POLITECHNIKA RZESZOWSKA im. IGNACEGO ŁUKASIEWICZA

Szeregi czasowe

Żak Maciej

Inżynieria i analiza danych

Rzeszów 16.06.2022r.

WYDZIAŁ MATEMATYKI I FIZYKI STOSOWANEJ POLITECHNIKI RZESZOWSKIEJ

POLITECHNIKA RZESZOWSKA
im. IGNACEGO ŁUKASIEWICZA

Spis treści

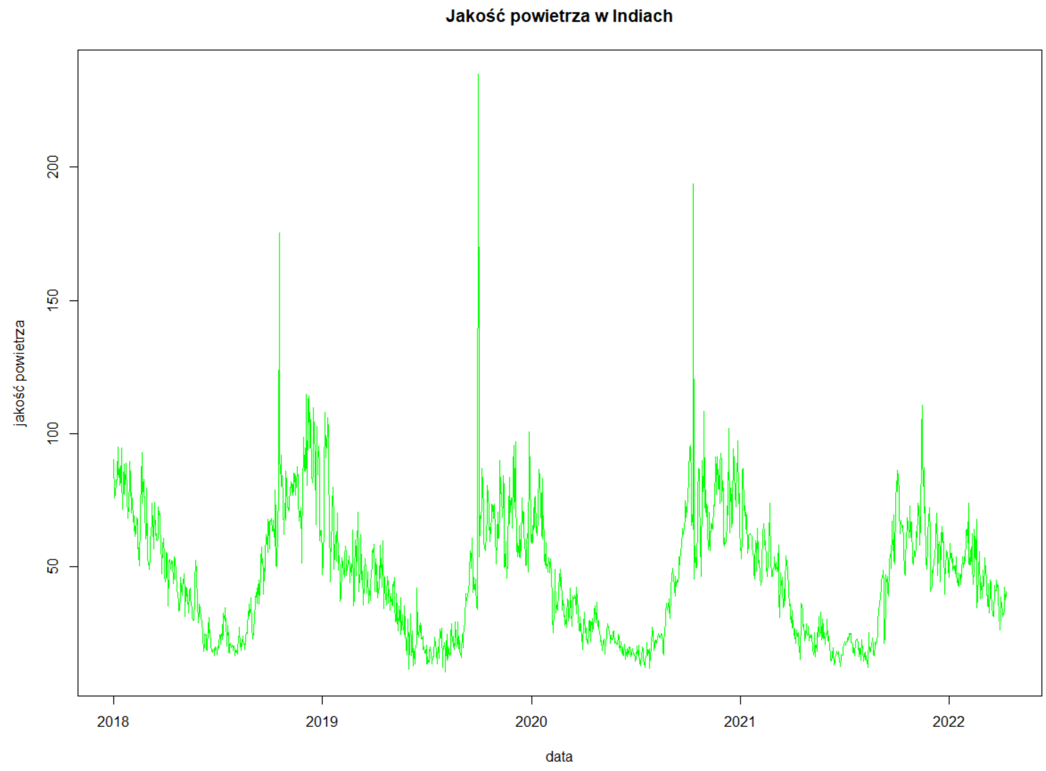
1. Dane

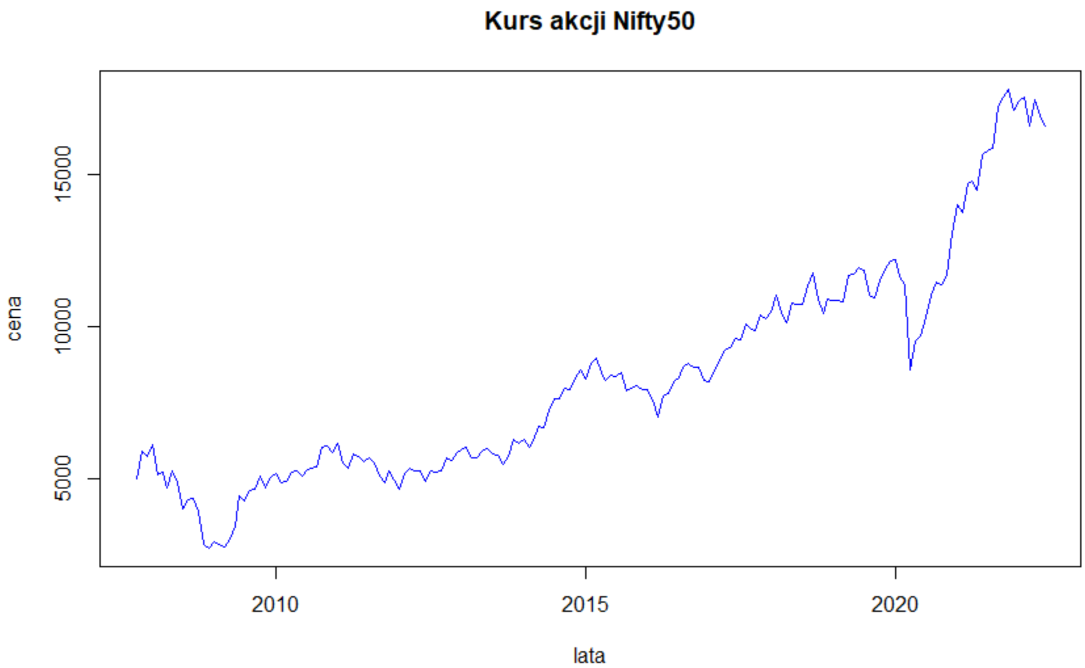
Dane, które wykorzystałem w projekcie pochodzą ze strony https://finance.yahoo.com oraz ze strony https://www.kaggle.com . Dane są dostępne w domenie publicznej tzn. nie są objęte prawami autorskimi.

Szeregi, które wykorzystane zostały w projekcie to:

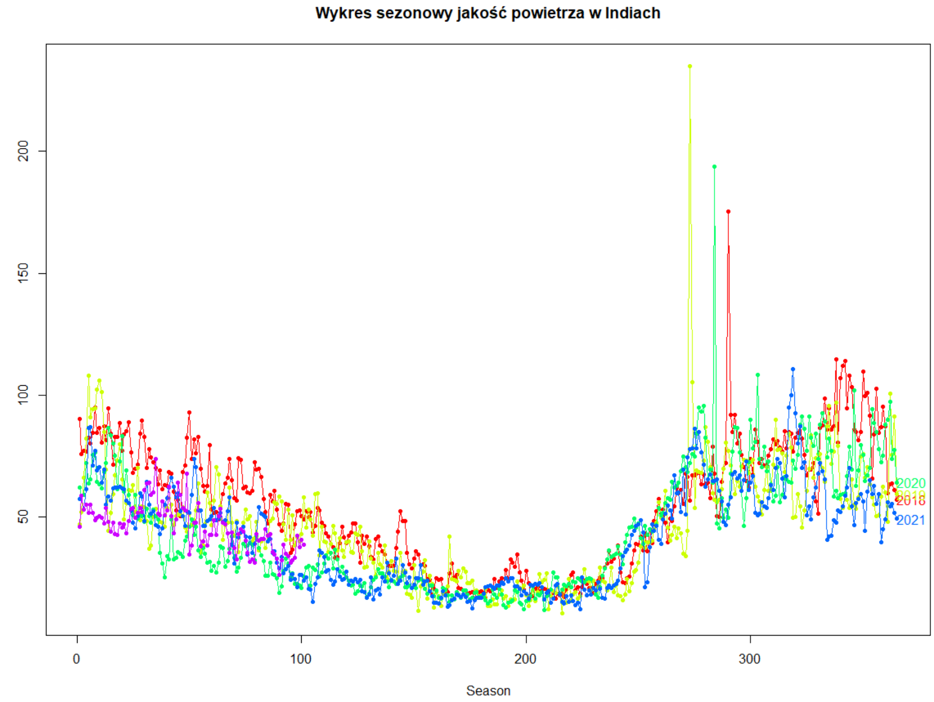
- Kurs Nifty 50 - S&P CNX Nifty – główny indeks giełdowy dużych spółek notowanych na Indyjskiej Narodowej Giełdzie Papierów Wartościowych (National Stock Exchange of India). W jego skład wchodzi 50 spółek reprezentujących 24 sektory gospodarki i reprezentujących około 77% kapitalizacji całej giełdy. Nifty 50 został wprowadzony 22 kwietnia 1996 roku i jest jednym z wielu indeksów giełdowych Nifty. Analiza kursu giełdowego, może nam pomóc przewidzieć wahania cen i dzięki temu dać nam okazję zarobić. Dane te obejmują okres od 2007-10-01 do 2022-06-01 roku.
- Jakość powietrza w Indiach – Zanieczyszczenie powietrza w Indiach jest porównywalne lub nawet większe niż w Chinach. Monitorowanie go i zrozumienie jego jakości ma ogromne znaczenie dla naszego dobrego samopoczucia. Korzystając z tego zestawu danych, można przeanalizować, jak zanieczyszczenie wygląda na przestrzeni roku. Zestaw danych zawiera godzinowe dane dotyczące jakości powietrza (PM 2,5) w Indiach. Aby ułatwić pracę na danych wezmę tylko jeden rekord z każdego dnia, zwykle mierzony o północy. Danę obejmują okres od 2017-11-07 do 2022-06-04 roku.

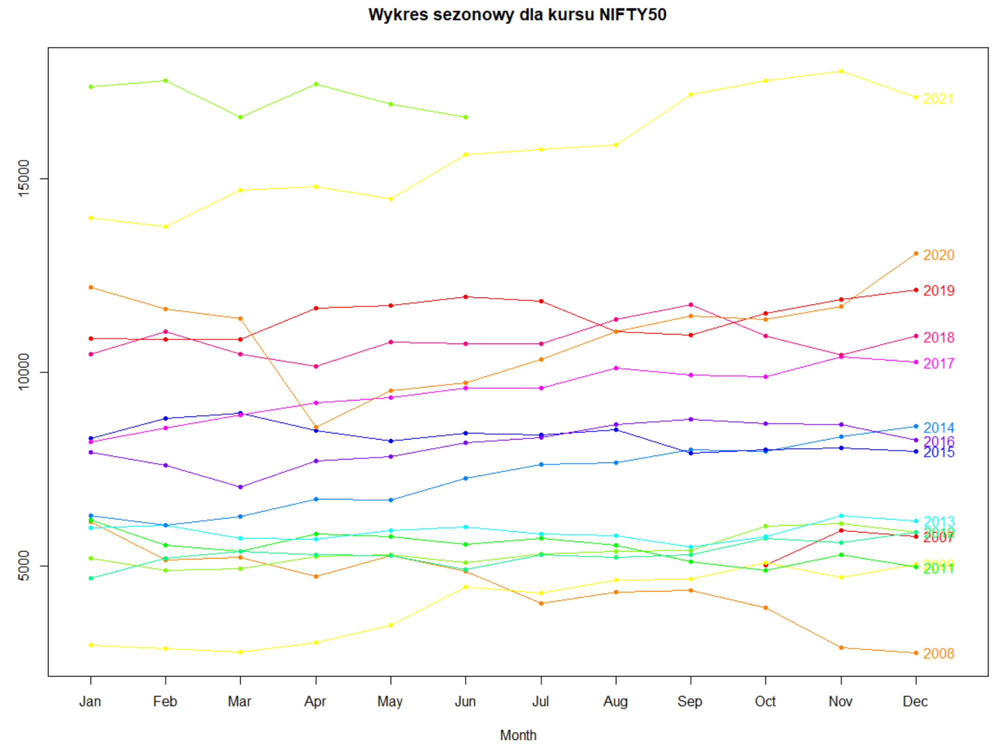
Wizualizacja szeregów

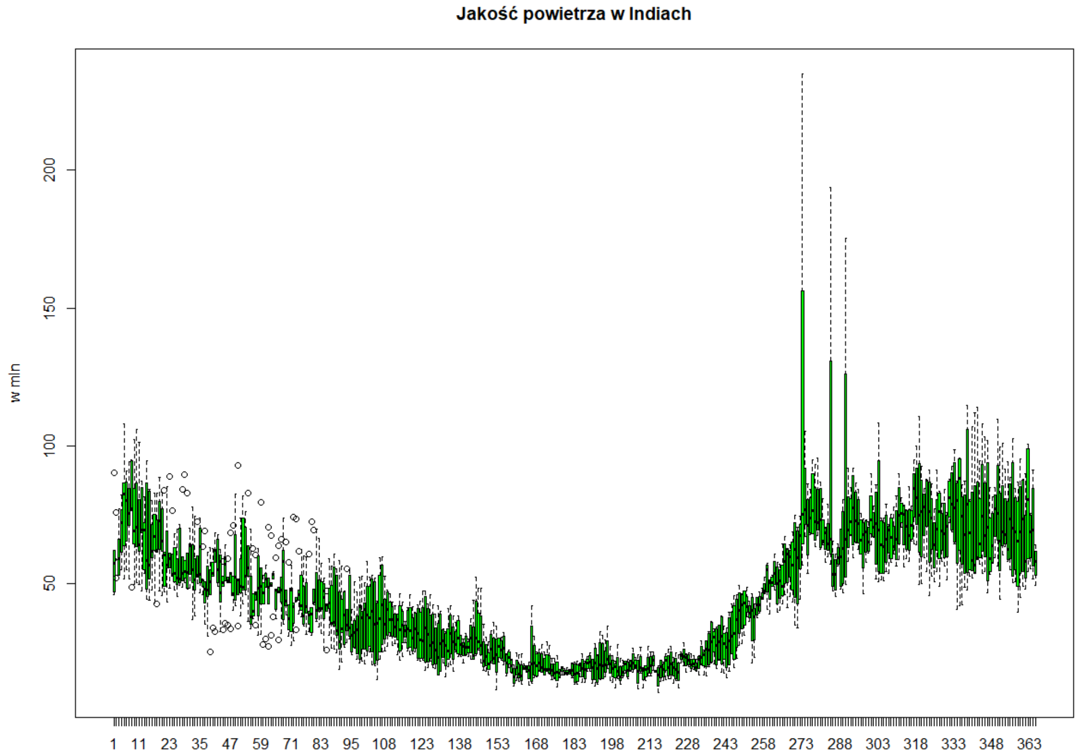


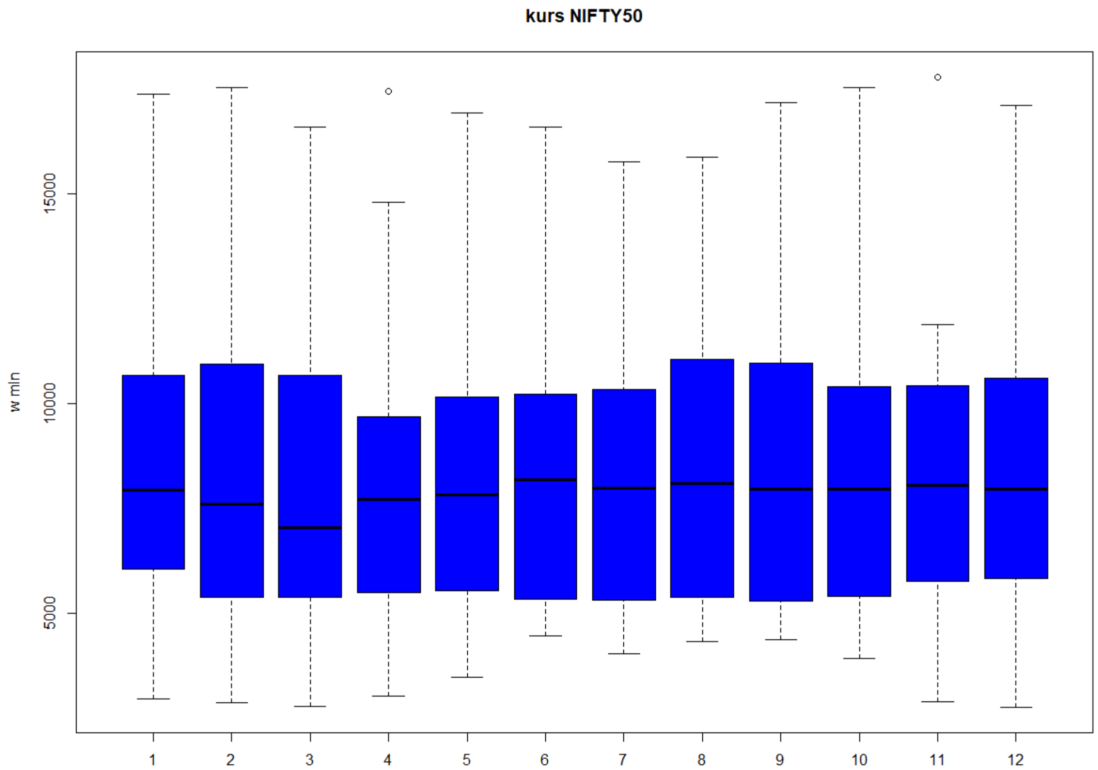


2. Wizualizacja

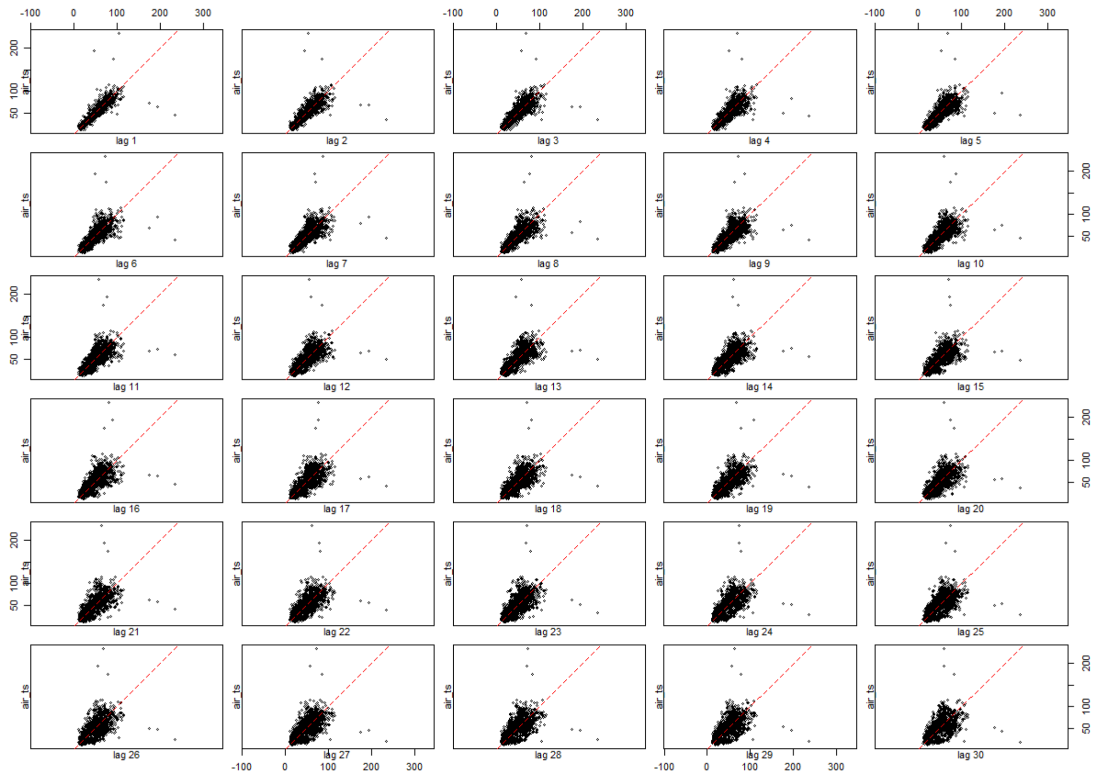




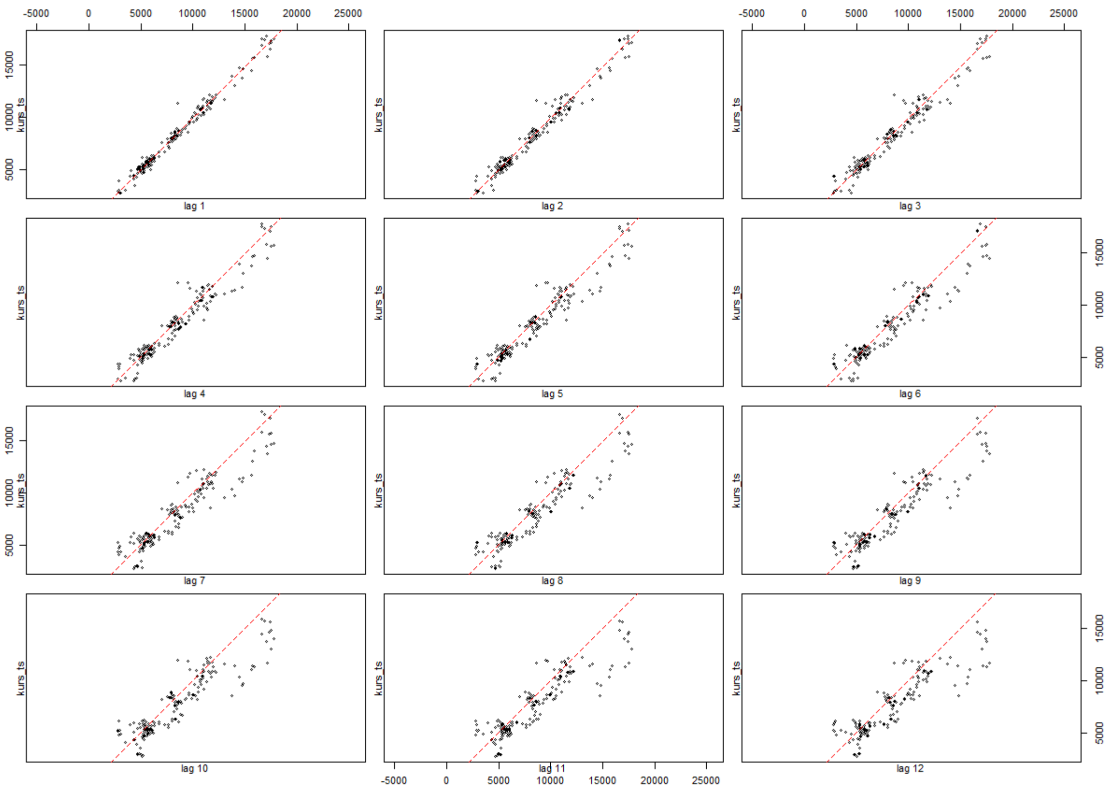

Jakość powietrza w Indiach
w mln
50
100
150
200
1 11 23 35 47 59 71 83 95 108 123 138 153 168 183 198 213 228 243 258 273 288 303 318 333 348 363


kurs NIFTY50
w mln
5000
10000
15000
1 2 3 4 5 6 7 8 9 10 11 12

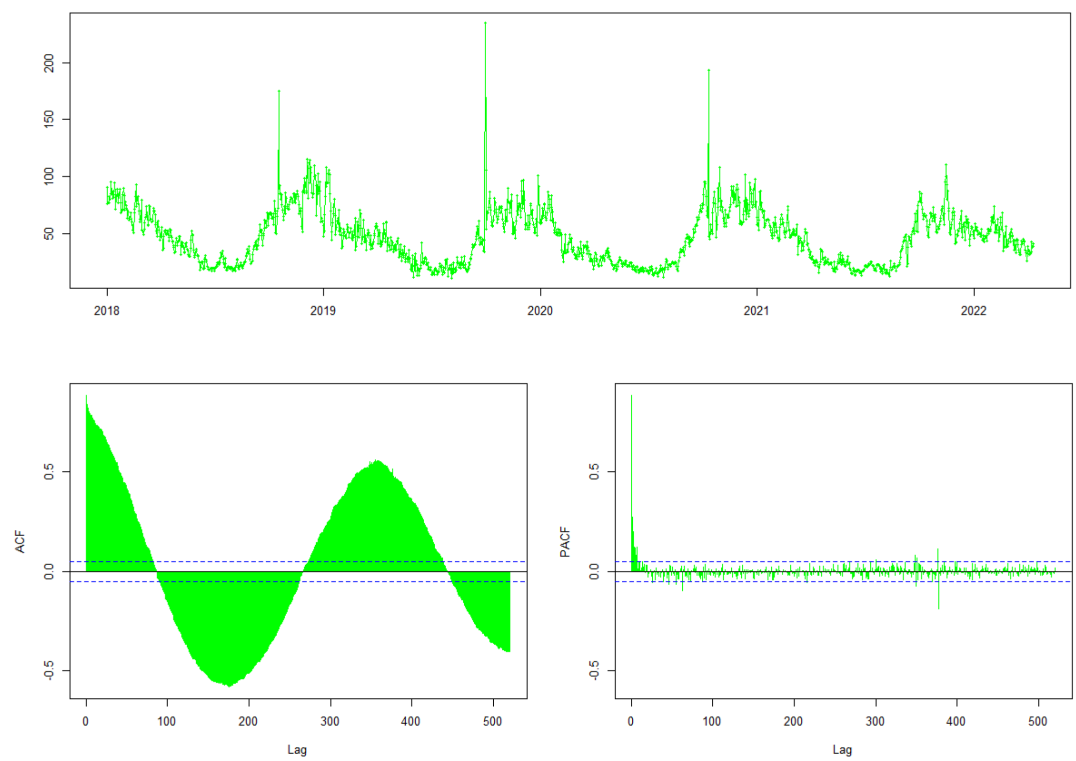
Wykres rozrzutu dla jakości powietrza



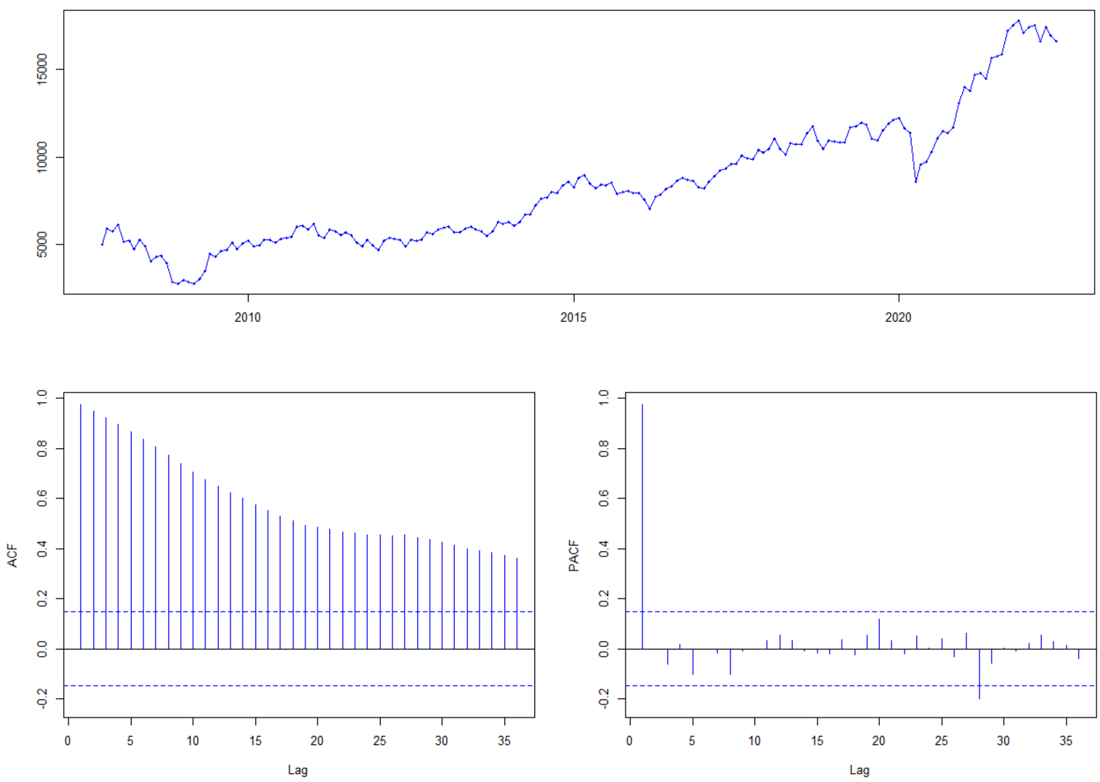
Wykres rozrzutu dla kursu NIFTY50



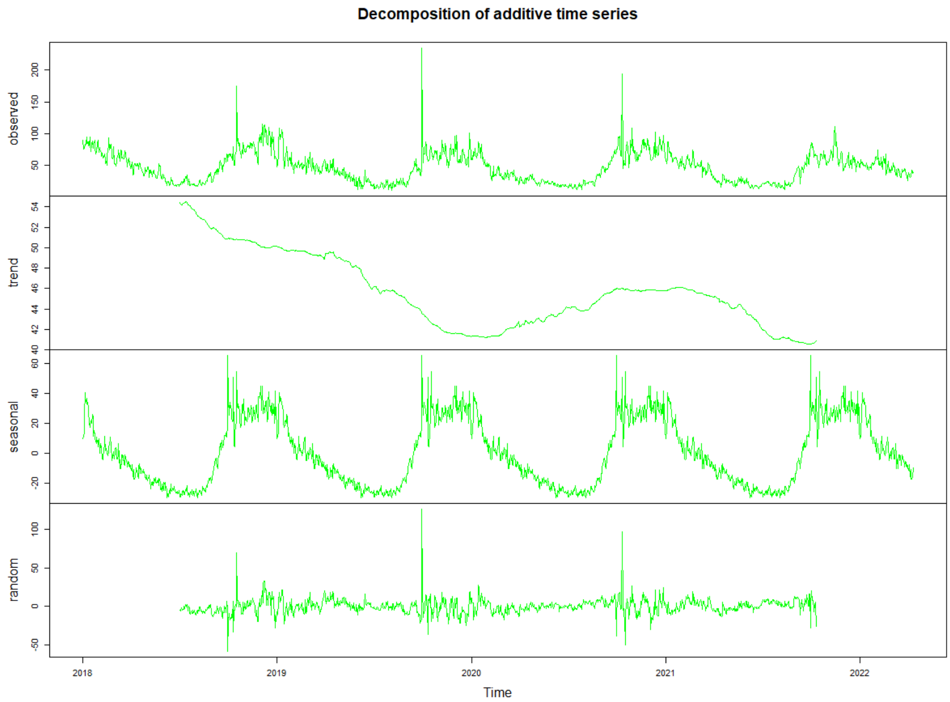
Wykres tsdisplay dla jakości powietrza w Indiach

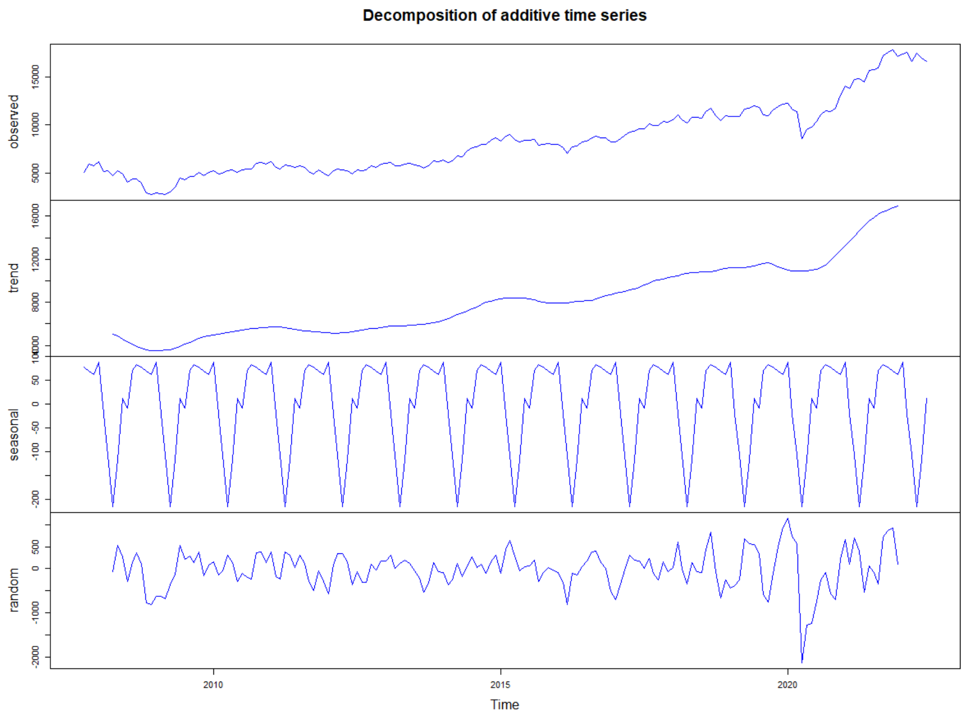


Wykres tsdisplay dla kursu NIFTY50

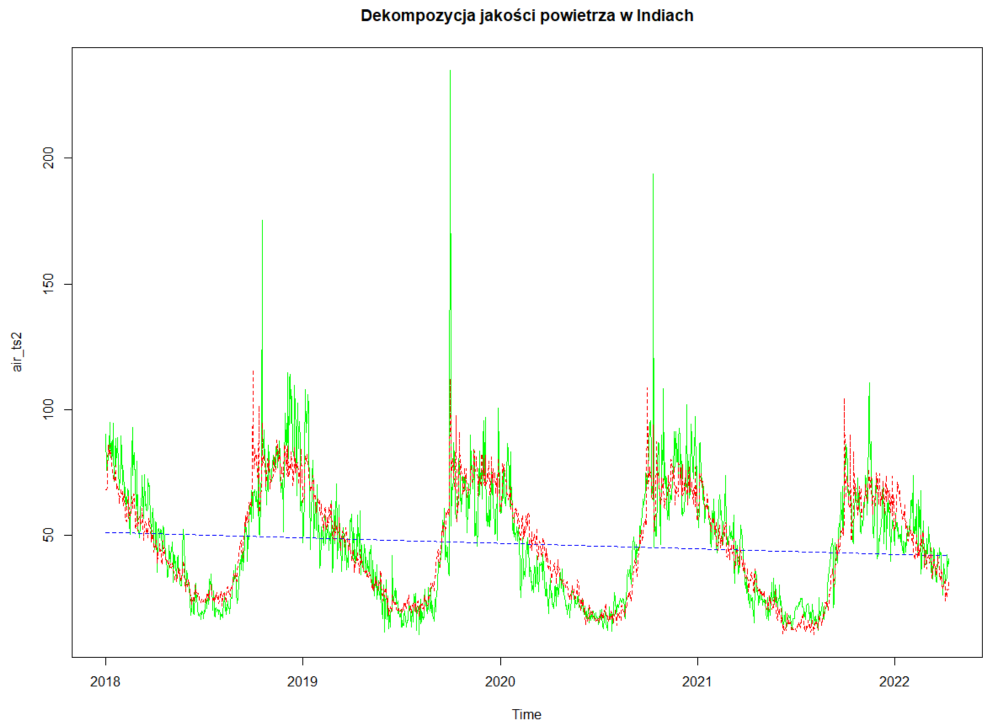


3. Dekompozycja na podstawie modelu regresji

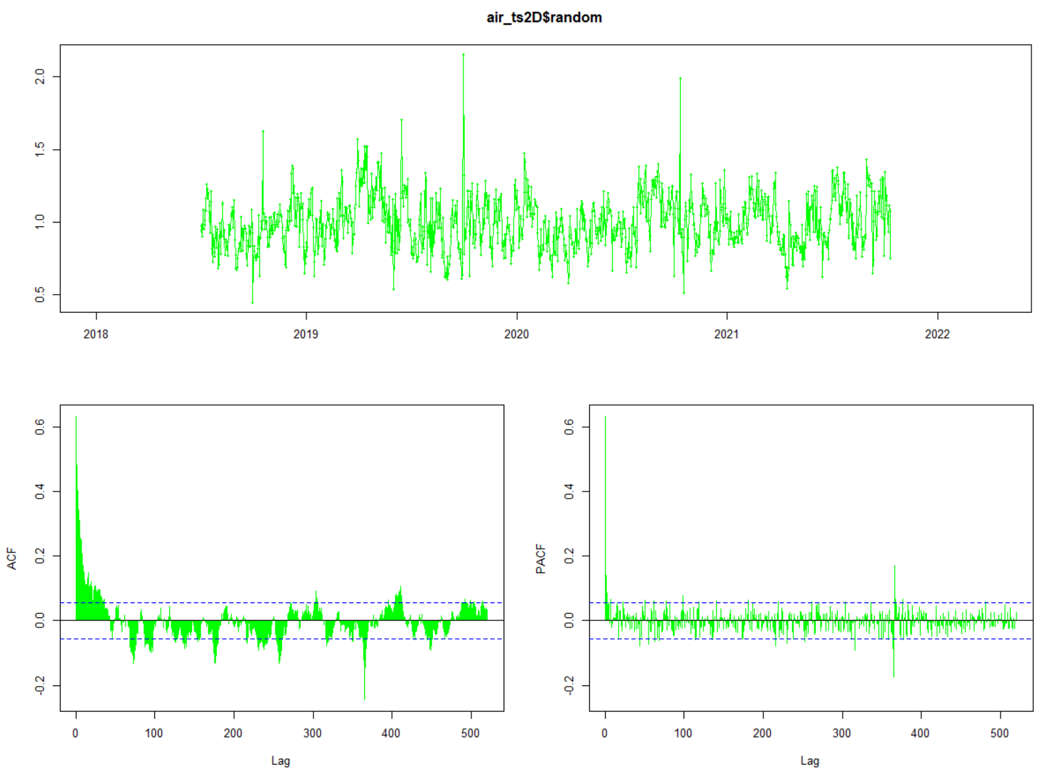


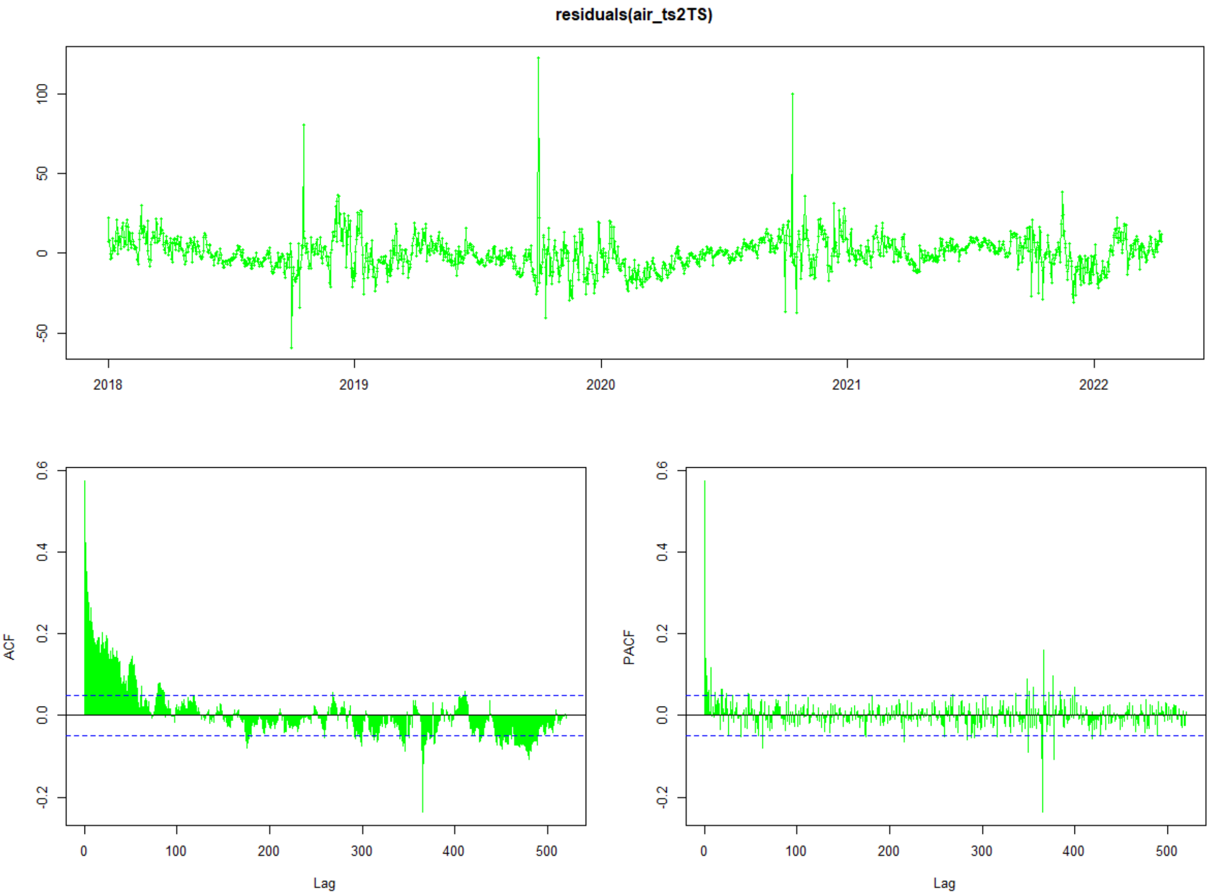


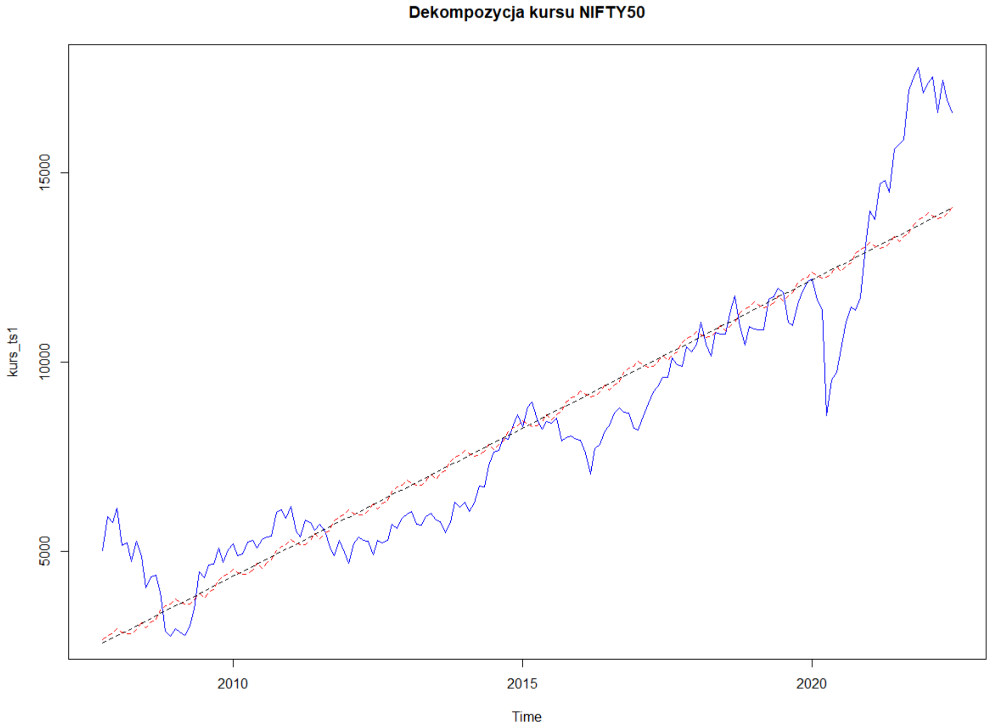
Pierwszy wykres dotyczy jakości powietrza, drugi kursu NIFTY50.



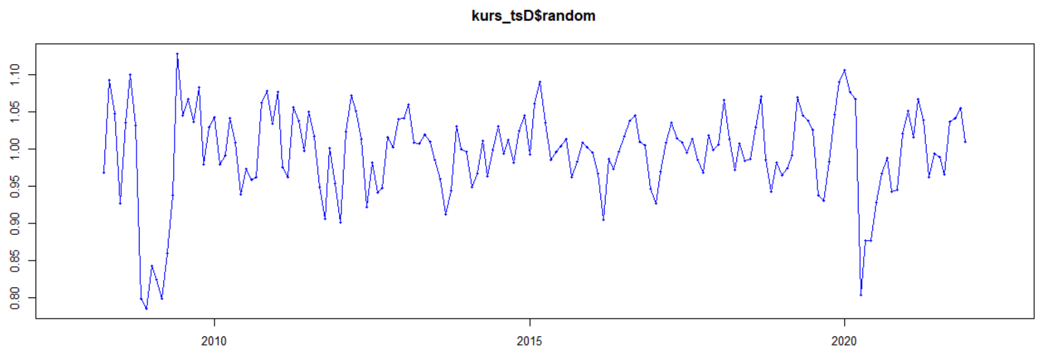
Na czerwono sezonowość, na niebiesko trend

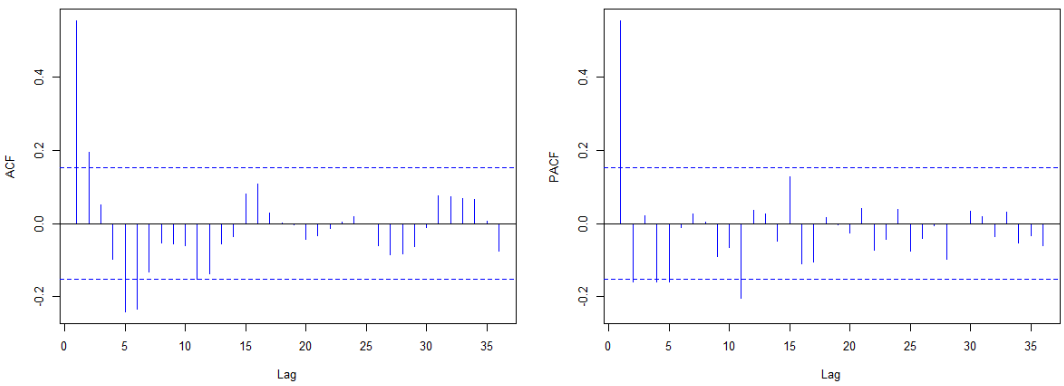


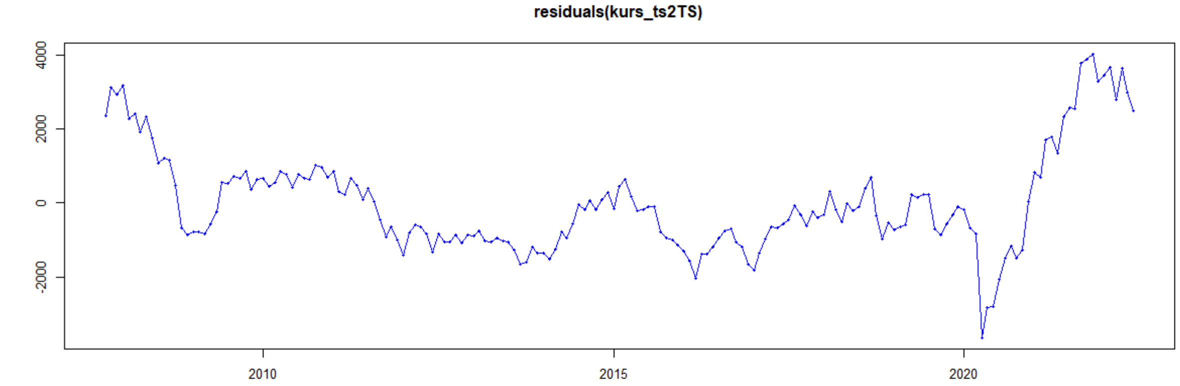

residuals(air_ts2TS)
-50
0
50
100
2018
2019
2020
2021
2022
ACF
-0.2
0.0
0.2
0.4
0.6
0
100
200
300
400
500
Lag
PACF
-0.2
0.0
0.2
0.4
0.6
0
100
200
300
400
500
Lag

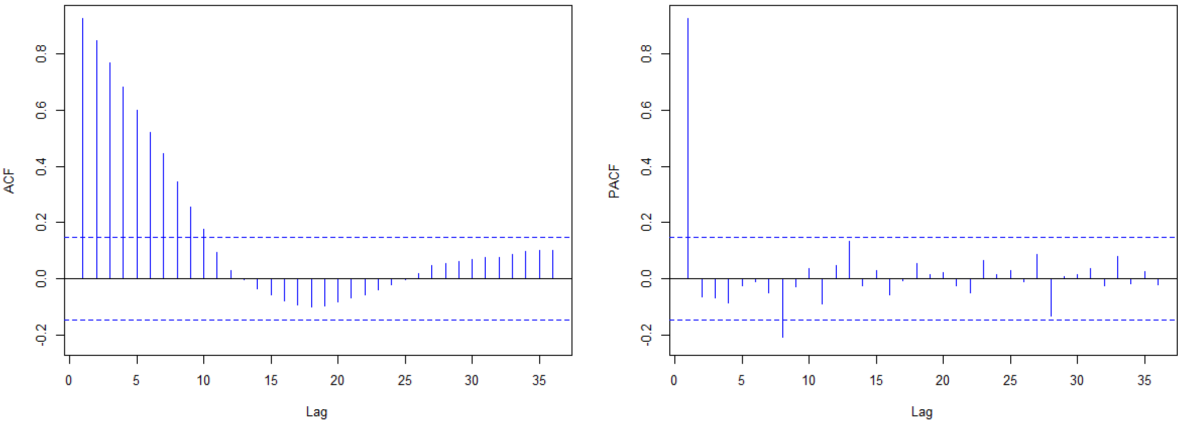


Na czerwono sezonowość, na czarno trend.

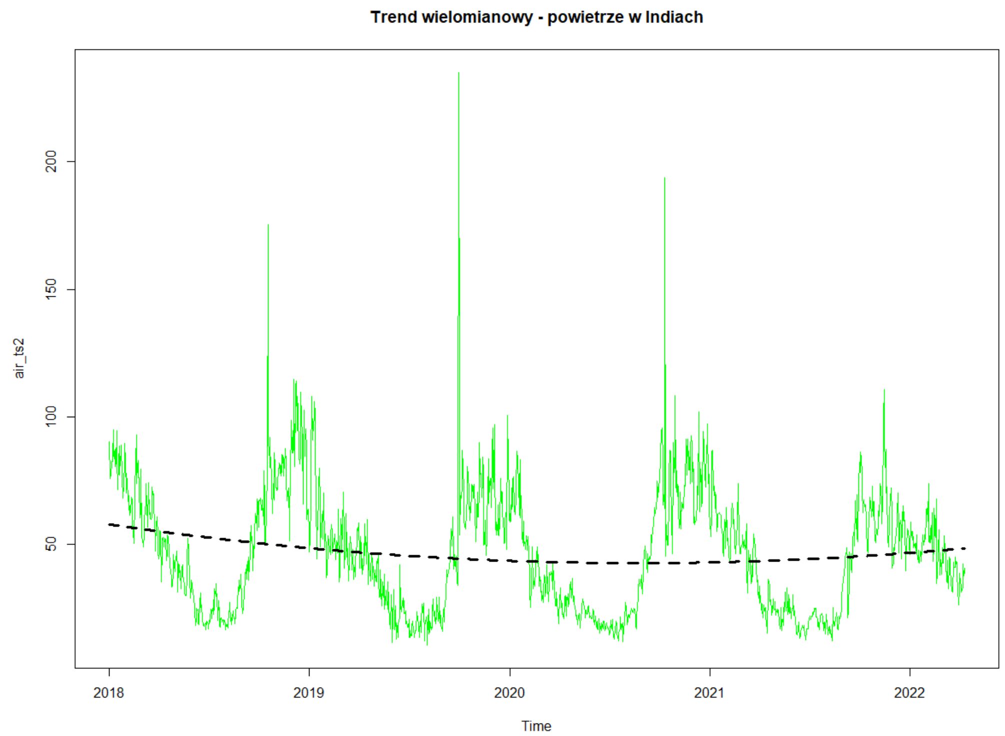


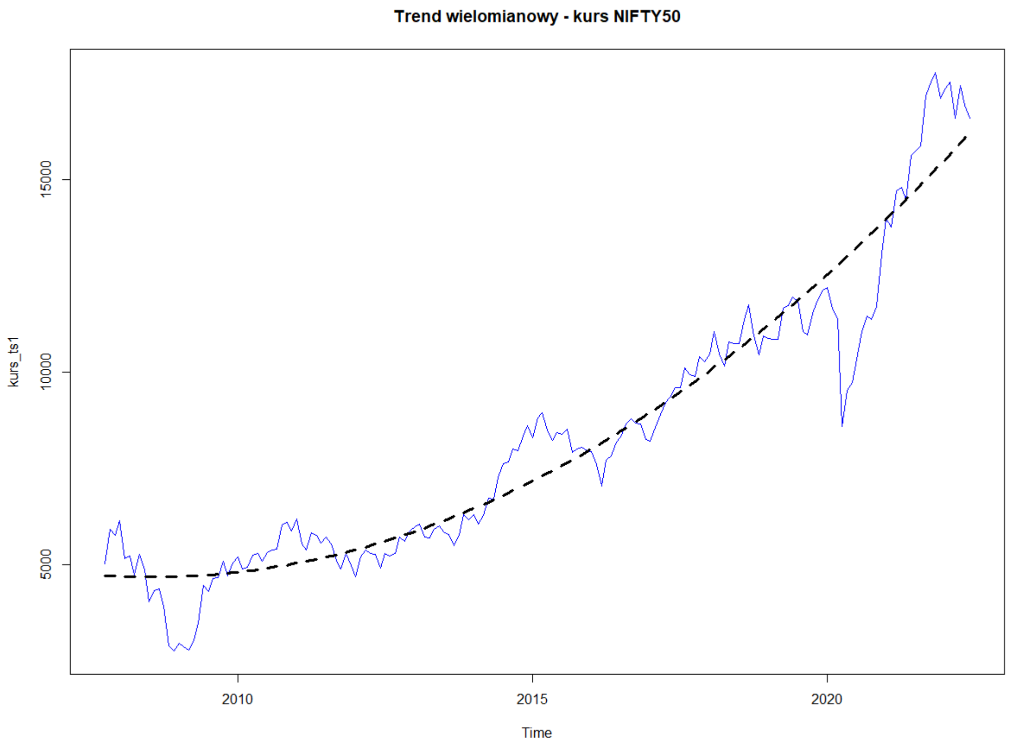



residuals(kurs_ts2TS)
4000
2000
0
-2000
2010
2015
2020

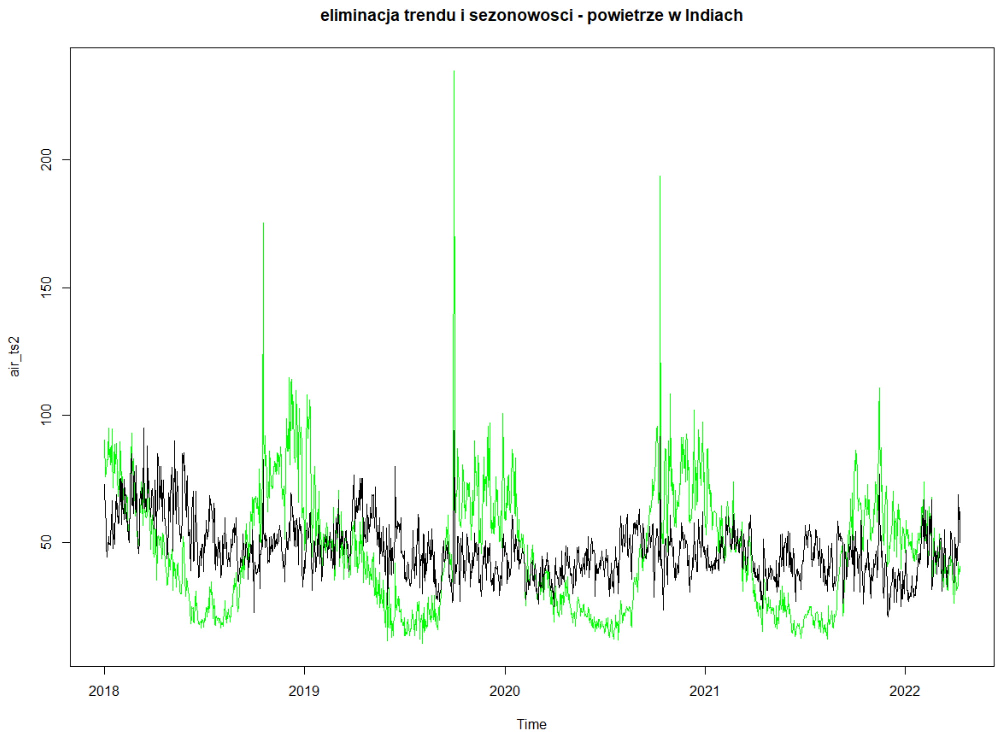

ACF
PACF
Lag
Lag
0.8
0.6
0.4
0.2
0.0
-0.2
0
5
10
15
20
25
30
35

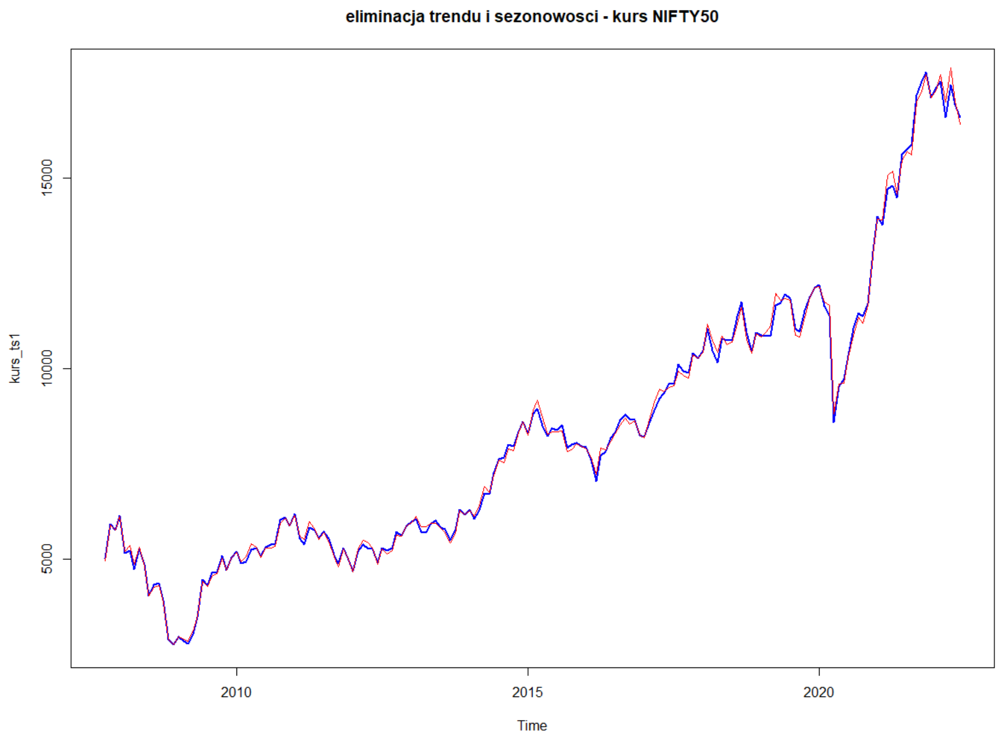
Dekompozycja na podstawie modelu regresji w trendzie wielomianowym



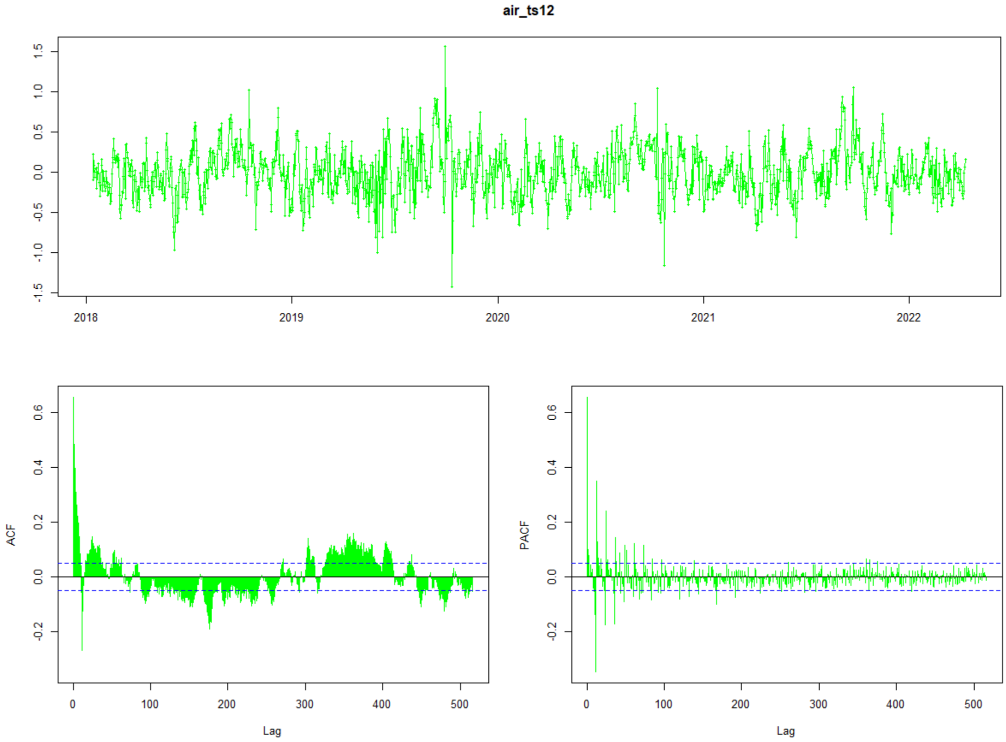


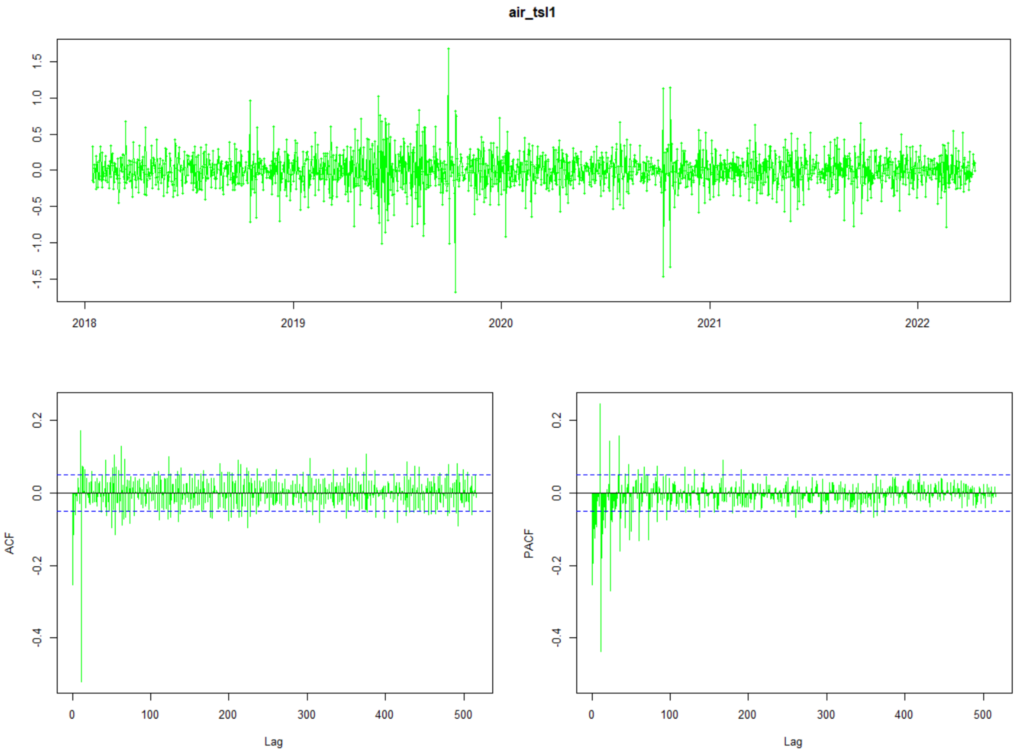
4. Eliminacja trendu i sezonowości

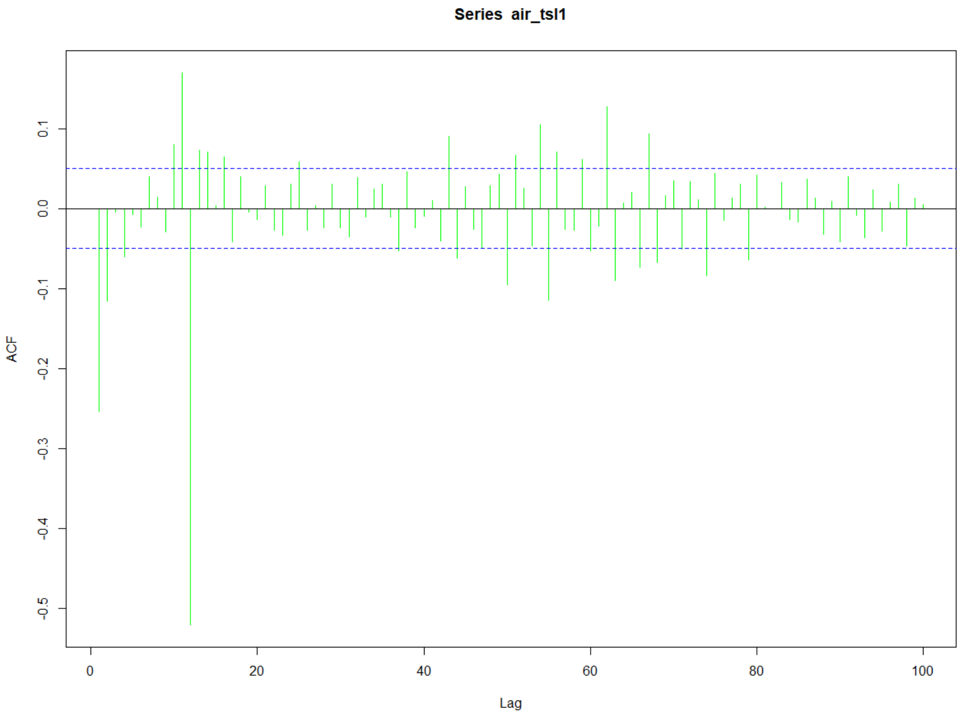




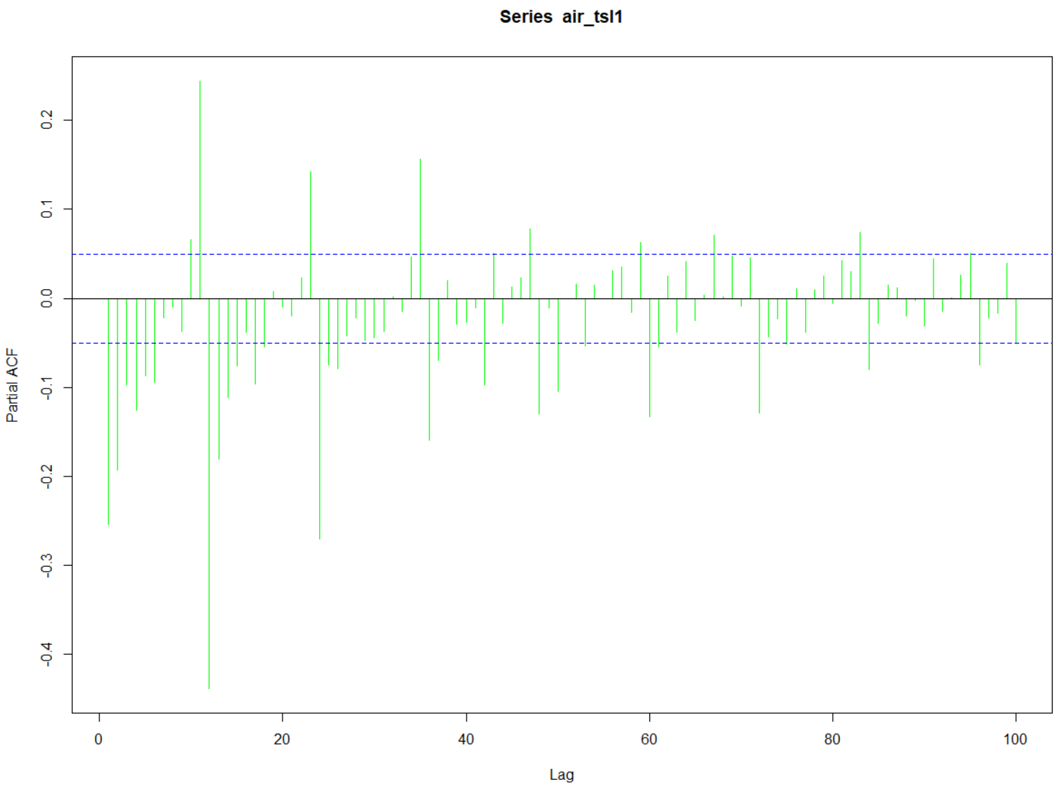
5. Uczynienie szeregów stacjonarnymi



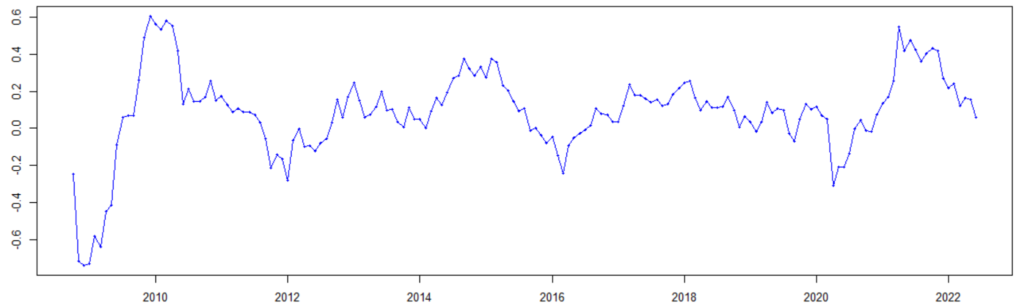


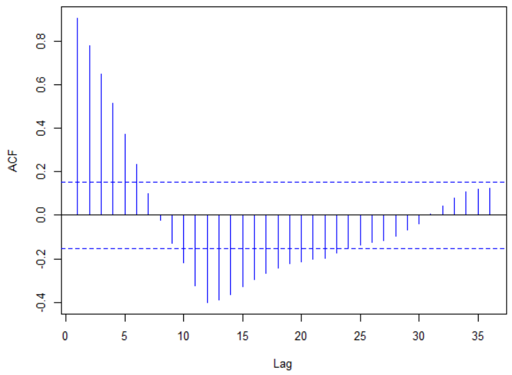


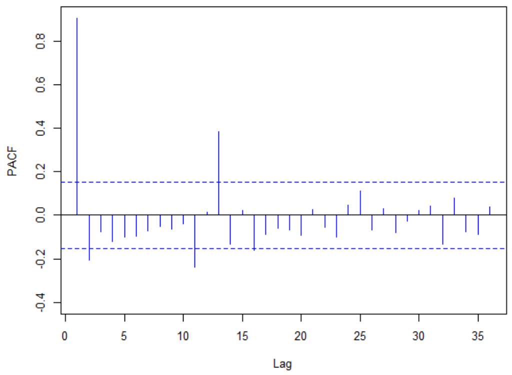
Szereg jakość powietrza w Indiach nie jest realizacją szumu białego.



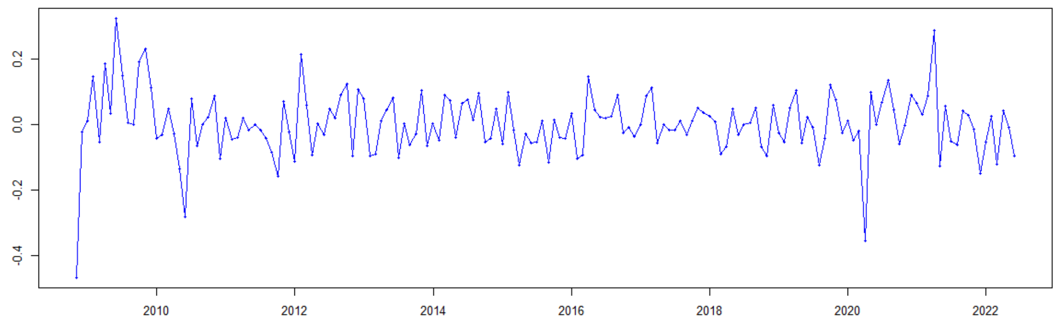
kurs_ts12

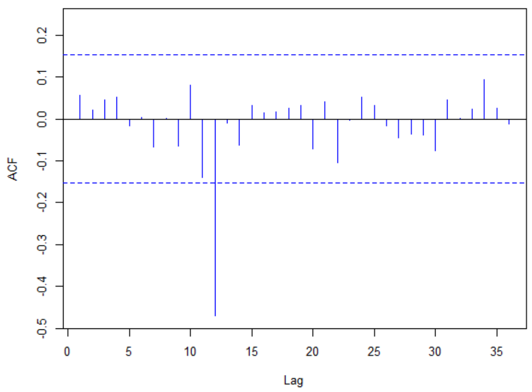


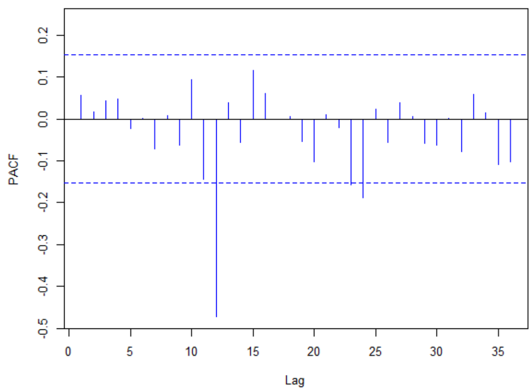


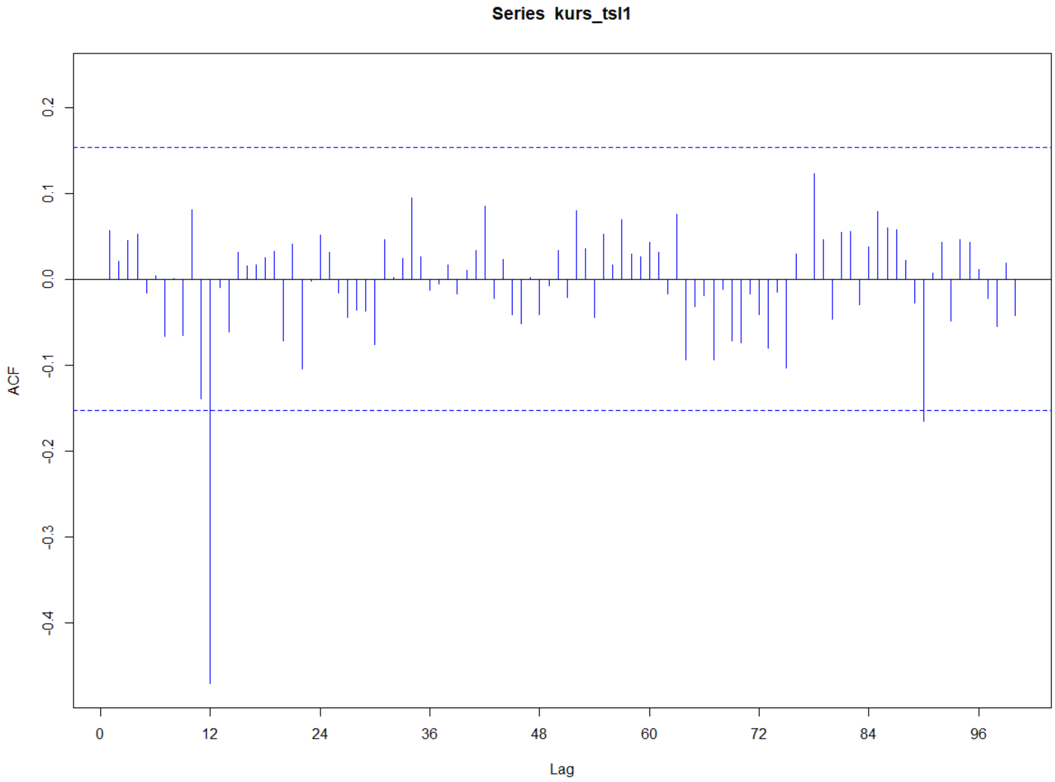


kurs_tsl1

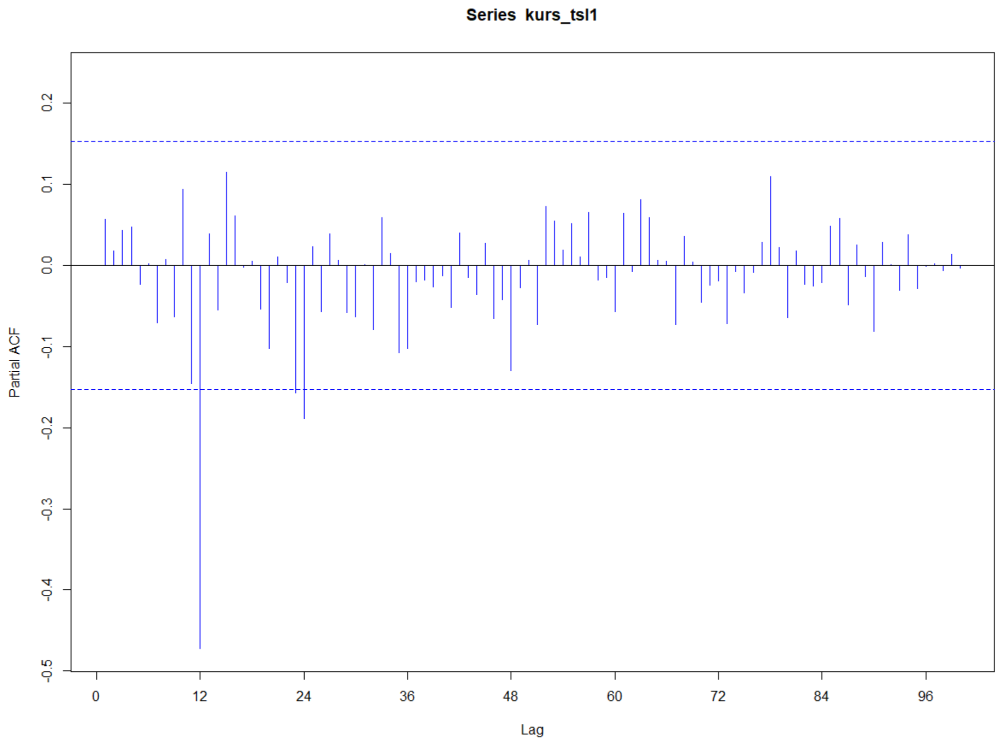




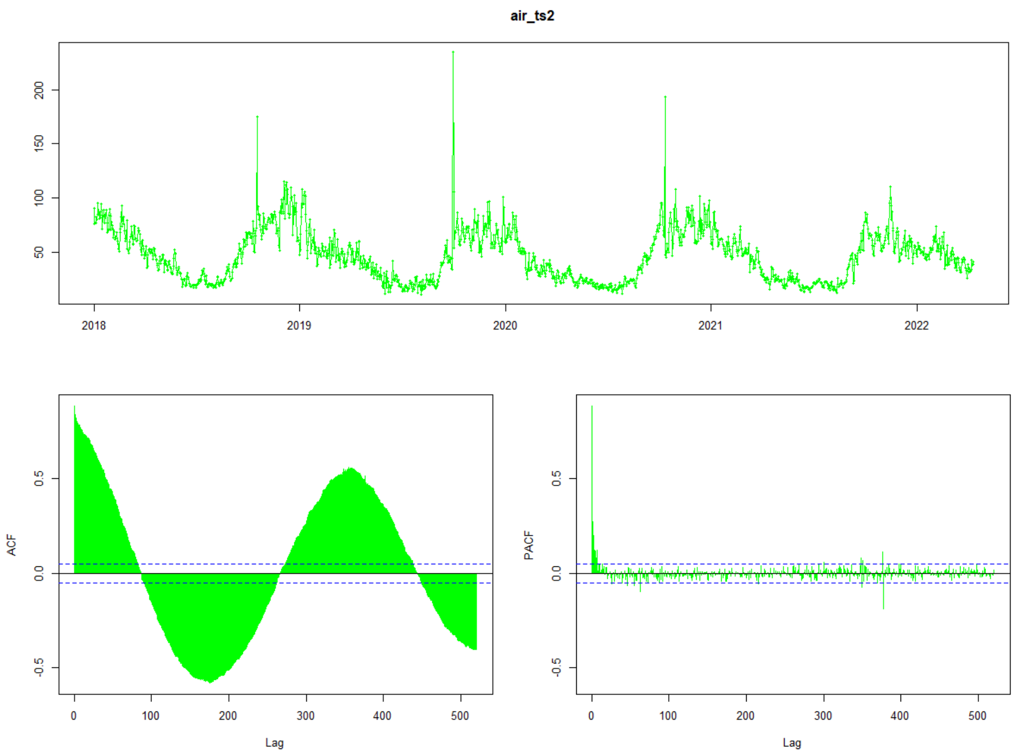


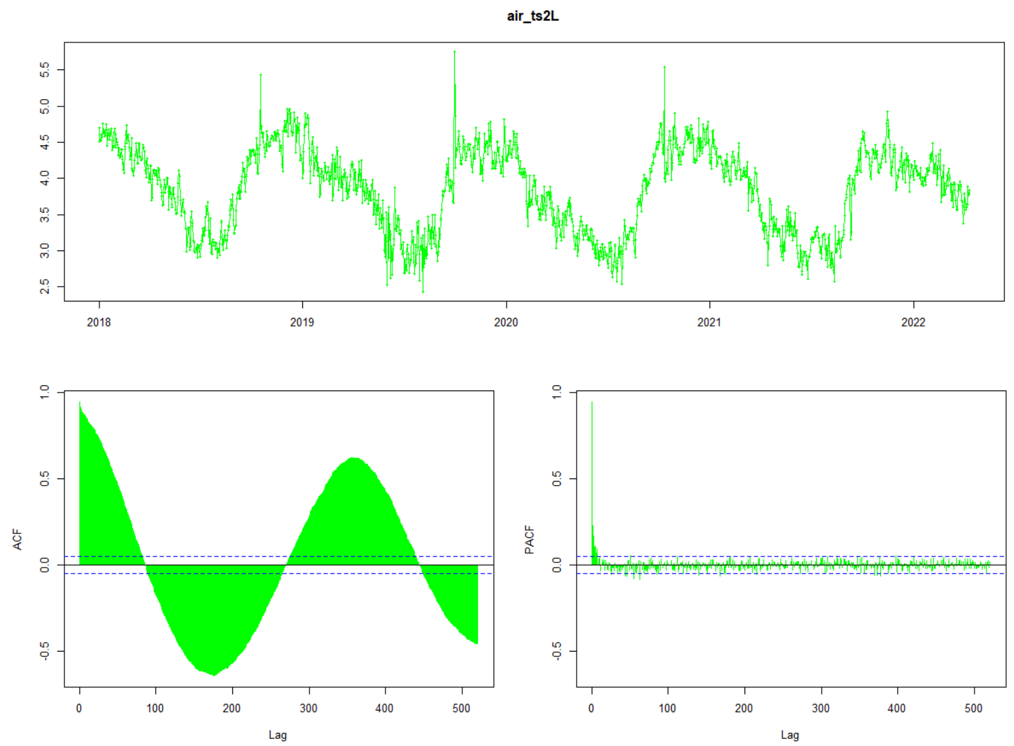


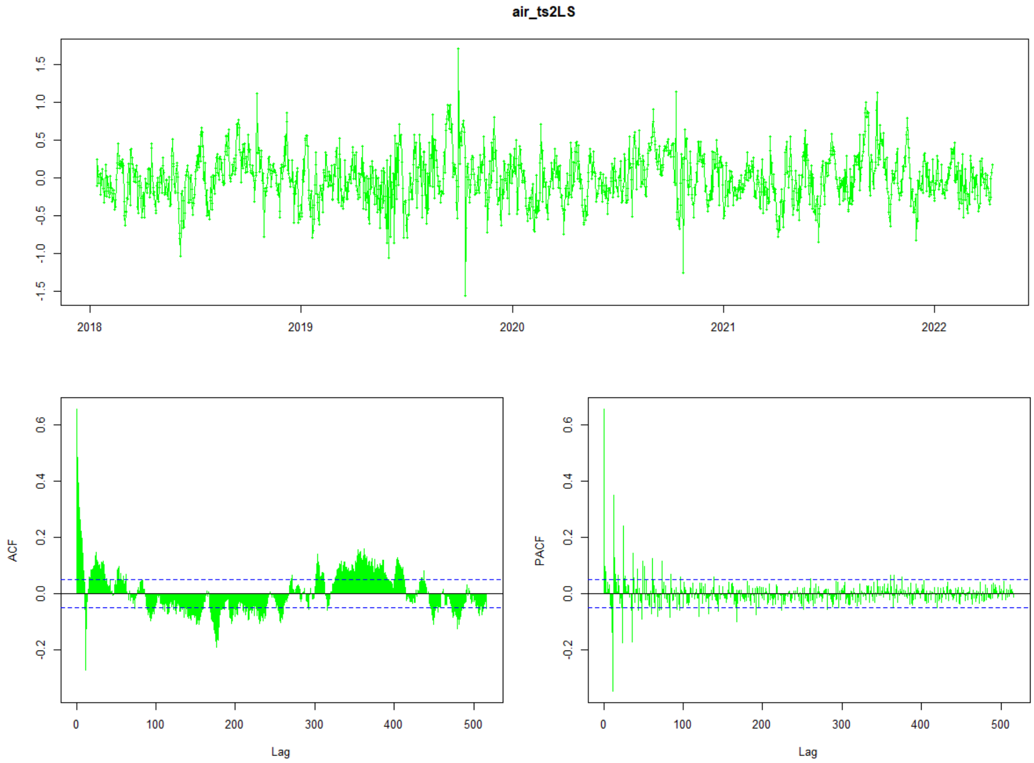
Szereg kurs NIFTY50 nie jest realizacją szumu białego.

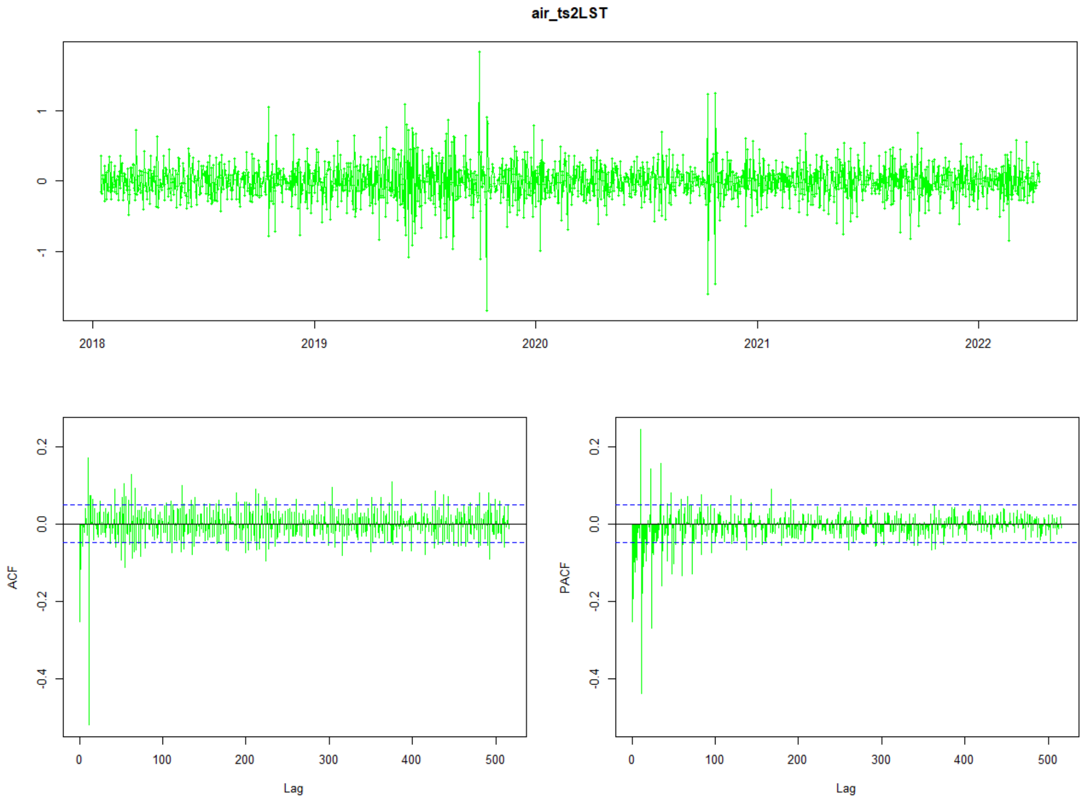


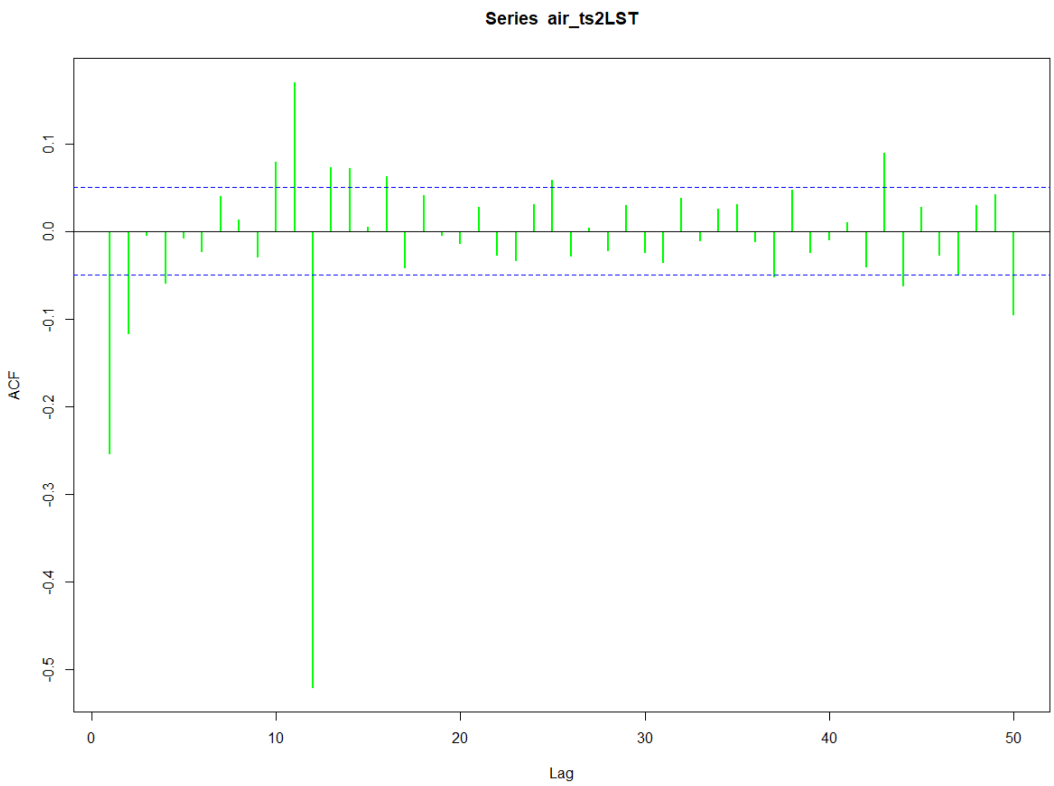
6. Wyznaczenie współczynników modelu AR

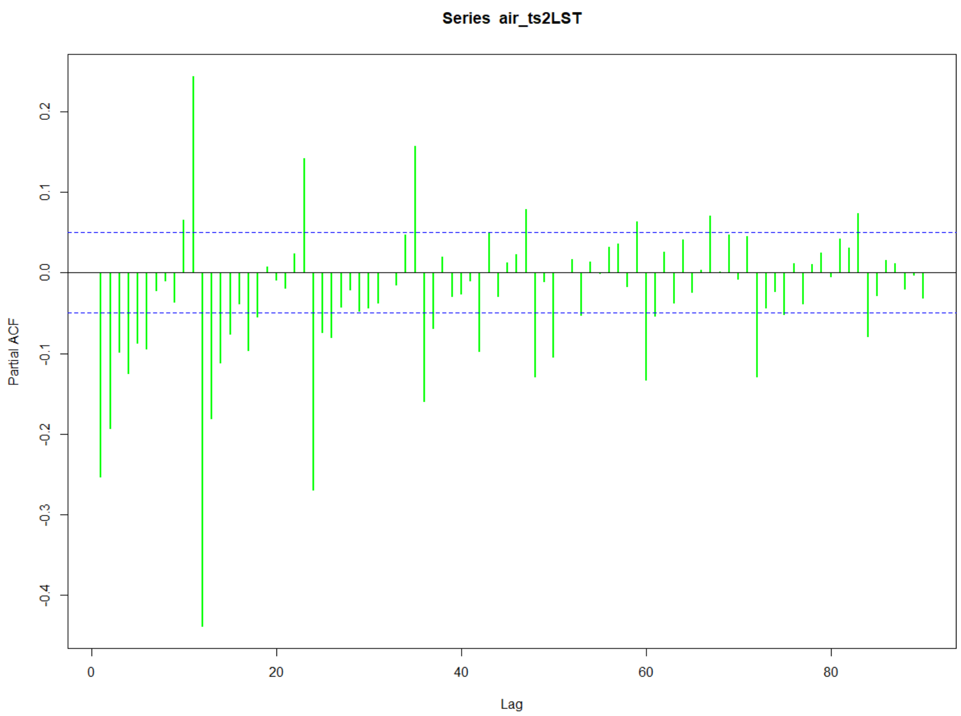





air_ts2LS
ACF
PACF
Lag
Lag


air_ts2LST
ACF
PACF
Lag
Lag


Series air_ts2LST
ACF
0.1
0.0
-0.1
-0.2
-0.3
-0.4
-0.5
0
10
20
30
40
50
Lag


Series air_ts2LST
Partial ACF
0.2
0.1
0.0
-0.1
-0.2
-0.3
-0.4
0
20
40
60
80
Lag

Wyznaczamy współczynnik przy użyciu metod yule-walker oraz mle, najpierw z określonym p, później z automatycznym.

```
> air_yw<- ar(air_ts2LST, aic = FALSE,order.max = 84, method = "yule-walker")
> print(air_yw)

Call:
ar(x = air_ts2LST, aic = FALSE, order.max = 84, method = "yule-walker")

Coefficients:
      1        2        3        4        5        6        7        8        9       10       11       12       13
-0.3506  -0.2889  -0.2263  -0.2002  -0.1701  -0.1341  -0.0578  -0.0912  -0.0913  -0.0422  -0.0082  -0.8882  -0.3676
     14       15       16       17       18       19       20       21       22       23       24       25       26
-0.2763  -0.2197  -0.1575  -0.1797  -0.1148  -0.0305  -0.0641  -0.0527  -0.0312   0.0261  -0.6909  -0.2271  -0.1831
     27       28       29       30       31       32       33       34       35       36       37       38       39
-0.1504  -0.0856  -0.1162  -0.0848   0.0075  -0.0199   0.0022   0.0076   0.0670  -0.5151  -0.1509  -0.0987  -0.0865
     40       41       42       43       44       45       46       47       48       49       50       51       52
-0.0295  -0.0695  -0.0505   0.0744  -0.0241   0.0279  -0.0436   0.0125  -0.4190  -0.1050  -0.0999  -0.0464   0.0388
     53       54       55       56       57       58       59       60       61       62       63       64       65
-0.0439   0.0567   0.0668   0.0297   0.0487  -0.0484   0.0121  -0.3334  -0.0824  -0.0056  -0.0570   0.0486  -0.0115
     66       67       68       69       70       71       72       73       74       75       76       77       78
 0.0503   0.0893   0.0082   0.0573  -0.0154   0.0094  -0.2262  -0.0567  -0.0320  -0.0444   0.0135  -0.0091   0.0350
     79       80       81       82       83       84
 0.0430   0.0202   0.0558   0.0334   0.0457  -0.0794

Order selected 84  sigma^2 estimated as  0.03429
```

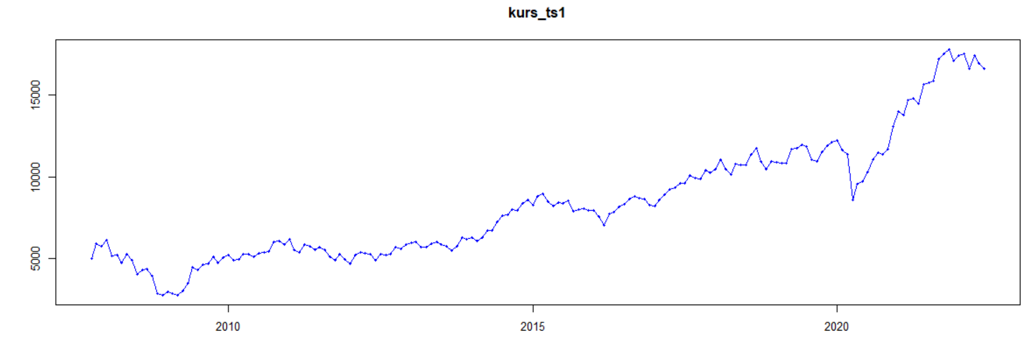
```
> air_mle<- ar(air_ts2LST, aic = FALSE,order.max = 24, method = "mle")
> print(air_mle)

Call:
ar(x = air_ts2LST, aic = FALSE, order.max = 24, method = "mle")

Coefficients:
      1        2        3        4        5        6        7        8        9       10       11       12       13
-0.3466  -0.2614  -0.2063  -0.2089  -0.1527  -0.1350  -0.0691  -0.0906  -0.0958  -0.0328  -0.0003  -0.6879  -0.2467
     14       15       16       17       18       19       20       21       22       23       24
-0.1615  -0.1347  -0.1007  -0.1081  -0.0636  -0.0096  -0.0358  -0.0288   0.0019   0.0373  -0.2709

Order selected 24  sigma^2 estimated as  0.03981
```

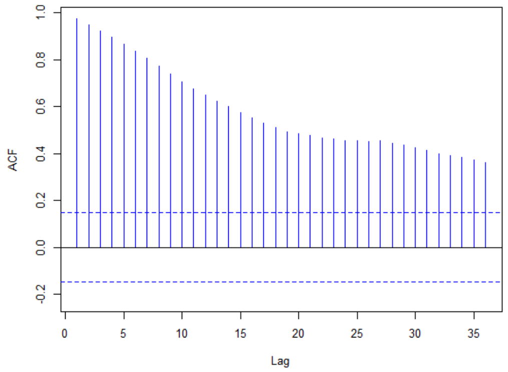
Dajemy automatyczne p.

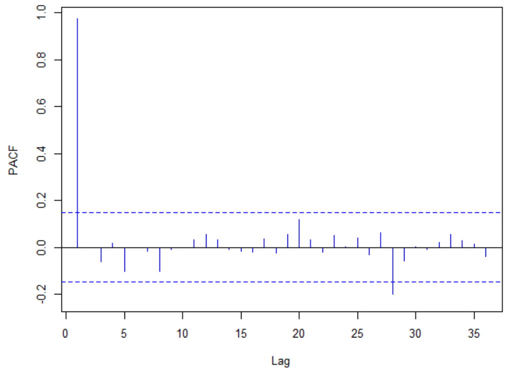
```
> air_yw2<- ar(air_ts2LST, aic = TRUE,order.max = 100, method = "yule-walker")
> print(air_yw2)

Call:
ar(x = air_ts2LST, aic = TRUE, order.max = 100, method = "yule-walker")

Coefficients:
      1        2        3        4        5        6        7        8        9       10       11       12       13
-0.3506  -0.2889  -0.2263  -0.2002  -0.1701  -0.1341  -0.0578  -0.0912  -0.0913  -0.0422  -0.0082  -0.8882  -0.3676
     14       15       16       17       18       19       20       21       22       23       24       25       26
-0.2763  -0.2197  -0.1575  -0.1797  -0.1148  -0.0305  -0.0641  -0.0527  -0.0312   0.0261  -0.6909  -0.2271  -0.1831
     27       28       29       30       31       32       33       34       35       36       37       38       39
-0.1504  -0.0856  -0.1162  -0.0848   0.0075  -0.0199   0.0022   0.0076   0.0670  -0.5151  -0.1509  -0.0987  -0.0865
     40       41       42       43       44       45       46       47       48       49       50       51       52
-0.0295  -0.0695  -0.0505   0.0744  -0.0241   0.0279  -0.0436   0.0125  -0.4190  -0.1050  -0.0999  -0.0464   0.0388
     53       54       55       56       57       58       59       60       61       62       63       64       65
-0.0439   0.0567   0.0668   0.0297   0.0487  -0.0484   0.0121  -0.3334  -0.0824  -0.0056  -0.0570   0.0486  -0.0115
     66       67       68       69       70       71       72       73       74       75       76       77       78
 0.0503   0.0893   0.0082   0.0573  -0.0154   0.0094  -0.2262  -0.0567  -0.0320  -0.0444   0.0135  -0.0091   0.0350
     79       80       81       82       83       84
 0.0430   0.0202   0.0558   0.0334   0.0457  -0.0794

Order selected 84  sigma^2 estimated as  0.03429
```

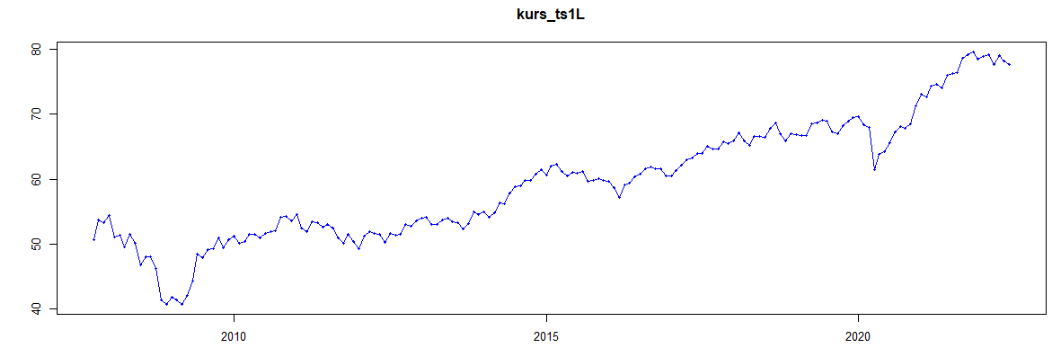
Do metody mle niestety nie działało.

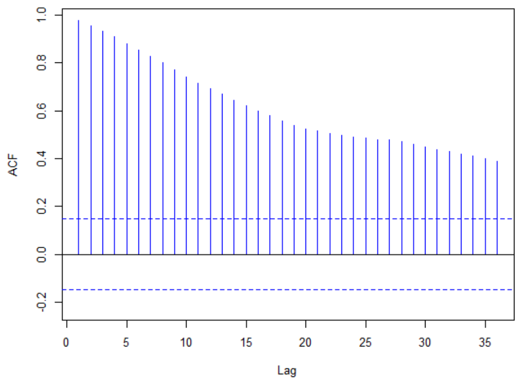
```
> air_mle2<- ar(air_ts2LST, aic = TRUE,order.max = 100, method = "mle")
Error in optim(init[mask], armaOf, method = "BFGS", hessian = TRUE, control = optim.control) :
  non-finite finite-difference value [11]
>
```

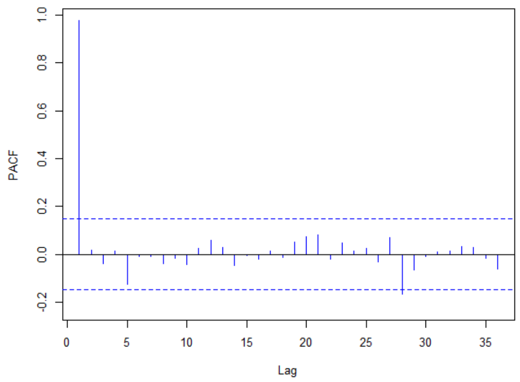

kurs_ts1
15000
10000
5000
2010
2015
2020


ACF
Lag

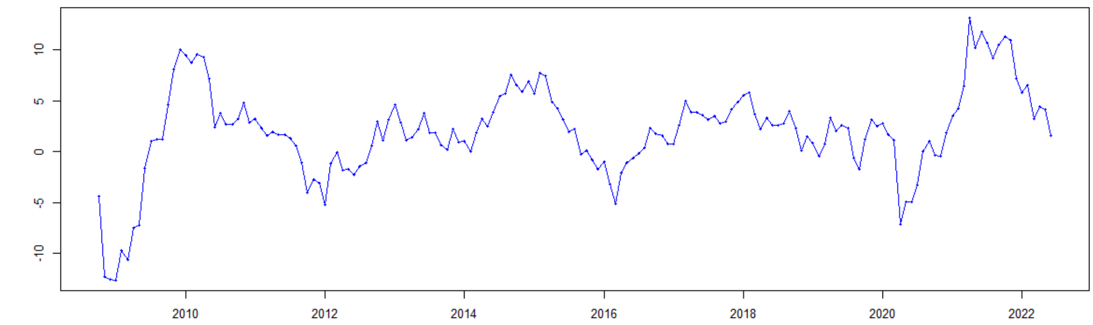

PACF
Lag

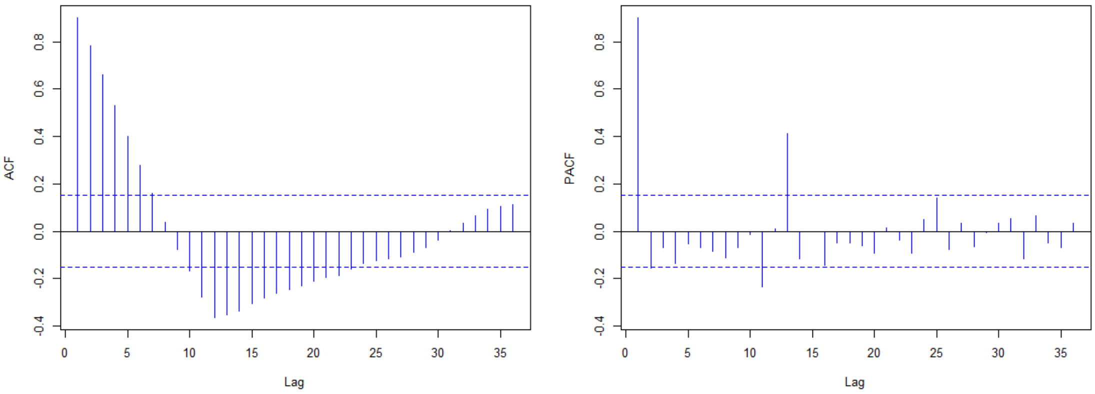

kurs_ts1L
80
70
60
50
40
2010
2015
2020


ACF
Lag

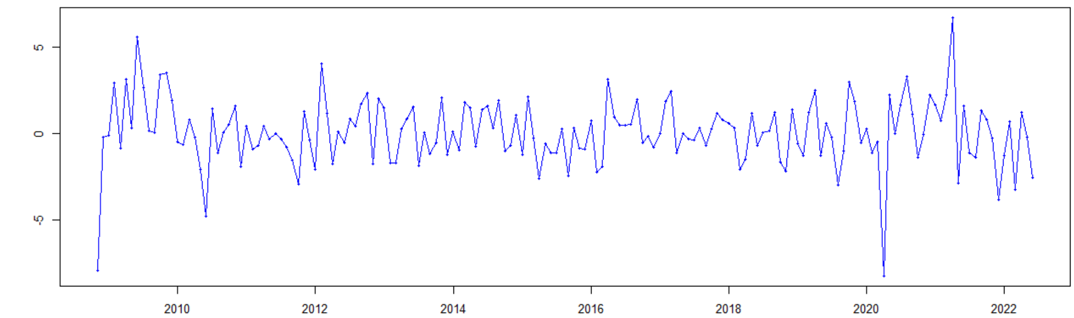

PACF
Lag

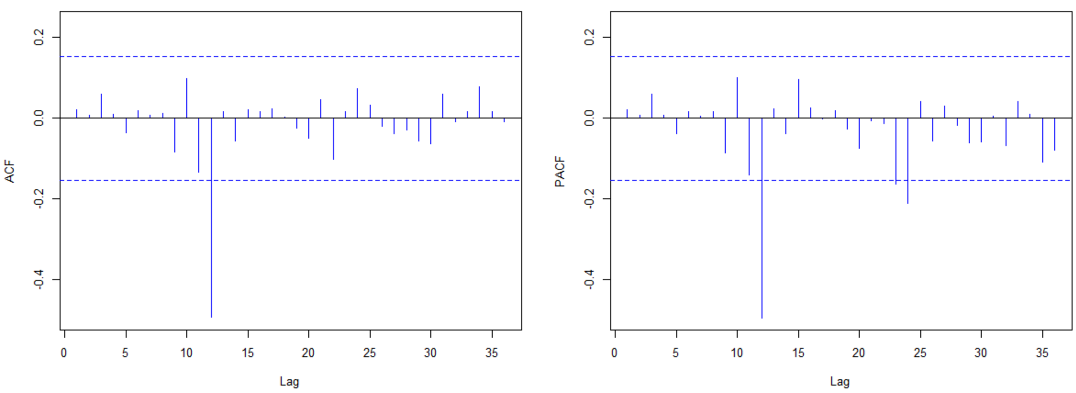
kurs_ts1LS

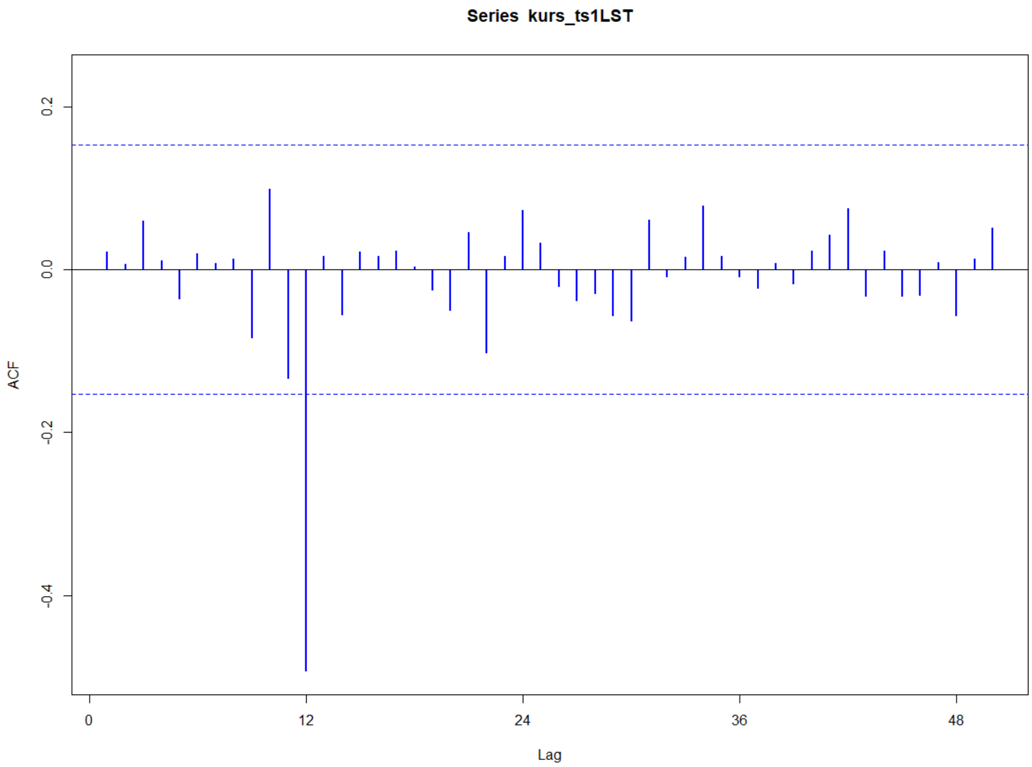


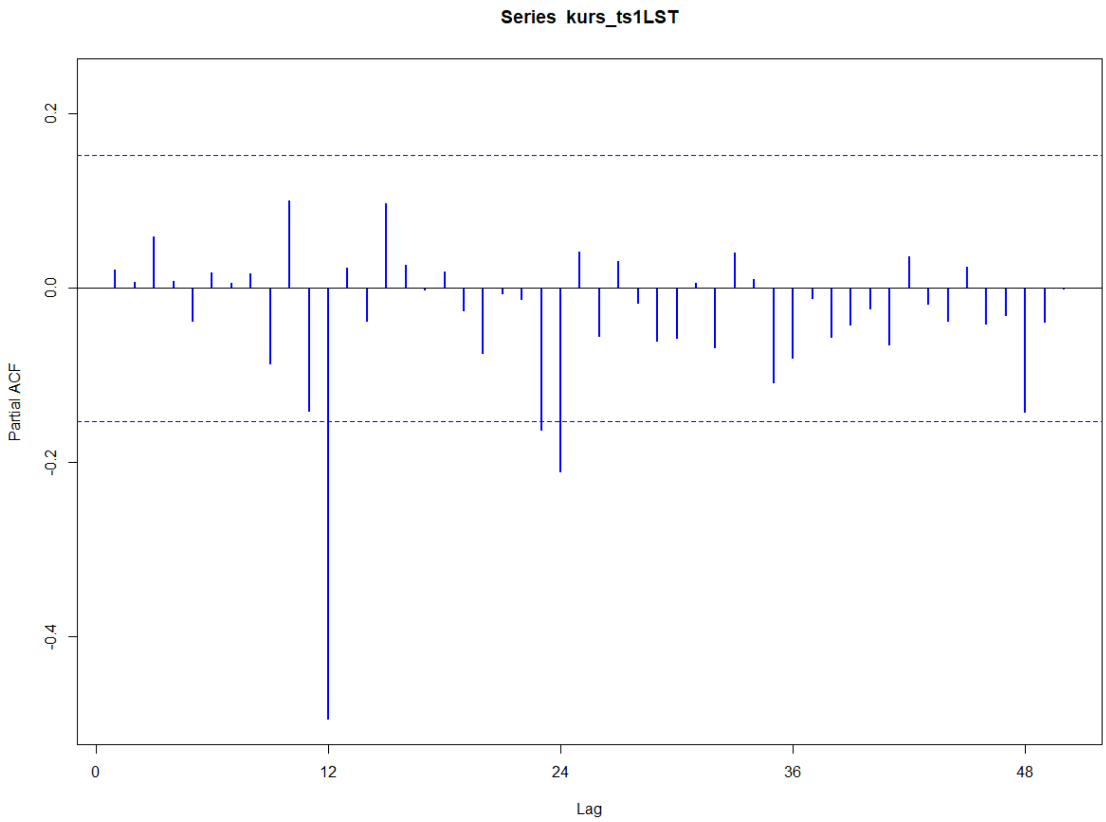


kurs_ts1LST






Series kurs_ts1LST
ACF
0.2
0.0
-0.2
-0.4
0
12
24
36
48
Lag


Series kurs_ts1LST
Partial ACF
0.2
0.0
-0.2
-0.4
0
12
24
36
48
Lag

Wyznaczamy współczynnik przy użyciu metod yule-walker oraz mle, najpierw z określonym p, później z automatycznym.

```
> kurs_yw<- ar(kurs_ts1LST, aic = FALSE,order.max = 24, method = "yule-walker")
> print(kurs_yw)

Call:
ar(x = kurs_ts1LST, aic = FALSE, order.max = 24, method = "yule-walker")

Coefficients:
      1        2        3        4        5        6        7        8        9       10       11       12       13  
-0.0491   0.0238   0.0447   0.0326  -0.0356   0.0417  -0.0180   0.0082  -0.0553   0.0957  -0.1968  -0.6208  -0.0092  
     14       15       16       17       18       19       20       21       22       23       24  
-0.0258   0.0763   0.0272   0.0046   0.0244  -0.0242  -0.0555   0.0081  -0.0089  -0.1655  -0.2113  

Order selected 24  sigma^2 estimated as  2.854
```

```
> kurs_mle <- ar(kurs_ts1LST, aic = FALSE,order.max = 24, method = "mle")
> print(kurs_mle)

Call:
ar(x = kurs_ts1LST, aic = FALSE, order.max = 24, method = "mle")

Coefficients:
      1        2        3        4        5        6        7        8        9       10       11       12       13  
-0.0722   0.0070   0.0645   0.0662  -0.0223   0.0056   0.0082   0.0331  -0.0326   0.0669  -0.2373  -0.8874  -0.0480  
     14       15       16       17       18       19       20       21       22       23       24  
-0.0492   0.1170   0.0456  -0.0221  -0.0238   0.0279   0.0047   0.0117  -0.0281  -0.1680  -0.4342  

Order selected 24  sigma^2 estimated as  1.843
```

Dajemy automatyczne p.

```
> kurs_yw1 <- ar(kurs_ts1LST, aic = TRUE, order.max = 100, method = "yule-walker")
> print(kurs_yw1)

Call:
ar(x = kurs_ts1LST, aic = TRUE, order.max = 100, method = "yule-walker")

Coefficients:
      1        2        3        4        5        6        7        8        9       10       11       12  
-0.0244   0.0453   0.0184   0.0155  -0.0309   0.0256  -0.0148   0.0275  -0.0574   0.1019  -0.1186  -0.4946  

Order selected 12  sigma^2 estimated as  2.879
```

7. Wyznaczenie współczynników dla modelu MA(q)

Model arima dla jakości powietrza

```
> air_arLST<- Arima(air_ts2LST, order = c(23,0,0))
> summary(air_arLST)
Series: air_ts2LST
ARIMA(23,0,0) with non-zero mean

Coefficients:
          ar1      ar2      ar3      ar4      ar5      ar6      ar7      ar8      ar9    ar10    ar11     ar12     ar13
      -0.3843  -0.2816  -0.2147  -0.2149  -0.1622  -0.1259  -0.0427  -0.0686  -0.0643  0.0132  0.0731  -0.5404  -0.2655
s.e.   0.0252   0.0269   0.0279   0.0284   0.0289   0.0292   0.0293   0.0292   0.0291  0.0288  0.0280   0.0244   0.0280
         ar14     ar15     ar16     ar17     ar18    ar19    ar20    ar21    ar22    ar23    mean
      -0.1644  -0.1164  -0.0823  -0.0967  -0.0287  0.0343  0.0217  0.0291  0.0786  0.1416  0.0001
s.e.   0.0288   0.0290   0.0291   0.0292   0.0291  0.0288  0.0283  0.0278  0.0269  0.0251  0.0015

sigma^2 = 0.0437:  log likelihood = 236.01
AIC=-422.02   AICc=-421.17   BIC=-288.41

Training set error measures:
                       ME      RMSE       MAE      MPE     MAPE      MASE       ACF1
Training set 4.520074e-05 0.2074174 0.1553256 92.88191 239.7471 0.5410859 0.03839131
```

```
> air_arLS <- Arima(air_ts2LS, order = c(23,1,0))
> summary(air_arLS)
Series: air_ts2LS
ARIMA(23,1,0)

Coefficients:
          ar1      ar2      ar3      ar4      ar5      ar6      ar7      ar8      ar9    ar10    ar11     ar12     ar13
      -0.3840  -0.2813  -0.2147  -0.2148  -0.1622  -0.1257  -0.0427  -0.0686  -0.0646  0.0131  0.0732  -0.5403  -0.2654
s.e.   0.0252   0.0269   0.0279   0.0284   0.0289   0.0292   0.0293   0.0292   0.0291  0.0288  0.0280   0.0244   0.0280
         ar14     ar15     ar16     ar17     ar18    ar19    ar20    ar21    ar22    ar23
      -0.1643  -0.1164  -0.0822  -0.0968  -0.0287  0.0343  0.0218  0.0291  0.0785  0.1416
s.e.   0.0288   0.0290   0.0291   0.0292   0.0291  0.0288  0.0283  0.0278  0.0269  0.0251

sigma^2 = 0.04367:  log likelihood = 236.01
AIC=-424.02   AICc=-423.23   BIC=-295.75

Training set error measures:
                       ME      RMSE       MAE      MPE     MAPE     MASE       ACF1
Training set 0.0002397845 0.2073506 0.1552331 31.93294 237.6565 0.455315 0.03811069
```

```
> air_arL <- Arima(air_ts2L, order = c(23,1,0),seasonal = list(order=c(0,1,0), period = 12))
> summary(air_arL)
Series: air_ts2L
ARIMA(23,1,0)(0,1,0)[12]

Coefficients:
          ar1      ar2      ar3      ar4      ar5      ar6      ar7      ar8      ar9    ar10    ar11     ar12     ar13
      -0.3840  -0.2813  -0.2147  -0.2148  -0.1622  -0.1257  -0.0427  -0.0686  -0.0646  0.0131  0.0732  -0.5403  -0.2654
s.e.   0.0252   0.0269   0.0279   0.0284   0.0289   0.0292   0.0293   0.0292   0.0291  0.0288  0.0280   0.0244   0.0280
         ar14     ar15     ar16     ar17     ar18    ar19    ar20    ar21    ar22    ar23
      -0.1643  -0.1164  -0.0822  -0.0968  -0.0287  0.0343  0.0218  0.0291  0.0785  0.1416
s.e.   0.0288   0.0290   0.0291   0.0292   0.0291  0.0288  0.0283  0.0278  0.0269  0.0251

sigma^2 = 0.04367:  log likelihood = 236.01
AIC=-424.02   AICc=-423.23   BIC=-295.75

Training set error measures:
                       ME      RMSE       MAE        MPE     MAPE      MASE       ACF1
Training set 0.0002304993 0.2065525 0.1540567 -0.1245738 4.126458 0.5607374 0.03804368
```

Model Arima dla kursu NIFTY50

```
> kurs_arLST<- Arima(kurs_ts1LST, order = c(23,0,0))
> summary(kurs_arLST)
Series: kurs_ts1LST
ARIMA(23,0,0) with non-zero mean

Coefficients:
          ar1     ar2     ar3     ar4      ar5     ar6     ar7     ar8      ar9    ar10    ar11     ar12     ar13
      -0.0307  0.0044  0.0868  0.0643  -0.0131  0.0193  0.0059  0.0067  -0.1010  0.1048  -0.250  -0.6340  -0.0044
s.e.   0.0810  0.0811  0.0844  0.0856   0.0854  0.0880  0.0875  0.0869   0.0867  0.0865   0.087   0.0665   0.0864
         ar14    ar15    ar16     ar17     ar18    ar19     ar20     ar21     ar22     ar23    mean
      -0.0944  0.1655  0.0180  -0.0113  -0.0203  0.0498  -0.0092  -0.0310  -0.0015  -0.1595  0.0389
s.e.   0.0865  0.0934  0.0949   0.0951   0.0951  0.0955   0.0957   0.0959   0.0964   0.0966  0.0660

sigma^2 = 2.534:  log likelihood = -299.82
AIC=649.64   AICc=659.06   BIC=727.14

Training set error measures:
                     ME     RMSE      MAE      MPE     MAPE      MASE        ACF1
Training set 0.02168771 1.470788 1.055357 491.4414 656.1482 0.4364495 -0.07278298
```

```
> kurs_arLS <- Arima(kurs_ts1LS, order = c(23,1,0))
> summary(kurs_arLS)
Series: kurs_ts1LS
ARIMA(23,1,0)

Coefficients:
          ar1     ar2     ar3     ar4      ar5     ar6     ar7     ar8      ar9    ar10     ar11     ar12     ar13
      -0.0274  0.0082  0.0894  0.0663  -0.0115  0.0206  0.0081  0.0087  -0.0995  0.1061  -0.2492  -0.6328  -0.0016
s.e.   0.0809  0.0809  0.0844  0.0856   0.0855  0.0881  0.0875  0.0870   0.0867  0.0866   0.0871   0.0666   0.0864
         ar14    ar15    ar16     ar17     ar18    ar19     ar20     ar21     ar22     ar23
      -0.0913  0.1671  0.0188  -0.0114  -0.0205  0.0502  -0.0085  -0.0304  -0.0013  -0.1599
s.e.   0.0865  0.0935  0.0950   0.0952   0.0952  0.0956   0.0958   0.0960   0.0965   0.0967

sigma^2 = 2.522:  log likelihood = -299.99
AIC=647.98   AICc=656.62   BIC=722.38

Training set error measures:
                    ME     RMSE    MAE       MPE     MAPE      MASE        ACF1
Training set 0.0862194 1.468013 1.0566 -226.6909 281.5794 0.2088281 -0.07618813
```

```
> kurs_arL <- Arima(kurs_ts1L, order = c(23,1,0),seasonal = list(order=c(0,1,0), period = 12))
> summary(kurs_arL)
Series: kurs_ts1L
ARIMA(23,1,0)(0,1,0)[12]

Coefficients:
          ar1     ar2     ar3     ar4      ar5     ar6     ar7     ar8      ar9    ar10     ar11     ar12     ar13
      -0.0274  0.0082  0.0894  0.0663  -0.0115  0.0206  0.0081  0.0087  -0.0995  0.1061  -0.2492  -0.6328  -0.0016
s.e.   0.0809  0.0809  0.0844  0.0856   0.0855  0.0881  0.0875  0.0870   0.0867  0.0866   0.0871   0.0666   0.0864
         ar14    ar15    ar16     ar17     ar18    ar19     ar20     ar21     ar22     ar23
      -0.0913  0.1671  0.0188  -0.0114  -0.0205  0.0502  -0.0085  -0.0304  -0.0013  -0.1599
s.e.   0.0865  0.0934  0.0950   0.0952   0.0952  0.0956   0.0958   0.0960   0.0965   0.0967

sigma^2 = 2.522:  log likelihood = -299.99
AIC=647.98   AICc=656.61   BIC=722.37

Training set error measures:
                     ME     RMSE       MAE       MPE     MAPE      MASE        ACF1
Training set 0.07950571 1.417431 0.9866235 0.1153632 1.701245 0.2636477 -0.07274862
```

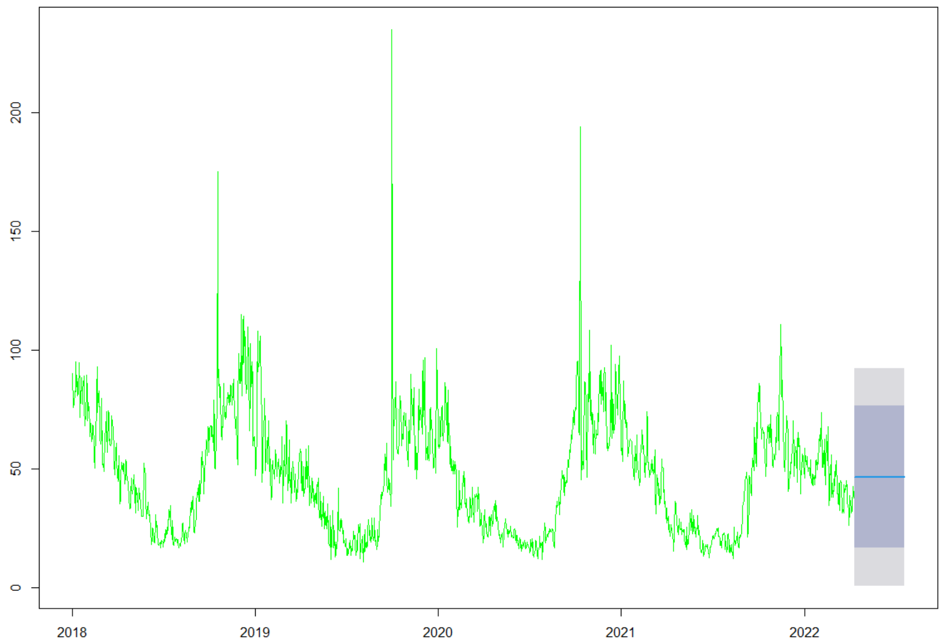
8. Wyznaczenie i porównywanie modeli z wykorzystaniem auto.arima

```
> summary(air_ts2LST_aicc)
Series: air_ts2LST
ARIMA(5,0,0) with zero mean

Coefficients:
          ar1      ar2      ar3      ar4      ar5
      -0.3442  -0.2627  -0.1598  -0.1537  -0.0870
s.e.   0.0253   0.0265   0.0270   0.0265   0.0253

sigma^2 = 0.06304:  log likelihood = -54.77
AIC=121.53   AICc=121.59   BIC=153.6

Training set error measures:
                      ME      RMSE       MAE      MPE     MAPE     MASE         ACF1
Training set 0.000197546 0.2506625 0.1857244 77.15786 187.7947 0.646982 -0.008266208
> summary(air_ts2LS_aicc)
Series: air_ts2LS
ARIMA(3,0,0) with zero mean

Coefficients:
         ar1     ar2     ar3
      0.5826  0.0507  0.0786
s.e.  0.0253  0.0293  0.0253

sigma^2 = 0.05878:  log likelihood = -1.77
AIC=11.54   AICc=11.57   BIC=32.92

Training set error measures:
                       ME     RMSE       MAE     MPE     MAPE      MASE         ACF1
Training set -0.001965013 0.242201 0.1806261 51.4159 227.6675 0.5297951 0.0001078446
```

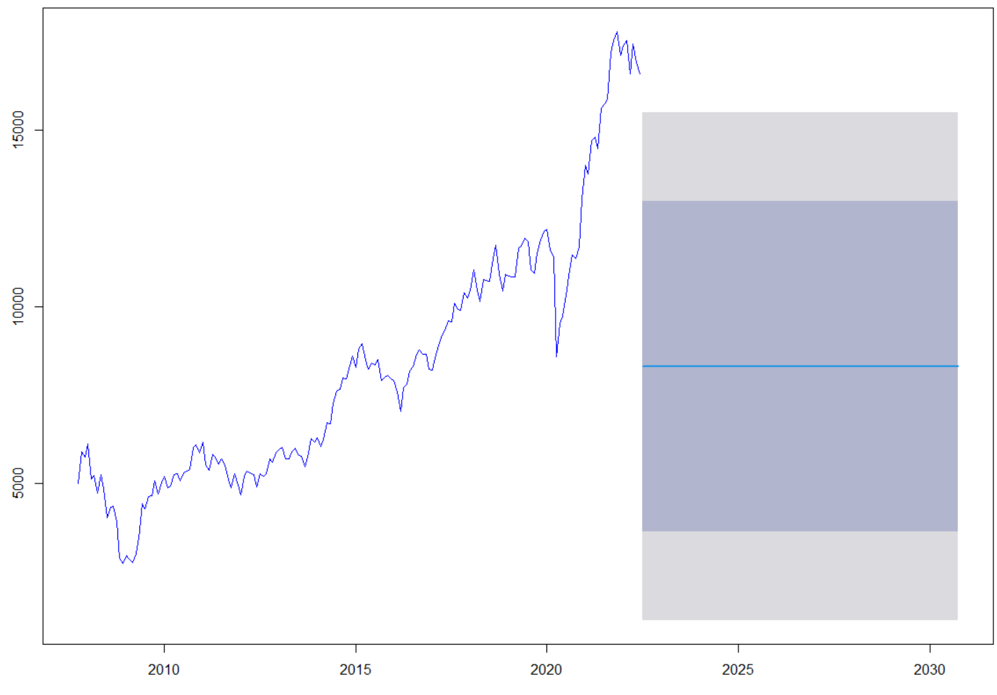
```
> summary(kurs_ts1LST_aicc)
Series: kurs_ts1LST
ARIMA(1,0,0)(1,0,0)[12] with zero mean

Coefficients:
          ar1     sar1
      -0.0545  -0.6276
s.e.   0.0822   0.0681

sigma^2 = 2.457:  log likelihood = -308.41
AIC=622.81   AICc=622.96   BIC=632.11

Training set error measures:
                     ME     RMSE      MAE      MPE     MAPE      MASE        ACF1
Training set 0.09241925 1.557782 1.129978 586.0447 700.7459 0.4673095 -0.02904176
> summary(kurs_ts1LS_aicc)
Series: kurs_ts1L
ARIMA(1,1,0)(2,0,0)[12] with drift

Coefficients:
          ar1     sar1     sar2   drift
      -0.0474  -0.1951  -0.0346  0.1578
s.e.   0.0738   0.0590   0.0712  0.0743

sigma^2 = 1.599:  log likelihood = -289.27
AIC=588.54   AICc=588.9   BIC=604.4

Training set error measures:
                      ME     RMSE       MAE         MPE     MAPE      MASE         ACF1
Training set -0.00631286 1.246702 0.9019191 -0.06710615 1.596275 0.2410128 -0.004442961
> summary(kurs_ts1L_aicc)
Series: kurs_ts1L
ARIMA(1,1,0)(2,0,0)[12] with drift

Coefficients:
          ar1     sar1     sar2   drift
      -0.0474  -0.1951  -0.0346  0.1578
s.e.   0.0738   0.0590   0.0712  0.0743

sigma^2 = 1.599:  log likelihood = -289.27
AIC=588.54   AICc=588.9   BIC=604.4

Training set error measures:
                      ME     RMSE       MAE         MPE     MAPE      MASE         ACF1
Training set -0.00631286 1.246702 0.9019191 -0.06710615 1.596275 0.2410128 -0.004442961
> summary(kurs_ts1_aicc)
Series: kurs_ts1
ARIMA(1,1,0)(2,0,0)[12] with drift
Box Cox transformation: lambda= 0.34102

Coefficients:
          ar1     sar1     sar2   drift
      -0.0483  -0.1962  -0.0345  0.1579
s.e.   0.0780   0.0784   0.0921  0.0742

sigma^2 = 1.599:  log likelihood = -289.27
AIC=588.54   AICc=588.9   BIC=604.4
```

9. Prognozowanie

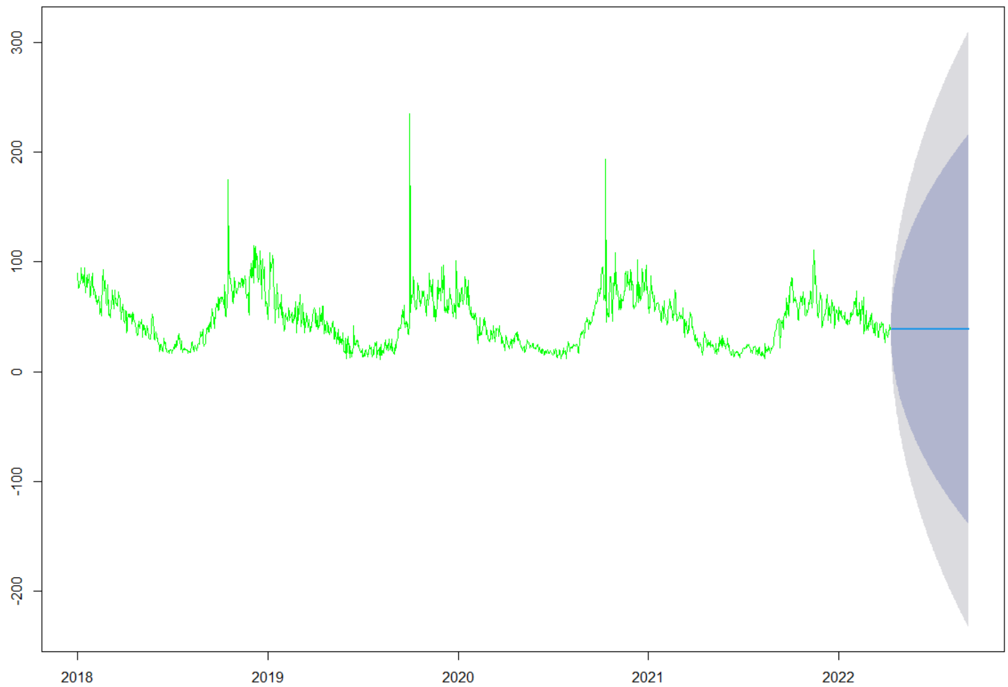
Prognozowanie jakosci poweitrza na podstawie sredniej



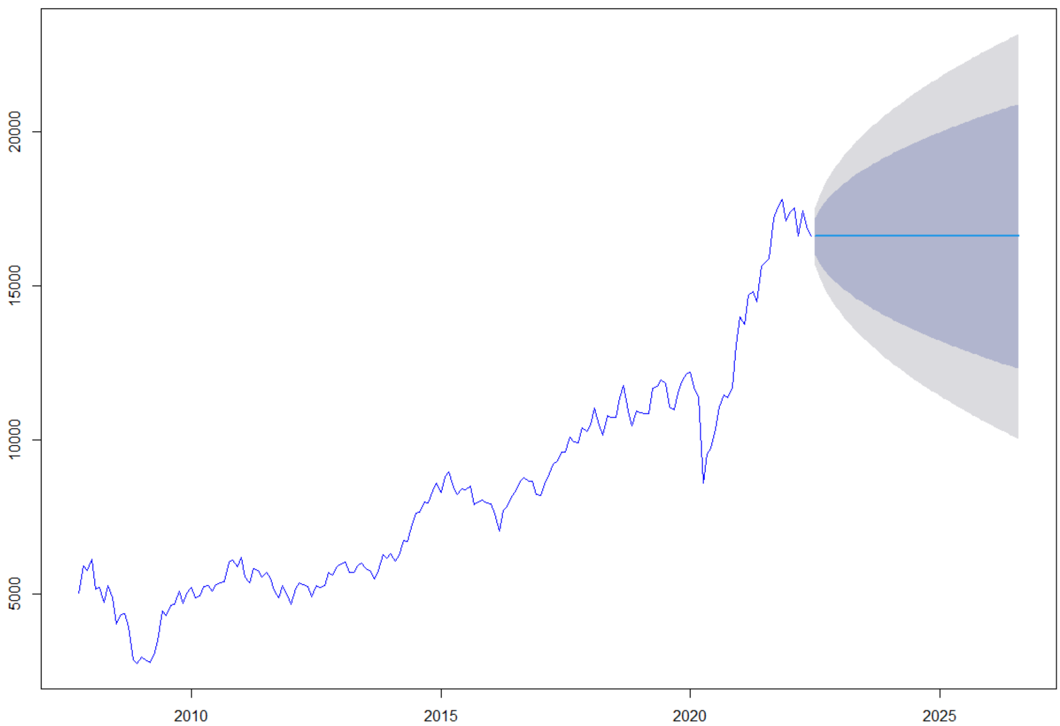
prognozowanie kursu na podstawie sredniej



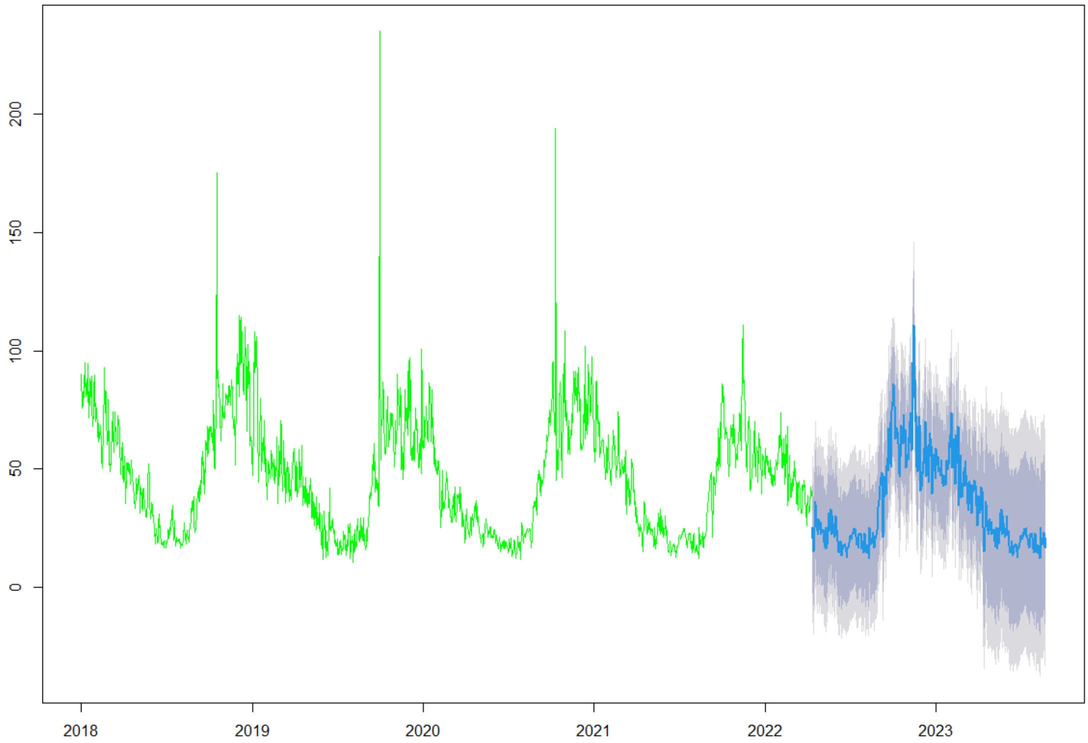
Prognoza jakosci powietrza z wykorzystaniem metody naiwnej



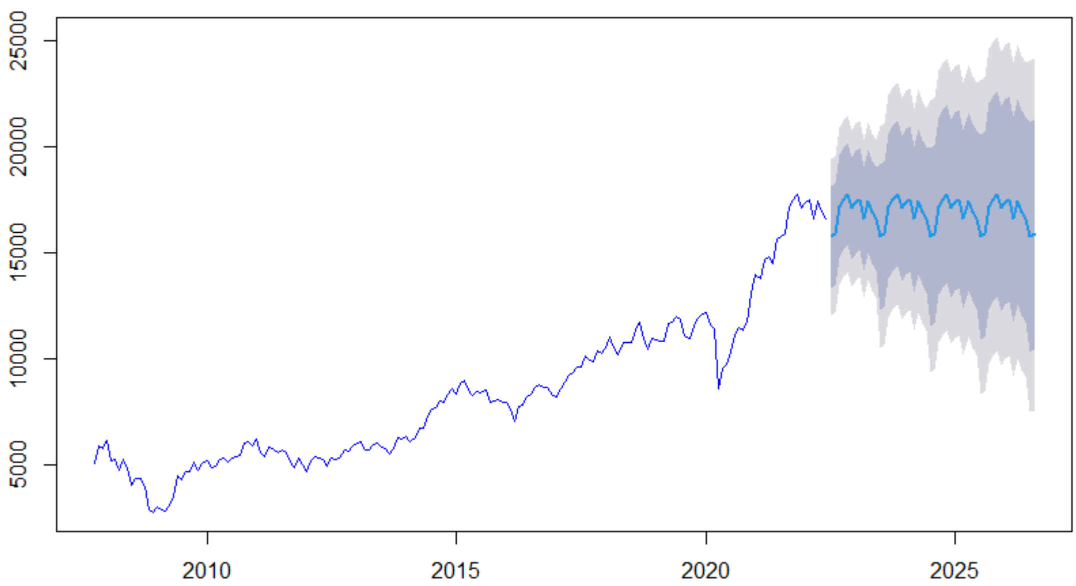
Prognoza kursu Nifty z wykorzystaniem metody naiwnej



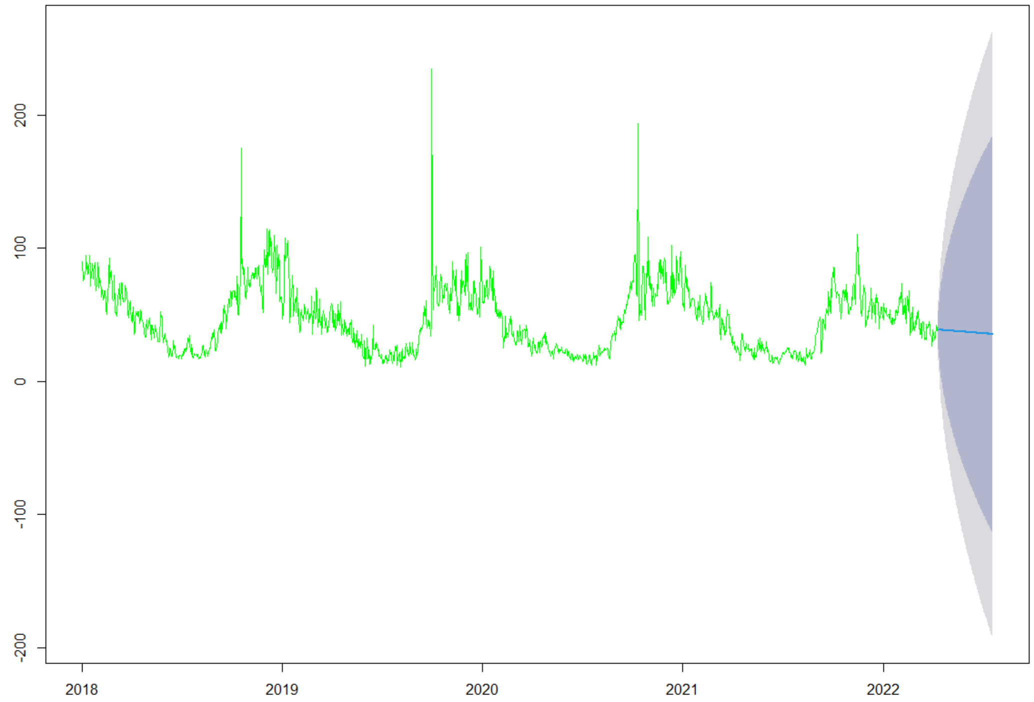
Prognoza jakosci powietrza na podstawie metody naiwnej sezonowej



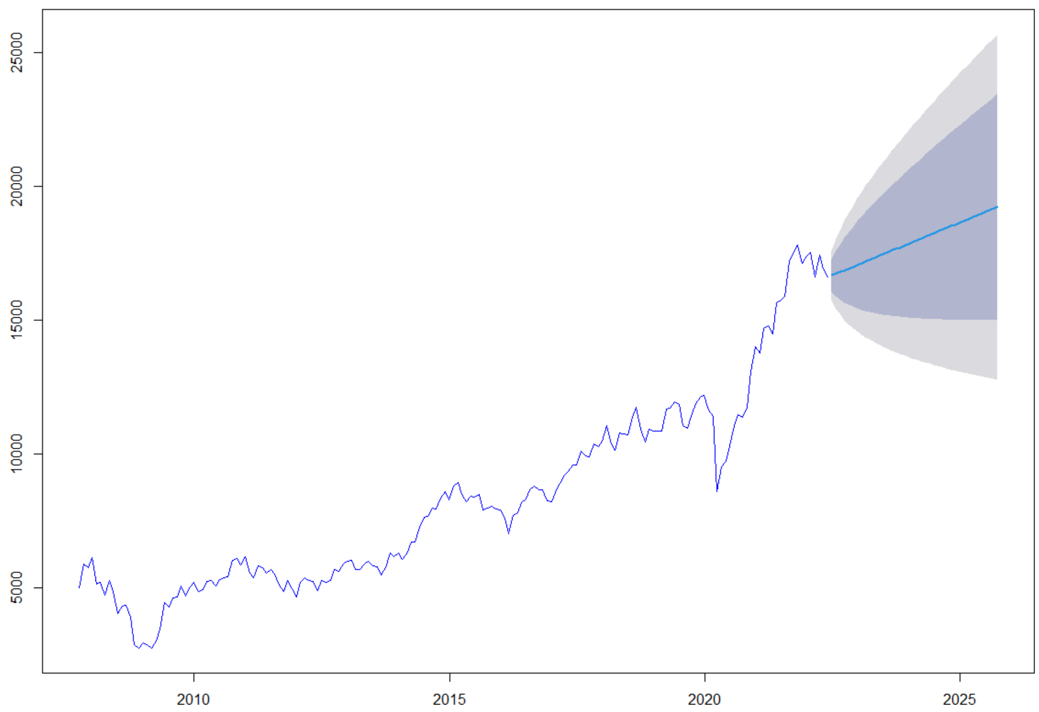
Prognoza kursu Nifty na podstawie metody naiwnej sezonowej



Prognoza jakosci powietrza na podstawie metody uwzgl. dryf



Prognoza kursu Nifty na podstawie metody uwzgl. dryf



```
> (accuracy(air_meanf))
                        ME    RMSE      MAE       MPE     MAPE     MASE      ACF1
Training set -2.304987e-15 23.3397 19.03301 -31.55826 56.85458 1.593311 0.8815051
> (accuracy(air_naive))
                      ME     RMSE      MAE       MPE     MAPE      MASE       ACF1
Training set -0.03294231 11.31044 5.733596 -1.618543 12.45824 0.4799765 -0.3142835
> (accuracy(air_snaive))
                    ME     RMSE      MAE       MPE     MAPE MASE      ACF1
Training set -4.141463 18.00664 11.94558 -14.39369 28.63967    1 0.5249599
> (accuracy(air_dryf))
                       ME    RMSE      MAE       MPE     MAPE      MASE       ACF1
Training set 3.732073e-16 11.3104 5.734445 -1.525603 12.45414 0.4800475 -0.3142835
```

Najlepsza metoda dla przewidywania jakości powietrza to medoda naiwna sezonowa.

```
> (accuracy(kurs_meanf))
                        ME     RMSE      MAE       MPE     MAPE     MASE      ACF1
Training set -5.391394e-13 3617.839 2923.803 -19.96192 41.83716 2.106965 0.9743575
> (accuracy(kurs_naive))
                   ME     RMSE      MAE       MPE     MAPE      MASE        ACF1
Training set 65.75512 473.4713 338.4767 0.4653284 4.581187 0.2439147 -0.04718614
> (accuracy(kurs_snaive))
                   ME     RMSE      MAE      MPE     MAPE MASE      ACF1
Training set 866.1327 1893.338 1387.685 5.895166 17.69829    1 0.9055516
> (accuracy(kurs_dryf))
                        ME     RMSE      MAE        MPE     MAPE      MASE        ACF1
Training set -3.565284e-13 468.8831 332.8774 -0.4808434 4.562074 0.2398797 -0.04718614
```

Najlepsza metoda dla przewidywania kursu NIFTY50 to metoda uwzględniająca dryf.

10.Źródła

- https://finance.yahoo.com/quote/%5ENSEI?p=^NSEI&.tsrc=fin-srch
- https://www.kaggle.com/datasets/fedesoriano/air-quality-data-in-india
- https://pl.wikipedia.org/wiki/Monitoring_powietrza_atmosferycznego