML',optim.control=list(maxit=1000))
par(mar=c(4,4,1,0))
acf(residuals(fit.ca),ylim=range(-1,1),lag.max=30,main='')
text(15,-.9,'ACF of residual of SARIMA fitted for CA data--Graph5')
```

```
library("forecast")
t.ca<-forecast(trend.ca,h=12)
```

```r
s.ca<-forecast(seasonal.ca,h=12)
m.ca<-forecast(fit.ca,h=12)
prediction.ca<-as.numeric(m.ca$mean)+as.numeric(t.ca$mean)+as.numeric(s.ca$mean)
# this step does the correction when the predicted value is below 0
for (i in 1:12){
  if(prediction.ca[i]<0)
    prediction.ca[i]=0
}

n<-192
par(mar=c(4,4,1,0))
plot(1:n,X.ca,type='l',xlim=range(1:(n+12)),ylim=range(c(X.ca,prediction.ca)), xlab='Month',ylab="coal c
points(1:n,X.ca,pch=19,cex=0.5)
lines(c(n,n+1),c(X.ca[n],prediction.ca[1]),col='red')
lines((n+1):(n+12),prediction.ca,col='red')
points((n+1):(n+12),prediction.ca,pch=19,cex=0.5,col='red')
```

```r
par(mar=c(4,4,1,0))
X.fl<-as.numeric(Y.fl)
plot(X.fl,pch=19,cex=0.4,xlab='Month',ylab="coal consumed in tons");lines(X.fl);title('Coal consumption
STL.fl<-stl(Y.fl,s.window = "periodic")
remainder.fl<-as.vector(STL.fl$time.series[,"remainder"])
trend.fl<-STL.fl$time.series[,"trend"]
seasonal.fl<-STL.fl$time.series[,"seasonal"]
par(mar=c(4,4,1,0))
plot(remainder.fl,pch=19,cex=.5,xlab="Month");lines(remainder.fl);title("FL data preprocessed by STL --
par(mar=c(4,4,1,0))
acf(remainder.fl,lag.max=30,ylim=range(-1,1),main='')
text(15,-0.9,'ACF of pre-processed data of FL --Graph9')
remainder.fl<-diff(remainder.fl,lag=1)
acf(remainder.fl,lag.max=30,ylim=range(-1,1),main='')
text(15,-0.9,'ACF of pre-processed data, differenced of FL --Graph10')
```

```r
#AIC.mat<-BIC.mat<-matrix(0,8,8)
#for(p in 0:7){
#for(q in 0:7){
#fit.fl<-arima(remainder.fl,order=c(p,1,q),
#include.mean=FALSE,method='ML',optim.control=list(maxit=1000))
#AIC.mat[p+1,q+1]<-AIC(fit.fl)

#}
#}
#rownames(AIC.mat)<-paste("p=",c(0:7),sep="");colnames(AIC.mat)<-paste("q=",c(0:7),sep="")
#round(AIC.mat-min(AIC.mat),3)
```

```r
fit.fl<-arima(remainder.fl,order=c(1,1,5),
include.mean=FALSE,method='ML',optim.control=list(maxit=1000))
par(mar=c(4,4,1,0))
acf(residuals(fit.fl),ylim=range(-1,1),lag.max=30,main='')
text(15,-.9,'ACF of residual of ARIMA fitted for FL data--Graph11')
```

```r
t.fl<-forecast(trend.fl,h=12)
s.fl<-forecast(seasonal.fl,h=12)
m.fl<-forecast(fit.fl,h=12)
```

```
prediction.fl<-as.numeric(m.fl$mean)+as.numeric(t.fl$mean)+as.numeric(s.fl$mean)
# this step does the correction when the predicted value is below 0
for (i in 1:12){
  if(prediction.fl[i]<0)
    prediction.fl[i]=0
}

n<-192
par(mar=c(4,4,1,0))
plot(1:n,X.fl,type='l',xlim=range(1:(n+12)),ylim=range(c(X.fl,prediction.fl)), xlab='Month',ylab="coal c
points(1:n,X.fl,pch=19,cex=0.5)
lines(c(n,n+1),c(X.fl[n],prediction.fl[1]),col='red')
lines((n+1):(n+12),prediction.fl,col='red')
points((n+1):(n+12),prediction.fl,pch=19,cex=0.5,col='red')
```

```
par(mar=c(4,4,1,0))
X.il<-as.numeric(Y.il)
plot(X.il,pch=19,cex=0.4,xlab='Month',ylab="coal consumed in tons");lines(X.il);title('Coal consumption
STL.il<-stl(Y.il,s.window = "periodic")

remainder.il<-as.vector(STL.il$time.series[,"remainder"])
trend.il<-STL.il$time.series[,"trend"]
seasonal.il<-STL.il$time.series[,"seasonal"]
par(mar=c(4,4,1,0))
plot(remainder.il,pch=19,cex=.5,xlab="Month");lines(remainder.il);title("IL data preprocessed by STL --
par(mar=c(4,4,1,0))
acf(remainder.il,lag.max=30,ylim=range(-1,1),main='')
text(15,-0.9,'ACF of pre-processed data of IL --Graph15')
remainder.il<-diff(remainder.il,lag=1)
#remainder.il<-diff(remainder.il,lag=12)
acf(remainder.il,lag.max=30,ylim=range(-1,1),main='')
text(15,-0.9,'ACF of pre-processed data, differenced of IL --Graph16')
```

```
#AIC.mat<-BIC.mat<-matrix(0,8,8)
#for(p in 0:7){
#for(q in 0:7){
#fit.il<-arima(remainder.il,order=c(p,1,q),
#include.mean=FALSE,method='ML',optim.control=list(maxit=1000))
#AIC.mat[p+1,q+1]<-AIC(fit.il)

#}
#}
#rownames(AIC.mat)<-paste("p=",c(0:7),sep="");colnames(AIC.mat)<-paste("q=",c(0:7),sep="")
#round(AIC.mat-min(AIC.mat),3)
```

```
fit.il<-arima(remainder.il,order=c(4,1,5),
include.mean=FALSE,method='ML',optim.control=list(maxit=1000))
par(mar=c(4,4,1,0))
acf(residuals(fit.il),ylim=range(-1,1),lag.max=30,main='')
text(15,-.9,'ACF of residual of ARIMA fitted for IL data--Graph17')
```

```
t.il<-forecast(trend.il,h=12)
s.il<-forecast(seasonal.il,h=12)
m.il<-forecast(fit.il,h=12)
```

```r
prediction.il<-as.numeric(m.il$mean)+as.numeric(t.il$mean)+as.numeric(s.il$mean)
# this step does the correction when the predicted value is below 0
for (i in 1:12){
  if(prediction.il[i]<0)
    prediction.il[i]=0
}

n<-192
par(mar=c(4,4,1,0))
plot(1:n,X.il,type='l',xlim=range(1:(n+12)),ylim=range(c(X.il,prediction.il)), xlab='Month',ylab="coal 
points(1:n,X.il,pch=19,cex=0.5)
lines(c(n,n+1),c(X.il[n],prediction.il[1]),col='red')
lines((n+1):(n+12),prediction.il,col='red')
points((n+1):(n+12),prediction.il,pch=19,cex=0.5,col='red')
```

```r
par(mar=c(4,4,1,0))
X.nc<-as.numeric(Y.nc)
plot(X.nc,pch=19,cex=0.4,xlab='Month',ylab="coal consumed in tons");lines(X.nc);title('Coal consumption

STL.nc<-stl(Y.nc,s.window = "periodic")
remainder.nc<-as.vector(STL.nc$time.series[,"remainder"])
trend.nc<-STL.nc$time.series[,"trend"]
seasonal.nc<-STL.nc$time.series[,"seasonal"]
par(mar=c(4,4,1,0))
plot(remainder.nc,pch=19,cex=.5,xlab="Month");lines(remainder.nc);title("NC data preprocessed by STL --
par(mar=c(4,4,1,0))
acf(remainder.nc,lag.max=30,ylim=range(-1,1),main='')
text(15,-0.9,'ACF of pre-processed data of NC --Graph21')
remainder.nc<-diff(remainder.nc,lag=1)
#remainder.nc<-diff(remainder.nc,lag=12)
acf(remainder.nc,lag.max=30,ylim=range(-1,1),main='')
text(15,-0.9,'ACF of pre-processed data, differenced of NC --Graph22')
```

```r
#AIC.mat<-BIC.mat<-matrix(0,8,8)
#for(p in 0:7){
#for(q in 0:7){
#fit.nc<-arima(remainder.nc,order=c(p,1,q),seasonal=list(order=c(0,0,1),period=12),
#include.mean=FALSE,method='ML',optim.control=list(maxit=1000))
#AIC.mat[p+1,q+1]<-AIC(fit.nc)

#}
#}
#rownames(AIC.mat)<-paste("p=",c(0:7),sep="");colnames(AIC.mat)<-paste("q=",c(0:7),sep="")
#round(AIC.mat-min(AIC.mat),3)
```

```r
fit.nc<-arima(remainder.nc,order=c(7,1,6),seasonal=list(order=c(0,0,1),period=12),
include.mean=FALSE,method='ML',optim.control=list(maxit=1000))
par(mar=c(4,4,1,0))
acf(residuals(fit.nc),ylim=range(-1,1),lag.max=30,main='')
text(15,-.9,'ACF of residual of SARIMA fitted for nc data--Graph23')
```

```r
t.nc<-forecast(trend.nc,h=12)
s.nc<-forecast(seasonal.nc,h=12)
m.nc<-forecast(fit.nc,h=12)
```

```
prediction.nc<-as.numeric(m.nc$mean)+as.numeric(t.nc$mean)+as.numeric(s.nc$mean)
# this step does the correction when the predicted value is below 0
for (i in 1:12){
  if(prediction.nc[i]<0)
    prediction.nc[i]=0
}

n<-192
par(mar=c(4,4,1,0))
plot(1:n,X.nc,type='l',xlim=range(1:(n+12)),ylim=range(c(X.nc,prediction.nc)), xlab='Month',ylab="coal 
points(1:n,X.nc,pch=19,cex=0.5)
lines(c(n,n+1),c(X.nc[n],prediction.nc[1]),col='red')
lines((n+1):(n+12),prediction.nc,col='red')
points((n+1):(n+12),prediction.nc,pch=19,cex=0.5,col='red')
```

```
par(mar=c(4,4,1,0))
X.pa<-as.numeric(Y.pa)
plot(X.pa,pch=19,cex=0.4,xlab='Month',ylab="coal consumed in tons");lines(X.pa);title('Coal consumption
STL.pa<-stl(Y.pa,s.window = "periodic")
remainder.pa<-as.vector(STL.pa$time.series[,"remainder"])
trend.pa<-STL.pa$time.series[,"trend"]
seasonal.pa<-STL.pa$time.series[,"seasonal"]
par(mar=c(4,4,1,0))
plot(remainder.pa,pch=19,cex=.5,xlab="Month");lines(remainder.pa);title("pa data preprocessed by STL --
par(mar=c(4,4,1,0))
acf(remainder.pa,lag.max=30,ylim=range(-1,1),main='')
text(15,-0.9,'ACF of pre-processed data of pa --Graph27')
remainder.pa<-diff(remainder.pa,lag=1)
#remainder.pa<-diff(remainder.pa,lag=12)
acf(remainder.pa,lag.max=30,ylim=range(-1,1),main='')
text(15,-0.9,'ACF of pre-processed data, differepaed of pa --Graph28')
```

```
#AIC.mat<-BIC.mat<-matrix(0,8,8)
#for(p in 0:7){
#for(q in 0:7){
#fit.pa<-arima(remainder.pa,order=c(p,1,q),
#include.mean=FALSE,method='ML',optim.control=list(maxit=1000))
#AIC.mat[p+1,q+1]<-AIC(fit.pa)

#}
#}
#rownames(AIC.mat)<-paste("p=",c(0:7),sep="");colnames(AIC.mat)<-paste("q=",c(0:7),sep="")
#round(AIC.mat-min(AIC.mat),3)
```

```
fit.pa<-arima(remainder.pa,order=c(5,1,4),
include.mean=FALSE,method='ML',optim.control=list(maxit=1000))
par(mar=c(4,4,1,0))
acf(residuals(fit.pa),ylim=range(-1,1),lag.max=30,main='')
text(15,-.9,'ACF of residual of SARIMA fitted for pa data--Graph29')
```

```
t.pa<-forecast(trend.pa,h=12)
s.pa<-forecast(seasonal.pa,h=12)
m.pa<-forecast(fit.pa,h=12)
prediction.pa<-as.numeric(m.pa$mean)+as.numeric(t.pa$mean)+as.numeric(s.pa$mean)
```

```r
# this step does the correction when the predicted value is below 0
for (i in 1:12){
  if(prediction.pa[i]<0)
    prediction.pa[i]=0
}

n<-192
par(mar=c(4,4,1,0))
plot(1:n,X.pa,type='l',xlim=range(1:(n+12)),ylim=range(c(X.pa,prediction.pa)), xlab='Month',ylab="coal c
points(1:n,X.pa,pch=19,cex=0.5)
lines(c(n,n+1),c(X.pa[n],prediction.pa[1]),col='red')
lines((n+1):(n+12),prediction.pa,col='red')
points((n+1):(n+12),prediction.pa,pch=19,cex=0.5,col='red')
```

```r
par(mar=c(4,4,1,0))
plot(STL.ca)
par(mar=c(4,4,1,0))
plot(STL.fl)
par(mar=c(4,4,1,0))
plot(STL.il)
par(mar=c(4,4,1,0))
plot(STL.nc)
par(mar=c(4,4,1,0))
plot(STL.pa)
```