Time Dependent Data Project

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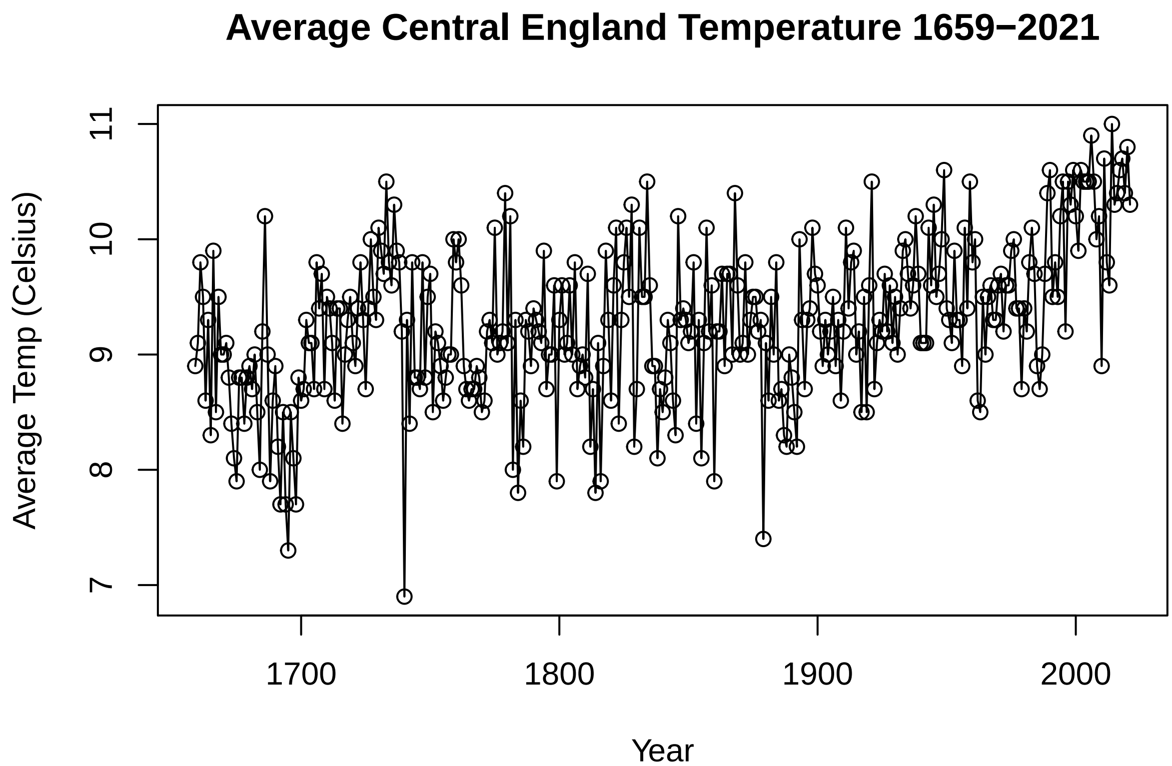
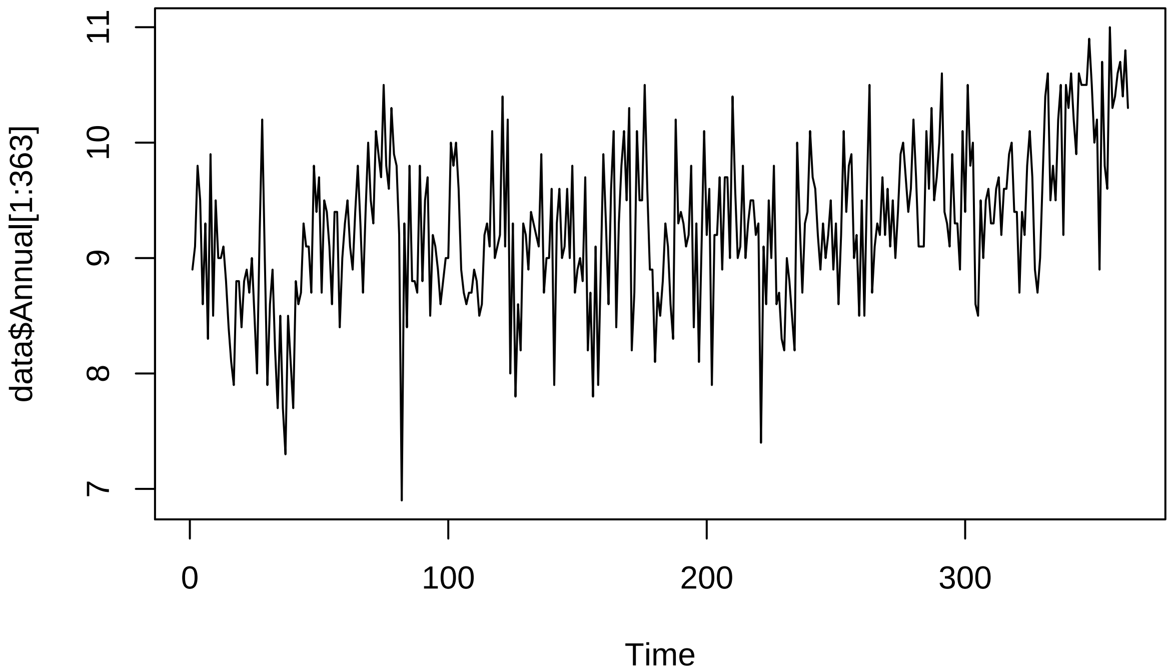
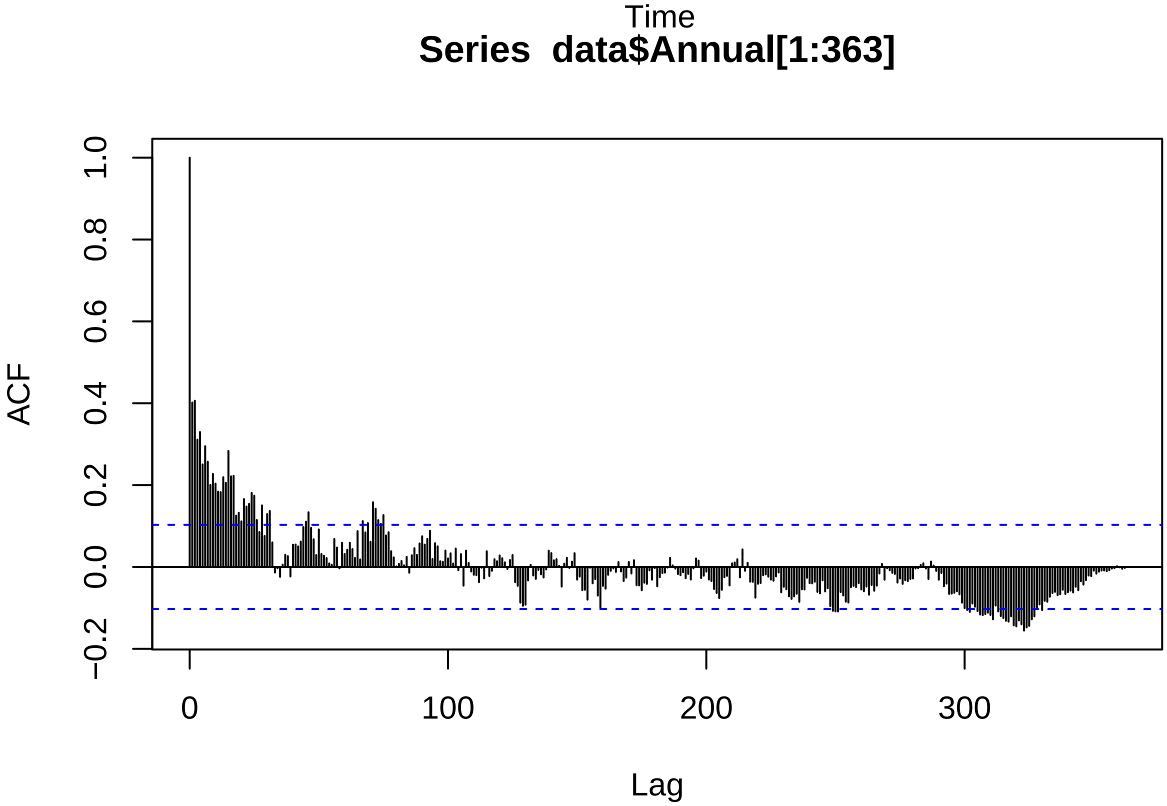
Rising temperatures have been a studied issue for a long time, with many useful datasets arising such as the monthly central England temperature series from 1659 to 2022. Taking a first look at this dataset, we can produce the following:



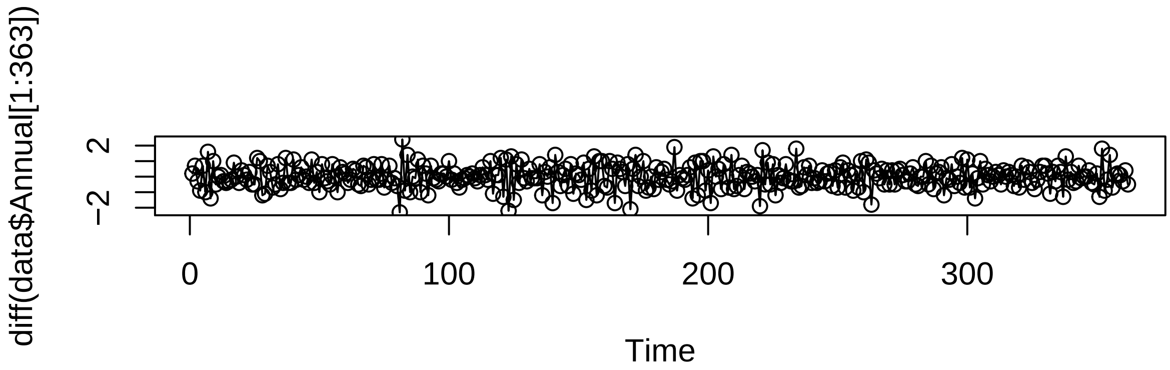
Simply looking at the above plot, it is fairly evident that there is an increase in temperature overtime.

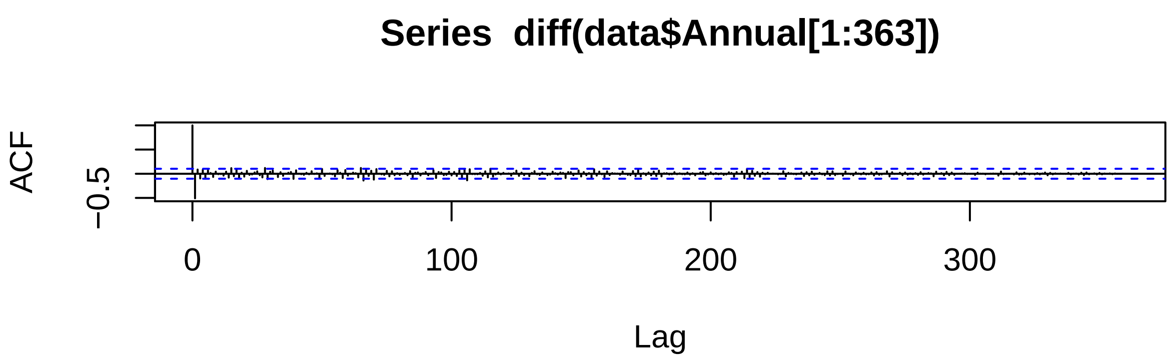




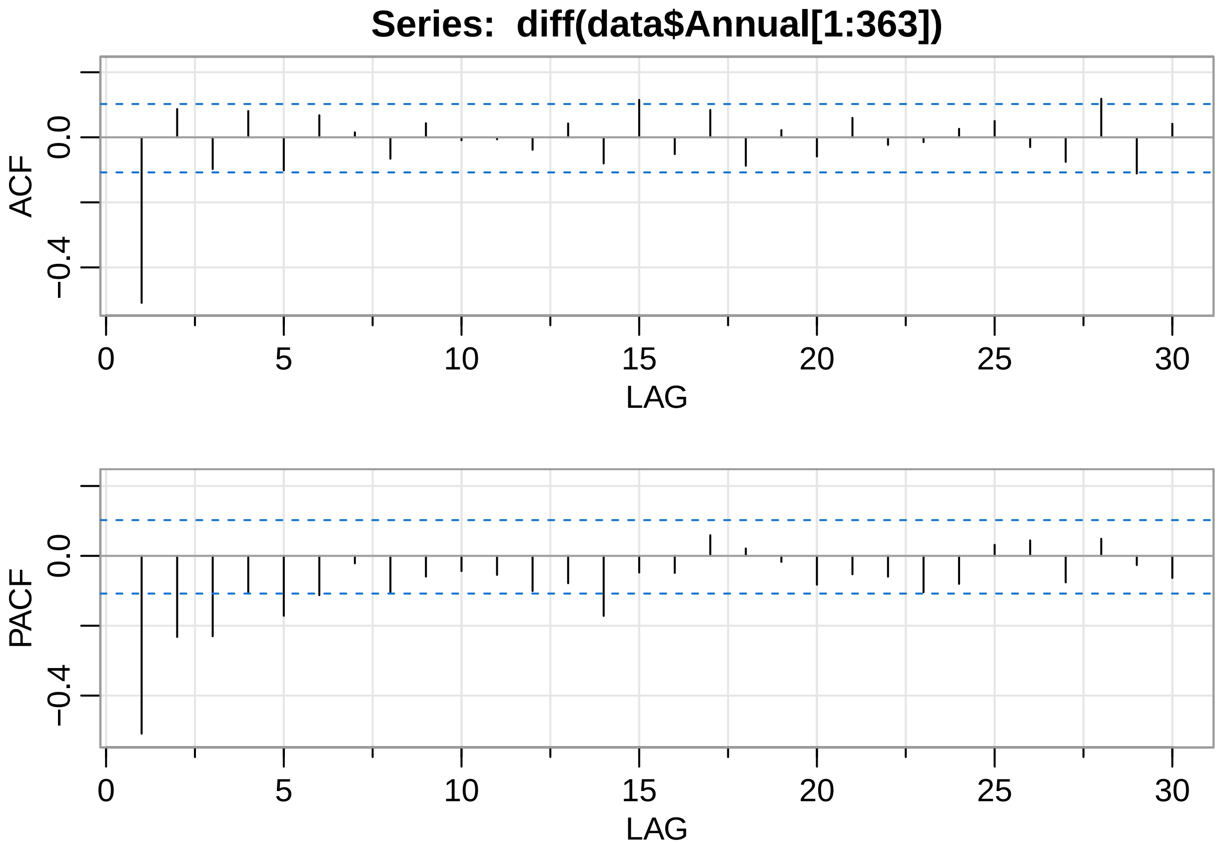
This data does not appear to be stationary based on both the ACF and plot, so we will diff it.

```
## [1] 0.003867403
```

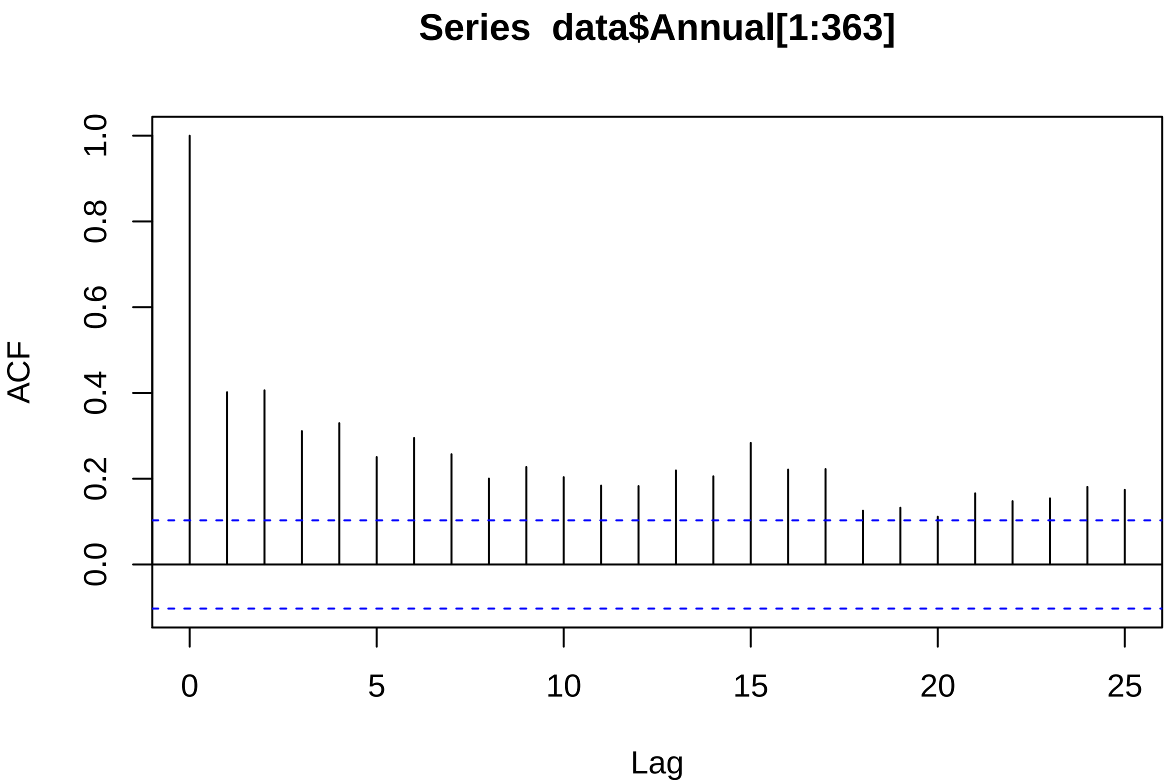




Now, the plot and the ACF both look stationary, meaning the data was correctly altered. We can now check the ACF2 to see if we can fit an ARMA model.



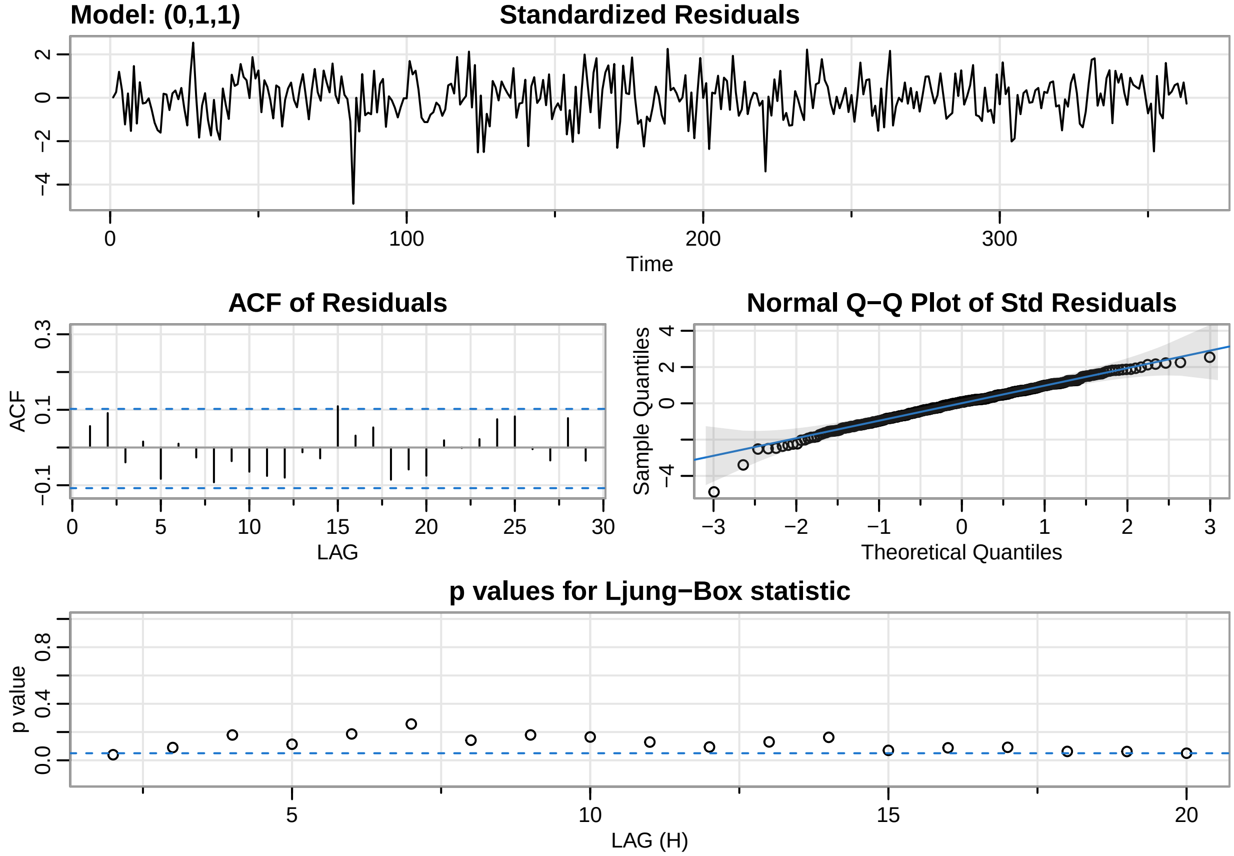

```
##       [,1]  [,2]  [,3]  [,4]  [,5]  [,6]  [,7]  [,8]  [,9] [,10] [,11] [,12]
## ACF  -0.51  0.09 -0.10  0.08 -0.10  0.07  0.02 -0.07  0.04 -0.01 -0.01 -0.04
## PACF -0.51 -0.23 -0.23 -0.11 -0.17 -0.11 -0.02 -0.10 -0.06 -0.04 -0.05 -0.10
##      [,13] [,14] [,15] [,16] [,17] [,18] [,19] [,20] [,21] [,22] [,23] [,24]
## ACF   0.04 -0.08  0.12 -0.05  0.08 -0.09  0.02 -0.06  0.06 -0.02 -0.01  0.03
## PACF -0.08 -0.17 -0.05 -0.05  0.06  0.02 -0.02 -0.08 -0.05 -0.06 -0.10 -0.08
##      [,25] [,26] [,27] [,28] [,29] [,30]
## ACF   0.05 -0.03 -0.08  0.12 -0.11  0.04
## PACF  0.03  0.04 -0.08  0.05 -0.03 -0.06
```



The ACF appears to cut off at a lag of 1 and the PACF seems to tail off, so it may be an MA(1). They also both seem to tail off, so we might be able to fit an ARMA(1,2) model. Later, with this in mind, we can make predictions.

```
## initial  value -0.302309
## iter   2 value -0.491835
## iter   3 value -0.514138
## iter   4 value -0.527866
## iter   5 value -0.531642
## iter   6 value -0.537901
## iter   7 value -0.539556
## iter   8 value -0.542087
## iter   9 value -0.542136
## iter  10 value -0.542408
## iter  11 value -0.542419
## iter  12 value -0.542419
## iter  13 value -0.542419
## iter  14 value -0.542419
## iter  15 value -0.542419
## iter  15 value -0.542419
## iter  15 value -0.542419
## final  value -0.542419
## converged
## initial  value -0.540938
## iter   2 value -0.540947
## iter   3 value -0.540981
## iter   4 value -0.540986
## iter   5 value -0.540986
## iter   5 value -0.540986
## iter   5 value -0.540986
```

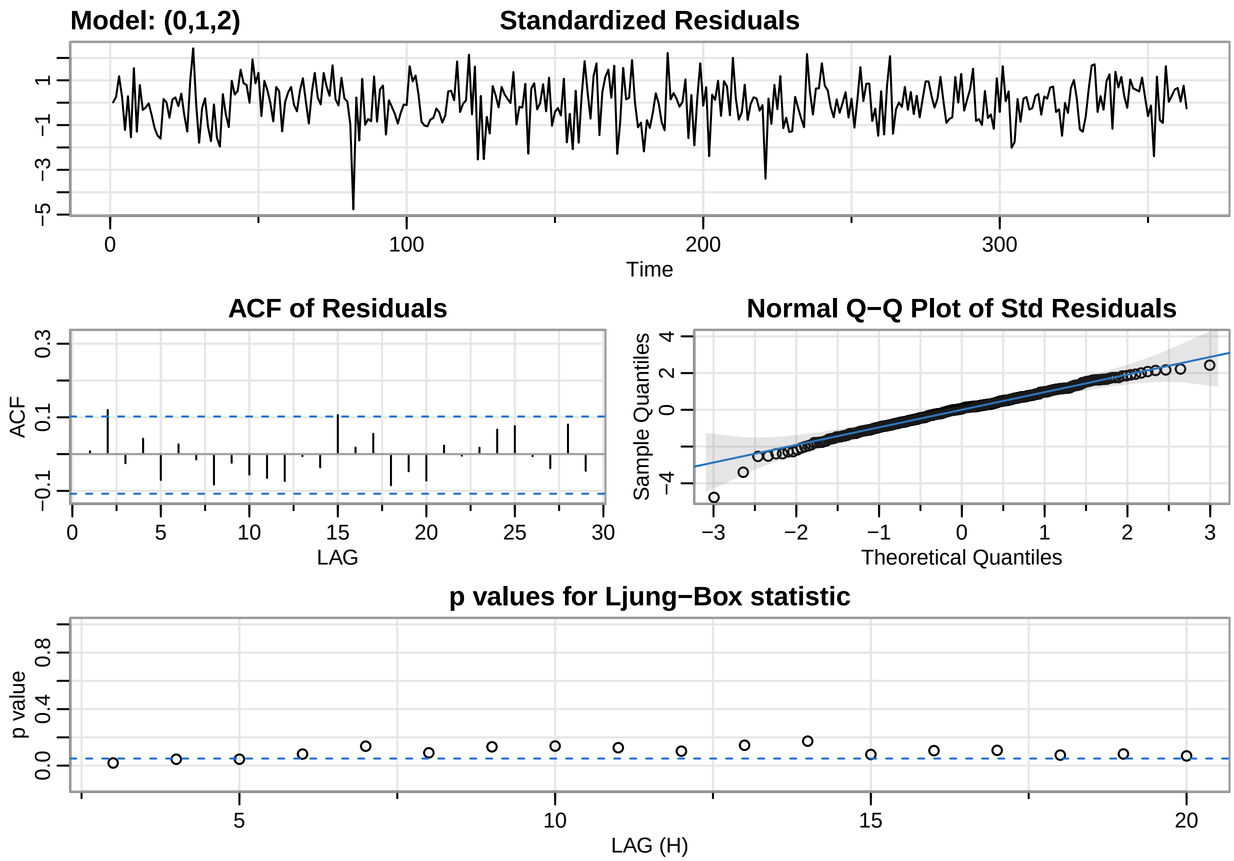
```
## final  value -0.540986
## converged
```




```
## [1] 1.77248
```

```
## initial  value -0.302309
## iter   2 value -0.479795
## iter   3 value -0.514268
## iter   4 value -0.533972
## iter   5 value -0.540735
## iter   6 value -0.543327
## iter   7 value -0.544058
## iter   8 value -0.544687
## iter   9 value -0.544998
## iter  10 value -0.545082
## iter  11 value -0.545104
## iter  12 value -0.545106
## iter  13 value -0.545106
## iter  13 value -0.545106
## iter  13 value -0.545106
## final  value -0.545106
## converged
## initial  value -0.543244
## iter   2 value -0.543275
## iter   3 value -0.543296
## iter   4 value -0.543304
## iter   5 value -0.543304
```

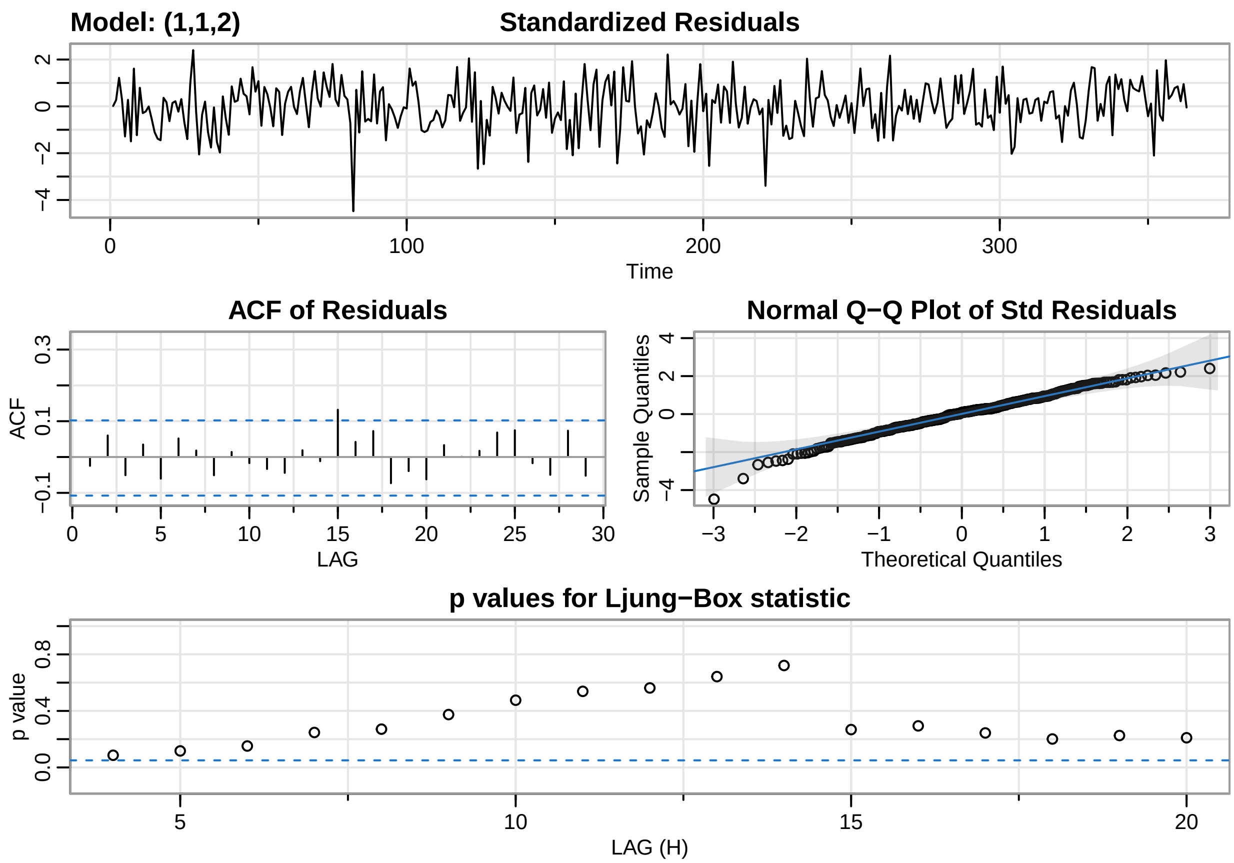
```
## iter   5 value -0.543304
## iter   5 value -0.543304
## final  value -0.543304
## converged
```




```
## [1] 1.773369
```

```
## initial  value -0.301023
## iter   2 value -0.433276
## iter   3 value -0.530347
## iter   4 value -0.541243
## iter   5 value -0.541340
## iter   6 value -0.541425
## iter   7 value -0.541589
## iter   8 value -0.541842
## iter   9 value -0.541857
## iter  10 value -0.541876
## iter  11 value -0.541876
## iter  12 value -0.541883
## iter  13 value -0.541907
## iter  14 value -0.541995
## iter  15 value -0.542278
## iter  16 value -0.542756
## iter  17 value -0.543364
## iter  18 value -0.544581
## iter  19 value -0.545525
## iter  20 value -0.545584
```

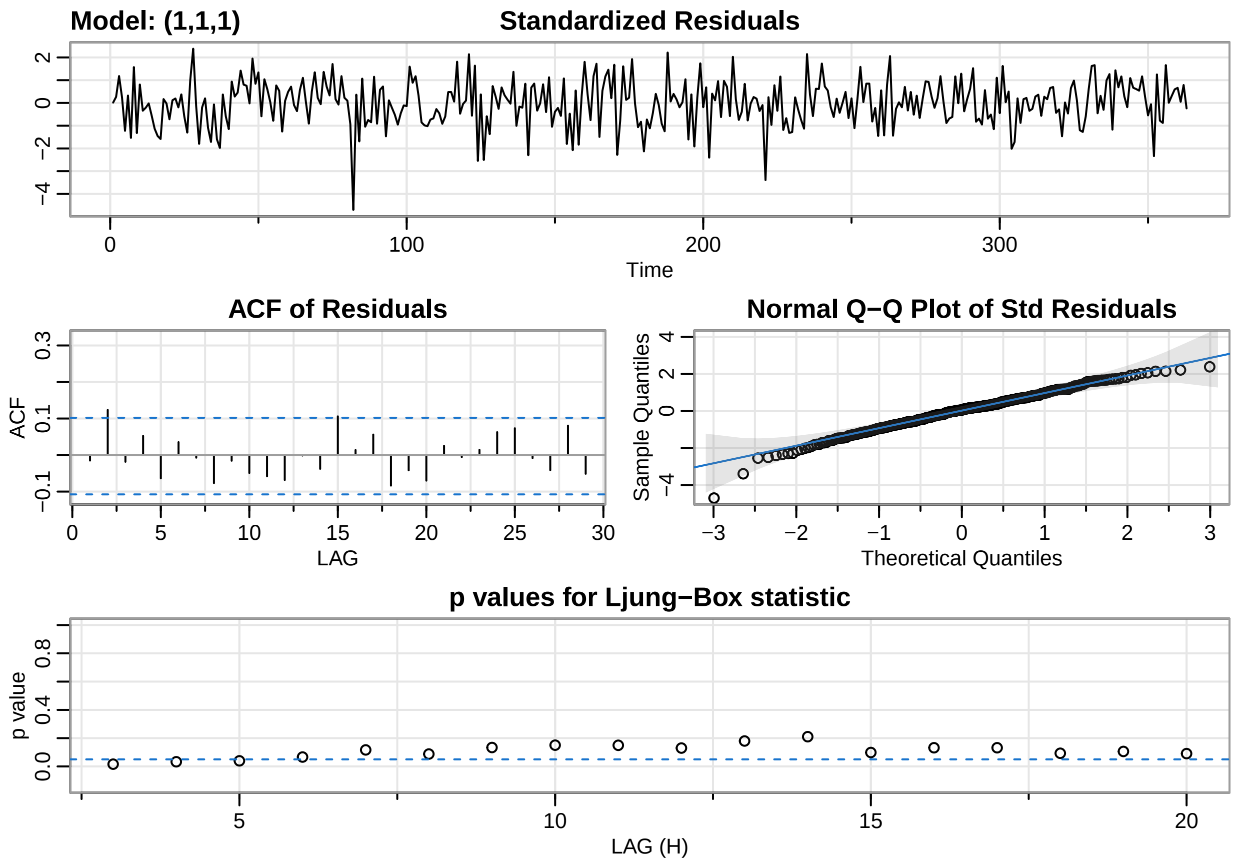
```
## iter  21 value -0.545598
## iter  22 value -0.545638
## iter  23 value -0.545753
## iter  24 value -0.546162
## iter  25 value -0.546778
## iter  26 value -0.547235
## iter  27 value -0.547575
## iter  28 value -0.547581
## iter  29 value -0.547584
## iter  30 value -0.547584
## iter  31 value -0.547585
## iter  32 value -0.547585
## iter  33 value -0.547585
## iter  34 value -0.547585
## iter  35 value -0.547585
## iter  36 value -0.547585
## iter  36 value -0.547585
## iter  36 value -0.547585
## final  value -0.547585
## converged
## initial  value -0.549568
## iter   2 value -0.549900
## iter   3 value -0.549977
## iter   4 value -0.550122
## iter   5 value -0.550235
## iter   6 value -0.552291
## iter   7 value -0.553018
## iter   8 value -0.553283
## iter   9 value -0.553362
## iter  10 value -0.553833
## iter  11 value -0.553873
## iter  12 value -0.553876
## iter  13 value -0.553918
## iter  14 value -0.553925
## iter  15 value -0.553936
## iter  16 value -0.553961
## iter  17 value -0.553994
## iter  18 value -0.554022
## iter  19 value -0.554035
## iter  20 value -0.554035
## iter  21 value -0.554035
## iter  22 value -0.554036
## iter  23 value -0.554036
## iter  23 value -0.554036
## iter  23 value -0.554036
## final  value -0.554036
## converged
```




```
## [1] 1.75743
```

```
## initial  value -0.301023
## iter   2 value -0.463514
## iter   3 value -0.503384
## iter   4 value -0.516626
## iter   5 value -0.526358
## iter   6 value -0.542492
## iter   7 value -0.544161
## iter   8 value -0.544522
## iter   9 value -0.544552
## iter  10 value -0.544581
## iter  11 value -0.544590
## iter  12 value -0.544601
## iter  13 value -0.544601
## iter  13 value -0.544601
## iter  13 value -0.544601
## final  value -0.544601
## converged
## initial  value -0.544301
## iter   2 value -0.544307
## iter   3 value -0.544316
## iter   4 value -0.544320
## iter   5 value -0.544323
## iter   5 value -0.544323
## iter   5 value -0.544323
## final  value -0.544323
```

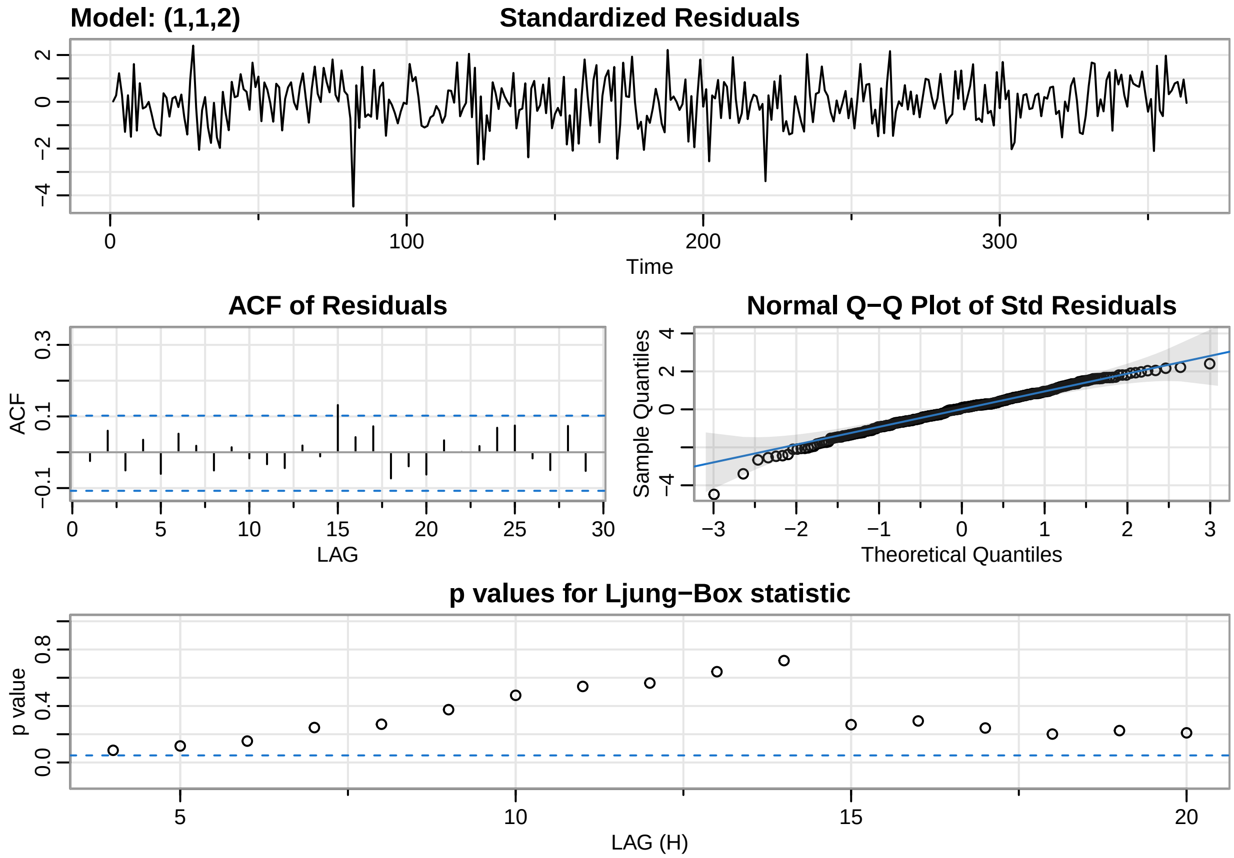
```
## converged
```



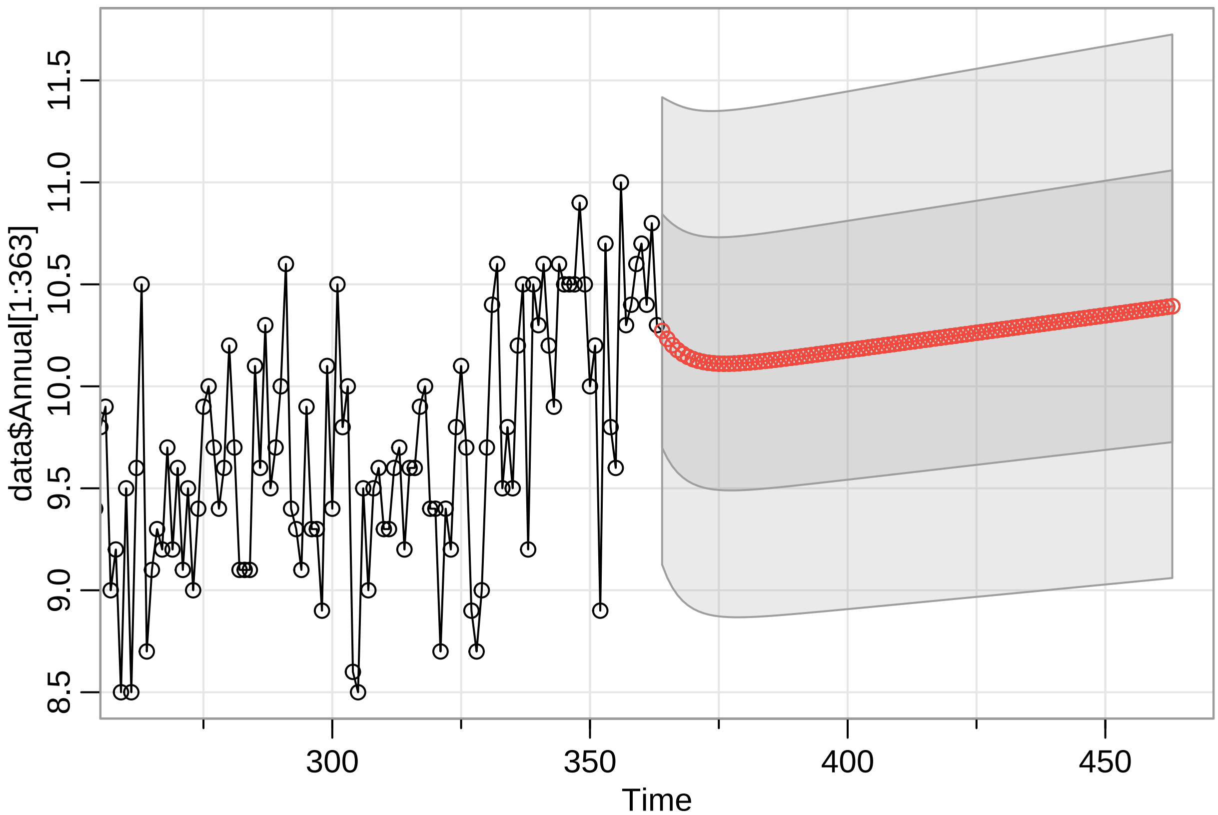

```
## [1] 1.771331
```

```
## initial  value -0.301023
## iter   2 value -0.433276
## iter   3 value -0.530347
## iter   4 value -0.541243
## iter   5 value -0.541340
## iter   6 value -0.541425
## iter   7 value -0.541589
## iter   8 value -0.541842
## iter   9 value -0.541857
## iter  10 value -0.541876
## iter  11 value -0.541876
## iter  12 value -0.541883
## iter  13 value -0.541907
## iter  14 value -0.541995
## iter  15 value -0.542278
## iter  16 value -0.542756
## iter  17 value -0.543364
## iter  18 value -0.544581
## iter  19 value -0.545525
## iter  20 value -0.545584
## iter  21 value -0.545598
## iter  22 value -0.545638
## iter  23 value -0.545753
```

```
## iter  24 value -0.546162
## iter  25 value -0.546778
## iter  26 value -0.547235
## iter  27 value -0.547575
## iter  28 value -0.547581
## iter  29 value -0.547584
## iter  30 value -0.547584
## iter  31 value -0.547585
## iter  32 value -0.547585
## iter  33 value -0.547585
## iter  34 value -0.547585
## iter  35 value -0.547585
## iter  36 value -0.547585
## iter  36 value -0.547585
## iter  36 value -0.547585
## final  value -0.547585
## converged
## initial  value -0.549568
## iter   2 value -0.549900
## iter   3 value -0.549977
## iter   4 value -0.550122
## iter   5 value -0.550235
## iter   6 value -0.552291
## iter   7 value -0.553018
## iter   8 value -0.553283
## iter   9 value -0.553362
## iter  10 value -0.553833
## iter  11 value -0.553873
## iter  12 value -0.553876
## iter  13 value -0.553918
## iter  14 value -0.553925
## iter  15 value -0.553936
## iter  16 value -0.553961
## iter  17 value -0.553994
## iter  18 value -0.554022
## iter  19 value -0.554035
## iter  20 value -0.554035
## iter  21 value -0.554035
## iter  22 value -0.554036
## iter  23 value -0.554036
## iter  23 value -0.554036
## iter  23 value -0.554036
## final  value -0.554036
## converged
```


Model: (1,1,2)
Standardized Residuals
Time
ACF of Residuals
ACF
LAG
Normal Q−Q Plot of Std Residuals
Sample Quantiles
Theoretical Quantiles
p values for Ljung−Box statistic
p value
LAG (H)

```
## [1] 1.75743
```

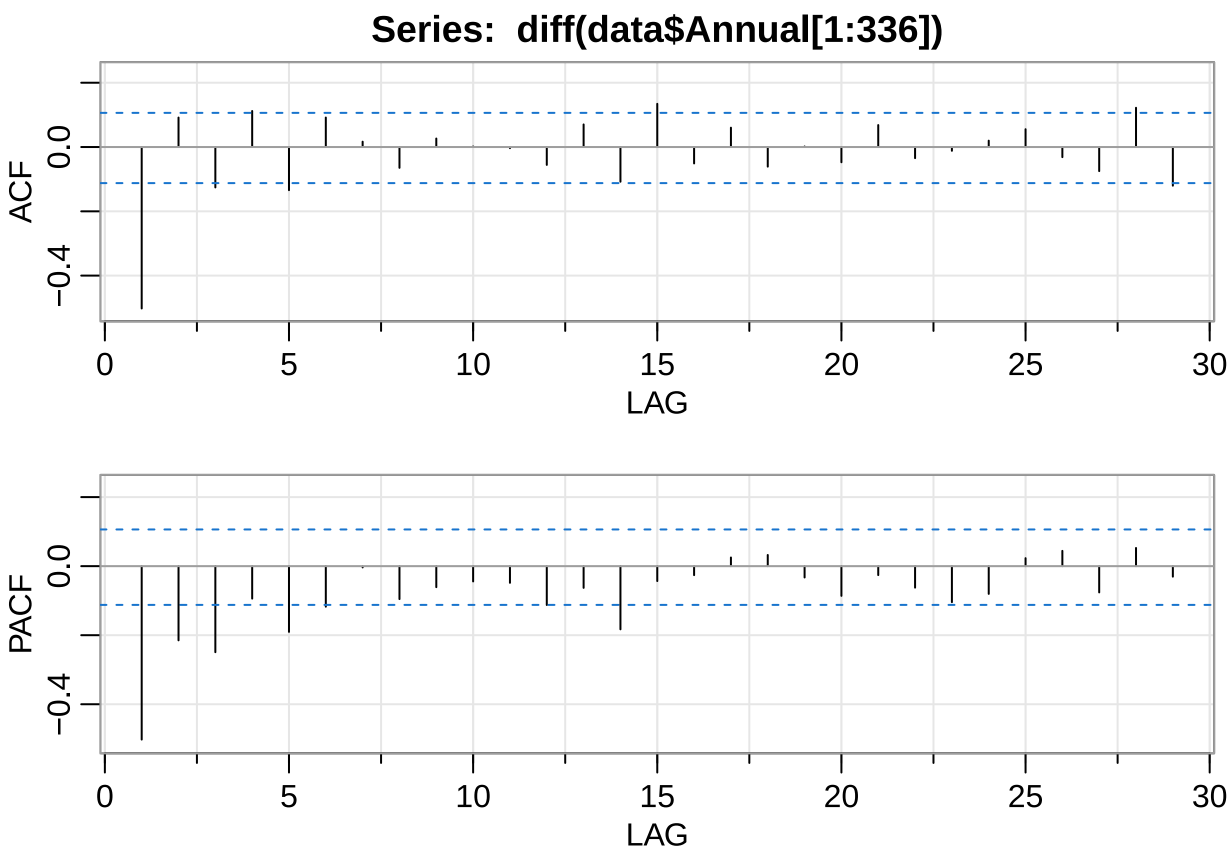



```
## $pred
## Time Series:
## Start = 364
## End = 463
## Frequency = 1
##   [1] 10.27165 10.23265 10.20190 10.17779 10.15903 10.14458 10.13361 10.12543
##   [9] 10.11951 10.11541 10.11277 10.11131 10.11080 10.11106 10.11193 10.11330
##  [17] 10.11507 10.11716 10.11951 10.12207 10.12480 10.12766 10.13064 10.13370
##  [25] 10.13683 10.14002 10.14326 10.14653 10.14984 10.15317 10.15651 10.15988
##  [33] 10.16325 10.16664 10.17003 10.17343 10.17684 10.18025 10.18366 10.18708
##  [41] 10.19050 10.19392 10.19734 10.20076 10.20419 10.20761 10.21104 10.21447
##  [49] 10.21789 10.22132 10.22475 10.22817 10.23160 10.23503 10.23846 10.24188
##  [57] 10.24531 10.24874 10.25217 10.25559 10.25902 10.26245 10.26588 10.26931
##  [65] 10.27273 10.27616 10.27959 10.28302 10.28645 10.28987 10.29330 10.29673
##  [73] 10.30016 10.30359 10.30701 10.31044 10.31387 10.31730 10.32073 10.32416
##  [81] 10.32758 10.33101 10.33444 10.33787 10.34130 10.34472 10.34815 10.35158
##  [89] 10.35501 10.35844 10.36186 10.36529 10.36872 10.37215 10.37558 10.37900
##  [97] 10.38243 10.38586 10.38929 10.39272
##
## $se
## Time Series:
## Start = 364
## End = 463
## Frequency = 1
##   [1] 0.5730332 0.5856091 0.5944635 0.6008429 0.6055456 0.6090941 0.6118362
##   [8] 0.6140070 0.6157675 0.6172293 0.6184712 0.6195490 0.6205032 0.6213634
##  [15] 0.6221512 0.6228831 0.6235713 0.6242252 0.6248521 0.6254575 0.6260459
##  [22] 0.6266205 0.6271842 0.6277391 0.6282868 0.6288287 0.6293658 0.6298990
```

```
##  [29] 0.6304290 0.6309564 0.6314816 0.6320049 0.6325266 0.6330469 0.6335661
##  [36] 0.6340843 0.6346015 0.6351180 0.6356337 0.6361487 0.6366632 0.6371770
##  [43] 0.6376903 0.6382031 0.6387154 0.6392272 0.6397386 0.6402495 0.6407599
##  [50] 0.6412699 0.6417795 0.6422887 0.6427974 0.6433058 0.6438137 0.6443212
##  [57] 0.6448283 0.6453350 0.6458413 0.6463473 0.6468528 0.6473579 0.6478626
##  [64] 0.6483669 0.6488708 0.6493744 0.6498775 0.6503803 0.6508826 0.6513846
##  [71] 0.6518862 0.6523874 0.6528882 0.6533887 0.6538887 0.6543884 0.6548877
##  [78] 0.6553866 0.6558851 0.6563833 0.6568810 0.6573784 0.6578755 0.6583721
##  [85] 0.6588684 0.6593643 0.6598598 0.6603549 0.6608497 0.6613441 0.6618382
##  [92] 0.6623319 0.6628252 0.6633181 0.6638107 0.6643029 0.6647947 0.6652862
##  [99] 0.6657773 0.6662681
```

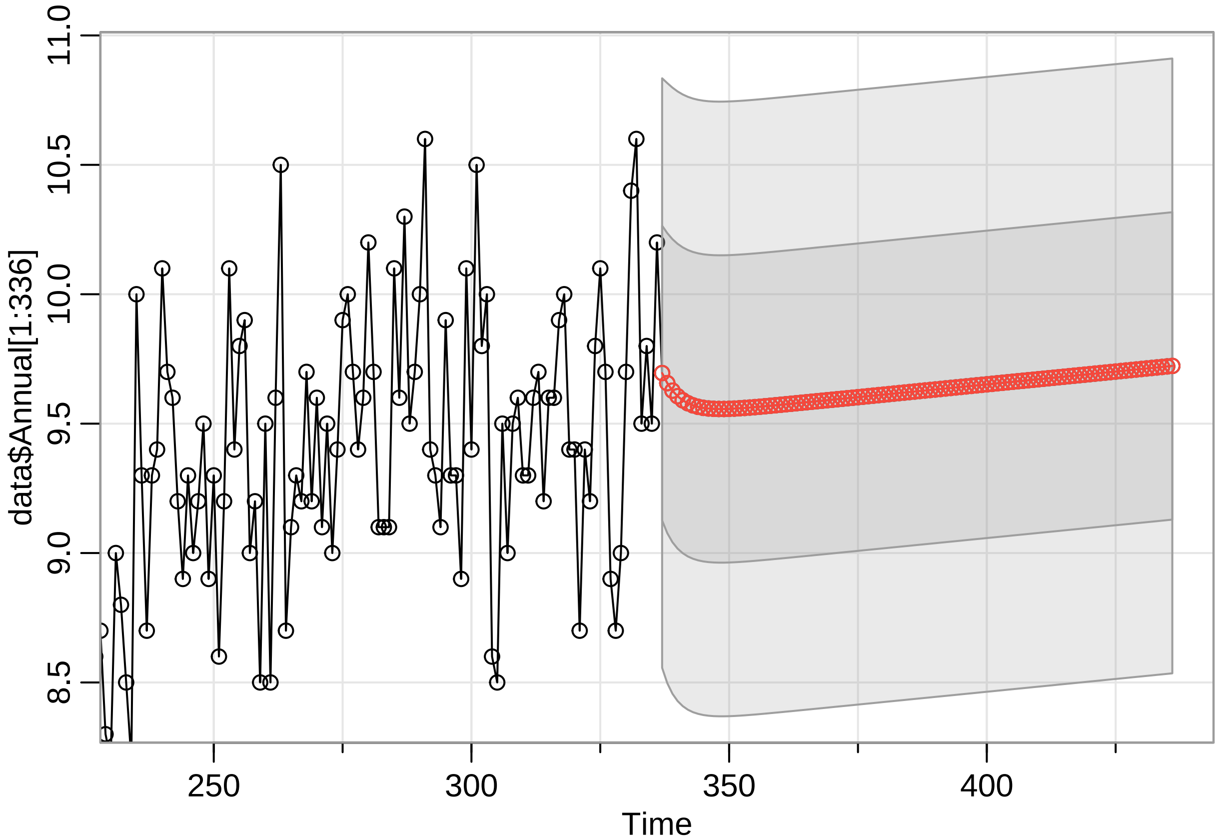
Our prediction here seems to be that the average annual temperature will decrease in the next few years before increasing.

Next, looking at Vaidyanathan (2016), there are claims that rising temperatures slowed in the 2000s, adding that in the 2010s the slowdown ended. To verify these results for Central England, I plan to first look at the data until 2000 and predict the following 20 years, then look at the difference from the actual temperature. If the resulting predictions are lower on average than the true results by a significant amount, the slowdown appears in our data. We can also see if trends continued as they used to for the following 10 years we now have data for.




```
##      [,1]  [,2]  [,3]  [,4]  [,5]  [,6] [,7]  [,8]  [,9] [,10] [,11] [,12]
## ACF  -0.5  0.09 -0.13  0.11 -0.13  0.09 0.02 -0.06  0.03  0.00  0.00 -0.06
## PACF -0.5 -0.21 -0.25 -0.09 -0.19 -0.12 0.00 -0.10 -0.06 -0.04 -0.05 -0.11
##      [,13] [,14] [,15] [,16] [,17] [,18] [,19] [,20] [,21] [,22] [,23] [,24]
## ACF   0.07 -0.11  0.13 -0.05  0.06 -0.06  0.00 -0.05  0.07 -0.03 -0.01  0.02
## PACF -0.06 -0.18 -0.04 -0.03  0.03  0.03 -0.03 -0.09 -0.03 -0.06 -0.10 -0.08
##      [,25] [,26] [,27] [,28] [,29]
```

```
## ACF   0.06 -0.03 -0.07  0.12 -0.12
## PACF  0.02  0.04 -0.08  0.05 -0.03
```




```
## $pred
## Time Series:
## Start = 337
## End = 436
## Frequency = 1
##   [1] 9.695472 9.656474 9.627447 9.605965 9.590193 9.578740 9.570556 9.564846
##   [9] 9.561006 9.558583 9.557230 9.556689 9.556761 9.557297 9.558184 9.559337
##  [17] 9.560691 9.562197 9.563819 9.565527 9.567301 9.569125 9.570987 9.572878
##  [25] 9.574790 9.576718 9.578659 9.580609 9.582566 9.584529 9.586495 9.588465
##  [33] 9.590437 9.592411 9.594386 9.596362 9.598339 9.600316 9.602294 9.604272
##  [41] 9.606250 9.608229 9.610208 9.612187 9.614165 9.616144 9.618124 9.620103
##  [49] 9.622082 9.624061 9.626040 9.628019 9.629998 9.631977 9.633957 9.635936
##  [57] 9.637915 9.639894 9.641873 9.643853 9.645832 9.647811 9.649790 9.651769
##  [65] 9.653749 9.655728 9.657707 9.659686 9.661665 9.663644 9.665624 9.667603
##  [73] 9.669582 9.671561 9.673540 9.675520 9.677499 9.679478 9.681457 9.683436
##  [81] 9.685416 9.687395 9.689374 9.691353 9.693332 9.695312 9.697291 9.699270
##  [89] 9.701249 9.703228 9.705207 9.707187 9.709166 9.711145 9.713124 9.715103
##  [97] 9.717083 9.719062 9.721041 9.723020
##
## $se
## Time Series:
## Start = 337
## End = 436
## Frequency = 1
##   [1] 0.5694690 0.5796238 0.5854573 0.5888454 0.5908326 0.5920096 0.5927145
```

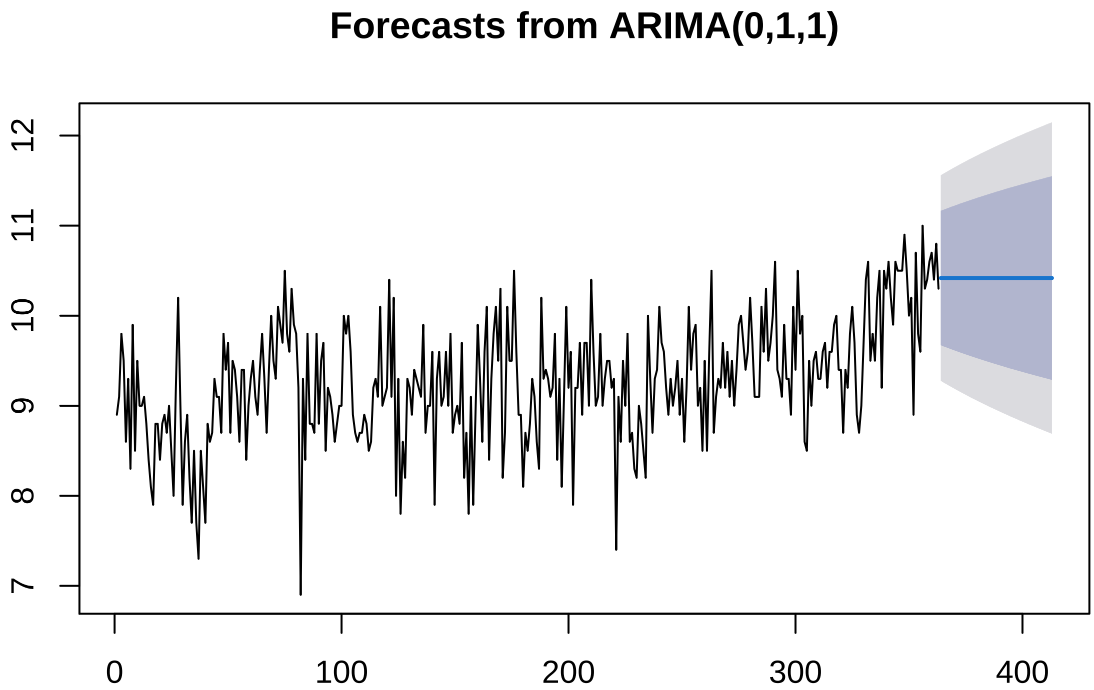
```
##    [8] 0.5931418 0.5934047 0.5935689 0.5936734 0.5937412 0.5937860 0.5938162
##   [15] 0.5938369 0.5938513 0.5938616 0.5938689 0.5938742 0.5938781 0.5938810
##   [22] 0.5938832 0.5938847 0.5938859 0.5938868 0.5938875 0.5938880 0.5938884
##   [29] 0.5938887 0.5938889 0.5938891 0.5938892 0.5938893 0.5938893 0.5938894
##   [36] 0.5938894 0.5938895 0.5938895 0.5938895 0.5938895 0.5938895 0.5938895
##   [43] 0.5938895 0.5938896 0.5938896 0.5938896 0.5938896 0.5938896 0.5938896
##   [50] 0.5938896 0.5938896 0.5938896 0.5938896 0.5938896 0.5938896 0.5938896
##   [57] 0.5938896 0.5938896 0.5938896 0.5938896 0.5938896 0.5938896 0.5938896
##   [64] 0.5938896 0.5938896 0.5938896 0.5938896 0.5938896 0.5938896 0.5938896
##   [71] 0.5938896 0.5938896 0.5938896 0.5938896 0.5938896 0.5938896 0.5938896
##   [78] 0.5938896 0.5938896 0.5938896 0.5938896 0.5938896 0.5938896 0.5938896
##   [85] 0.5938896 0.5938896 0.5938896 0.5938896 0.5938896 0.5938896 0.5938896
##   [92] 0.5938896 0.5938896 0.5938896 0.5938896 0.5938896 0.5938896 0.5938896
##   [99] 0.5938896 0.5938896
```

Thus we can get predictions of the differenced data for the 2000s as seen above. Looking at the plot, it seems that there was not a slowdown. The trends are continuing to be followed as said by NOAA. In the long run, there is still warming occurring. The dip still follows the prediction of the best model, albeit a bit slow; while my prediction does not go above 10 for a little while, annual average temperature has gone back up to 10s already and even reached 11.

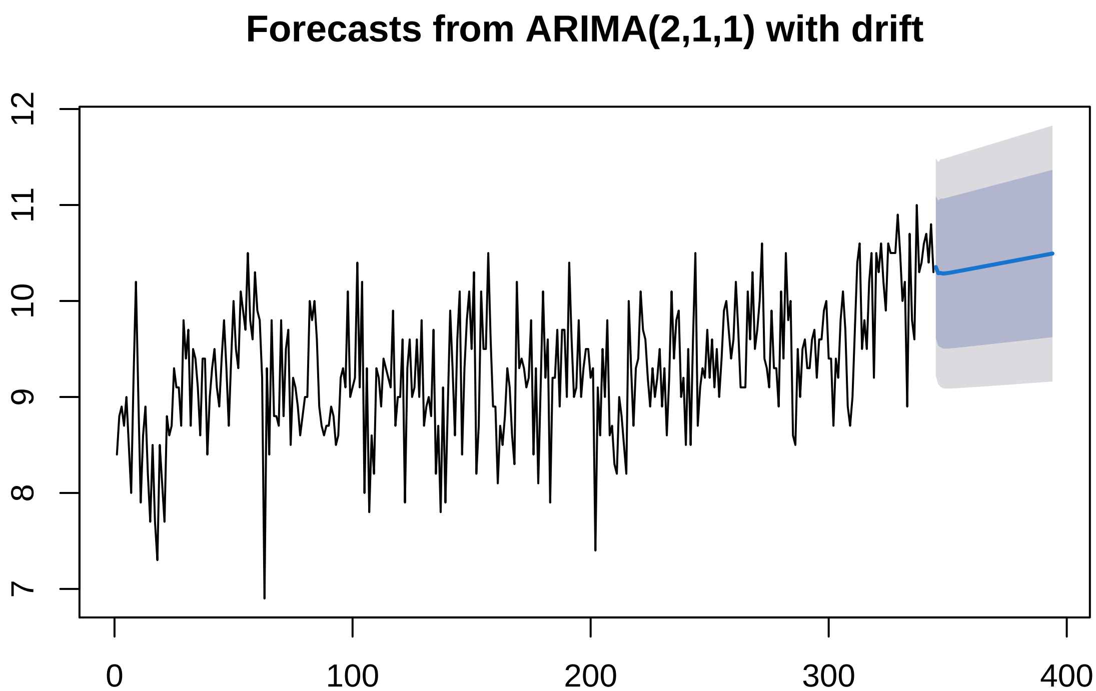
It was in consideration to use SARIMA for the modelling, however there is a break in the data from 1970 to 2000 as explained in one of the journals. Thus, to avoid errors, I used ARMA without seasonal inputs.

Additionally, we can also try using auto.arima to see if we get different results:

```
## Warning: package 'forecast' was built under R version 4.0.5

## Registered S3 method overwritten by 'quantmod':
##   method            from
##   as.zoo.data.frame zoo

##
## Attaching package: 'forecast'

## The following object is masked from 'package:astsa':
##
##     gas
```

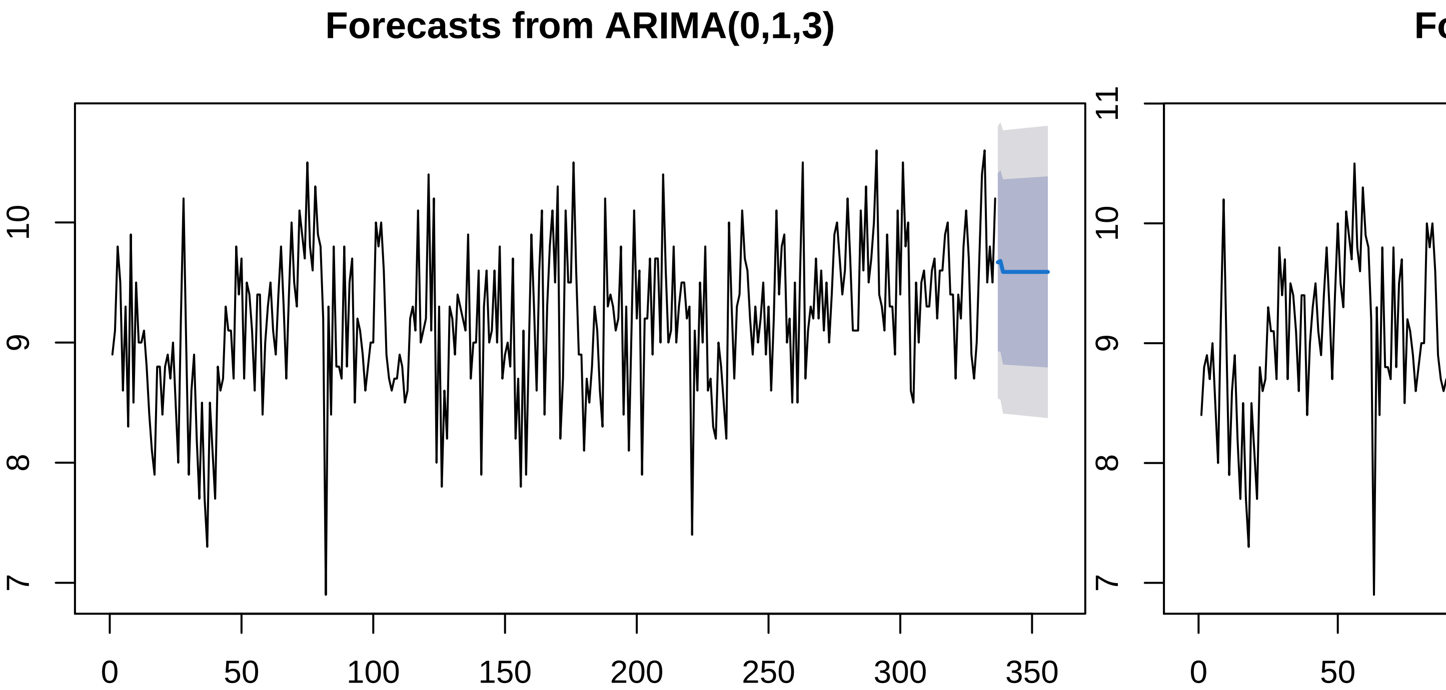


and using data from 20-363 to train gives different information:



This assigned an MA(1) with the full dataset and ARMA(2,1) with drift for the shorter dataset and proposes that the temperature will be the same and slowly increase, respectively.

Finally, trying to predict the 2000s given the prior data as before, we get that the temperature stagnates after an initial dip, agreeing with the statement that the slowdown follows the same pattern:


Forecasts from ARIMA(0,1,3)
Fo
7
8
9
10
11
0
50
100
150
200
250
300
350