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Running head: Breeding bird surveillance

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**Evaluation of the Association of Long-Term Breeding Bird Surveys
and Audubon Christmas Count Data with the Transmission of St.
Louis Encephalitis Virus and West Nile Virus to Sentinel Chickens**

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ABSTRACT

We have known for some time that the relationships and interactions between environmental conditions, virus, mosquito vector, and avian hosts set the stage for Saint Louis encephalitis virus (SLEV) and/or West Nile virus (WNV) amplification and transmission in Florida. Field studies have indicated that Blue Jay, Common Grackle, Mourning Dove, Northern Cardinal, and Northern Mockingbird populations provide the critical amplification link necessary to support SLEV and WNV epidemics. Currently, mosquito control programs in Florida can track the amplification and transmission of arbovirus through the use of sentinel chicken flocks. Along with the estimation of mosquito vector populations and real-time tracking of environmental factors that can trigger epidemics, local mosquito control arbovirus surveillance programs have a host of tools to calculate the risk of arboviral transmission to humans. One tool that is not readily available to mosquito control is the annual avian breeding success and the distribution of fledgling birds. These two important components of avian populations directly impact arboviral amplification, transmission, and the probability of widespread arboviral epidemics. To fill this gap, we investigated the association of Breeding Bird Survey and Christmas Bird Count Data with SLEV transmission to sentinel chickens from 1978 to 2015 across Peninsular Florida using data from 37 counties. Using a modified ARIMA (Box-Jenkins) Modeling Algorithm for Time Series, we compared both BBS average counts per route and trend indexes against SLE sentinel chicken seroconversions on an annual basis. We identified positive correlations between SLE transmission to sentinel chickens and Common Grackle population averages 4 and 5 years prior. Various other significant positive and negative correlations were found between BBS data and SLE transmission to sentinel chickens in prior years for Blue Jay, Common Grackle, Northern Cardinal and Northern Mockingbird species. No correlations were evident for Mourning Dove populations. Further analysis of each significant for Granger causality identified only one significant correlation in which SLE transmission leads Northern Mockingbird average by 9 years. The output of the study has shown that the Common Grackle may be useful as an indicator for increased SLE transmission across Peninsular Florida in following years and requires further study. Further examination of the correlations identified in this study would be beneficial to Florida mosquito control programs by adding to their arboviral surveillance capabilities without added costs to their program.

Key Words

arboviral surveillance, breeding birds, arboviral transmission

INTRODUCTION

The relationships and interactions between environmental conditions, virus, mosquito vector, and avian hosts have been shown to determine the state of Saint Louis encephalitis virus (SLEV) and/or West Nile virus (WNV) amplification and transmission in Florida. In an effort to better understand those relationships and interactions, these four factors have been classified into two groups: Primers and Triggers. Primers are defined as the biotic conditions that align in space and time before major SLEV/WNV epidemics and include the virus, mosquito vectors, and avian hosts. Triggers, which are typically abiotic in nature, would include environmental conditions and patterns. The proper alignment of the primers leads to increase amplification of the virus in both the mosquito vector and avian hosts (wild birds). If the amplification of the virus reaches a threshold and environmental trigger is introduced, an epidemic is possible (Day 2001).

In an effort to predict and prepare for epidemics, many mosquito control programs in Florida run arboviral surveillance programs. To date, the most reliable surveillance tool for amplification and timely indication of actual viral transmission available to mosquito control programs is a long-term sentinel chicken flock (Day, 1989). Mosquito control programs have also become highly effective in monitoring mosquito vector populations and dispersal. And with the advent of the internet, monitoring local environmental conditions has never been easier or more accurate. The one factor in epidemics that is not easily measured is the properties of the avian host populations.

The importance of the avian hosts in the amplification phase of SLEV and WNV in Florida has been demonstrated in various studies (McLean and Bowen 1980; Shaman and Day, 2002). Specifically, four species of birds have been identified to play the most importance in the amplification cycle: Blue Jay, Common Grackle, Mourning Dove, and Northern Cardinal (Day 2001, Day and Stark 1999). The distributions of these four important avian species are shown in [Figure 1](#). Depending upon environmental conditions, these host species can produce large numbers of susceptible offspring,

leading to increased arbovirus amplification and the possibility of reaching the primer threshold (Day, 2001).

To accurately gauge avian host amplification levels, host serosurveys are generally conducted. The primary downside to such serosurveys is that they are labor intensive. Other issues also include the requirement to obtain and keep the proper State and Federal permits, a commitment to establish baseline data sets through long-term sampling, and a general lack of experience in accurately interpreting the results (Day and Lewis, 1991). Due to such issues, host serosurveys are typically beyond the scope of most mosquito control surveillance programs in Florida.

While increased amplification is no guarantee of transmission to humans, any increased amplification of arbovirus in wild birds may increase the relative risk of transmission to humans and must be included in any serious risk analysis protocol. However, host amplification levels are only one of many wild bird factors that must be considered. Other factors, such as avian breeding success, percentage of the population that is susceptible, distribution, and relative abundance can be equally important to any risk analysis. The inability of mosquito control programs in Florida to monitor avian host factors leaves a large deficit in any effort by their arboviral surveillance programs to effectively evaluate risk to the human population.

The North American Breeding Bird Survey (BBS) provides data specific to population change and relative abundance for ~420 bird species in the United States and Canada (Sauer et al. 2008). Observers conduct fifty counts of 3 minutes in length, along predefined routes. Within the Peninsular Florida (PF) Bird Conservation Region (BCR) ([Figure 2](#)) the BBS consists of 75 routes with each route being ~39 km long with stops at approximately 0.8 km intervals. At each stop, every bird seen within a 0.4 km radius or heard is counted (BBS website, <http://www.mbr-pwrc.usgs.gov/bbs/bbs.html>). The BBS surveys are conducted during the peak of the nesting season, May – June) in Peninsular Florida. Data collected annually includes the total number of individuals (count) detected of the species and a modeled

population index (trend). Those data are available online on the BBS website:
<https://www.pwrc.usgs.gov/BBS>.

Starting in 1978, a state-wide sentinel chicken surveillance program was established in 36 Florida counties (Day and Lewis 1991) across Florida. Currently, there are over 40 organizations participating in the Florida sentinel chicken surveillance program, with approximately 340 sentinel chicken flocks located throughout the state. Current test protocols for sentinel chickens in Florida recommend that serum be drawn once a week from each chicken in each flock (Florida Department of Health, 2014). The collected serum samples are then shipped overnight to the Florida Department of Health (DOH) Bureau of Laboratory Services Activities (BLSA) in Tampa, FL for testing of the following viruses: eastern equine encephalitis virus (EEEV), Highlands J virus (HJV), St. Louis encephalitis virus (SLEV), and West Nile virus (WNV) via hemagglutination inhibition assay (HAI). Chickens with HAI titers of >1:10 are considered first time positive (FTP) test results.

The overall objective of this study was to evaluate the long-term association between and identify any temporal correlations between BBS data for the Blue Jay (BJ), Common Grackle (CG), Mourning Dove (MD), Northern Cardinal (NC), and Northern Mockingbird (NM) species and SLE virus transmission to sentinel chickens. Christmas Bird Count (CBC) data was also considered for analysis, but discarded based upon the timing of the counts being outside the main amplification and transmission season of SLE in Peninsular Florida. A time series analysis was used to explore the statistical relationship between the datasets at an annual frequency for the time period 1978 to 2015. Temporal correlations between the datasets were identified and analyzed using several statistical methods for the identified species and SLE seroconversions within the PF BCR. Identification of the statistical relationships, if any, between BBS data and SLE transmission in Florida may help with improvement of Arboviral transmission forecasting methods in support of mosquito control and statewide decision makers.

MATERIALS AND METHODS

Data Acquisition

Count data for Blue Jay, Common Grackle, Mourning Dove, Northern Cardinal, and Northern Mockingbird species were acquired for all 75 routes in the PF BCR via the BBS website. Spatially, raw counts are available at the individual route level and trend indexes are calculated at the BCR level. Aggregate count data and a BCR specific trend index were downloaded and prepared for analysis. The raw count data dataset covers the years 1966 to 2015 while the trend index consists of data from 1966 to 2013.

Weekly FTP seroconversions for SLE were acquired for the 37 counties located within the PF BCR. The dataset contains all FTP SLE seroconversions for the time period of 1978 to 2015 and was temporally aggregated to an annual level to match the BBS dataset.

Preliminary Data Analysis

In accordance with the study goals, an exploratory routine was used to determine the suitability of different Breeding Bird Survey datasets for time series analysis with the sentinel chicken seroconversion dataset. Breeding Bird Survey data raw counts and trend indexes were plotted and visually checked for changes in mean and variance (trend nonstationary) over time. The raw count datasets appeared to have stationary variance values but did exhibit a problematic change (increase) in mean values prior to 1987 and 1988 and after. Further research revealed that in 1988 the BBS saw an increase in data collection effort which caused the change in mean values between the two time periods. The modeled trend index data also appeared to have stationary variance values and did not exhibit the same change in means between the time periods that the raw count data exhibited. However, the trend index data did exhibit long term changes in mean values over the complete dataset time period. The long-term change was not unexpected as the modeled trend index values are used as an indicator of the abundance of bird species over time (trend). Due to the issues with both the raw

counts and trend index datasets, a 3rd dataset was created for the analysis. Annual *averages per route* for the BCR were calculated using the raw count dataset. Visual exploration of plots of the calculated averages revealed more stationary mean and variance values than the raw count or trend index datasets. As such, the BBS calculated **averages** and modeled **trends** data sets were chosen for inclusion in the study along with the SLE seroconversions datasets. Spatially, BBS routes aligned poorly with a set of four counties that were initially chosen for the study (Indian River, Orange, Pinellas, and Volusia) ([Figure 2](#)). Due to the poor spatial alignment, it was decided to analyze the data at the PF BCR level to include a broader range of counties (37). A fifth bird species (Northern Mocking bird) was included in the analysis for broader scope, based upon the changes made to the study plan. The SLE seroconversions datasets were log-transformed before analysis to normalize the distribution and minimize standard error.

Time Series Analysis

The following datasets (1978 to 2015) were used in this analysis:

1. Blue Jay Average per Route - (1978 to 2015)
2. Common Grackle Average per Route - (1978 to 2015)
3. Mourning Dove Average per Route - (1978 to 2015)
4. Northern Cardinal Average per Route - (1978 to 2015)
5. Northern Mockingbird Average per Route - (1978 to 2015)
6. SLE Sentinel Chicken Seroconversions - (1978 to 2015)
7. Blue Jay Trend Index - (1978 to 2013)
8. Common Grackle Trend Index - (1978 to 2013)
9. Mourning Dove Trend Index - (1978 to 2013)
10. Northern Cardinal Trend Index - (1978 to 2013)
11. Northern Mockingbird Trend Index - (1978 to 2013)

The methods used in this research followed a modified ARIMA (Box-Jenkins) Modeling Algorithm for Time Series.

1. Check Time Series for Stable Variance and Normal Distribution
2. Transform Time Series if necessary
3. Check Time Series for Trends
4. Apply Regular and/or Seasonal Differencing if necessary
5. Select ARIMA Model for Independent Variable (x)
6. Check ARIMA Model Residuals for Correlation and Normal Distribution
7. Modify Model and/or Model Parameter Values if necessary
8. Fit Independent Variable (x) ARIMA Model to Dependent Variable (y) to prewhiten
9. Calculate Cross Correlation Function Values for all Time Series Lag Values
10. Calculate Granger Causality for any Significant Cross Correlation Function Values

The annual SLE Seroconversions Count was treated as dependent variable, and species specific BBS Averages and Trend Indexes were independent variables (10 total). Within the PF BCR, the statistical relationship between BBS count and SLE transmission over the period 1976 to 2015 and between BBS index and SLE transmission over the period 1976 to 2013 was examined. To account for autocorrelation among both dependent and independent variables over time, autoregressive integrated moving average (ARIMA) models were fitted to each independent variable and used to pre-whiten all variables. Cross-correlations were then calculated up to ten time lags and examined for statistical significance. Significantly cross-correlated time lags were then tested for Granger causality to determine the ability of BBS data to predict changes in SLE transmission to sentinel chickens, or, in some cases, the ability of SLE transmission to sentinel chickens to predict changes in BBS data.

The detailed statistical methods of the analysis can be found at the end of this report in the section titled [BBS Analysis](#).

RESULTS

For cross-correlation analysis with pre-whitening, ARIMA models were fitted to each variable as listed in [Table 1](#). The purpose of pre-whitening is to eliminate any spurious correlations that may exist within or between datasets caused by either autocorrelation or similar trends within the data. The trend index datasets tended to exhibit better fits by the ARIMA models in general based upon the AIC scores. Each dataset was fitted for several ARIMA models and the AIC was used as the criteria for the best fit. Only the MD Index was fitted with an auto-regressive terms and all datasets exhibited a need for differencing via the Integrated term of the ARIMA models. All model residual auto-correlation and partial auto-correlation plots resembled white noise, indicating a good fit of the ARIMA models.

The cross-correlation coefficients for the association between pre-whitened BBS data and SLE transmission can be observed in [Figures 7 – 16](#). All cross-correlation plots exhibited random fluctuations, indicating effective pre-whitening. The only plot with any significant correlations of interest was the CG avg x SLE plot ([Figure 8](#)), which indicated a significant positive correlation between SLE transmission to sentinel chickens and Common Grackle averages four and five years prior. The positive correlations were admittedly weak with coefficients just above 0.3 at a 95% confidence level. No other significant positive or negative correlations indicating a correlation between SLE transmission to sentinel chickens and prior BBS average or index data is visible within the plots. The plots do indicate various (9 total) significant correlations between BBS average or index data and prior SLE transmission to sentinel chickens, specifically Blue Jay average, Northern Cardinal average, Northern Mockingbird average, and Common Grackle index.

Both Granger causality testing results of SLE to previous BBS and BBS to previous SLE correlations are listed in [Table 2](#). Only the Northern Mockingbird BBS to previous SLE nine years prior was significant.

DATASET	ARIMA MODEL	AIC
BLUE JAY AVERAGE	ARIMA(0,1,1)	206.89
COMMON GRACKLE AVERAGE	ARIMA(0,1,1)	286.71
MOURNING DOVE AVERAGE	ARIMA(0,1,1)	246.2
NORTHERN CARDINAL AVERAGE	ARIMA(0,1,0)	229.48
NORTHERN MOCKINGBIRD AVERAGE	ARIMA(0,1,1)	335.49
BLUE JAY INDEX	ARIMA(0,1,1)	71.27
COMMON GRACKLE INDEX	ARIMA(0,1,1)	190.43
MOURNING DOVE INDEX	ARIMA(1,1,0)	202.98
NORTHERN CARDINAL INDEX	ARIMA(0,1,2)	126.69
NORTHERN MOCKINGBIRD INDEX	ARIMA(0,1,0)	133.51

Table 1.

Correlation	Years Prior	Correlation Coefficient	Granger Causality Pr(>F)
SLE transmission leads Blue Jay average	8	+0.364*	0.356
Common Grackle average leads SLE transmission	4	+0.325*	0.4088
Common Grackle average leads SLE transmission	5	+0.353*	0.4727
SLE transmission leads Common Grackle average	9	0.347*	0.1595
SLE transmission leads Northern Cardinal average	2	-0.426*	0.2672
SLE transmission leads Northern Cardinal average	8	0.323*	0.4819
SLE transmission leads Northern Cardinal average	9	-0.419*	0.363
SLE transmission leads Northern Mockingbird average	8	-0.363*	0.3234
SLE transmission leads Northern Mockingbird average	9	0.336*	0.0352*
SLE transmission leads Common Grackle index	2	0.467*	0.1595

* significant at 0.05 level

Table 2.

DISCUSSION

The relationship between avian hosts and SLE transmission in Florida is a complex one with the effect(s) of year to year fluctuations of avian host populations on the transmission of SLE not well documented. While avian bird populations play a pivotal role in the SLE amplification and transmission cycle in Florida, quantifying this role can be challenging. Research has shown that environmental factors are the driving force behind high SLE transmission years as they drive avian and mosquito populations together for increased amplification. This study hoped to reveal quantifiable correlations between BBS data and SLE seroconversions across Peninsular Florida for two reasons: (1) Identifying associations between bird data and SLE transmission may be helpful in forecasting and prevention of human SLE cases and (2) determination of the direction, strength, and time differences of the associations may be useful in furthering our understanding of the SLE amplification/transmission cycle.

The results of the study showed a significant positive correlation between BBS Common Grackles annual averages and SLE annual counts of transmission to sentinel chickens across Peninsular Florida 4 and 5 years prior. This result indicates that increasing Common Grackles abundance is associated with increased SLE transmission to sentinel chickens 4 to 5 years later. A biological explanation for the association is not readily apparent but one explanation would be a very small statistical co-integration of the datasets due to similar driving forces such as environmental conditions.

The apparent lack of significant positive correlations between SLE transmission to sentinel chickens and prior BBS data counts for four of the five species examined is not surprising. Identifying correlations in time series datasets can be difficult when the sample size is below 50 and determining causality of any identified correlations can be tenuous at best. Statistically, checking for correlations between time series datasets can be problematic. Feedback loops between datasets and autocorrelations within datasets must be eliminated through the process of noise whitening. While most testing methods for autocorrelations are considered robust for larger (>50) datasets, some

statisticians have argued that autocorrelations in smaller datasets, even after pre-whitening, can be hard to detect.

Our analysis indicated decreased SLE transmission to sentinel chickens lead decreases in Blue Jay abundance at 8 years, Common Grackle abundance at 2 and 9 years, Northern Cardinal abundance at 2, 8, and 9 years, and Northern Mockingbird abundance at 8 and 9 years. The only correlation exhibiting any Granger causality was the Northern Mockingbird at 9 years. Some research has implied that West Nile virus has had an ecological impact on various North American bird populations (LaDeau et al. -2007, Koenig et al. – 2007) . Could this explain the significant negative correlations of SLE transmission leading BBS avian abundance averages and trend indexes? It would be hard to imagine any significant impact upon wild bird populations by SLE transmission levels at 8 or 9 years. The associations at 2 years would be more likely, but one would expect to see a range of years (1 to 3) that would have correlations. Again, biological explanations for these associations are not readily apparent.

The purpose of the study was to provide evidence of any strong signals between BBS count data and SLE transmission to sentinel chickens. With a lack of any strong associations between the datasets we must assume one of two ideas. First, if we assume bird abundance does have a strong association or effect on SLE transmission to sentinel chickens, then the BBS data may not be well suited to capture the nuances of bird abundance that influence or drive SLE transmission. Second, if we assume that assume that bird abundance does NOT have a strong association or effect on SLE transmission to sentinel chickens, then perhaps the bird abundance is only part of the equation. Again, the factors that drive amplification and transmission of SLE in Peninsular Florida are integrated in a complex manner in which the strength on any one factor may not lead to an increase in SLE transmission. The abundance of specific arboviruses, and mosquito or bird species in any given year will not drive SLE amplification and transmission. Only when they are aligned spatially and temporally by driving environmental conditions do we see an increase in the transmission of SLE. An approach to deriving these complex

integrations between virus, mosquito, avian, and environmental factors is the collection of more data over time. There can be no doubt that this study highlights the importance of the sentinel chicken programs throughout Florida is giving us important data to combat the spread of arboviruses.

ACKNOWLEDGMENTS

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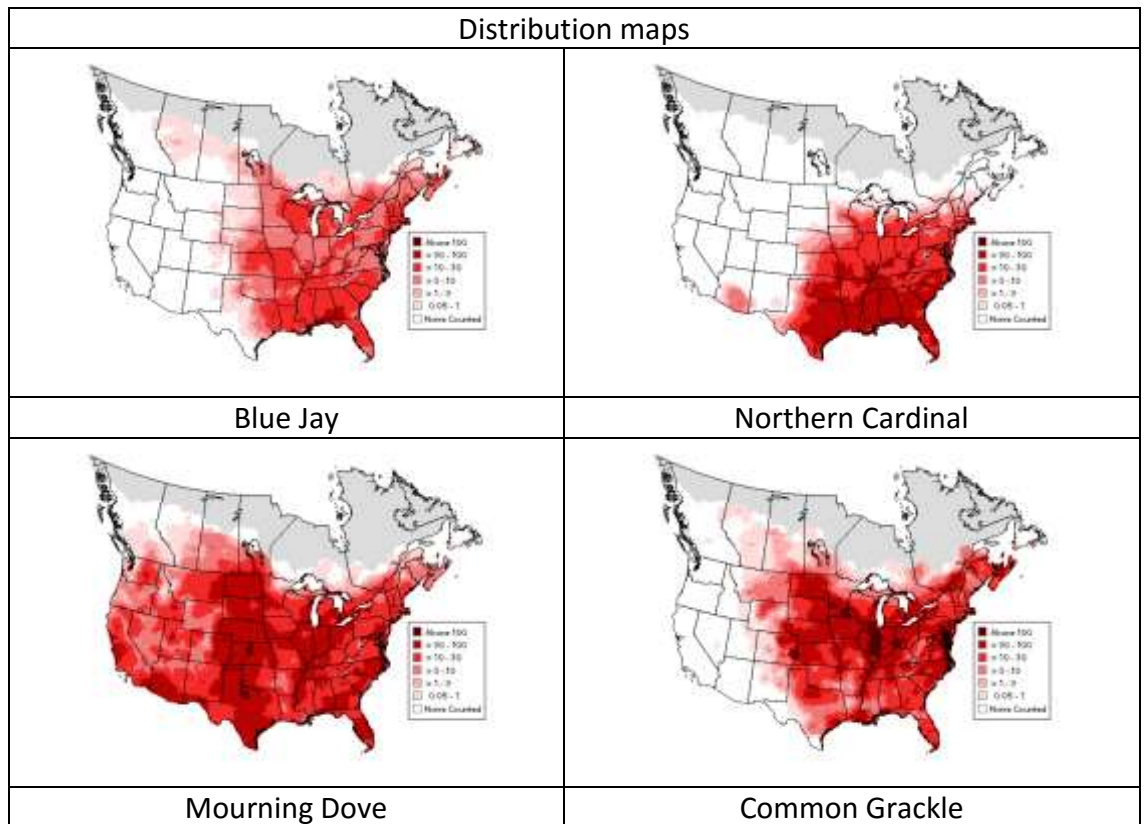
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FIGURES

Figure 1.



Maps produced by the USGS Patuxent Wildlife Research Center at <http://www.mbr-pwrc.usgs.gov/bbs/>

Figure 2.

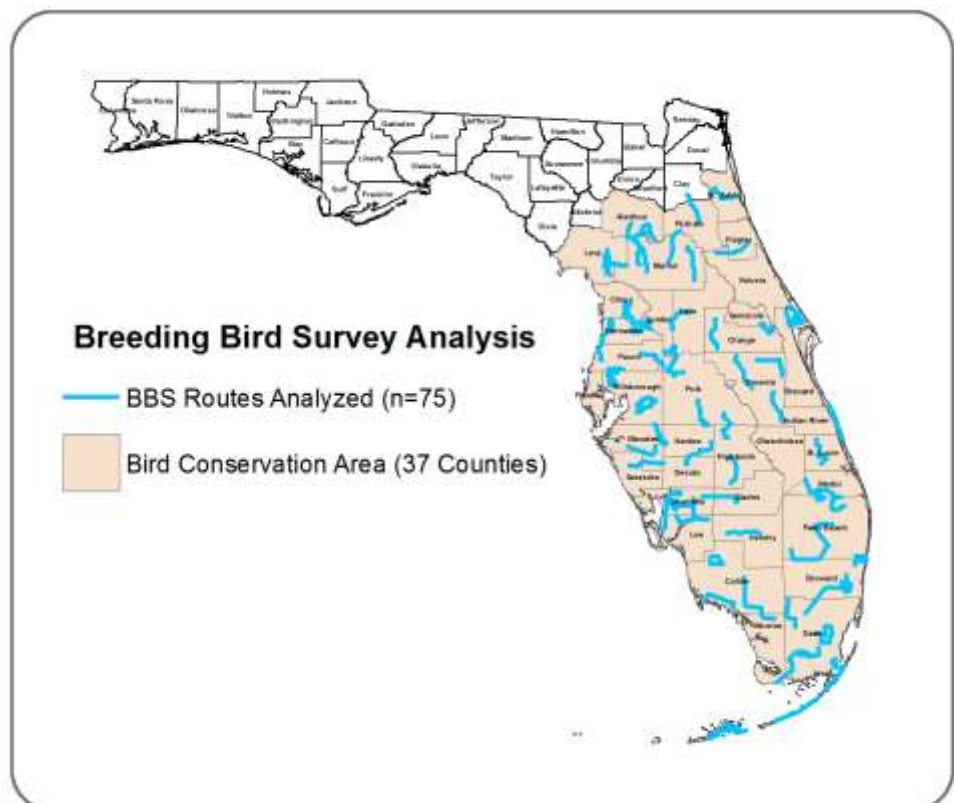


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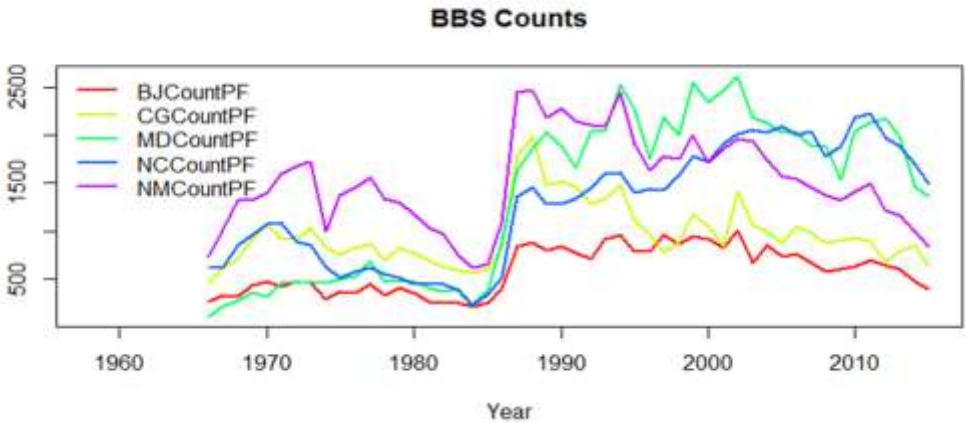


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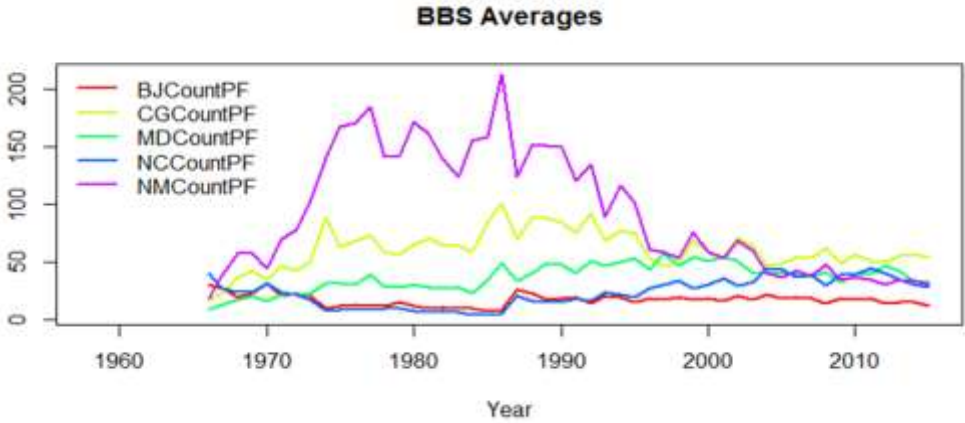


Figure 5.

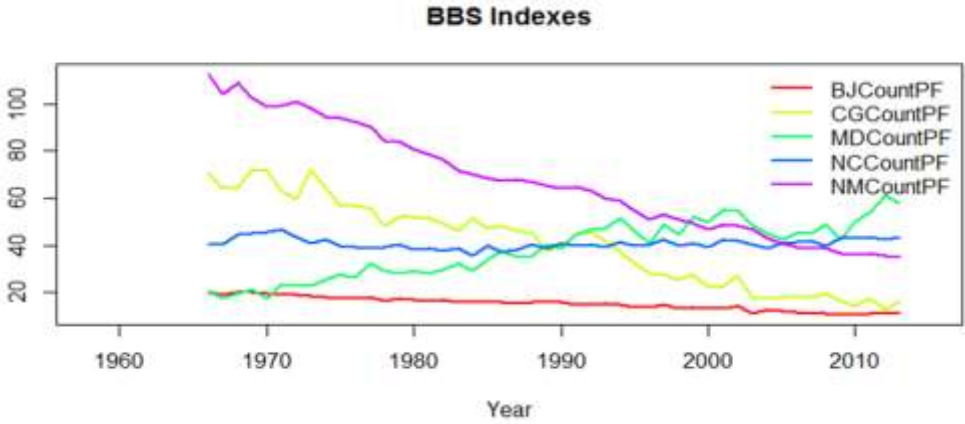
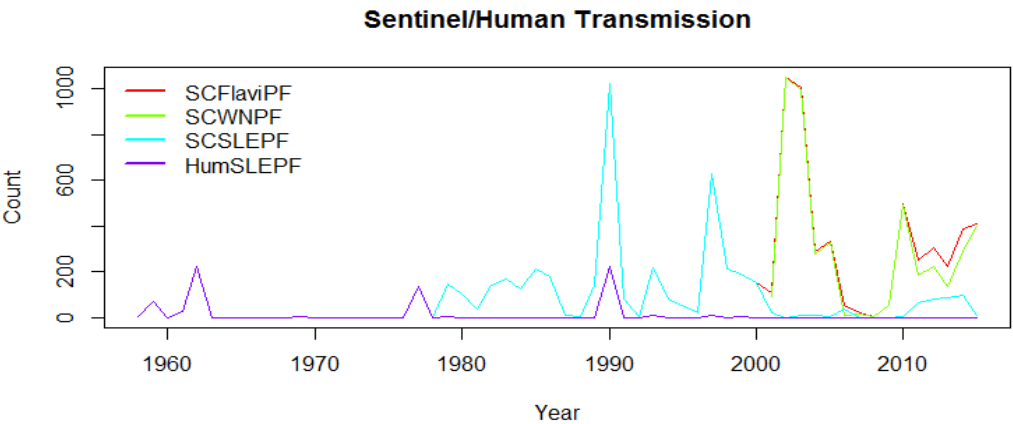


Figure 6.



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376 **Figure 7.**
377 **BJ avg x SLE**

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382 **Figure 8.**
383 **CG avg x SLE**

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387 **Figure 9.**
388 **MD avg x SLE**

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392 **Figure 10.**
393 **NC avg x SLE**

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398 **Figure 11.**
399 **NM avg x SLE**

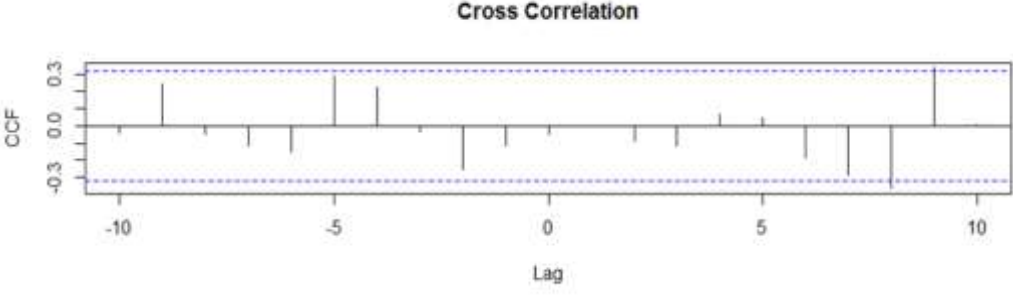
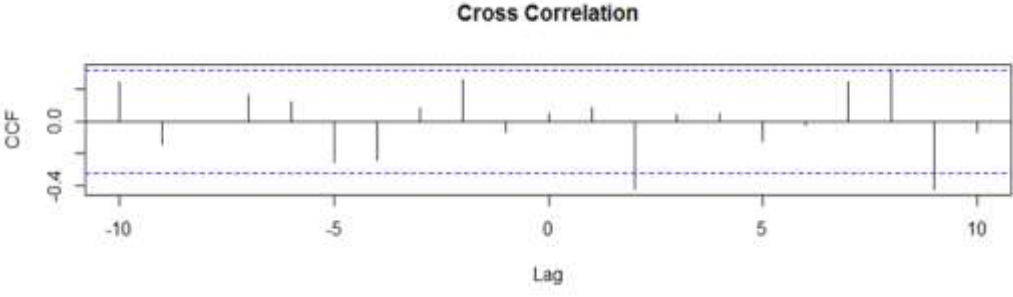
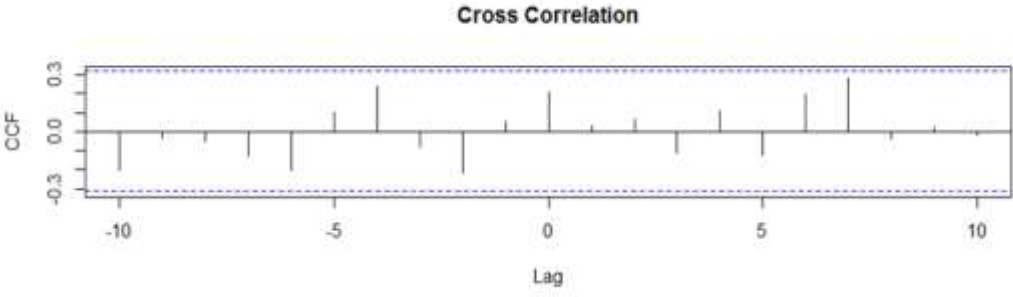
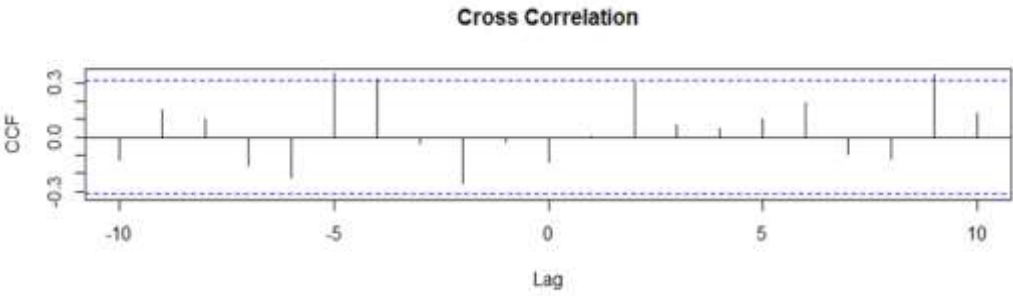
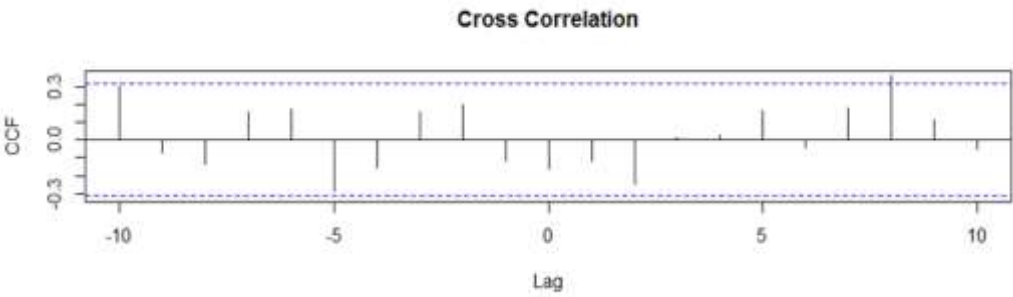


Figure 12.
BJ ind x SLE

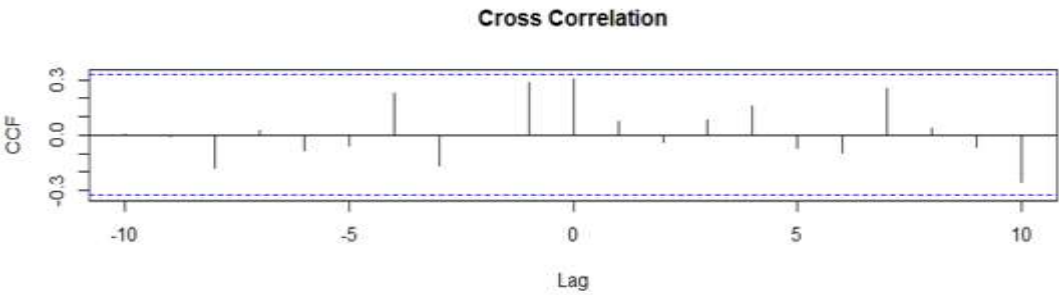


Figure 13.
CG ind x SLE

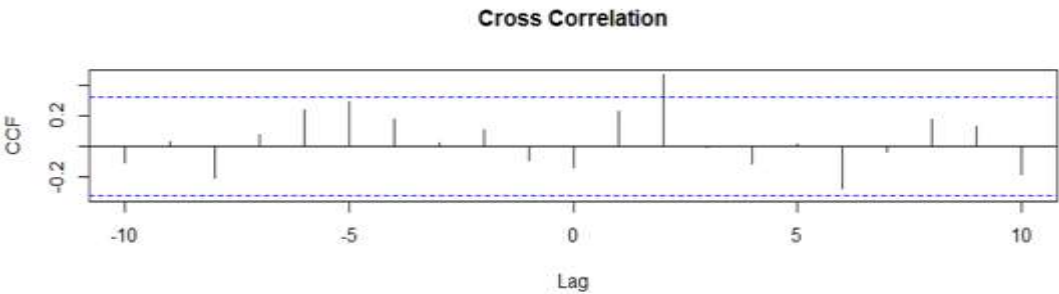


Figure 14.
MD ind x SLE

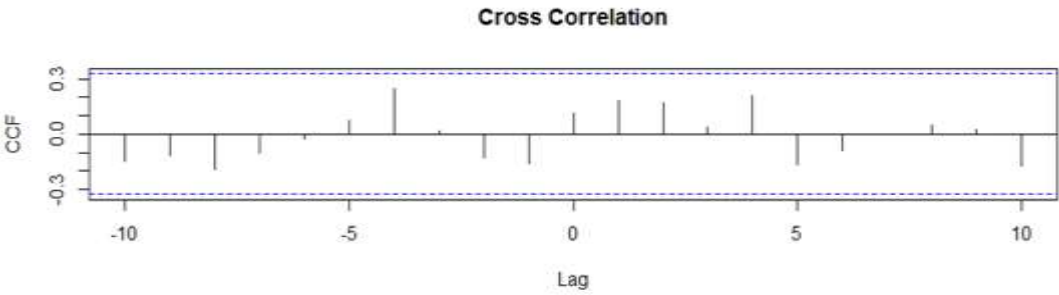


Figure 15.
NC ind x SLE

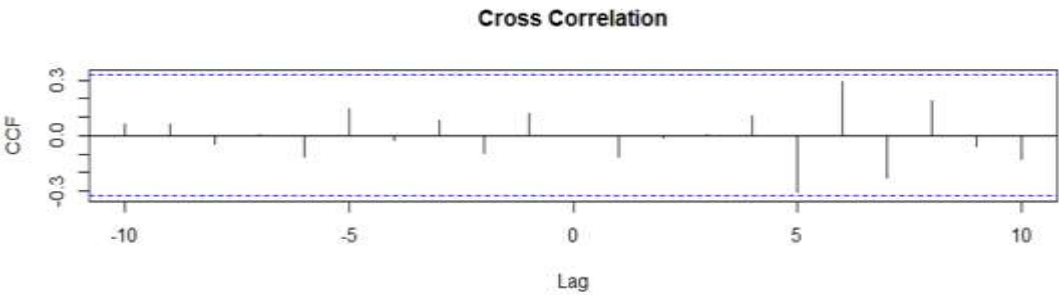
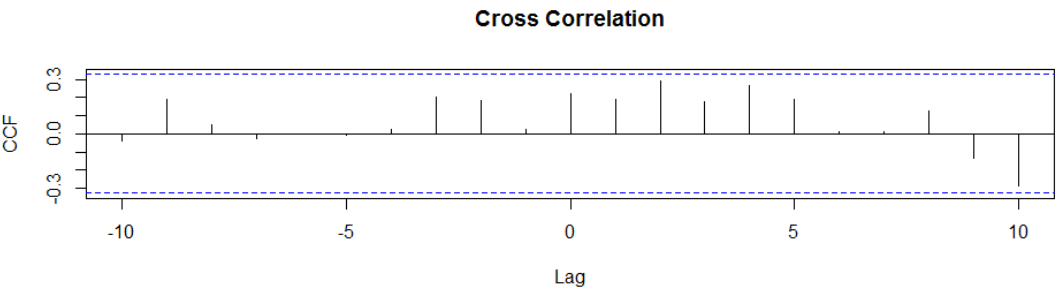


Figure 16.
NM ind x LE



BBS Analysis

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August 8, 2016

This study is done in a reproducible research manner. All statistical analysis and figures below were created in the open source software package R.

Setup

Load packages, get dataset, and load variables. Dataset consists of a csv file with annual counts of data. Dataste is then filtered and subsetted into various time series. Variables are then created from the time series. All Variables are Annual Counts.

```
knitr::opts_chunk$set(echo = TRUE, warning=FALSE, message=FALSE, comment = NA)
options(width = 90)

# List of needed packages
list.of.packages <- c("tsoutliers", "nortest", "fitdistrplus", "tseries", "forecast",
                     "TSA", "egcm", "lmtest", "gplots", "forecast", "moments", "RCurl", "pander")

# List of packages that are not installed
new.packages <- list.of.packages[!(list.of.packages %in% installed.packages()
[, "Package"])]

# install needed packages
if(length(new.packages)) install.packages(new.packages,
    repos = "http://cran.us.r-project.org")

library("tsoutliers", lib.loc=~R/win-library/3.2")
library("forecast", lib.loc=~R/win-library/3.2")
library("nortest", lib.loc=~R/win-library/3.2")
library("fitdistrplus", lib.loc=~R/win-library/3.2")
library("tseries", lib.loc=~R/win-library/3.2")
library("TSA", lib.loc=~R/win-library/3.2")
library("egcm", lib.loc=~R/win-library/3.2")
library("lmtest", lib.loc=~R/win-library/3.2")
library("gplots", lib.loc=~R/win-library/3.2")
library("stats", lib.loc="C:/Program Files/Microsoft/MRO/R-3.2.3/library")
library("moments", lib.loc=~R/win-library/3.2")
library("RCurl", lib.loc=~R/win-library/3.2")
library("pander", lib.loc=~R/win-library/3.2")

# List information about R software session
sessionInfo()

## R version 3.2.3 (2015-12-10)
## Platform: i386-w64-mingw32/i386 (32-bit)
## Running under: Windows 10 x64 (build 10240)
##
## locale:
## [1] LC_COLLATE=English_United States.1252 LC_CTYPE=English_United States.1252
## [3] LC_MONETARY=English_United States.1252 LC_NUMERIC=C
## [5] LC_TIME=English_United States.1252
##
## attached base packages:
## [1] stats      graphics  grDevices  utils      datasets  methods   base
##
## other attached packages:
## [1] pander_0.6.0      RCurl_1.95-4.8    bitops_1.0-6      moments_0.14
## [5] gplots_2.17.0     lmtest_0.9-34     egcm_1.0.8        TTR_0.23-0
```

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480 ## [9] xts_0.9-7          TSA_1.01          mgcv_1.8-9        nlme_3.1-122
481 ## [13] locfit_1.5-9.1      leaps_2.9         tseries_0.10-34   fitdistrplus_1.0-6
482 ## [17] MASS_7.3-45        nortest_1.0-4     forecast_6.2       timeDate_3012.100
483 ## [21] zoo_1.7-12         tsoutliers_0.6
484 ##
485 ## loaded via a namespace (and not attached):
486 ## [1] gdata_2.17.0        ggplot2_2.0.0      timeSeries_3022.101.2
487 ## [4] lattice_0.20-33     formatR_1.2.1      stringr_1.0.0
488 ## [7] gtools_3.5.0        parallel_3.2.3     polynom_1.3-8
489 ## [10] Rcpp_0.12.6         plyr_1.8.3         tools_3.2.3
490 ## [13] rmarkdown_1.0.9002  fArma_3010.79      knitr_1.13
491 ## [16] scales_0.3.0        nnet_7.3-11        digest_0.6.8
492 ## [19] evaluate_0.9        gtable_0.1.2       stsm_1.7
493 ## [22] KernSmooth_2.23-15  Matrix_1.2-3       stringi_1.1.1
494 ## [25] caTools_1.17.1      fBasics_3011.87    htmltools_0.3.5
495 ## [28] munSELL_0.4.2       grid_3.2.3         colorspace_1.2-6
496 ## [31] fracdiff_1.4-2      quadprog_1.5-5     magrittr_1.5
497 ## [34] splines_3.2.3       yaml_2.1.13        survival_2.38-3
498 ## [37] urca_1.2-8          KFKSDS_1.6

499 # clear working environment
500 rm(list = ls())
501
502 # Load data from online repository
503 bbs = read.csv("https://dl.dropboxusercontent.com/u/10866552/research/BBS/bbs.csv")
504 attach(bbs)
505
506 # create filtered dataframes
507 bbs66to13<- subset(bbs, bbs$Year>1965 & bbs$Year<2014)
508 bbs66to15<- subset(bbs, bbs$Year>1965)
509 bbs78to13<- subset(bbs, bbs$Year>1977 & bbs$Year<2014)
510 bbs78to15<- subset(bbs, bbs$Year>1977)
511 bbs01to13<- subset(bbs, bbs$Year>2000 & bbs$Year<2014)
512 bbs01to15<- subset(bbs, bbs$Year>2000)
513
514 # create filtered time series
515
516 # 1958 to 2015 Times series
517 bbs58to15ts <- ts(bbs, start = 1958, end = 2015, frequency = 1)
518 # 1966 to 2013 Times series
519 bbs66to13ts <- ts(bbs66to13, start = 1966, end = 2013, frequency = 1)
520 # 1966 to 2015 Times series
521 bbs66to15ts <- ts(bbs66to15, start = 1966, end = 2015, frequency = 1)
522 # 1978 to 2013 Times series
523 bbs78to13ts <- ts(bbs78to13, start = 1978, end = 2013, frequency = 1)
524 # 1978 to 2015 Times series
525 bbs78to15ts <- ts(bbs78to15, start = 1978, end = 2015, frequency = 1)
526 # 2001 to 2013 Times series
527 bbs01to13ts <- ts(bbs78to13, start = 2001, end = 2013, frequency = 1)
528 # 2001 to 2015 Times series
529 bbs01to15ts <- ts(bbs78to15, start = 2001, end = 2015, frequency = 1)
530
531 # BBS Variables
532 # 1966 to 2015 Counts
533 # Blue Jay Counts 1966 to 2015
534 BJCountPF66to15<- subset(bbs$BJCountPF, bbs$Year>1965)
535 # Blue Jay Counts 1966 to 2015 Time Series
536 BJCountPF66to15ts<- ts(BJCountPF66to15, start = 1966, end = 2015, frequency = 1)
537 # Common Grackle Counts 1966 to 2015
538 CGCountPF66to15<- subset(bbs$CGCountPF, bbs$Year>1965)
539 # Common Grackle Counts 1966 to 2015 Time Series
540 CGCountPF66to15ts<- ts(CGCountPF66to15, start = 1966, end = 2015, frequency = 1)
541 # Mourning Dove Counts 1966 to 2015
542 MDCountPF66to15<- subset(bbs$MDCountPF, bbs$Year>1965)
543 # Mourning Dove Counts 1966 to 2015 Time Series

```

```

544 MDCountPF66to15ts<- ts(MDCountPF66to15, start = 1966, end = 2015, frequency = 1)
545 # Northern Cardinal Counts 1966 to 2015
546 NCCountPF66to15<- subset(bbs$NCCountPF, bbs$Year>1965)
547 # Northern Cardinal Counts 1966 to 2015 Time Series
548 NCCountPF66to15ts<- ts(NCCountPF66to15, start = 1966, end = 2015, frequency = 1)
549 # Northern Mockingbird Counts 1966 to 2015
550 NMCountPF66to15<- subset(bbs$NMCountPF, bbs$Year>1965)
551 # Northern Mockingbird Counts 1966 to 2015 Time Series
552 NMCountPF66to15ts<- ts(NMCountPF66to15, start = 1966, end = 2015, frequency = 1)
553
554 # 1978 to 2015 Counts
555 # Blue Jay Counts 1978 to 2015
556 BJCountPF78to15<- subset(bbs$BJCountPF, bbs$Year>1977)
557 # Blue Jay Counts 1978 to 2015 Time Series
558 BJCountPF78to15ts<- ts(BJCountPF78to15, start = 1978, end = 2015, frequency = 1)
559 # Common Grackle Counts 1978 to 2015 Time Series
560 CGCountPF78to15<- subset(bbs$CGCountPF, bbs$Year>1977)
561 # Common Grackle Counts 1978 to 2015 Time Series
562 CGCountPF78to15ts<- ts(CGCountPF78to15, start = 1978, end = 2015, frequency = 1)
563 # Mourning Dove Counts 1978 to 2015
564 MDCountPF78to15<- subset(bbs$MDCountPF, bbs$Year>1977)
565 # Mourning Dove Counts 1978 to 2015 Time Series
566 MDCountPF78to15ts<- ts(MDCountPF78to15, start = 1978, end = 2015, frequency = 1)
567 # Northern Cardinal Counts 1978 to 2015
568 NCCountPF78to15<- subset(bbs$NCCountPF, bbs$Year>1977)
569 # Northern Cardinal Counts 1978 to 2015 Time Series
570 NCCountPF78to15ts<- ts(NCCountPF78to15, start = 1978, end = 2015, frequency = 1)
571 # Northern Mockingbird Counts 1978 to 2015
572 NMCountPF78to15<- subset(bbs$NMCountPF, bbs$Year>1977)
573 # Northern Mockingbird Counts 1978 to 2015 Time Series
574 NMCountPF78to15ts<- ts(NMCountPF78to15, start = 1978, end = 2015, frequency = 1)
575
576 # 2001 to 2015 Counts
577 # Blue Jay Counts 2001 to 2015
578 BJCountPF01to15<- subset(bbs$BJCountPF, bbs$Year>2000)
579 # Blue Jay Counts 2001 to 2015 Time Series
580 BJCountPF01to15ts<- ts(BJCountPF01to15, start = 2001, end = 2015, frequency = 1)
581 # Common Grackle Counts 2001 to 2015
582 CGCountPF01to15<- subset(bbs$CGCountPF, bbs$Year>2000)
583 # Common Grackle Counts 2001 to 2015 Time Series
584 CGCountPF01to15ts<- ts(CGCountPF01to15, start = 2001, end = 2015, frequency = 1)
585 # Mourning Dove Counts 2001 to 2015
586 MDCountPF01to15<- subset(bbs$MDCountPF, bbs$Year>2000)
587 # Mourning Dove Counts 2001 to 2015 Time Series
588 MDCountPF01to15ts<- ts(MDCountPF01to15, start = 2001, end = 2015, frequency = 1)
589 # Northern Cardinal Counts 2001 to 2015
590 NCCountPF01to15<- subset(bbs$NCCountPF, bbs$Year>2000)
591 # Northern Cardinal Counts 2001 to 2015 Time Series
592 NCCountPF01to15ts<- ts(NCCountPF01to15, start = 2001, end = 2015, frequency = 1)
593 # Northern Mockingbird Counts 2001 to 2015
594 NMCountPF01to15<- subset(bbs$NMCountPF, bbs$Year>2000)
595 # Northern Mockingbird Counts 2001 to 2015 Time Series
596 NMCountPF01to15ts<- ts(NMCountPF01to15, start = 2001, end = 2015, frequency = 1)
597
598 # 1966 to 2015 Averages
599 # Blue Jay Averages 1966 to 2015
600 BJAveragePF66to15<- subset(bbs$BJAveragePF, bbs$Year>1965)
601 # Blue Jay Averages 1966 to 2015 Time Series
602 BJAveragePF66to15ts<- ts(BJAveragePF66to15, start = 1966, end = 2015, frequency = 1)
603 # Common Grackle Averages 1966 to 2015
604 CGAveragePF66to15<- subset(bbs$CGAveragePF, bbs$Year>1965)
605 # Common Grackle Averages 1966 to 2015 Time Series
606 CGAveragePF66to15ts<- ts(CGAveragePF66to15, start = 1966, end = 2015, frequency = 1)
607 # Mourning Dove Averages 1966 to 2015
608 MDAveragePF66to15<- subset(bbs$MDAveragePF, bbs$Year>1965)

```



```

609 # Mourning Dove Averages 1966 to 2015 Time Series
610 MDAveragePF66to15ts<- ts(MDAveragePF66to15, start = 1966, end = 2015, frequency = 1)
611 # Northern Cardinal Averages 1966 to 2015
612 NCAveragePF66to15<- subset(bbs$NCAveragePF, bbs$Year>1965)
613 # Northern Cardinal Averages 1966 to 2015 Time Series
614 NCAveragePF66to15ts<- ts(NCAveragePF66to15, start = 1966, end = 2015, frequency = 1)
615 # Northern Mockingbird Averages 1966 to 2015
616 NMAveragePF66to15<- subset(bbs$NMAveragePF, bbs$Year>1965)
617 # Northern Mockingbird Averages 1966 to 2015 Time Series
618 NMAveragePF66to15ts<- ts(NMAveragePF66to15, start = 1966, end = 2015, frequency = 1)
619
620 # 1978 to 2015 Averages
621 # Blue Jay Averages 1978 to 2015
622 BJAveragePF78to15<- subset(bbs$BJAveragePF, bbs$Year>1977)
623 # Blue Jay Averages 1978 to 2015 Time Series
624 BJAveragePF78to15ts<- ts(BJAveragePF78to15, start = 1978, end = 2015, frequency = 1)
625 # Common Grackle Averages 1978 to 2015
626 CGAveragePF78to15<- subset(bbs$CGAveragePF, bbs$Year>1977)
627 # Common Grackle Averages 1978 to 2015 Time Series
628 CGAveragePF78to15ts<- ts(CGAveragePF78to15, start = 1978, end = 2015, frequency = 1)
629 # Mourning Dove Averages 1978 to 2015
630 MDAveragePF78to15<- subset(bbs$MDAveragePF, bbs$Year>1977)
631 # Mourning Dove Averages 1978 to 2015 Time Series
632 MDAveragePF78to15ts<- ts(MDAveragePF78to15, start = 1978, end = 2015, frequency = 1)
633 # Northern Cardinal Averages 1978 to 2015
634 NCAveragePF78to15<- subset(bbs$NCAveragePF, bbs$Year>1977)
635 # Northern Cardinal Averages 1978 to 2015 Time Series
636 NCAveragePF78to15ts<- ts(NCAveragePF78to15, start = 1978, end = 2015, frequency = 1)
637 # Northern Mockingbird Averages 1978 to 2015
638 NMAveragePF78to15<- subset(bbs$NMAveragePF, bbs$Year>1977)
639 # Northern Mockingbird Averages 1978 to 2015 Time Series
640 NMAveragePF78to15ts<- ts(NMAveragePF78to15, start = 1978, end = 2015, frequency = 1)
641
642 # 2001 to 2015 Averages
643 # Blue Jay Averages 2001 to 2015
644 BJAveragePF01to15<- subset(bbs$BJAveragePF, bbs$Year>2000)
645 # Blue Jay Averages 2001 to 2015 Time Series
646 BJAveragePF01to15ts<- ts(BJAveragePF01to15, start = 2001, end = 2015, frequency = 1)
647 # Common Grackle Averages 2001 to 2015
648 CGAveragePF01to15<- subset(bbs$CGAveragePF, bbs$Year>2000)
649 # Common Grackle Averages 2001 to 2015 Time Series
650 CGAveragePF01to15ts<- ts(CGAveragePF01to15, start = 2001, end = 2015, frequency = 1)
651 # Mourning Dove Averages 2001 to 2015
652 MDAveragePF01to15<- subset(bbs$MDAveragePF, bbs$Year>2000)
653 # Mourning Dove Averages 2001 to 2015 Time Series
654 MDAveragePF01to15ts<- ts(MDAveragePF01to15, start = 2001, end = 2015, frequency = 1)
655 # Northern Cardinal Averages 2001 to 2015
656 NCAveragePF01to15<- subset(bbs$NCAveragePF, bbs$Year>2000)
657 # Northern Cardinal Averages 2001 to 2015 Time Series
658 NCAveragePF01to15ts<- ts(NCAveragePF01to15, start = 2001, end = 2015, frequency = 1)
659 # Northern Mockingbird Averages 2001 to 2015
660 NMAveragePF01to15<- subset(bbs$NMAveragePF, bbs$Year>2000)
661 # Northern Mockingbird Averages 2001 to 2015 Time Series
662 NMAveragePF01to15ts<- ts(NMAveragePF01to15, start = 2001, end = 2015, frequency = 1)
663
664 # 1966 to 2013 Index
665 # Blue Jay Index 1966 to 2013
666 BJIndexPF66to13<- subset(bbs$BJIndexPF, bbs$Year>1965 & bbs$Year<2014)
667 # Blue Jay Index 1966 to 2013 Time Series
668 BJIndexPF66to13ts<- ts(BJIndexPF66to13, start = 1966, end = 2013, frequency = 1)
669 # Common Grackle Index 1966 to 2013
670 CGIndexPF66to13<- subset(bbs$CGIndexPF, bbs$Year>1965 & bbs$Year<2014)
671 # Common Grackle Index 1966 to 2013 Time Series
672 CGIndexPF66to13ts<- ts(CGIndexPF66to13, start = 1966, end = 2013, frequency = 1)
673 # Mourning Dove Index 1966 to 2013

```

```

674 MDIndexPF66to13<- subset(bbs$MDIndexPF, bbs$Year>1965 & bbs$Year<2014)
675 # Mourning Dove Index 1966 to 2013 Time Series
676 MDIndexPF66to13ts<- ts(MDIndexPF66to13, start = 1966, end = 2013, frequency = 1)
677 # Northern Cardinal Index 1966 to 2013
678 NCIndexPF66to13<- subset(bbs$NCIndexPF, bbs$Year>1965 & bbs$Year<2014)
679 # Northern Cardinal Index 1966 to 2013 Time Series
680 NCIndexPF66to13ts<- ts(NCIndexPF66to13, start = 1966, end = 2013, frequency = 1)
681 # Northern Mockingbird Index 1966 to 2013
682 NMIndexPF66to13<- subset(bbs$NMIndexPF, bbs$Year>1965 & bbs$Year<2014)
683 # Northern Mockingbird Index 1966 to 2013 Time Series
684 NMIndexPF66to13ts<- ts(NMIndexPF66to13, start = 1966, end = 2013, frequency = 1)
685
686 # 1978 to 2013 Index
687 # Blue Jay Index 1978 to 2013
688 BJIndexPF78to13<- subset(bbs$BJIndexPF, bbs$Year>1977 & bbs$Year<2014)
689 # Blue Jay Index 1978 to 2013 Time Series
690 BJIndexPF78to13ts<- ts(BJIndexPF78to13, start = 1978, end = 2013, frequency = 1)
691 # Common Grackle Index 1978 to 2013 Time Series
692 CGIndexPF78to13<- subset(bbs$CGIndexPF, bbs$Year>1977 & bbs$Year<2014)
693 # Common Grackle Index 1978 to 2013 Time Series
694 CGIndexPF78to13ts<- ts(CGIndexPF78to13, start = 1978, end = 2013, frequency = 1)
695 # Mourning Dove Index 1978 to 2013
696 MDIndexPF78to13<- subset(bbs$MDIndexPF, bbs$Year>1977 & bbs$Year<2014)
697 # Mourning Dove Index 1978 to 2013 Time Series
698 MDIndexPF78to13ts<- ts(MDIndexPF78to13, start = 1978, end = 2013, frequency = 1)
699 # Northern Cardinal Index 1978 to 2013
700 NCIndexPF78to13<- subset(bbs$NCIndexPF, bbs$Year>1977 & bbs$Year<2014)
701 # Northern Cardinal Index 1978 to 2013 Time Series
702 NCIndexPF78to13ts<- ts(NCIndexPF78to13, start = 1978, end = 2013, frequency = 1)
703 # Northern Mockingbird Index 1978 to 2013
704 NMIndexPF78to13<- subset(bbs$NMIndexPF, bbs$Year>1977 & bbs$Year<2014)
705 # Northern Mockingbird Index 1978 to 2013 Time Series
706 NMIndexPF78to13ts<- ts(NMIndexPF78to13, start = 1978, end = 2013, frequency = 1)
707
708 # 2001 to 2013 Index
709 # Blue Jay Index 2001 to 2013
710 BJIndexPF01to13<- subset(bbs$BJIndexPF, bbs$Year>2000 & bbs$Year<2014)
711 # Blue Jay Index 2001 to 2013 Time Series
712 BJIndexPF01to13ts<- ts(BJIndexPF01to13, start = 2001, end = 2013, frequency = 1)
713 # Common Grackle Index 2001 to 2013
714 CGIndexPF01to13<- subset(bbs$CGIndexPF, bbs$Year>2000 & bbs$Year<2014)
715 # Common Grackle Index 2001 to 2013 Time Series
716 CGIndexPF01to13ts<- ts(CGIndexPF01to13, start = 2001, end = 2013, frequency = 1)
717 # Mourning Dove Index 2001 to 2013
718 MDIndexPF01to13<- subset(bbs$MDIndexPF, bbs$Year>2000 & bbs$Year<2014)
719 # Mourning Dove Index 2001 to 2013 Time Series
720 MDIndexPF01to13ts<- ts(MDIndexPF01to13, start = 2001, end = 2013, frequency = 1)
721 # Northern Cardinal Index 2001 to 2013
722 NCIndexPF01to13<- subset(bbs$NCIndexPF, bbs$Year>2000 & bbs$Year<2014)
723 # Northern Cardinal Index 2001 to 2013 Time Series
724 NCIndexPF01to13ts<- ts(NCIndexPF01to13, start = 2001, end = 2013, frequency = 1)
725 # Northern Mockingbird Index 2001 to 2013
726 NMIndexPF01to13<- subset(bbs$NMIndexPF, bbs$Year>2000 & bbs$Year<2014)
727 # Northern Mockingbird Indexs 2001 to 2013 Time Series
728 NMIndexPF01to13ts<- ts(NMIndexPF01to13, start = 2001, end = 2013, frequency = 1)
729
730 # Transmission variables
731 # Sentinel Chicken SLE/WN/FLavi Variables
732 # Sentinel Chicken SLE Seroconversion 1978 to 2015
733 SCSLEPF78to15<- subset(bbs$SCSLEPF, bbs$Year>1977)
734 # Sentinel Chicken SLE Seroconversion 1978 to 2015 Time Series
735 SCSLEPF78to15ts<- ts(SCSLEPF78to15, start = 1978, end = 2015, frequency = 1)
736 # Sentinel Chicken SLE Seroconversion 1978 to 2013
737 SCSLEPF78to13<- subset(bbs$SCSLEPF, bbs$Year>1977 & bbs$Year<2014)
738 # Sentinel Chicken SLE Seroconversion 1978 to 2013 Time Series

```

```

739 SCSLEPF78to13ts<- ts(SCSLEPF78to13, start = 1978, end = 2013, frequency = 1)
740 # Sentinel Chicken SLE Seroconversion 2001 to 2015
741 SCSLEPF01to15<- subset(bbs$SCSLEPF, bbs$Year>2000)
742 # Sentinel Chicken SLE Seroconversion 2001 to 2015 Time Series
743 SCSLEPF01to15ts<- ts(SCSLEPF01to15, start = 2001, end = 2015, frequency = 1)
744 # Sentinel Chicken WN Seroconversion 1978 to 2015
745 SCWNPF78to15<- subset(bbs$SCWNPF, bbs$Year>1977)
746 # Sentinel Chicken WN Seroconversion 1978 to 2015 Time Series
747 SCWNPF78to15ts<- ts(SCWNPF78to15, start = 1978, end = 2015, frequency = 1)
748 # Sentinel Chicken WN Seroconversion 1978 to 2013
749 SCWNPF78to13<- subset(bbs$SCWNPF, bbs$Year>1977 & bbs$Year<2014)
750 # Sentinel Chicken WN Seroconversion 1978 to 2013 Time Series
751 SCWNPF78to13ts<- ts(SCWNPF78to13, start = 1978, end = 2013, frequency = 1)
752 # Sentinel Chicken WN Seroconversion 2001 to 2015
753 SCWNPF01to15<- subset(bbs$SCWNPF, bbs$Year>2000)
754 # Sentinel Chicken WN Seroconversion 2001 to 2015 Time Series
755 SCWNPF01to15ts<- ts(SCWNPF01to15, start = 2001, end = 2015, frequency = 1)
756 # Sentinel Chicken WN Seroconversion 1978 to 2015
757 SCFlaviPF78to15<- subset(bbs$SCFlaviPF, bbs$Year>1977)
758 # Sentinel Chicken Flavi Seroconversion 1978 to 2015 Time Series
759 SCFlaviPF78to15ts<- ts(SCFlaviPF78to15, start = 1978, end = 2015, frequency = 1)
760 # Sentinel Chicken Flavi Seroconversion 1978 to 2013
761 SCFlaviPF78to13<- subset(bbs$SCFlaviPF, bbs$Year>1977 & bbs$Year<2014)
762 # Sentinel Chicken Flavi Seroconversion 1978 to 2013 Time Series
763 SCFlaviPF78to13ts<- ts(SCFlaviPF78to13, start = 1978, end = 2013, frequency = 1)
764 # Sentinel Chicken Flavi Seroconversion 2001 to 2015
765 SCFlaviPF01to15<- subset(bbs$SCFlaviPF, bbs$Year>2000)
766 # Sentinel Chicken Flavi Seroconversion 2001 to 2015 Time Series
767 SCFlaviPF01to15ts<- ts(SCFlaviPF01to15, start = 2001, end = 2015, frequency = 1)
768
769 # Human SLE/WN Variables
770 # Human SLE Cases 1958 to 2015
771 HumSLEPF58to15<- bbs$HumSLEPF
772 # Human SLE Cases 1958 to 2015 Time Series
773 HumSLEPF58to15ts<- ts(HumSLEPF58to15, start = 1958, end = 2015, frequency = 1)
774 # Human SLE Cases 1966 to 2015
775 HumSLEPF66to15<- subset(bbs$HumSLEPF, bbs$Year>1965)
776 # Human SLE Cases 1966 to 2015 Time Series
777 HumSLEPF66to15ts<- ts(HumSLEPF66to15, start = 1966, end = 2015, frequency = 1)
778 # Human SLE Cases 1966 to 2013
779 HumSLEPF66to13<- subset(bbs$HumSLEPF, bbs$Year>1965 & bbs$Year<2014)
780 # Human SLE Cases 1966 to 2013 Time Series
781 HumSLEPF66to13ts<- ts(HumSLEPF66to13, start = 1966, end = 2013, frequency = 1)
782 # Human SLE Cases 1978 to 2015
783 HumSLEPF78to15<- subset(bbs$HumSLEPF, bbs$Year>1977)
784 # Human SLE Cases 1978 to 2015 Time Series
785 HumSLEPF78to15ts<- ts(HumSLEPF78to15, start = 1978, end = 2015, frequency = 1)
786 # Human SLE Cases 2001 to 2015
787 HumSLEPF01to15<- subset(bbs$HumSLEPF, bbs$Year>2000)
788 # Human SLE Cases 2001 to 2015 Time Series
789 HumSLEPF01to15ts<- ts(HumSLEPF01to15, start = 2001, end = 2015, frequency = 1)
790 # Human WN Cases 2001 to 2015
791 HumWNPF01to15<- subset(bbs$HumSLEPF, bbs$Year>2000)
792 # Human WN Cases 2001 to 2015 Time Series
793 HumWNPF01to15ts<- ts(HumWNPF01to15, start = 2001, end = 2015, frequency = 1)

```

794 Preliminary Data Analysis

795 Summarize Data

796 Data Summary

```

797 # Dataset
798 pander(bbs)

```


Year	RoutesPF	BJCountPF	CGCountPF	MDCountPF	NCCCountPF	NMCountPF
1958	NA	NA	NA	NA	NA	NA
1959	NA	NA	NA	NA	NA	NA
1960	NA	NA	NA	NA	NA	NA
1961	NA	NA	NA	NA	NA	NA
1962	NA	NA	NA	NA	NA	NA
1963	NA	NA	NA	NA	NA	NA
1964	NA	NA	NA	NA	NA	NA
1965	NA	NA	NA	NA	NA	NA
1966	13	265	470	114	626	737
1967	17	328	617	212	617	1009
1968	17	325	708	285	852	1328
1969	18	439	917	359	960	1330
1970	21	478	1073	322	1078	1400
1971	22	420	920	468	1084	1602
1972	21	482	918	458	891	1682
1973	21	461	1027	479	849	1727
1974	15	294	837	467	636	1002
1975	16	374	748	503	514	1370
1976	18	362	834	534	585	1459
1977	18	456	863	692	616	1565
1978	17	339	704	482	555	1332
1979	17	409	823	476	514	1300
1980	16	361	778	482	445	1178
1981	15	270	693	412	455	1036
1982	14	261	636	369	448	967
1983	14	260	592	395	390	753
1984	11	217	569	245	233	621
1985	11	251	611	380	349	658
1986	18	401	825	882	514	1087
1987	50	845	1775	1638	1361	2446
1988	47	882	1987	1862	1448	2469
1989	42	807	1477	2022	1282	2189
1990	40	847	1514	1881	1279	2273
1991	42	774	1462	1668	1334	2148
1992	40	710	1281	2047	1448	2106
1993	44	920	1343	2040	1593	2099
1994	51	957	1484	2525	1610	2438
1995	43	789	1116	2275	1405	1913
1996	41	791	974	1757	1438	1641
1997	38	954	778	2180	1427	1783
1998	43	870	900	2003	1584	1757
1999	47	947	1184	2545	1784	2004
2000	46	918	1050	2345	1723	1718
2001	46	825	836	2465	1910	1852
2002	52	1014	1416	2615	2012	1960
2003	54	675	1067	2178	2059	1934
2004	54	861	1002	2138	2023	1745
2005	50	737	882	2025	2089	1576
2006	52	764	1056	2029	1995	1548
2007	52	673	985	1890	2041	1459

2008	46	586	876	1899	1782	1371
2009	47	606	902	1534	1887	1326
2010	53	640	931	2042	2185	1410
2011	53	705	892	2130	2225	1493
2012	47	646	685	2177	1972	1223
2013	47	611	796	1985	1889	1169
2014	46	483	857	1470	1704	1002
2015	41	394	637	1366	1488	844

800 *Table continues below*

BJAveragePF	CGAveragePF	MDAveragePF	NCAveragePF	NMAveragePF
NA	NA	NA	NA	NA
NA	NA	NA	NA	NA
NA	NA	NA	NA	NA
NA	NA	NA	NA	NA
NA	NA	NA	NA	NA
NA	NA	NA	NA	NA
NA	NA	NA	NA	NA
NA	NA	NA	NA	NA
30.22	15.55	8.769	40.25	18.31
26.3	23.46	12.47	26.3	38.36
19.39	36.52	16.77	23.33	56.92
22.01	41.66	19.94	23.04	57.72
31.17	34.42	15.33	31.32	44.7
19.74	46.6	21.27	23.26	68.86
22.1	41.54	21.81	21.45	78.41
20.21	50.81	22.81	16.71	103.4
9.443	88.64	31.13	7.176	139.6
11.9	62.88	31.44	8.175	167.6
12.2	68.35	29.67	8.559	170.5
11.86	72.76	38.44	8.466	184.8
11.96	58.88	28.35	9.426	141.3
14.61	56.34	28	9.123	142.5
11.98	64.92	30.12	6.854	171.9
9.83	70.5	27.47	6.454	160.5
9.902	64.23	26.36	6.975	138.6
9.215	64.24	28.21	6.071	124
9.743	58.4	22.27	3.99	155.7
7.266	84.09	34.55	4.15	158.5
8.184	100.8	49	5.099	213.2
25.79	68.81	32.76	19.78	123.7
22.26	89.25	39.62	16.22	152.2
16.76	88.11	48.14	14.55	150.5
18.01	84.06	47.02	15.22	149.4
19.49	75.02	39.71	17.78	120.8
13.87	92.33	51.17	15.68	134.3
19.84	67.68	46.36	23.54	89.18
19.33	76.77	49.51	20.97	116.3
14.91	74.83	52.91	18.77	101.9
18.46	52.77	42.85	27.25	60.22
16.63	46.78	57.37	30.5	58.46
18.68	48.19	46.58	32.87	53.45
17.49	67.7	54.15	26.35	76.05

18.01	58.31	50.98	29.55	58.14
15.4	54.3	53.59	35.17	52.65
20.16	70.22	50.29	28.65	68.41
16.74	63.76	40.33	32.3	59.89
21.75	46.08	39.59	43.91	39.74
18.2	48.47	40.5	43.1	36.57
19.58	53.93	39.02	36.99	41.85
18.52	53.2	36.35	38.37	38.03
14.2	61.71	41.28	28.88	47.48
18.57	48.58	32.64	38.84	34.14
16.61	56.05	38.53	38.98	36.17
17.54	50.85	40.19	43.76	34.12
13.95	49.12	46.32	40.15	30.46
14.47	55.02	42.23	34.33	34.05
15.11	56.7	31.96	30.05	33.34
11.83	53.87	33.32	27.62	30.55

801 *Table continues below*

BJIndexPF	CGIndexPF	MDIndexPF	NCIndexPF	NMIndexPF	SCFlaviPF	SCWNPf
NA	NA	NA	NA	NA	NA	NA
NA	NA	NA	NA	NA	NA	NA
NA	NA	NA	NA	NA	NA	NA
NA	NA	NA	NA	NA	NA	NA
NA	NA	NA	NA	NA	NA	NA
NA	NA	NA	NA	NA	NA	NA
NA	NA	NA	NA	NA	NA	NA
20.09	70.92	20.76	40.68	112.7	NA	NA
19.19	64.05	17.63	40.64	103.9	NA	NA
20.05	64.86	19.47	44.46	108.9	NA	NA
20.21	72.42	21.4	44.94	102.4	NA	NA
19.49	71.92	17.76	45.89	98.87	NA	NA
18.9	63.07	23.51	46.87	99.37	NA	NA
19.03	59.62	22.71	43.46	101.2	NA	NA
18.45	72.37	22.93	40.7	98.35	NA	NA
17.85	64.4	25.74	42.52	94.36	NA	NA
17.7	56.86	27.54	39.78	93.95	NA	NA
17.35	56.93	26.56	39.27	92.2	NA	NA
18.29	56.03	32.27	38.77	90.46	NA	NA
16.59	48.41	29.09	39.28	84.43	0	NA
17.44	52	28.27	40.42	83.78	147	NA
17.11	52.03	29.1	38.43	80.57	105	NA
16.59	51.76	28.15	38.62	78.77	35	NA
16.86	49.5	29.96	37.91	76.41	143	NA
16.18	46.36	32.44	38.62	71.99	169	NA
15.91	51.55	29.09	35.33	69.96	124	NA
16.19	47.12	34.21	39.87	68.66	212	NA
16.13	48.09	37.93	37.37	67.58	182	NA
15.36	46.16	35	38	67.77	10	NA
15.8	44.99	35.65	40.59	66.98	6	NA
16.09	37.48	40.56	38.94	65.09	141	NA
15.76	39.81	38.63	40.79	64.36	1023	NA
15.03	44.82	44.79	40.05	64.77	80	NA

14.87	45.6	46.77	40.54	63.48	4	NA
15.35	41.93	47.27	39.32	59.88	218	NA
14.92	37.08	51.56	41.19	58.97	84	NA
13.76	32.55	46.18	39.73	54.55	54	NA
13.91	28.16	40.83	40.6	51.07	21	NA
14.97	27.4	48.66	42.61	53.24	628	NA
13.36	25.47	44.49	39.85	50.94	213	NA
14.01	27.7	52.07	40.97	49.22	193	NA
13.38	22.17	49.91	39.53	46.64	155	NA
13.31	22.73	55.39	42.29	48.95	109	90
14.28	27.12	54.98	41.73	48.44	1050	1050
11.19	17.57	48.53	40.21	46.51	1008	997
12.93	17.57	45.27	39.03	42.83	289	278
12.16	17.88	42.42	41.14	40.7	331	326
11.47	18.06	45.1	41.32	39.28	53	13
11.11	18.08	45.32	41.85	38.58	20	18
11.14	19.85	49.13	39.98	38.52	7	7
10.67	16.56	42.39	43.28	36.82	55	55
10.84	14.4	50.2	43.24	36.21	499	494
11.25	17.52	54.21	43.39	36.82	249	185
11.24	12.54	61.27	42.46	35.79	308	226
10.98	16.48	57.97	43.61	34.8	223	135
NA	NA	NA	NA	NA	389	291
NA	NA	NA	NA	NA	410	401
SCSLEPF	HumSLEPF	Row				
NA	5	1				
NA	70	2				
NA	0	3				
NA	25	4				
NA	222	5				
NA	0	6				
NA	0	7				
NA	0	8				
NA	0	9				
NA	0	10				
NA	0	11				
NA	3	12				
NA	0	13				
NA	0	14				
NA	0	15				
NA	0	16				
NA	0	17				
NA	0	18				
NA	0	19				
NA	138	20				
0	0	21				
147	6	22				
105	1	23				
35	1	24				
143	1	25				
169	0	26				
124	0	27				
212	1	28				

182	0	29
10	0	30
6	0	31
141	0	32
1023	223	33
80	0	34
4	0	35
218	8	36
84	0	37
54	0	38
21	0	39
628	9	40
213	2	41
193	3	42
155	0	43
19	0	44
0	0	45
11	0	46
11	0	47
5	0	48
40	0	49
2	0	50
0	0	51
0	0	52
5	0	53
64	0	54
82	0	55
88	0	56
98	0	57
9	0	58

802 # Summarize BBS and Transmission Data
803 summary(bbs)

804	Year	RoutesPF	BJCountPF	CGCountPF	MDCountPF
805	Min. :1958	Min. :11.00	Min. : 217.0	Min. : 470.0	Min. : 114
806	1st Qu.:1972	1st Qu.:17.25	1st Qu.: 379.0	1st Qu.: 778.0	1st Qu.: 470
807	Median :1986	Median :41.00	Median : 608.5	Median : 896.0	Median :1653
808	Mean :1986	Mean :34.08	Mean : 593.7	Mean : 966.2	Mean :1355
809	3rd Qu.:2001	3rd Qu.:47.00	3rd Qu.: 803.0	3rd Qu.:1064.2	3rd Qu.:2042
810	Max. :2015	Max. :54.00	Max. :1014.0	Max. :1987.0	Max. :2615
811		NA's :8	NA's :8	NA's :8	NA's :8
812	NCCountPF	NMCountPF	BJAveragePF	CGAveragePF	MDAveragePF
813	Min. : 233.0	Min. : 621	Min. : 7.266	Min. : 15.55	Min. : 8.769
814	1st Qu.: 619.2	1st Qu.:1189	1st Qu.:12.620	1st Qu.: 49.54	1st Qu.:28.249
815	Median :1383.0	Median :1476	Median :17.126	Median : 58.35	Median :38.486
816	Mean :1263.8	Mean :1521	Mean :16.828	Mean : 60.36	Mean :36.189
817	3rd Qu.:1783.5	3rd Qu.:1835	3rd Qu.:19.557	3rd Qu.: 69.87	3rd Qu.:46.353
818	Max. :2225.0	Max. :2469	Max. :31.174	Max. :100.81	Max. :57.368
819	NA's :8	NA's :8	NA's :8	NA's :8	NA's :8
820	NCAveragePF	NMAveragePF	BJIndexPF	CGIndexPF	MDIndexPF
821	Min. : 3.99	Min. : 18.31	Min. :10.67	Min. :12.54	Min. :17.63
822	1st Qu.:10.71	1st Qu.: 42.56	1st Qu.:13.35	1st Qu.:22.59	1st Qu.:28.24
823	Median :23.30	Median : 72.46	Median :15.56	Median :44.91	Median :39.59
824	Mean :22.93	Mean : 91.95	Mean :15.31	Mean :40.79	Mean :38.15
825	3rd Qu.:32.05	3rd Qu.:140.90	3rd Qu.:17.37	3rd Qu.:53.03	3rd Qu.:47.59
826	Max. :43.91	Max. :213.19	Max. :20.21	Max. :72.42	Max. :61.27
827	NA's :8	NA's :8	NA's :10	NA's :10	NA's :10
828	NCIndexPF	NMIndexPF	SCFlaviPF	SCWNPF	SCSLEPF
829	Min. :35.33	Min. : 34.80	Min. : 0.00	Min. : 7.0	Min. : 0.00
830	1st Qu.:39.31	1st Qu.: 47.99	1st Qu.: 54.25	1st Qu.: 72.5	1st Qu.: 9.25
831	Median :40.59	Median : 64.93	Median : 151.00	Median : 226.0	Median : 72.00
832	Mean :40.83	Mean : 67.08	Mean : 235.45	Mean : 304.4	Mean : 115.29

```

833 3rd Qu.:42.33 3rd Qu.: 85.94 3rd Qu.: 279.00 3rd Qu.: 363.5 3rd Qu.: 146.00
834 Max. :46.87 Max. :112.70 Max. :1050.00 Max. :1050.0 Max. :1023.00
835 NA's :10 NA's :10 NA's :20 NA's :43 NA's :20
836 HumSLEPF Row
837 Min. : 0.00 Min. : 1.00
838 1st Qu.: 0.00 1st Qu.:15.25
839 Median : 0.00 Median :29.50
840 Mean : 12.38 Mean :29.50
841 3rd Qu.: 1.00 3rd Qu.:43.75
842 Max. :223.00 Max. :58.00
843

```

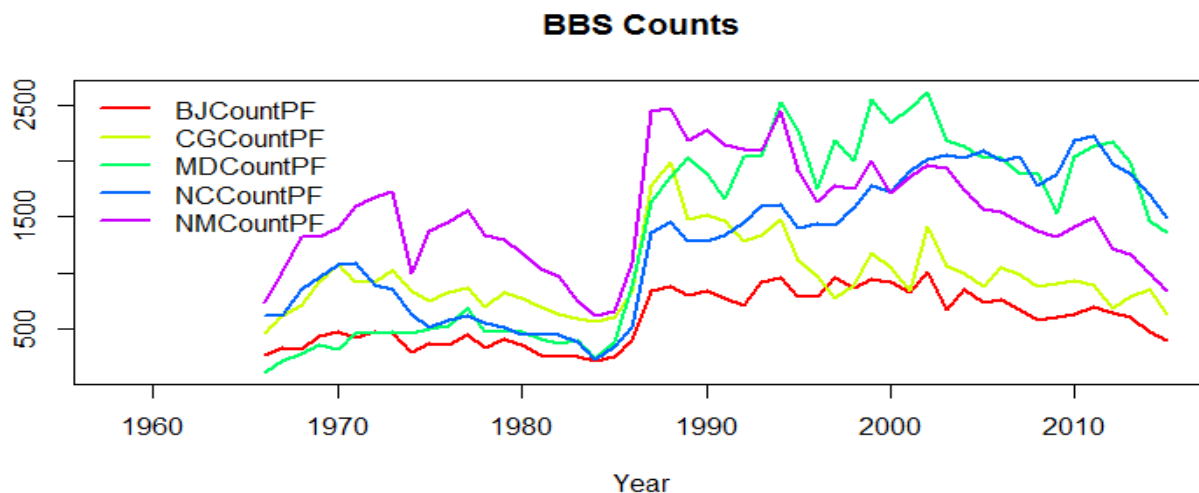
844 Plot Data

845 Plot BBS Data

```

846 # Plot BBS Counts
847 ts.plot(bbs58to15ts[,3:7],gpars= list(col=rainbow(5)),lty=1,lwd=2, main="BBS Counts",
848        xlab="Year")
849 legend("topleft", colnames(bbs58to15ts[,3:7]), lty=1, col=rainbow(5), bty="n", cex=1,
850        lwd=2)

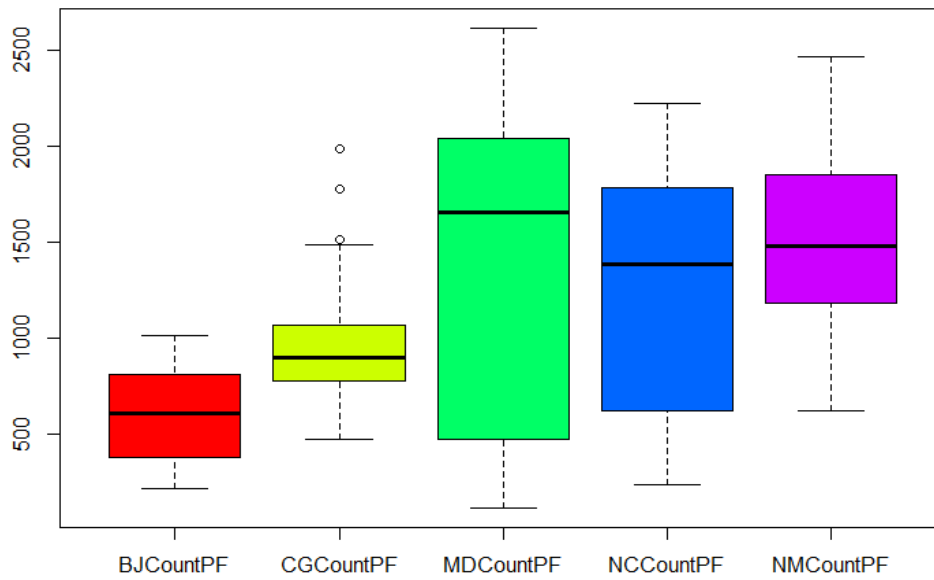
```



```

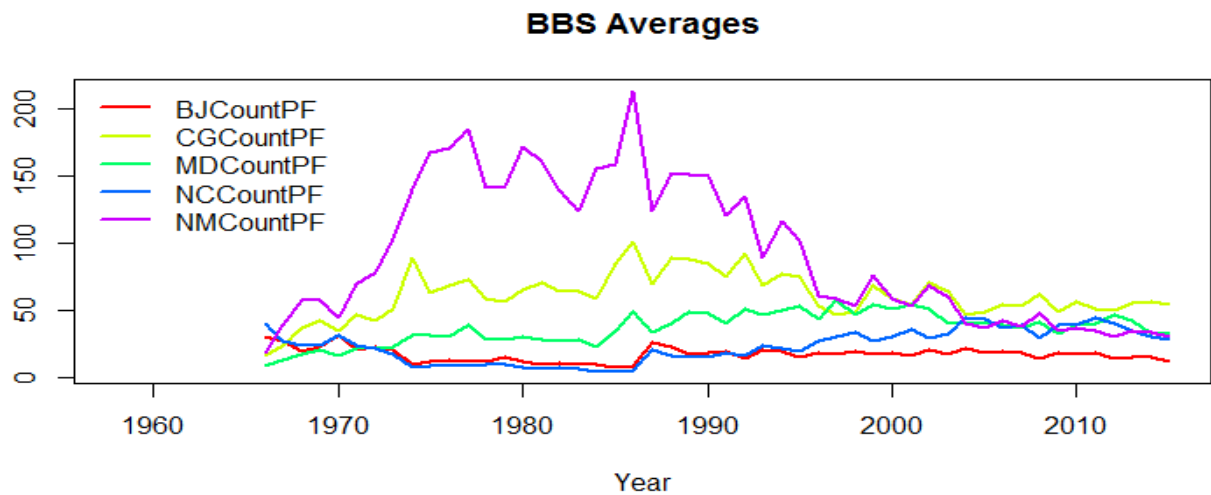
851
852 # BBS Counts Boxplot
853 boxplot(bbs58to15ts[,3:7], col=rainbow(5))

```



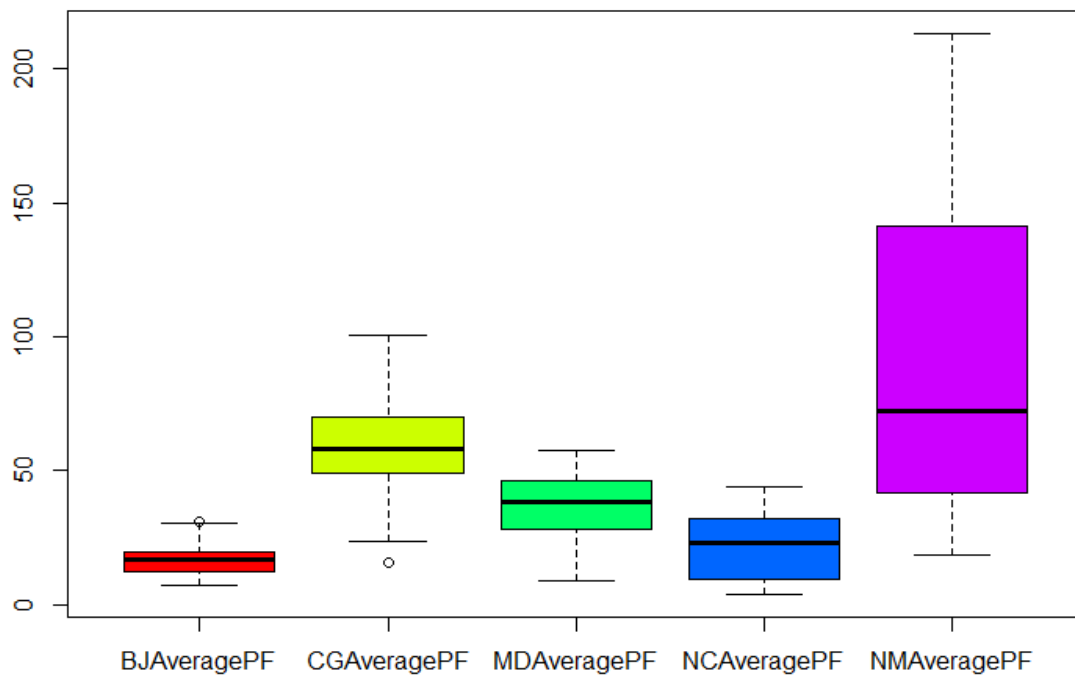
854

```
855 # Plot BBS Averages
856 ts.plot(bbs58to15ts[,8:12],gpars= list(col=rainbow(5)),lty=1,lwd=2,
857        main="BBS Averages", xlab="Year")
858 legend("topleft", colnames(bbs58to15ts[,3:7]), lty=1, col=rainbow(5),
859        bty="n", cex=1, lwd=2)
```



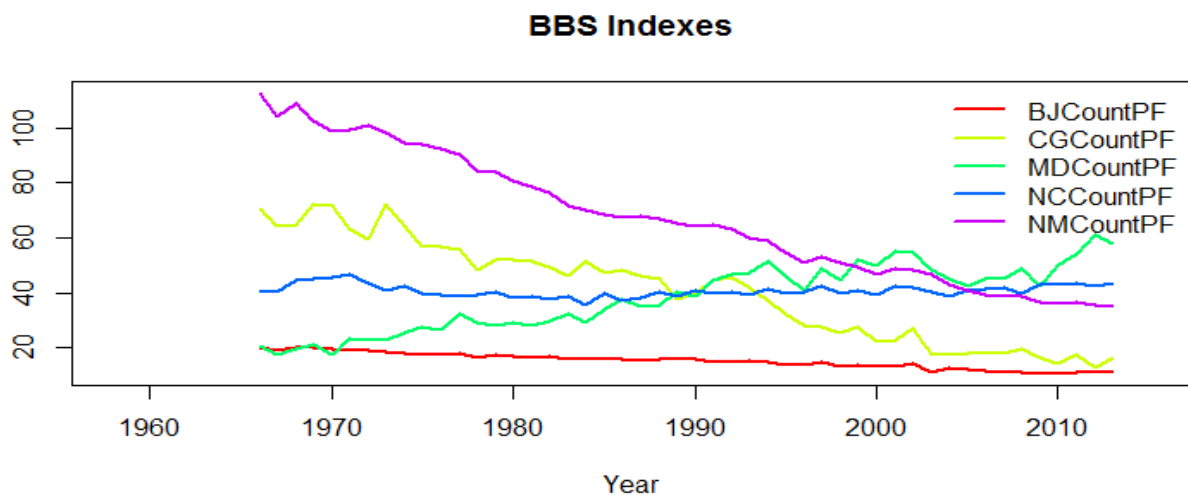
860

```
861 # BBS Counts Boxplot
862 boxplot(bbs58to15ts[,8:12], col=rainbow(5))
```



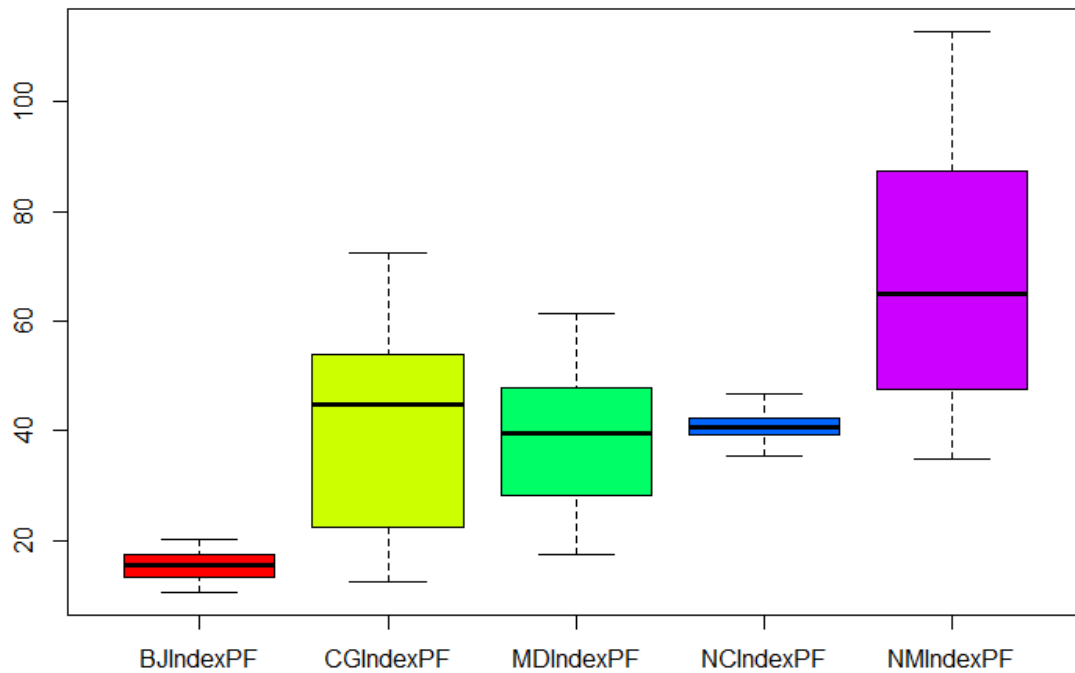
863

```
864 # Plot BBS Index
865 ts.plot(bbs58to15ts[,13:17],gpars= list(col=rainbow(5)),lty=1,lwd=2,
866        main="BBS Indexes", xlab="Year")
867 legend("topright", colnames(bbs58to15ts[,3:7]), lty=1, col=rainbow(5),
868        bty="n", cex=1, lwd=2)
```



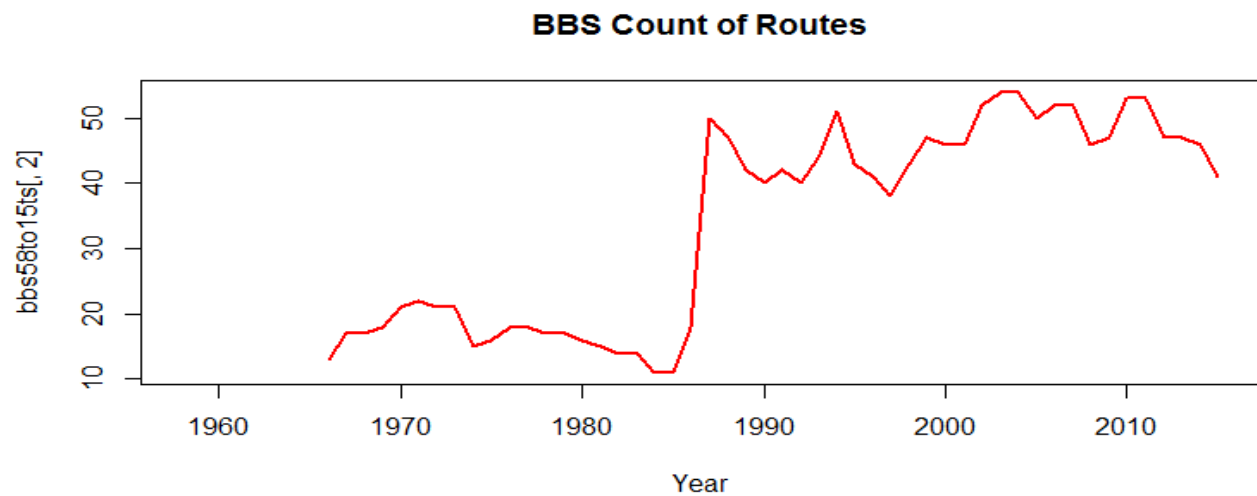
869

```
870 # BBS Index Boxplot
871 boxplot(bbs58to15ts[,13:17], col=rainbow(5))
```

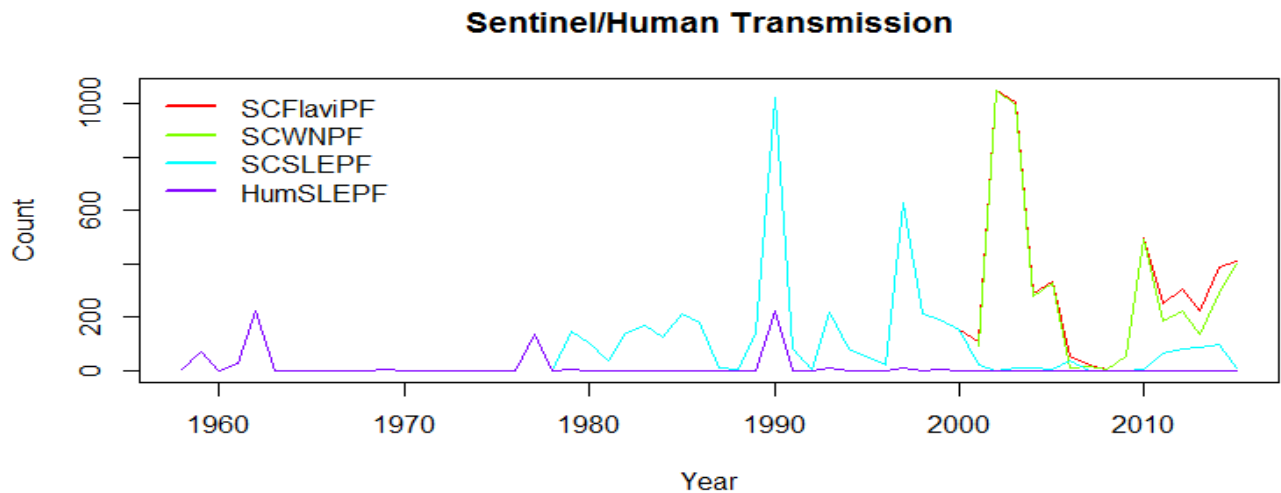
872

```
873 # Plot BBS Count of Routes
874 ts.plot(bbs58to15ts[,2], gpars= list(col=rainbow(5)), lty=1, lwd=2,
875        main="BBS Count of Routes", xlab="Year")
```



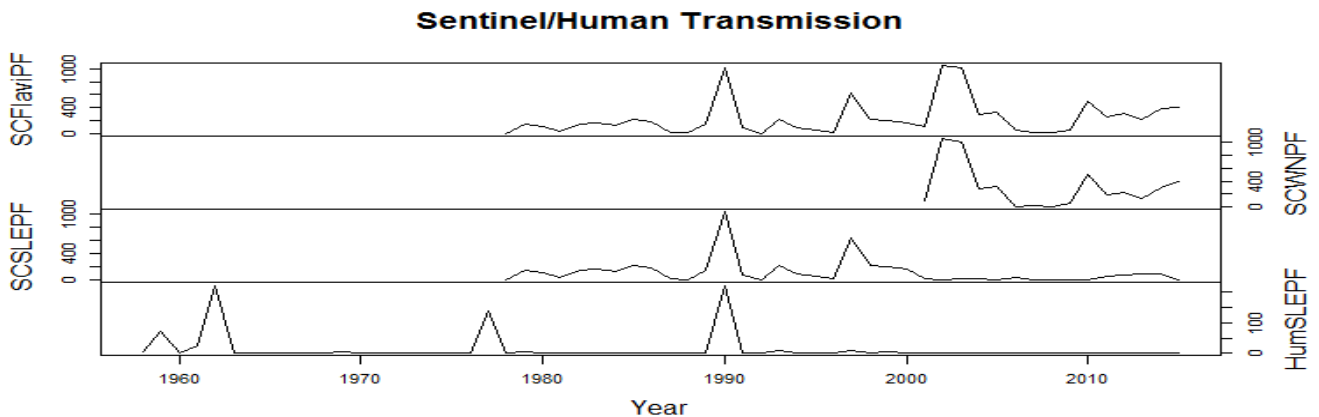
876

```
877 Plot Transmission Data
878 # Plot Transmission Counts
879 ts.plot(bbs58to15ts[,18:21], main="Sentinel/Human Transmission",
880        xlab="Year", ylab="Count", gpars= list(col=rainbow(4)))
881 legend("topleft", colnames(bbs58to15ts[,18:21]), lty=1, col=rainbow(4),
882        bty="n", cex=1, lwd=2)
```



883

```
884 plot.ts(bbs58to15ts[,18:21], main="Sentinel/Human Transmission", xlab="Year",
885 yax.flip=TRUE)
```



886

887 Check Data Distribution

888 BBS Count Data Distribution

889 Note: Data has been filtered from the time period of 1966-2015 to 1978-2015 to match Transmission data.

890 Blue Jay Count Data

```
891 gofstat(list(fitdist(BJCountPF78to15, "pois"), fitdist(BJCountPF78to15,
892 "nbinom")),fitnames = c("Poisson","negative binomial"))
```

893 Chi-squared statistic: 1.701847e+65 16.67283

894 Degree of freedom of the Chi-squared distribution: 5 4

895 Chi-squared p-value: 0 0.002237288

896 the p-value may be wrong with some theoretical counts < 5

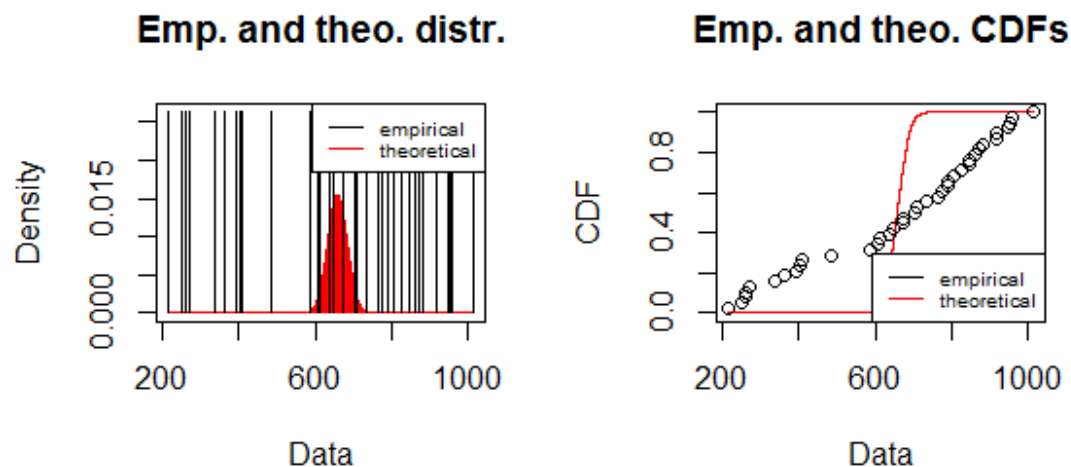
897 Chi-squared table:

	obscounts	theo Poisson	theo negative binomial
899	<= 270	5 1.468992e-64	1.475122
900	<= 409	5 4.281669e-24	5.086137
901	<= 640	5 9.497877e+00	13.490714
902	<= 710	5 2.769906e+01	3.810044
903	<= 791	5 8.030560e-01	3.763373
904	<= 861	5 8.293156e-06	2.636885
905	> 861	8 6.581402e-13	7.737726

```

906
907 Goodness-of-fit criteria
908                                     Poisson negative binomial
909 Aikake's Information Criterion 3887.792      532.1100
910 Bayesian Information Criterion 3889.430      535.3851
911 plot(fitdist(BJCountPF78to15, "pois"))

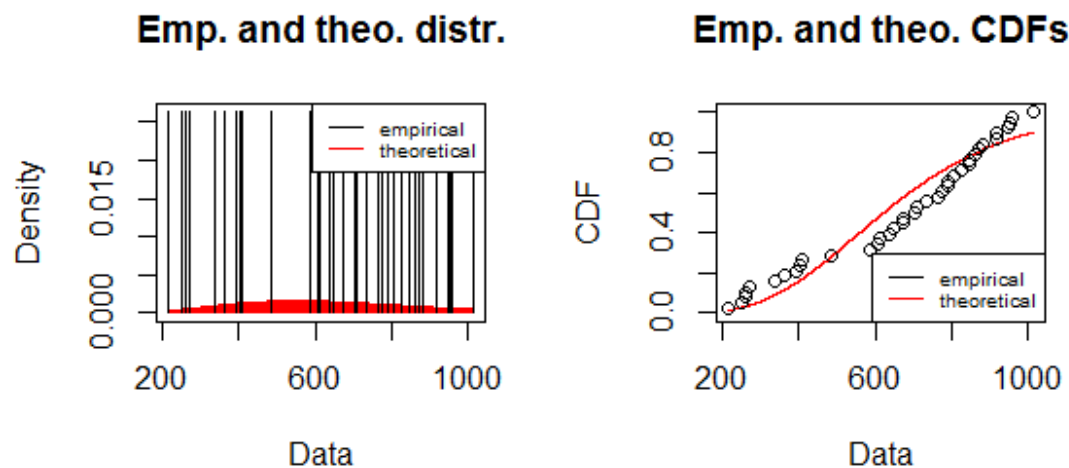
```



```

912
913 plot(fitdist(BJCountPF78to15, "nbinom"))

```



```

914
915 Common Grackle Count Data
916 gofstat(list(fitdist(CGCountPF78to15, "pois"), fitdist(CGCountPF78to15,
917 "nbinom")), fitnames = c("Poisson", "negative binomial"))
918 Chi-squared statistic:  4.44328e+35  6.304185
919 Degree of freedom of the Chi-squared distribution:  5 4
920 Chi-squared p-value:  0 0.1775541
921 the p-value may be wrong with some theoretical counts < 5
922 Chi-squared table:
923      obscounts theo Poisson theo negative binomial
924 <= 637      5 5.626474e-35      4.048452
925 <= 778      5 6.341631e-13      5.344474
926 <= 857      5 1.652901e-05      3.722909

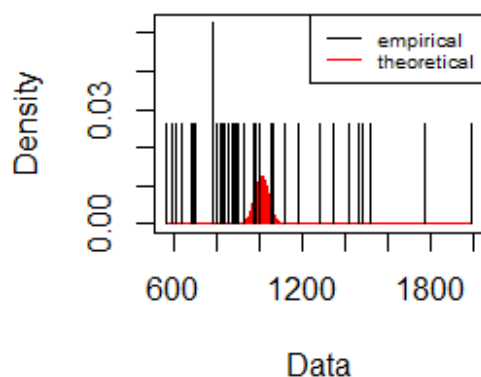
```

```

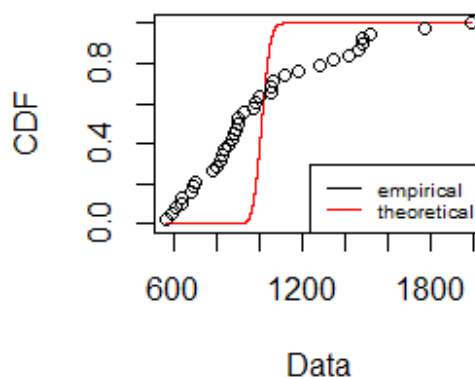
927 <= 902      5 1.116675e-02      2.222108
928 <= 1050    5 3.414180e+01      7.124919
929 <= 1281    5 3.847012e+00      8.436609
930 > 1281     8 4.218847e-15      7.100530
931
932 Goodness-of-fit criteria
933                               Poisson negative binomial
934 Aikake's Information Criterion 4320.188      547.3024
935 Bayesian Information Criterion 4321.826      550.5776
936 plot(fitdist(CGCountPF78to15, "pois"))

```

Emp. and theo. distr.



Emp. and theo. CDFs

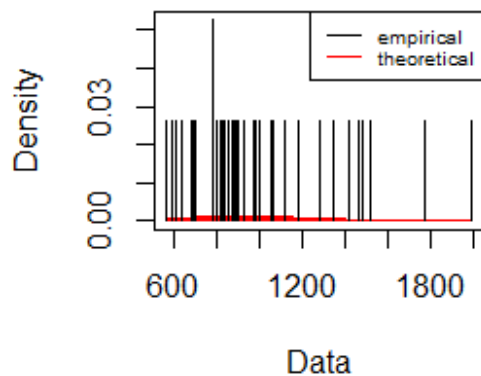


```

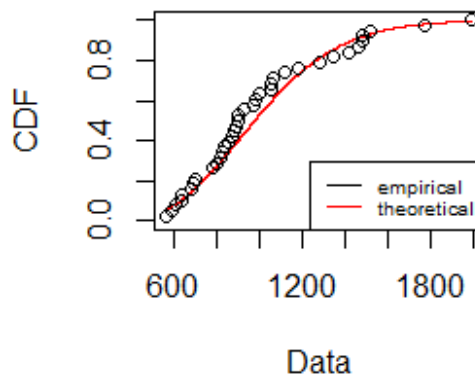
937
938 plot(fitdist(CGCountPF78to15, "nbinom"))

```

Emp. and theo. distr.



Emp. and theo. CDFs



939

940 Mourning Dove Count Data

```
941 gofstat(list(fitdist(MDCountPF78to15, "pois"), fitdist(MDCountPF78to15,
942 "nbinom")), fitnames = c("Poisson", "negative binomial"))
```

```
943 Chi-squared statistic: Inf 53.85901
944 Degree of freedom of the Chi-squared distribution: 5 4
945 Chi-squared p-value: 0 5.632849e-11
946 the p-value may be wrong with some theoretical counts < 5
```

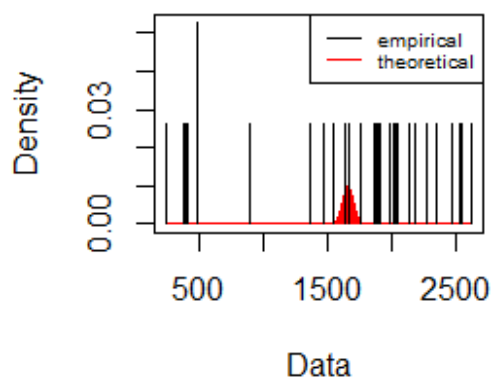
```
947 Chi-squared table:
948 obscounts  theo Poisson  theo negative binomial
949 <= 412      5 1.929814e-291      1.4462055
950 <= 1366     5 6.001212e-12       15.5732262
951 <= 1757     5 3.777816e+01       6.4213815
952 <= 1985     5 2.218443e-01       3.0768532
953 <= 2040     5 5.062617e-14       0.6638387
954 <= 2177     5 0.000000e+00       1.5241102
955 > 2177      8 0.000000e+00       9.2943848
```

```
956 Goodness-of-fit criteria
```

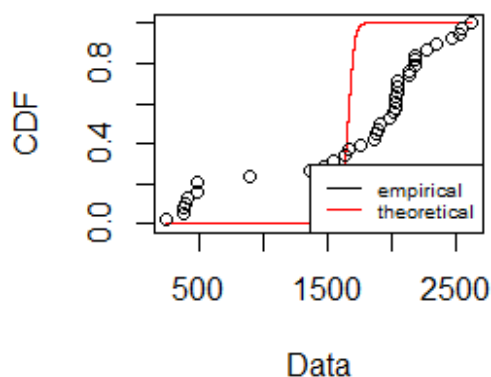
	Poisson	negative binomial
Aikake's Information Criterion	15391.23	623.4892
Bayesian Information Criterion	15392.87	626.7643

```
961 plot(fitdist(MDCountPF78to15, "pois"))
```

Emp. and theo. distr.



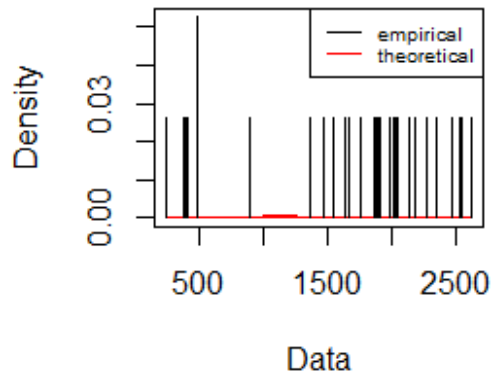
Emp. and theo. CDFs



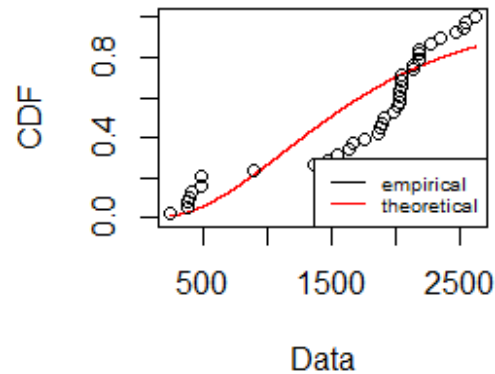
962

```
963 plot(fitdist(MDCountPF78to15, "nbinom"))
```

Emp. and theo. distr.



Emp. and theo. CDFs



964

965 Northern Cardinal Count Data

```
966 gofstat(list(fitdist(NCCountPF78to15, "pois"), fitdist(NCCountPF78to15,
967 "nbinom")), fitnames = c("Poisson", "negative binomial"))
```

```
968 Chi-squared statistic: Inf 19.66904
969 Degree of freedom of the Chi-squared distribution: 5 4
970 Chi-squared p-value: 0 0.0005804062
971 the p-value may be wrong with some theoretical counts < 5
972 Chi-squared table:
```

	obscounts	theo Poisson	theo negative binomial
973			
974	<= 448	5 9.198400e-198	2.001736
975	<= 1279	5 3.592193e-03	16.865214
976	<= 1427	5 2.288257e+01	3.020797
977	<= 1584	5 1.511357e+01	2.873381
978	<= 1782	5 2.631727e-04	3.090476
979	<= 1972	5 0.000000e+00	2.413790
980	> 1972	8 0.000000e+00	7.734606

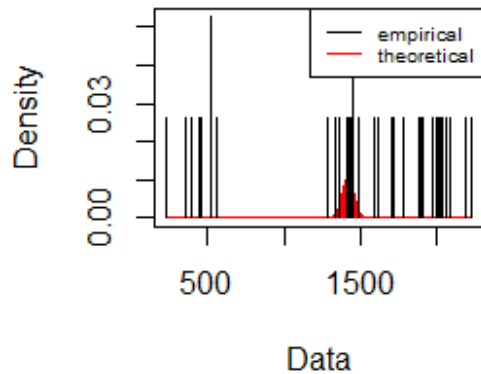
981

982 Goodness-of-fit criteria

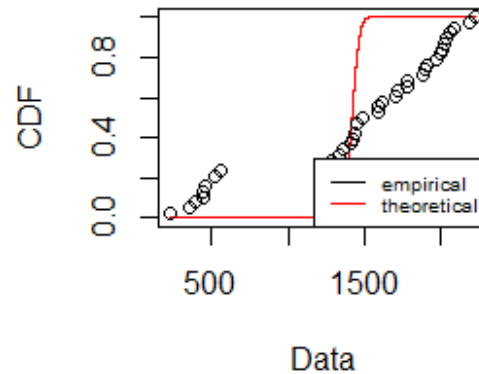
	Poisson	negative binomial
983		
984	Aikake's Information Criterion 12202.38	607.9049
985	Bayesian Information Criterion 12204.01	611.1801

```
986 plot(fitdist(NCCountPF78to15, "pois"))
```

Emp. and theo. distr.



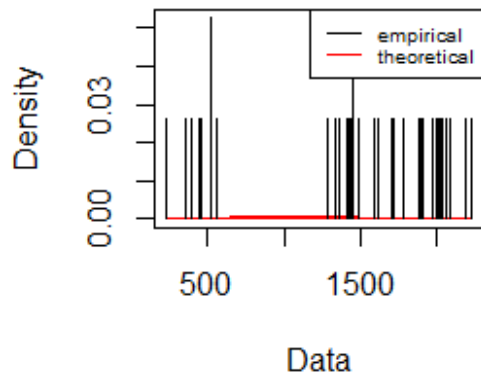
Emp. and theo. CDFs



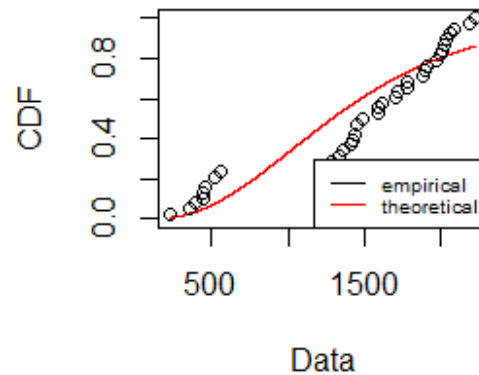
987

988 `plot(fitdist(NCCountPF78to15, "nbinom"))`

Emp. and theo. distr.



Emp. and theo. CDFs



989

990 **Northern Mockingbird Count Data**

991 `gofstat(list(fitdist(NMCountPF78to15, "pois"), fitdist(NMCountPF78to15,`
992 `"nbinom"))), fitnames = c("Poisson", "negative binomial"))`

993 Chi-squared statistic: Inf 0.4396675

994 Degree of freedom of the Chi-squared distribution: 5 4

995 Chi-squared p-value: 0 0.9791023

996 the p-value may be wrong with some theoretical counts < 5

997 Chi-squared table:

	obscounts	theo Poisson	theo negative binomial
998	<= 967	5 1.021725e-59	4.354095
999	<= 1178	5 2.996759e-24	4.912066
1000	<= 1371	5 3.291339e-06	5.533249
1001	<= 1576	5 1.985732e+01	5.975441
1002	<= 1783	5 1.814267e+01	5.309187
1003	<= 2004	5 4.623188e-06	4.395894
1004	> 2004	8 0.000000e+00	7.520069

1006

1007 Goodness-of-fit criteria

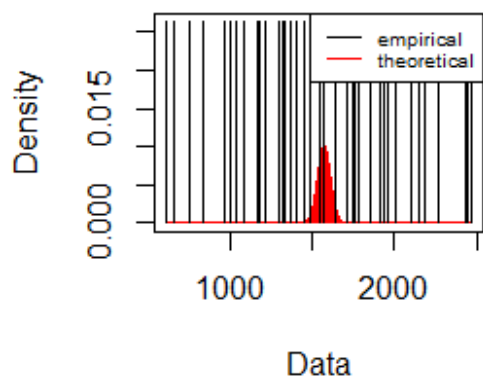
1008 Poisson negative binomial

```

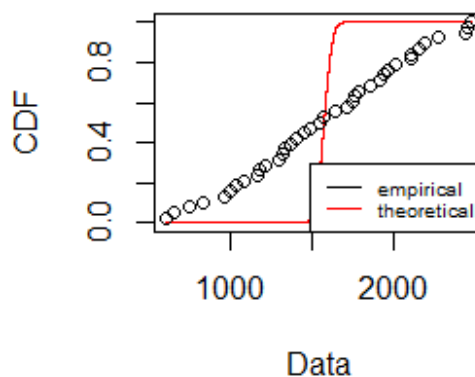
1009 Aikake's Information Criterion 6825.623      586.5488
1010 Bayesian Information Criterion 6827.261     589.8239
1011 plot(fitdist(NMCountPF78to15, "pois"))

```

Emp. and theo. distr.



Emp. and theo. CDFs

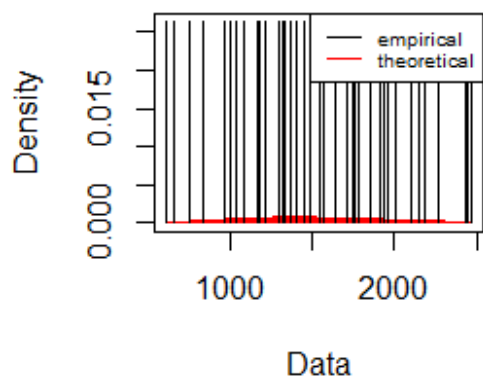


```

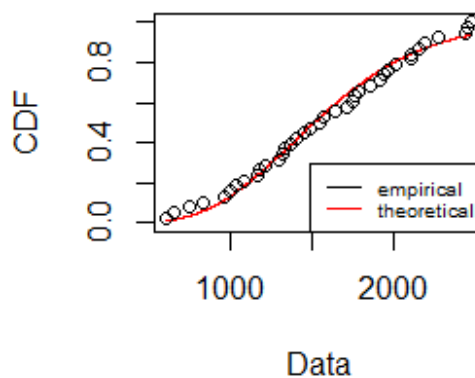
1012
1013 plot(fitdist(NMCountPF78to15, "nbinom"))

```

Emp. and theo. distr.



Emp. and theo. CDFs



```

1014
1015 BBS Averages Data Distribution

```

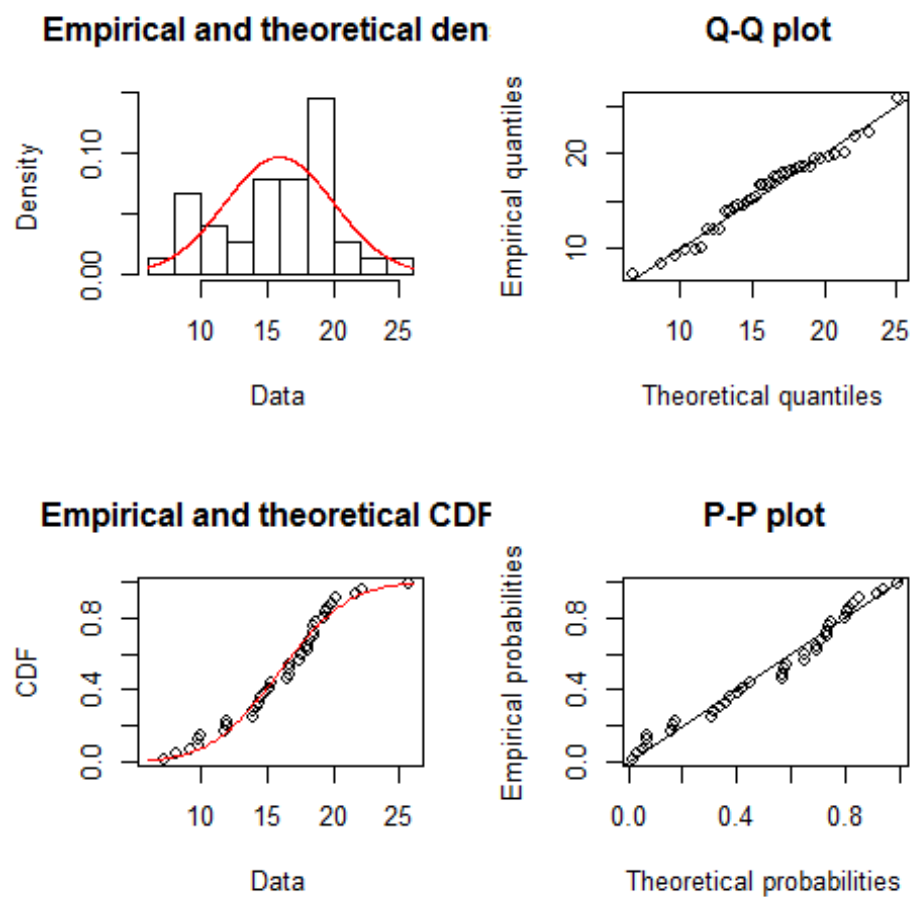
Blue Jay Average per Route Data

```

1017 gofstat(list(fitdist(BJAveragePF78to15, "norm"), fitdist(BJAveragePF78to15,
1018               "lnorm")), fitnames = c("normal", "lognormal"))
1019
1019 Goodness-of-fit statistics
1020                               normal lognormal
1021 Kolmogorov-Smirnov statistic 0.11939840 0.1633584
1022 Cramer-von Mises statistic   0.07913803 0.1955069
1023 Anderson-Darling statistic   0.48131266 1.1127937
1024
1025 Goodness-of-fit criteria
1026                               normal lognormal
1027 Aikake's Information Criterion 219.6162 224.7589
1028 Bayesian Information Criterion 222.8914 228.0341

```

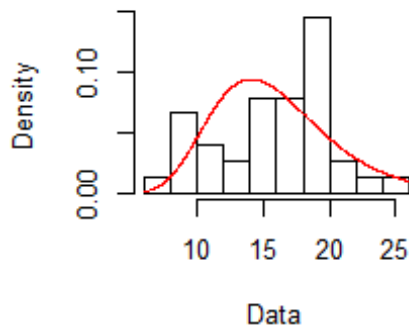

1029 `plot(fitdist(BJAveragePF78to15, "norm"))`



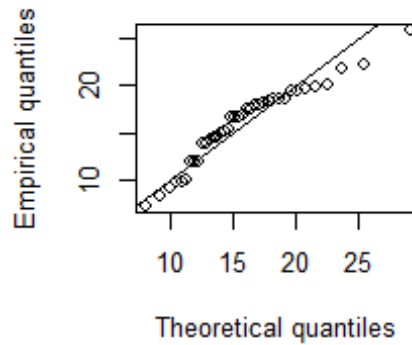
1030

1031 `plot(fitdist(BJAveragePF78to15, "lnorm"))`

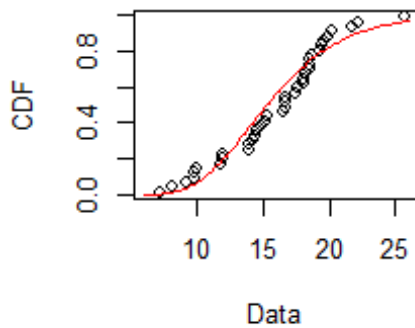
Empirical and theoretical den



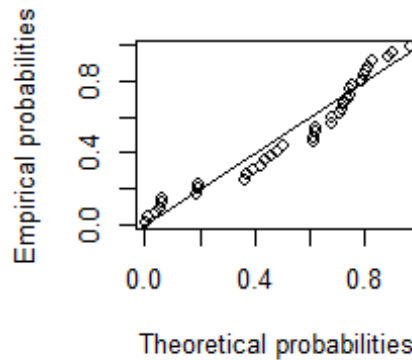
Q-Q plot



Empirical and theoretical CDF



P-P plot



1032

1033 **Common Grackle Average per Route Data**

```
1034 gofstat(list(fitdist(CGAveragePF78to15, "norm"), fitdist(CGAveragePF78to15,
1035 "lnorm")),fitnames = c("normal","lognormal"))
```

1036 Goodness-of-fit statistics

	normal	lognormal
Kolmogorov-Smirnov statistic	0.1456513	0.11933031
Cramer-von Mises statistic	0.1560498	0.08276156
Anderson-Darling statistic	0.9951086	0.55429903

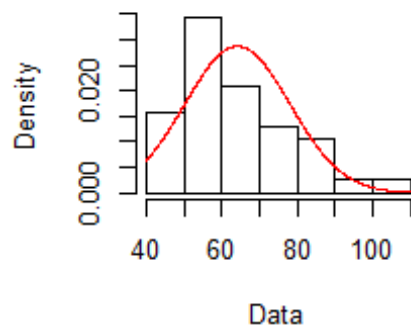
1041

1042 Goodness-of-fit criteria

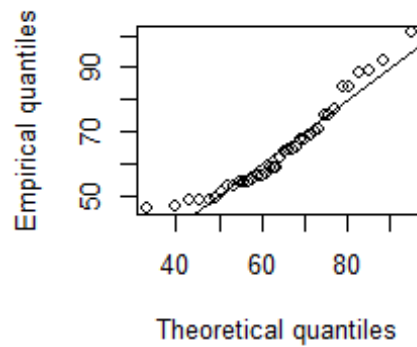
	normal	lognormal
Aikake's Information Criterion	311.9038	306.3401
Bayesian Information Criterion	315.1790	309.6152

```
1046 plot(fitdist(CGAveragePF78to15, "norm"))
```

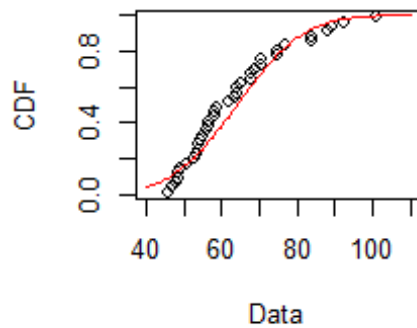
Empirical and theoretical den



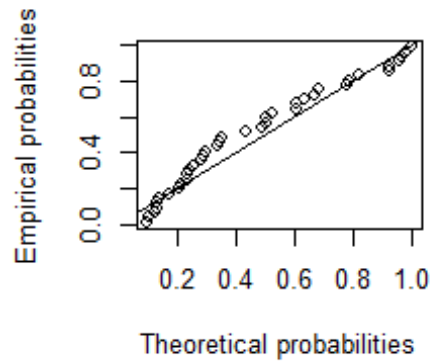
Q-Q plot



Empirical and theoretical CDF



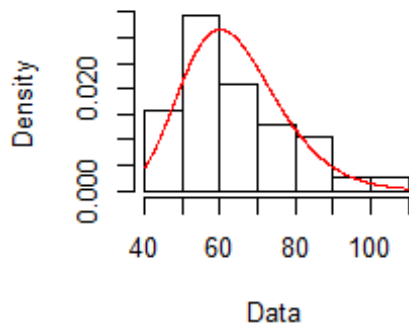
P-P plot



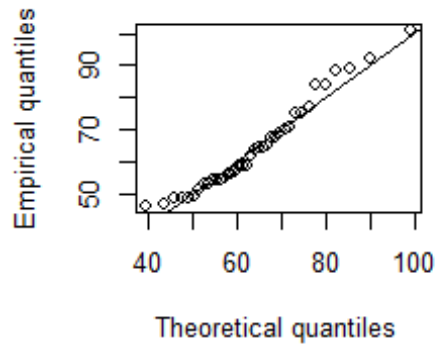
1047

1048 `plot(fitdist(CGAveragePF78to15, "lnorm"))`

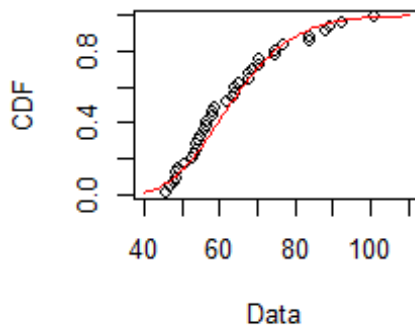
Empirical and theoretical den



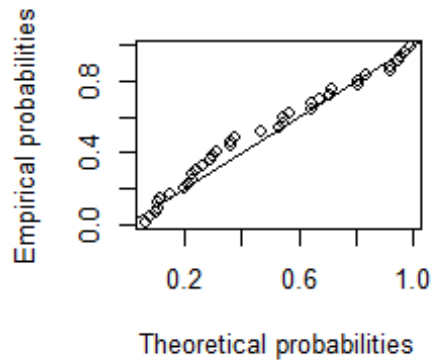
Q-Q plot



Empirical and theoretical CDF



P-P plot



1049

1050 **Mourning Dove Average per Route Data**

```
1051 gofstat(list(fitdist(MDAveragePF78to15, "norm"), fitdist(MDAveragePF78to15,
1052 "lnorm")),fitnames = c("normal","lognormal"))
```

1053 Goodness-of-fit statistics

	normal	lognormal
Kolmogorov-Smirnov statistic	0.10962314	0.12168779
Cramer-von Mises statistic	0.06282804	0.09443359
Anderson-Darling statistic	0.40472381	0.58905531

1058

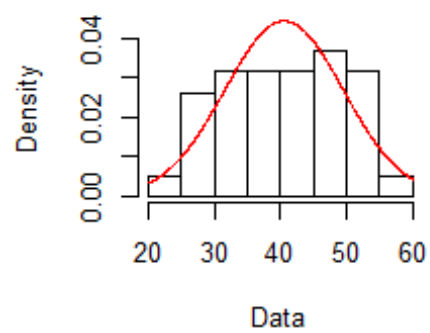
1059 Goodness-of-fit criteria

	normal	lognormal
Aikake's Information Criterion	278.5597	280.7233
Bayesian Information Criterion	281.8348	283.9984

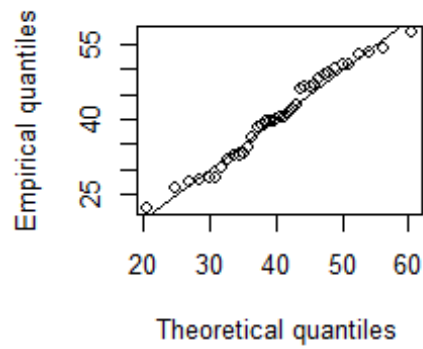
1062

```
1063 plot(fitdist(MDAveragePF78to15, "norm"))
```

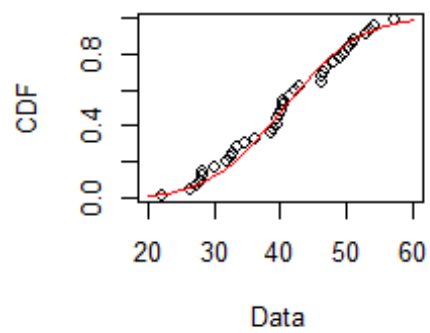
Empirical and theoretical den



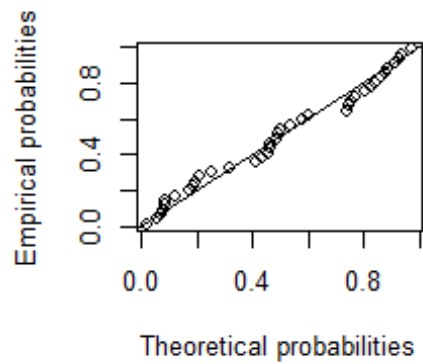
Q-Q plot



Empirical and theoretical CDF



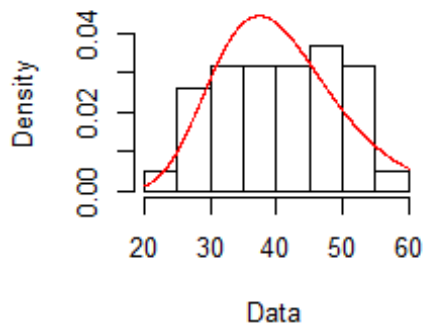
P-P plot



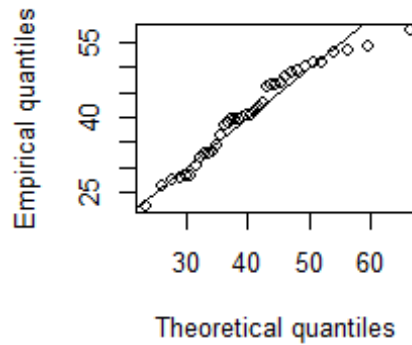
1064

1065 `plot(fitdist(MDAveragePF78to15, "lnorm"))`

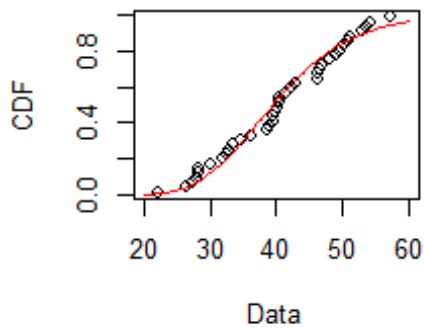
Empirical and theoretical den



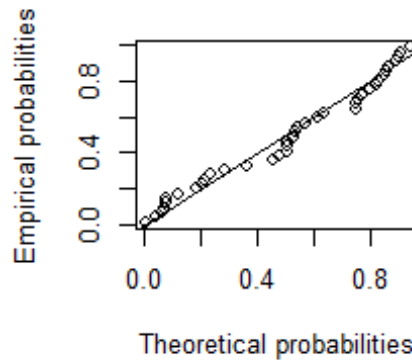
Q-Q plot



Empirical and theoretical CDF



P-P plot



1066

1067 **Northern Cardinal Average per Route Data**

```
1068 gofstat(list(fitdist(NCAveragePF78to15, "norm"), fitdist(NCAveragePF78to15,
1069               "lnorm")),fitnames = c("normal","lognormal"))
```

1070 Goodness-of-fit statistics

	normal	lognormal
Kolmogorov-Smirnov statistic	0.11252537	0.1896369
Cramer-von Mises statistic	0.09954104	0.2937678
Anderson-Darling statistic	0.69765544	1.7577813

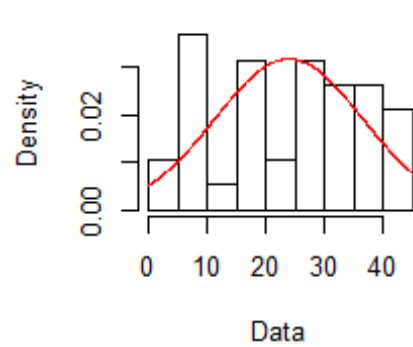
1075

1076 Goodness-of-fit criteria

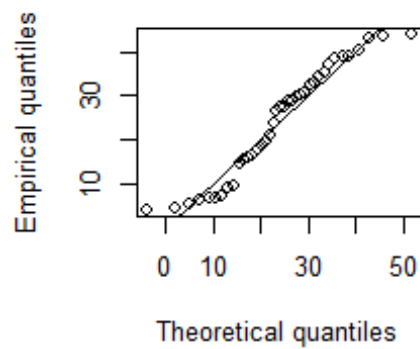
	normal	lognormal
Aikake's Information Criterion	304.0857	312.1668
Bayesian Information Criterion	307.3609	315.4420

```
1080 plot(fitdist(NCAveragePF78to15, "norm"))
```

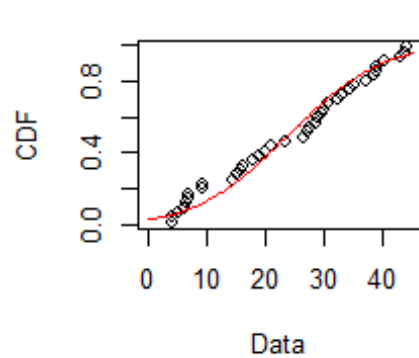
Empirical and theoretical den



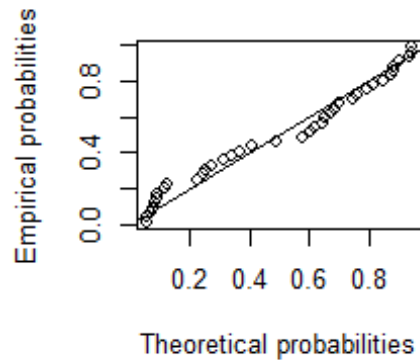
Q-Q plot



Empirical and theoretical CDF



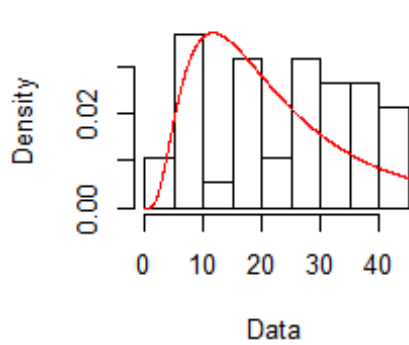
P-P plot



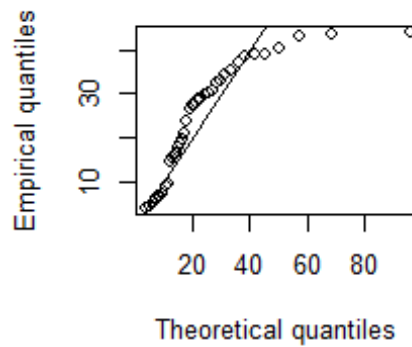
1081

1082 `plot(fitdist(NCAveragePF78to15, "lnorm"))`

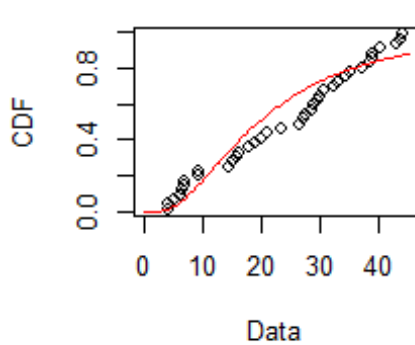
Empirical and theoretical den



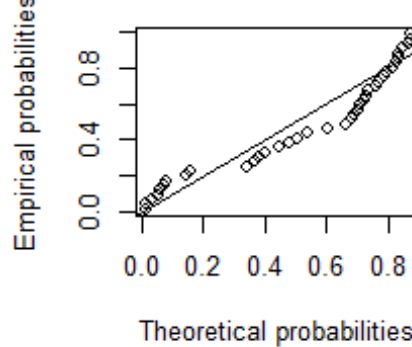
Q-Q plot



Empirical and theoretical CDF



P-P plot



1083

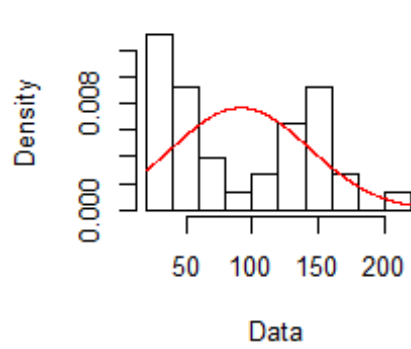
1084 **Northern Mockingbird Average per Route Data**

```
1085 gofstat(list(fitdist(NMAveragePF78to15, "norm"), fitdist(NMAveragePF78to15,
1086 "lnorm")),fitnames = c("normal","lognormal"))
```

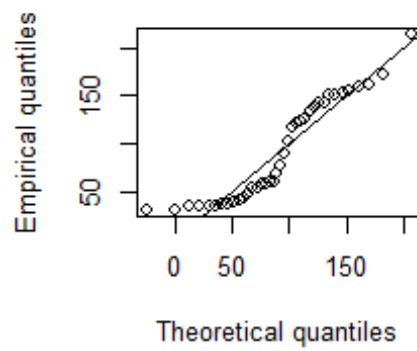
1087 Goodness-of-fit statistics

	normal	lognormal
Kolmogorov-Smirnov statistic	0.1986121	0.1739295
Cramer-von Mises statistic	0.2974952	0.2459064
Anderson-Darling statistic	1.7330332	1.5334864

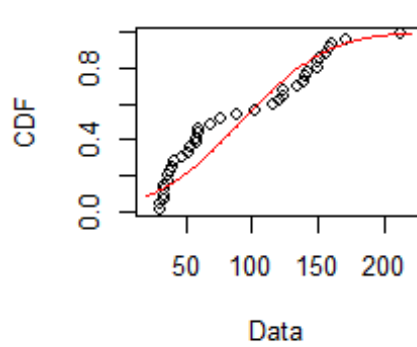
Empirical and theoretical den



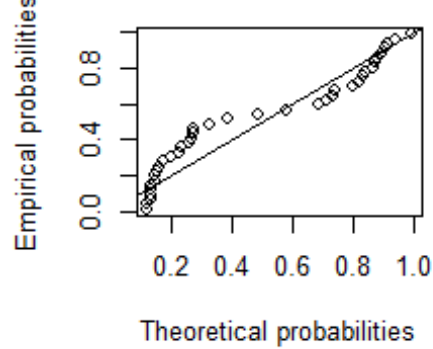
Q-Q plot



Empirical and theoretical CDF



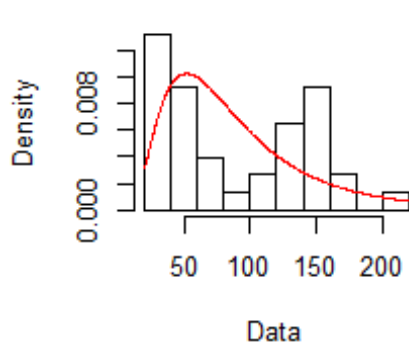
P-P plot



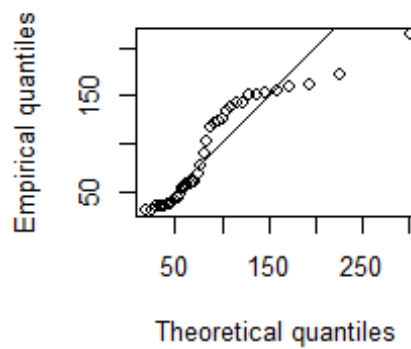
1098

1099 `plot(fitdist(NMAveragePF78to15, "lnorm"))`

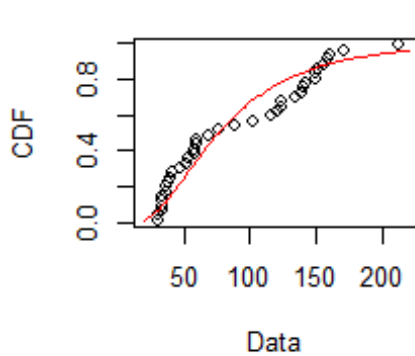
Empirical and theoretical den



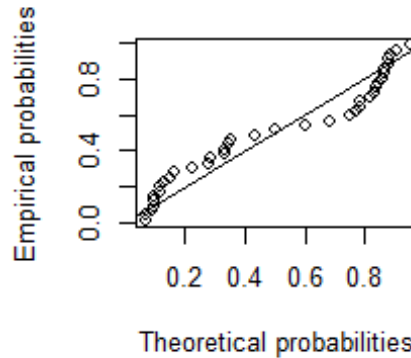
Q-Q plot



Empirical and theoretical CDF



P-P plot



1100

1101 BBS Trend Data Distribution

1102 Blue Jay Trend Index Data

```
1103 gofstat(list(fitdist(BJIndexPF66to13, "norm"), fitdist(BJIndexPF66to13,  
1104 "lnorm")),fitnames = c("normal","lognormal"))
```

1105 Goodness-of-fit statistics

	normal	lognormal
Kolmogorov-Smirnov statistic	0.10243763	0.1119496
Cramer-von Mises statistic	0.05528419	0.1046562
Anderson-Darling statistic	0.52425819	0.8182633

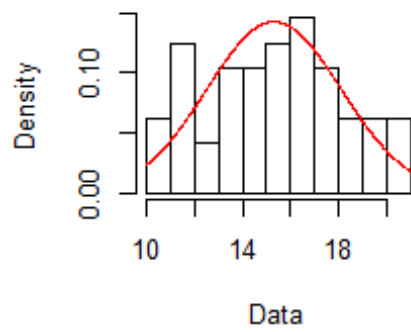
1110

1111 Goodness-of-fit criteria

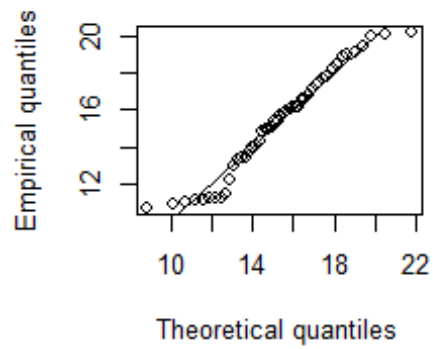
	normal	lognormal
Aikake's Information Criterion	238.9624	240.4658
Bayesian Information Criterion	242.7048	244.2082

```
1115 plot(fitdist(BJIndexPF66to13, "norm"))
```

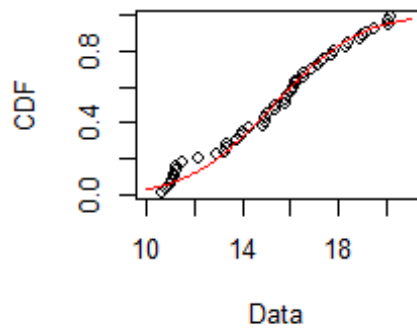
Empirical and theoretical den



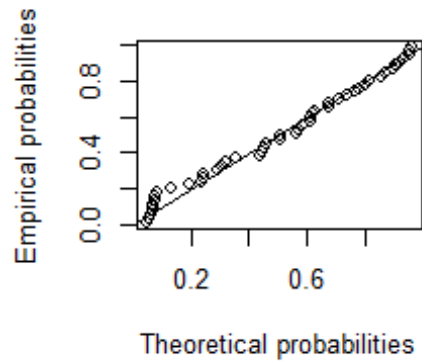
Q-Q plot



Empirical and theoretical CDF



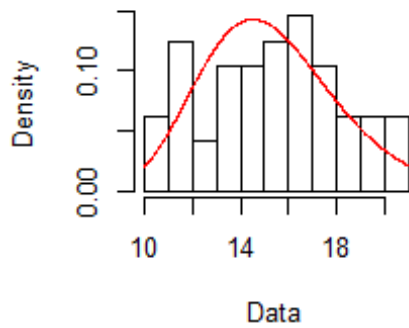
P-P plot



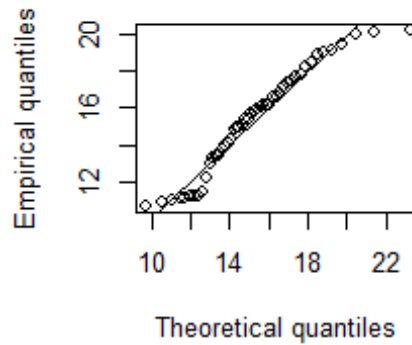
1116

1117 `plot(fitdist(BJIndexPF66to13, "lnorm"))`

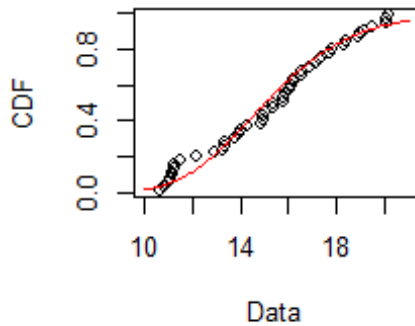
Empirical and theoretical den



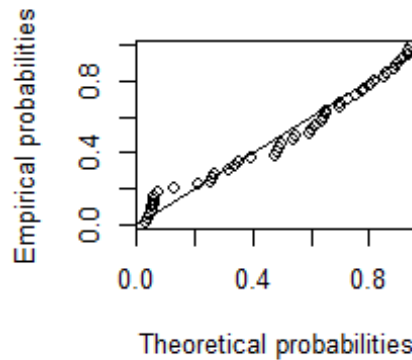
Q-Q plot



Empirical and theoretical CDF



P-P plot



1118

1119 **Common Grackle Trend Index Data**

```
1120 gofstat(list(fitdist(CGIndexPF66to13, "norm"), fitdist(CGIndexPF66to13,
1121 "lnorm")),fitnames = c("normal","lognormal"))
```

1122 Goodness-of-fit statistics

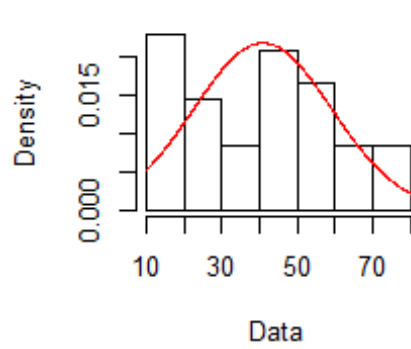
	normal	lognormal
Kolmogorov-Smirnov statistic	0.1306454	0.1821228
Cramer-von Mises statistic	0.1494840	0.2801951
Anderson-Darling statistic	1.0099181	1.6223607

1128 Goodness-of-fit criteria

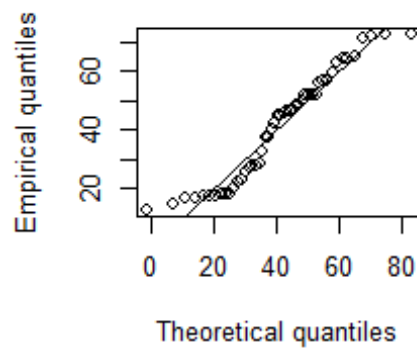
	normal	lognormal
Aikake's Information Criterion	418.9799	420.8320
Bayesian Information Criterion	422.7223	424.5744

```
1132 plot(fitdist(CGIndexPF66to13, "norm"))
```

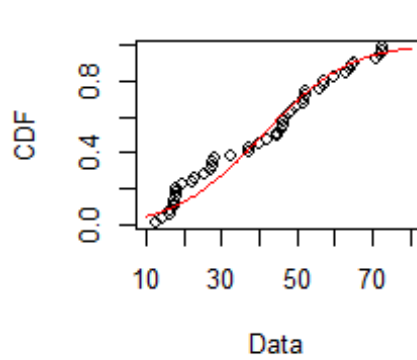
Empirical and theoretical den



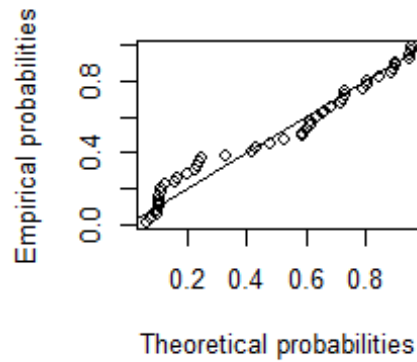
Q-Q plot



Empirical and theoretical CDF



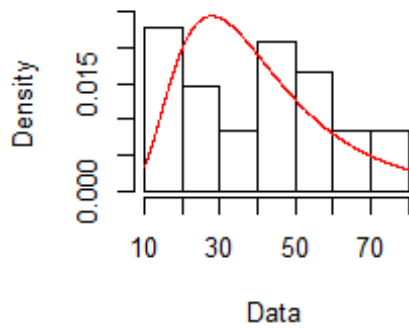
P-P plot



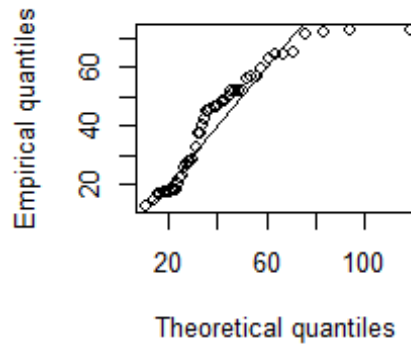
1133

1134 `plot(fitdist(CGIndexPF66to13, "lnorm"))`

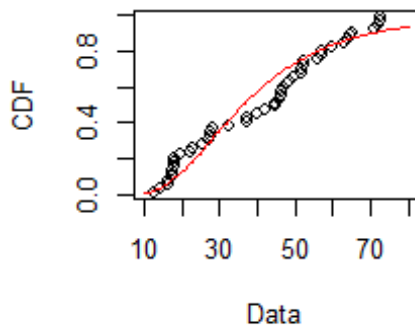
Empirical and theoretical den



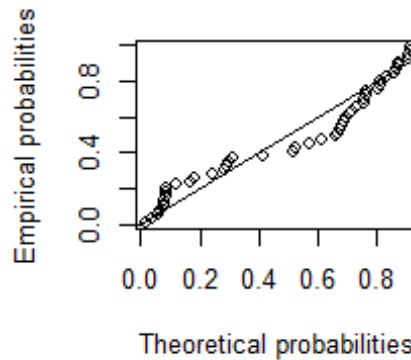
Q-Q plot



Empirical and theoretical CDF



P-P plot



1135

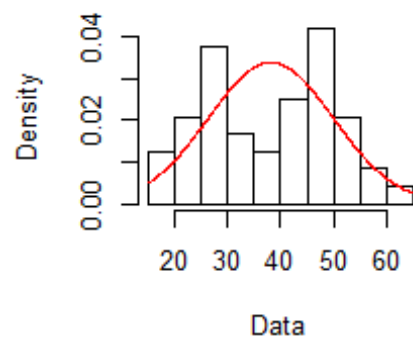
1136 **Mourning Dove Trend Index Data**

```
1137 gofstat(list(fitdist(MDIndexPF66to13, "norm"), fitdist(MDIndexPF66to13,
1138               "lnorm")),fitnames = c("normal","lognormal"))
```

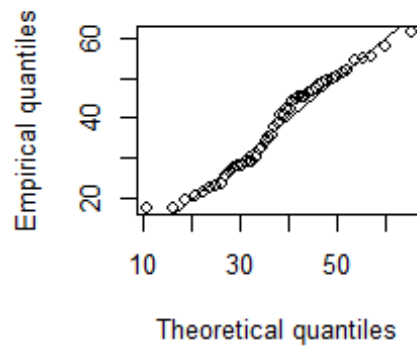
1139 Goodness-of-fit statistics

	normal	lognormal
Kolmogorov-Smirnov statistic	0.1205500	0.1468991
Cramer-von Mises statistic	0.1267768	0.1768854
Anderson-Darling statistic	0.7075533	1.0204126

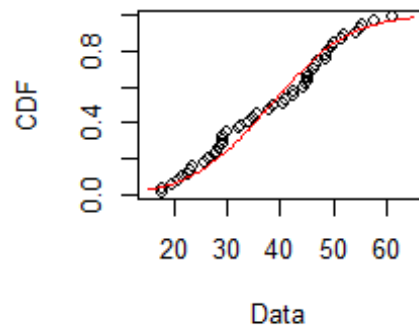
Empirical and theoretical den



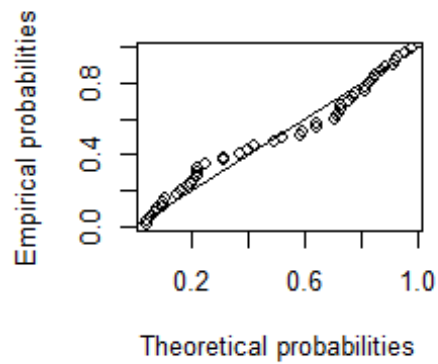
Q-Q plot



Empirical and theoretical CDF



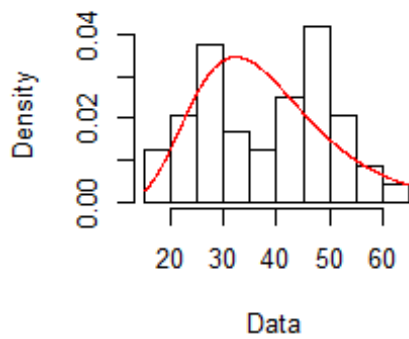
P-P plot



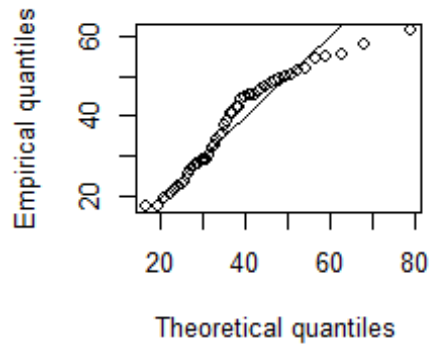
1150

1151 `plot(fitdist(MDIndexPF66to13, "lnorm"))`

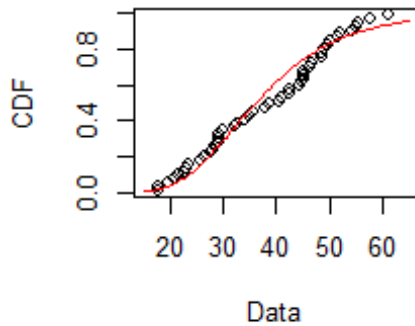
Empirical and theoretical den



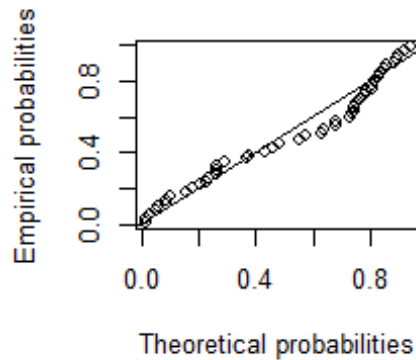
Q-Q plot



Empirical and theoretical CDF



P-P plot



1152

1153 **Northern Cardinal Trend Index Data**

```
1154 gofstat(list(fitdist(NCIndexPF66to13, "norm"), fitdist(NCIndexPF66to13,
1155               "lnorm")),fitnames = c("normal","lognormal"))
```

1156 Goodness-of-fit statistics

	normal	lognormal
Kolmogorov-Smirnov statistic	0.11217744	0.10138763
Cramer-von Mises statistic	0.09178284	0.07016553
Anderson-Darling statistic	0.51098706	0.39811196

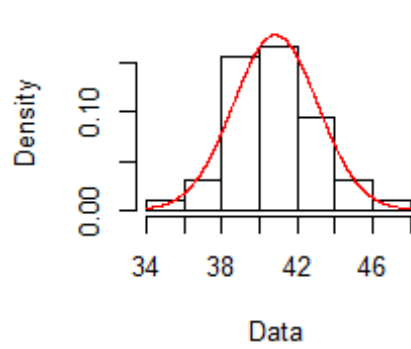
1161

1162 Goodness-of-fit criteria

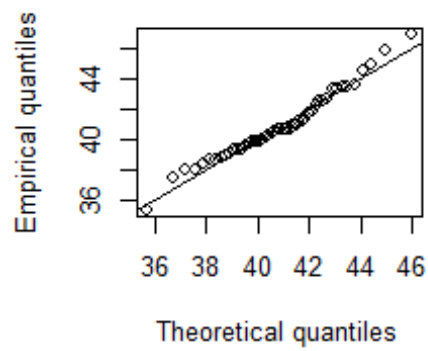
	normal	lognormal
Aikake's Information Criterion	217.2321	216.3121
Bayesian Information Criterion	220.9745	220.0545

```
1166 plot(fitdist(NCIndexPF66to13, "norm"))
```

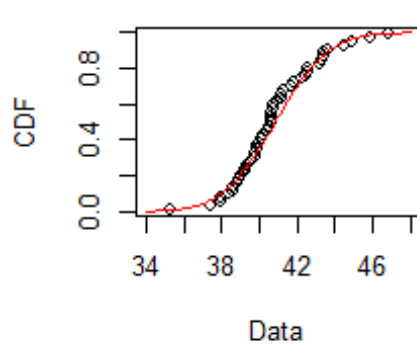

Empirical and theoretical den



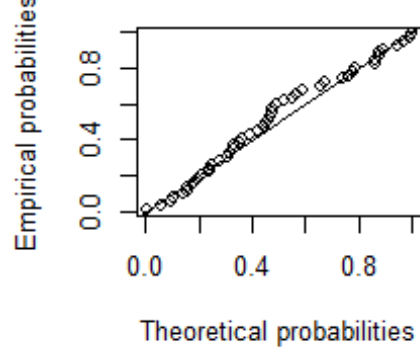
Q-Q plot



Empirical and theoretical CDF



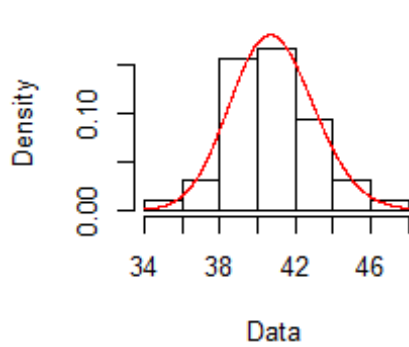
P-P plot



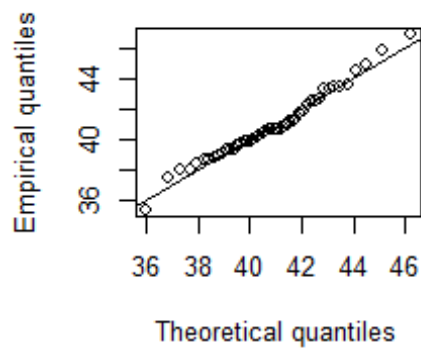
1167

1168 `plot(fitdist(NCIndexPF66to13, "lnorm"))`

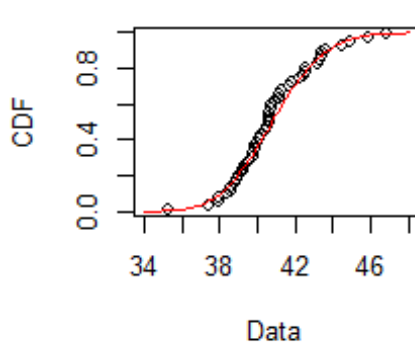
Empirical and theoretical den



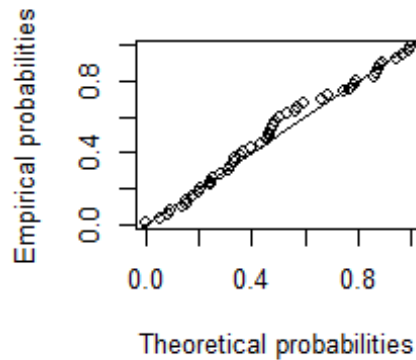
Q-Q plot



Empirical and theoretical CDF



P-P plot



1169

1170 **Northern Mockingbird Trend Index Data**

```
1171 gofstat(list(fitdist(NMIndexPF66to13, "norm"), fitdist(NMIndexPF66to13,
1172 "lnorm")), fitnames = c("normal", "lognormal"))
```

1173 Goodness-of-fit statistics

	normal	lognormal
Kolmogorov-Smirnov statistic	0.1100049	0.09510032
Cramer-von Mises statistic	0.1310815	0.09637673
Anderson-Darling statistic	0.9297053	0.74769324

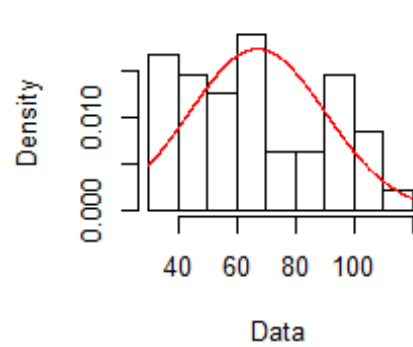
1178

1179 Goodness-of-fit criteria

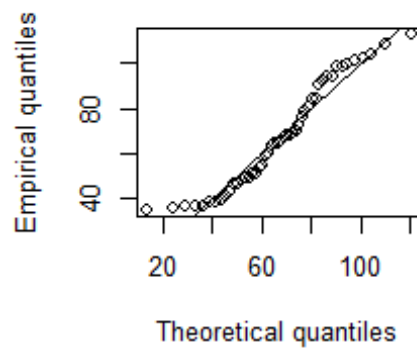
	normal	lognormal
Aikake's Information Criterion	441.6778	438.6402
Bayesian Information Criterion	445.4202	442.3826

```
1183 plot(fitdist(NMIndexPF66to13, "norm"))
```

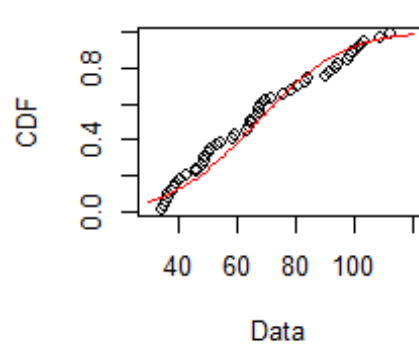
Empirical and theoretical den



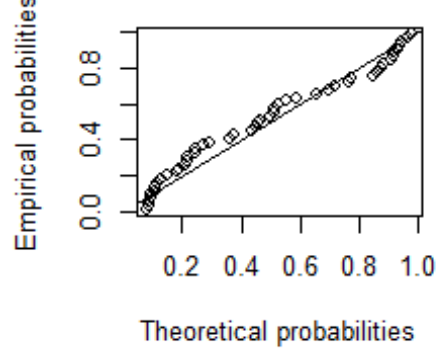
Q-Q plot



Empirical and theoretical CDF



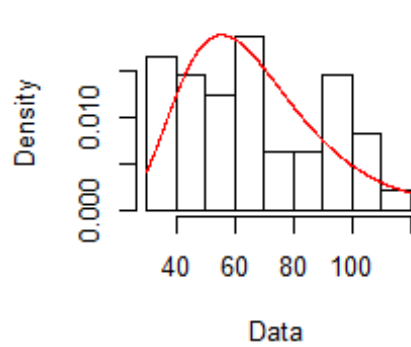
P-P plot



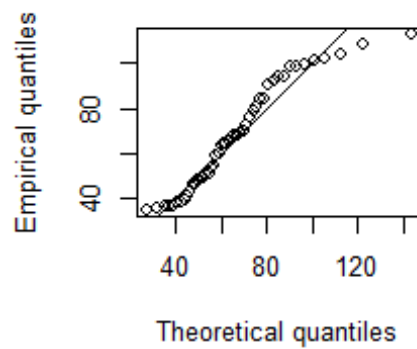
1184

1185 `plot(fitdist(NMIndexPF66to13, "lnorm"))`

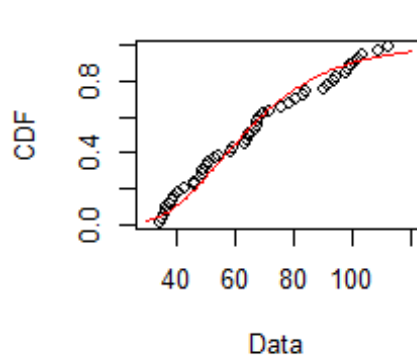
Empirical and theoretical den



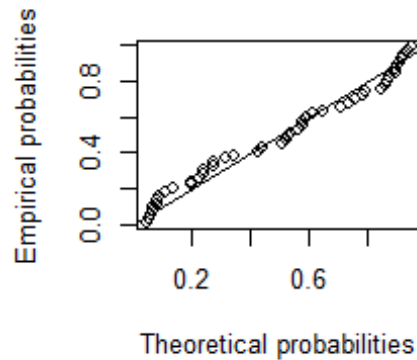
Q-Q plot



Empirical and theoretical CDF



P-P plot



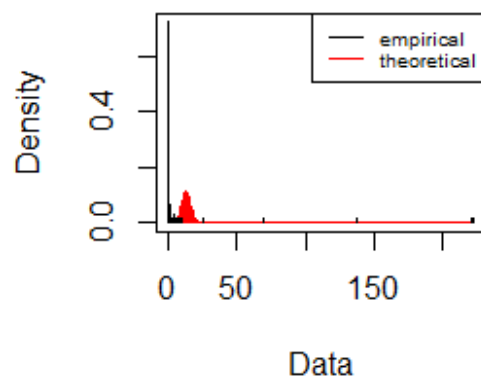
1186

1187 **Transmission Count Data**

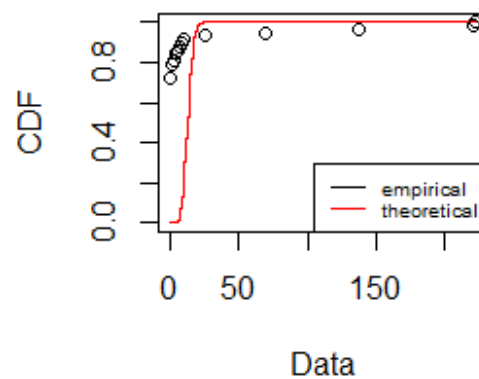
1188 **Human SLE Count Data**

1189 `plot(fitdist(HumSLEPF58to15, "pois"))`

Emp. and theo. distr.



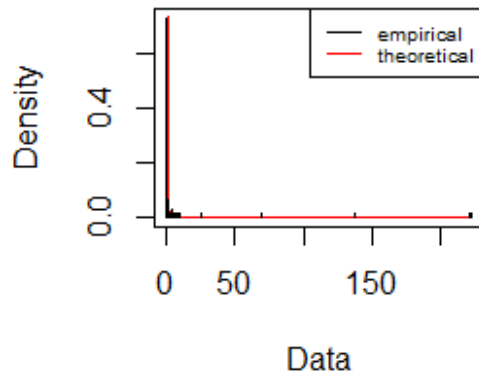
Emp. and theo. CDFs



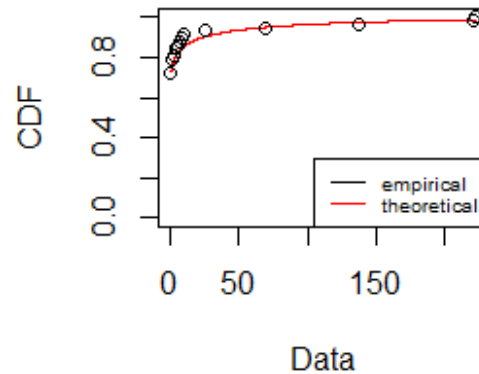
1190

1191 `plot(fitdist(HumSLEPF58to15, "nbinom"))`

Emp. and theo. distr.



Emp. and theo. CDFs



1192

1193 **Sentinel Chicken Seroconversions Flavivirus Count Data**

```
1194 gofstat(list(fitdist(SCFlaviPF78to15, "pois"), fitdist(SCFlaviPF78to15,
1195 "nbinom")), fitnames = c("Poisson", "negative binomial"))
```

1196 Chi-squared statistic: 7.829065e+84 3.088814

1197 Degree of freedom of the Chi-squared distribution: 5 4

1198 Chi-squared p-value: 0 0.5430742

1199 the p-value may be wrong with some theoretical counts < 5

1200 Chi-squared table:

	obscounts	theo Poisson	theo negative binomial
1202	<= 10	5 3.193229e-84	3.466152
1203	<= 54	5 1.437744e-44	7.179539
1204	<= 109	5 9.339203e-19	5.843009
1205	<= 155	5 5.576040e-07	3.645904
1206	<= 213	5 2.834518e+00	3.579746
1207	<= 308	5 3.516538e+01	4.230030
1208	> 308	8 1.008057e-04	10.055620

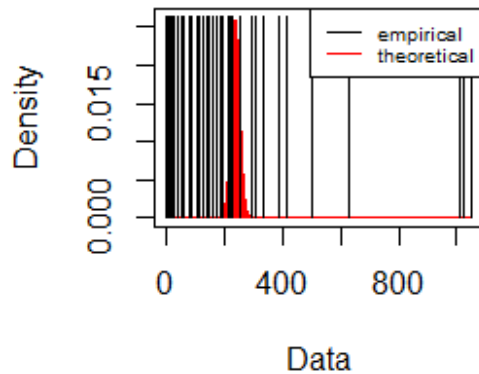
1209

1210 Goodness-of-fit criteria

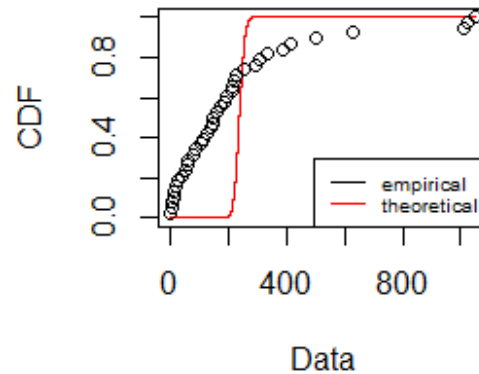
	Poisson	negative binomial
1212	Aikake's Information Criterion 9864.054	492.5814
1213	Bayesian Information Criterion 9865.692	495.8566

```
1214 plot(fitdist(SCFlaviPF78to15, "pois"))
```

Emp. and theo. distr.



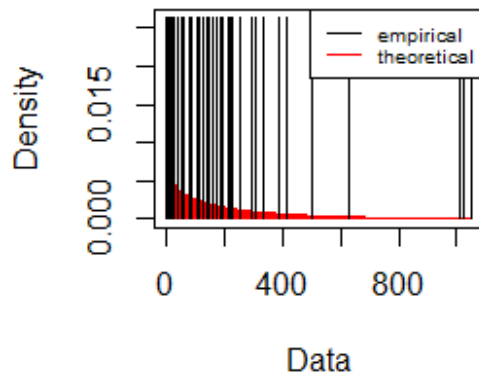
Emp. and theo. CDFs



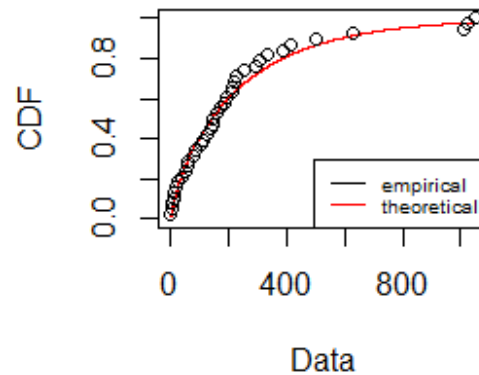
1215

1216 `plot(fitdist(SCFlaviPF78to15, "nbinom"))`

Emp. and theo. distr.



Emp. and theo. CDFs



1217

1218 **Sentinel Chicken Seroconversions SLE Count Data**

1219 `gofstat(list(fitdist(SCSLEPF78to15, "pois"), fitdist(SCSLEPF78to15,`
1220 `"nbinom")),fitnames = c("Poisson","negative binomial"))`

1221 Chi-squared statistic: 1.141973e+46 6.818649

1222 Degree of freedom of the Chi-squared distribution: 5 4

1223 Chi-squared p-value: 0 0.1457878

1224 the p-value may be wrong with some theoretical counts < 5

1225 Chi-squared table:

1226 obscounts theo Poisson theo negative binomial

1227 <= 2 5 2.189194e-45 5.626289

1228 <= 9 5 3.479410e-36 4.194254

1229 <= 21 5 1.533796e-25 4.032481

1230 <= 80 5 1.228404e-02 9.414020

1231 <= 105 5 6.887959e+00 2.277792

1232 <= 155 5 3.109294e+01 3.288626

1233 > 155 8 6.818445e-03 9.166538

1234

1235 Goodness-of-fit criteria

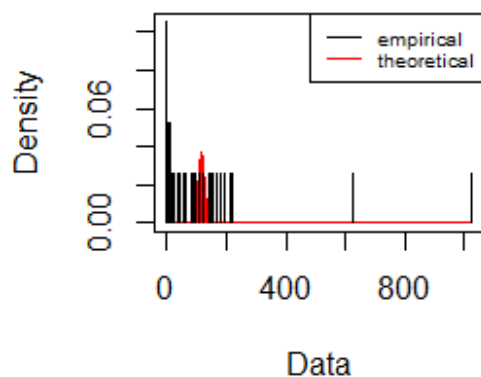
1236 Poisson negative binomial

```

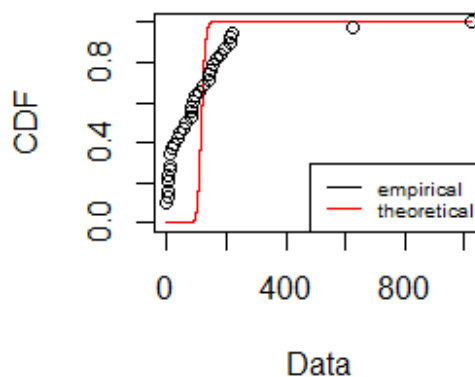
1237 Aikake's Information Criterion 7314.927      422.4761
1238 Bayesian Information Criterion 7316.564     425.7512
1239 plot(fitdist(SCSLEPF78to15, "pois"))

```

Emp. and theo. distr.



Emp. and theo. CDFs

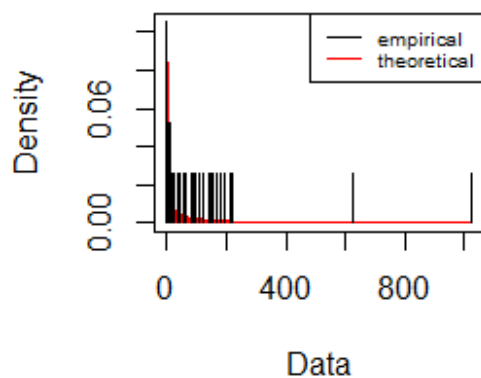


```

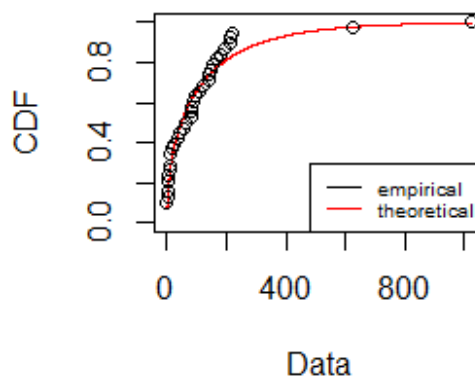
1240
1241 plot(fitdist(SCSLEPF78to15, "nbinom"))

```

Emp. and theo. distr.



Emp. and theo. CDFs



```

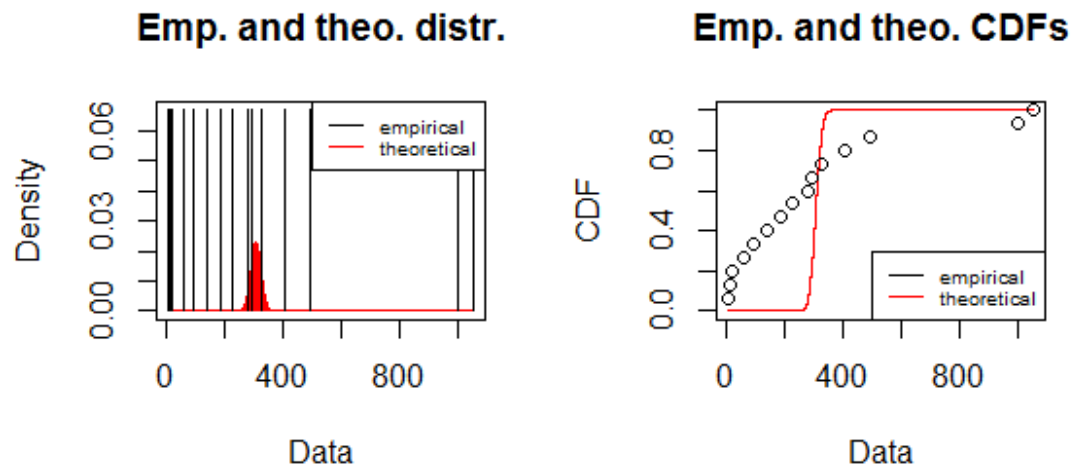
1242
1243 Sentinel Chicken Seroconversions West Nile Count Data
1244 gofstat(list(fitdist(SCWNPF01to15, "pois"), fitdist(SCWNPF01to15, "nbinom")),
1245          fitnames = c("Poisson", "negative binomial"))
1246 Chi-squared statistic:  1.135931e+103 3.461011
1247 Degree of freedom of the Chi-squared distribution:  3 2
1248 Chi-squared p-value:  0 0.1771949
1249   the p-value may be wrong with some theoretical counts < 5
1250 Chi-squared table:
1251   obscounts  theo Poisson  theo negative binomial
1252 <= 18        3 7.923018e-103      1.421954
1253 <= 135       3 1.160337e-26       4.632383
1254 <= 278       3 1.008676e+00       3.219105
1255 <= 401       3 1.399132e+01       1.755545
1256 > 401        3 8.124348e-07       3.971014
1257

```

```

1258 Goodness-of-fit criteria
1259                                     Poisson negative binomial
1260 Aikake's Information Criterion 4555.084      205.0827
1261 Bayesian Information Criterion 4555.792      206.4988
1262 plot(fitdist(SCWNPf01to15, "pois"))

```



```

1263
1264 plot(fitdist(SCWNPf01to15, "nbinom"))

```



```

1265
1266 Transformations
1267 Data transformation needed to meet normal distribution assumption for ARIMA modeling.
1268 BBS Data Transformation
1269 BBs Counts data are not going to be used in analysis, so no transformation needed.
1270 BBS Averages data fit a normal distribution, so no transformation needed.
1271 Transmission Data Transformation
1272 Transmission data log transformed to fit a normal distribution model.

```



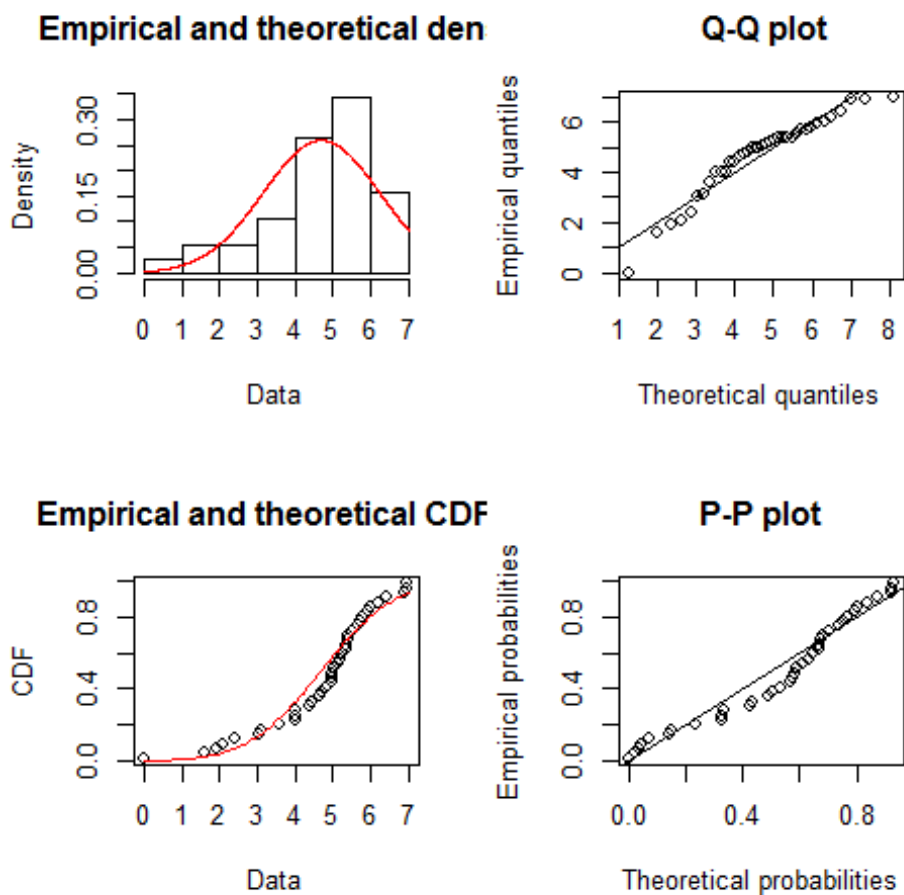
```

1273 Flavivirus Sentinel Chicken Seroconversion Count Data
1274 gofstat(fitdist(log(SCFlaviPF78to15+1), "norm"), fitnames = "normal")

1275 Goodness-of-fit statistics
1276                                     normal
1277 Kolmogorov-Smirnov statistic 0.1518629
1278 Cramer-von Mises statistic   0.1831915
1279 Anderson-Darling statistic   1.0037106
1280
1281 Goodness-of-fit criteria
1282                                     normal
1283 Aikake's Information Criterion 144.6611
1284 Bayesian Information Criterion 147.9362

1285 plot(fitdist(log(SCFlaviPF78to15+1), "norm"))

```



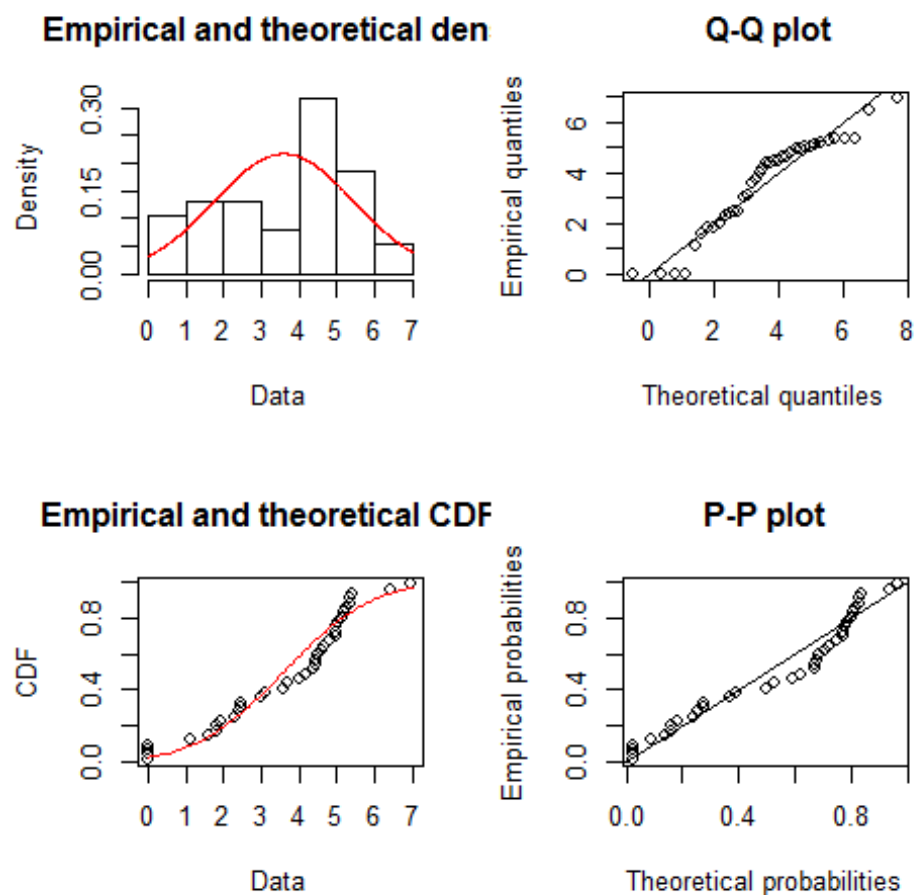
```

1286
1287 SLE Sentinel Chicken Seroconversion SLE Count Data
1288 gofstat(fitdist(log(SCSLEPF78to15+1), "norm"), fitnames = "normal")

1289 Goodness-of-fit statistics
1290                                     normal
1291 Kolmogorov-Smirnov statistic 0.1692318
1292 Cramer-von Mises statistic   0.1826596
1293 Anderson-Darling statistic   1.0691424
1294
1295 Goodness-of-fit criteria
1296                                     normal
1297 Aikake's Information Criterion 158.1715
1298 Bayesian Information Criterion 161.4467

```

```
1299 plot(fitdist(log(SCSLEPF78to15+1), "norm"))
```



```
1300
```

```
1301 WN Sentinel Chicken Seroconversion Count Data
```

```
1302 gofstat(fitdist(log(SCWNPF01to15+1), "norm"), fitnames = "normal")
```

```
1303 Goodness-of-fit statistics
```

```
1304                                     normal
```

```
1305 Kolmogorov-Smirnov statistic 0.16361837
```

```
1306 Cramer-von Mises statistic 0.08140702
```

```
1307 Anderson-Darling statistic 0.49611714
```

```
1308
```

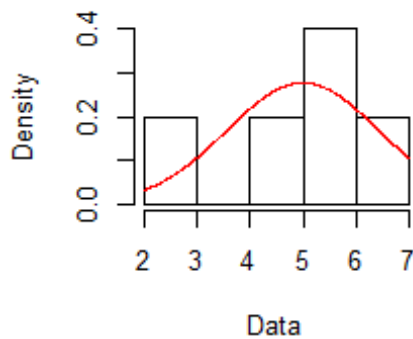
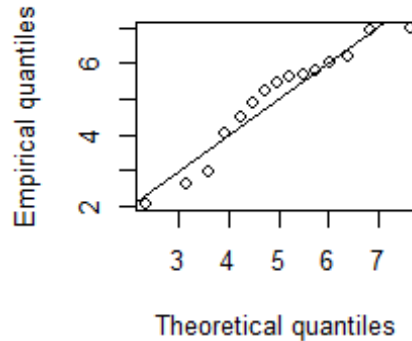
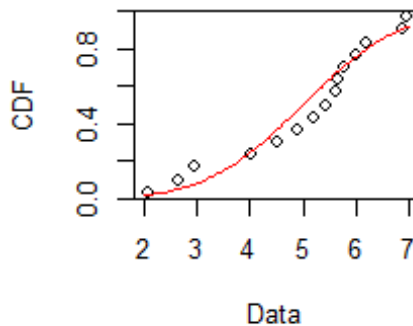
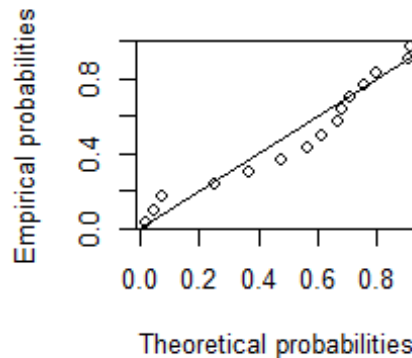
```
1309 Goodness-of-fit criteria
```

```
1310                                     normal
```

```
1311 Aikake's Information Criterion 57.52724
```

```
1312 Bayesian Information Criterion 58.94334
```

```
1313 plot(fitdist(log(SCWNPF01to15+1), "norm"))
```

Empirical and theoretical den**Q-Q plot****Empirical and theoretical CDF****P-P plot**

1314

1315

Check for Stationarity

1316 This is just a preliminary check for differences needed to meet stationary assumption for ARIMA modeling. Fitting of
 1317 ARIMA models in Model Fitting phase will check for and apply differencing as needed.

1318 The Augmented Dickey-Fuller (ADF) t-statistic test: small p-values suggest the data is stationary and doesn't need to be
 1319 differenced stationary.

1320 The Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test; here accepting the null hypothesis means that the series is stationary,
 1321 and small p-values suggest that the series is not stationary and a differencing is required.

1322

BBS Data Differences

1323

Blue Jay Averages

```
1324 cat("Calculated differences needed for stationary via KPSS: ",
1325     ndiffs(BJAveragePF78to15ts, alpha=0.05, test="kpss"))
```

1326 Calculated differences needed for stationary via KPSS: 1

```
1327 cat("\n")
```

```
1328 adf.test(BJAveragePF78to15ts, alternative = "stationary")
```

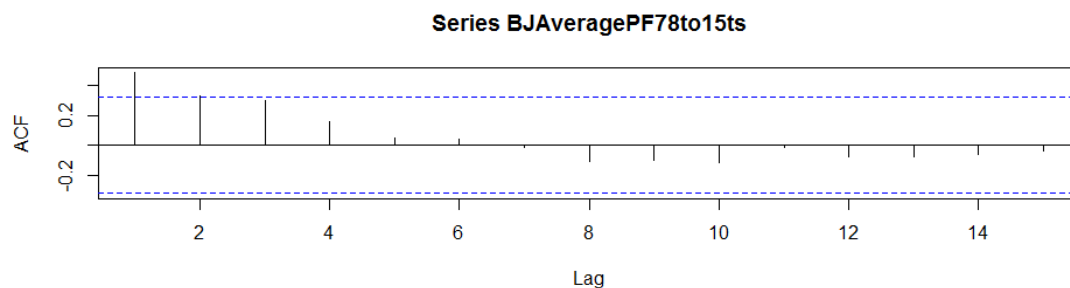
```
1329
1330     Augmented Dickey-Fuller Test
```

```
1331 data: BJAveragePF78to15ts
1332 Dickey-Fuller = -1.7219, Lag order = 3, p-value = 0.682
1333 alternative hypothesis: stationary
```

```

1335 adf.test(diff(BJAveragePF78to15ts), alternative = "stationary")
1336
1337     Augmented Dickey-Fuller Test
1338
1339 data: diff(BJAveragePF78to15ts)
1340 Dickey-Fuller = -3.745, Lag order = 3, p-value = 0.03559
1341 alternative hypothesis: stationary
1342
1343     kpss.test(BJAveragePF78to15ts)
1344
1345     KPSS Test for Level Stationarity
1346 data: BJAveragePF78to15ts
1347 KPSS Level = 0.48798, Truncation lag parameter = 1, p-value = 0.04437
1348
1349     kpss.test(diff(BJAveragePF78to15ts))
1350
1351     KPSS Test for Level Stationarity
1352 data: diff(BJAveragePF78to15ts)
1353 KPSS Level = 0.079917, Truncation lag parameter = 1, p-value = 0.1
1354
1355     acf(BJAveragePF78to15ts)

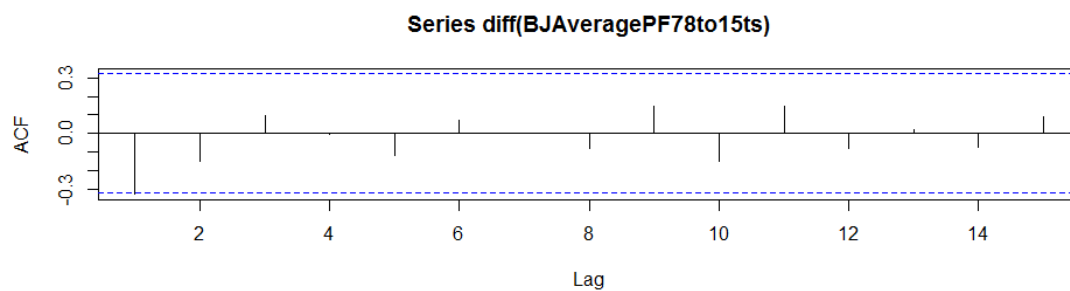
```



```

1355
1356     acf(diff(BJAveragePF78to15ts))

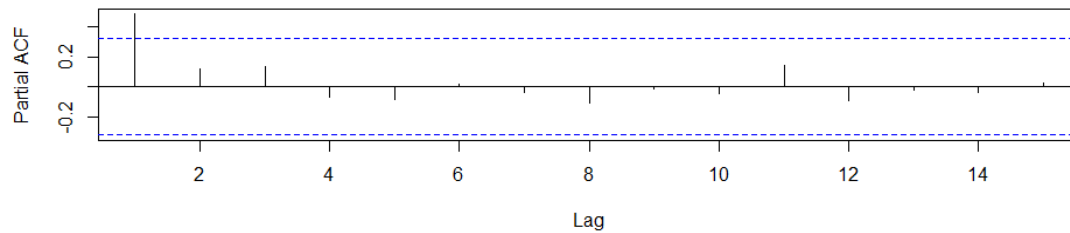
```



```

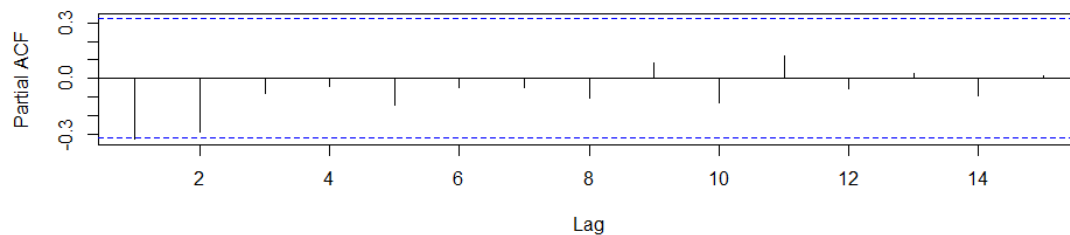
1357
1358     pacf(BJAveragePF78to15ts, main="")

```



1359

1360 `pacf(diff(BJAveragePF78to15ts), main="")`



1361

1362 **Common Grackle Averages**

1363 `cat("Calculated differences needed for stationary via KPSS: ",`
 1364 `ndiffs(CGAveragePF78to15ts, alpha=0.05, test="kpss"))`

1365 Calculated differences needed for stationary via KPSS: 1

1366 `cat("\n")`

1367 `Box.test(CGAveragePF78to15ts, type = "Ljung-Box")`

1368

1369 Box-Ljung test

1370

1371 data: CGAveragePF78to15ts

1372 X-squared = 14.99, df = 1, p-value = 0.0001081

1373 `adf.test(CGAveragePF78to15ts, alternative = "stationary")`

1374

1375 Augmented Dickey-Fuller Test

1376

1377 data: CGAveragePF78to15ts

1378 Dickey-Fuller = -2.1757, Lag order = 3, p-value = 0.5047

1379 alternative hypothesis: stationary

1380 `adf.test(diff(CGAveragePF78to15ts), alternative = "stationary")`

1381

1382 Augmented Dickey-Fuller Test

1383

1384 data: diff(CGAveragePF78to15ts)

1385 Dickey-Fuller = -3.2048, Lag order = 3, p-value = 0.1034

1386 alternative hypothesis: stationary

1387 `kpss.test(CGAveragePF78to15ts)`

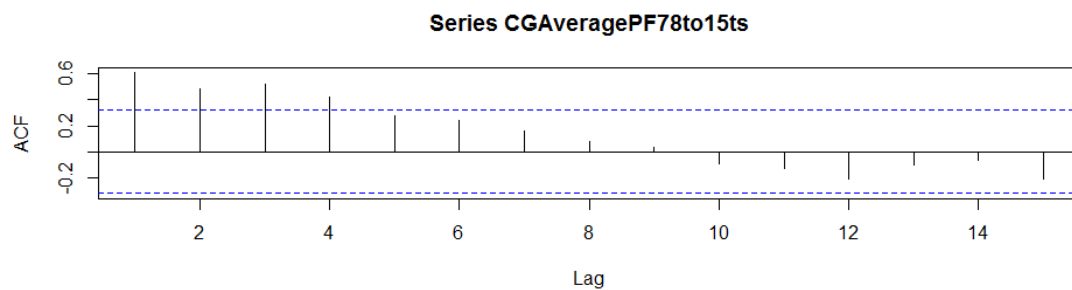
1388

1389 KPSS Test for Level Stationarity

```

1390
1391 data: CGAveragePF78to15ts
1392 KPSS Level = 0.878, Truncation lag parameter = 1, p-value = 0.01
1393
1394 kpss.test(diff(CGAveragePF78to15ts))
1395
1396 KPSS Test for Level Stationarity
1397 data: diff(CGAveragePF78to15ts)
1398 KPSS Level = 0.06529, Truncation lag parameter = 1, p-value = 0.1
1399
1400 acf(CGAveragePF78to15ts)

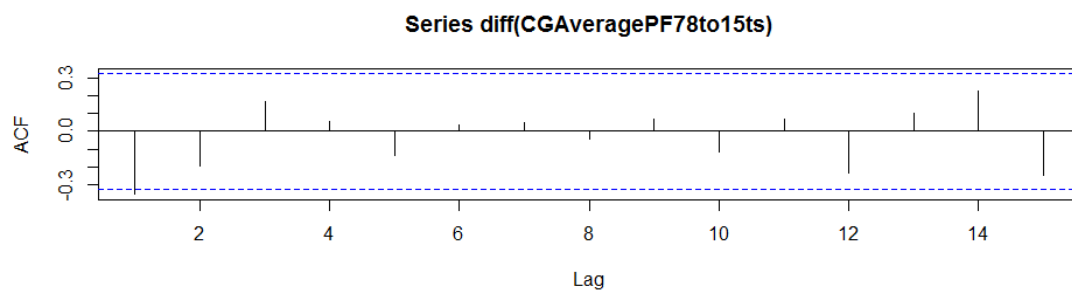
```



```

1400
1401 acf(diff(CGAveragePF78to15ts))

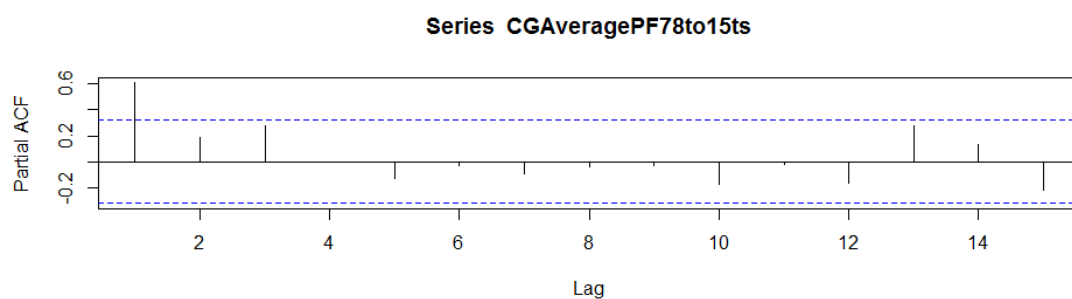
```



```

1402
1403 pacf(CGAveragePF78to15ts)

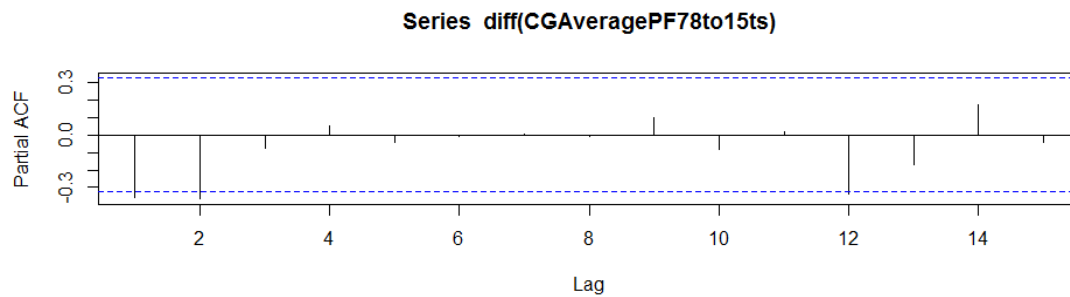
```



```

1404
1405 pacf(diff(CGAveragePF78to15ts))

```



1406

1407 Mourning Dove Averages

```
1408 cat("Calculated differences needed for stationary via KPSS: ",
1409     ndiffs(MDAveragePF78to15ts, alpha=0.05, test="kpss"))
```

1410 Calculated differences needed for stationary via KPSS: 1

```
1411 cat("\n")
```

```
1412 Box.test(MDAveragePF78to15ts, type = "Ljung-Box")
```

1413
1414 Box-Ljung test

1415 data: MDAveragePF78to15ts
1416 X-squared = 17.297, df = 1, p-value = 3.197e-05

```
1418 adf.test(MDAveragePF78to15ts, alternative = "stationary")
```

1419
1420 Augmented Dickey-Fuller Test

1421 data: MDAveragePF78to15ts
1422 Dickey-Fuller = -1.0925, Lag order = 3, p-value = 0.9108
1423 alternative hypothesis: stationary

```
1425 adf.test(diff(MDAveragePF78to15ts), alternative = "stationary")
```

1426
1427 Augmented Dickey-Fuller Test

1428 data: diff(MDAveragePF78to15ts)
1429 Dickey-Fuller = -3.477, Lag order = 3, p-value = 0.06154
1430 alternative hypothesis: stationary

```
1432 kpss.test(MDAveragePF78to15ts)
```

1433
1434 KPSS Test for Level Stationarity

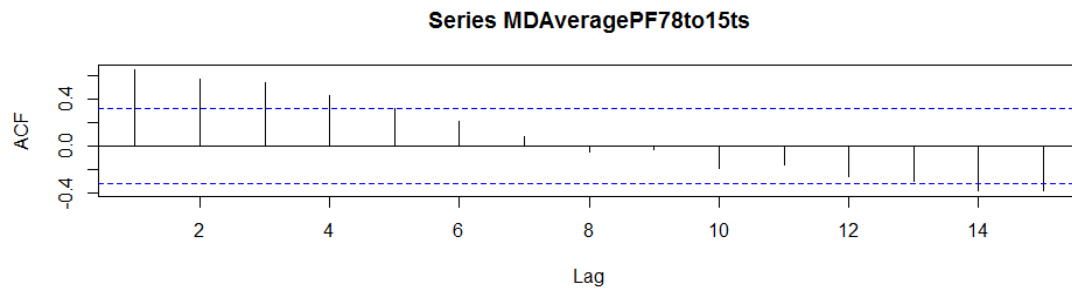
1435 data: MDAveragePF78to15ts
1436 KPSS Level = 0.5571, Truncation lag parameter = 1, p-value = 0.02881

```
1438 kpss.test(diff(MDAveragePF78to15ts))
```

1439
1440 KPSS Test for Level Stationarity

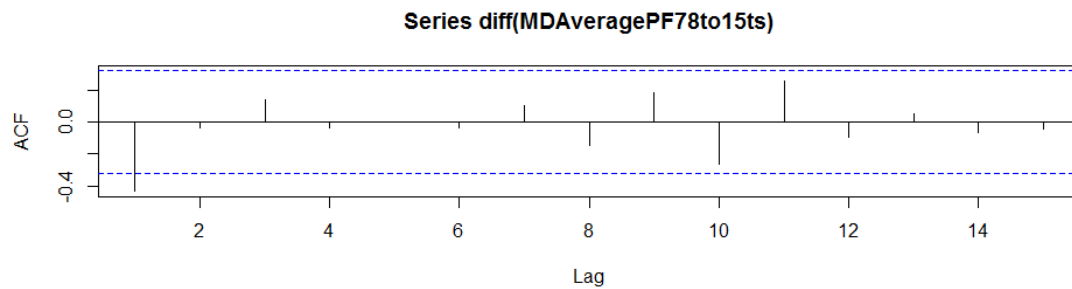
1441 data: diff(MDAveragePF78to15ts)
1442 KPSS Level = 0.15723, Truncation lag parameter = 1, p-value = 0.1

```
1444 acf(MDAveragePF78to15ts)
```



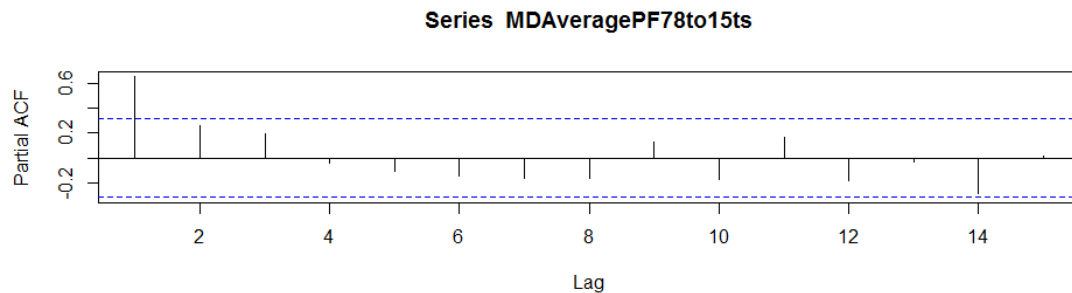
1445

1446 `acf(diff(MDAveragePF78to15ts))`



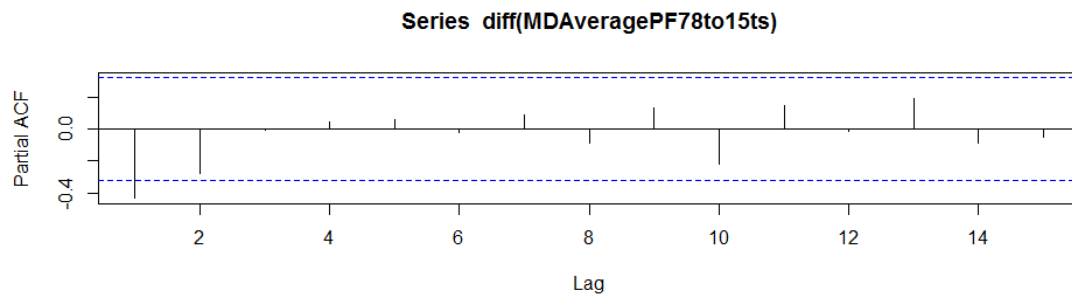
1447

1448 `pacf(MDAveragePF78to15ts)`



1449

1450 `pacf(diff(MDAveragePF78to15ts))`



1451

1452 **Northern Cardinal Averages**

1453 `cat("Calculated differences needed for stationary via KPSS: ",`
 1454 `ndiffs(NCAveragePF78to15ts, alpha=0.05, test="kpss"))`

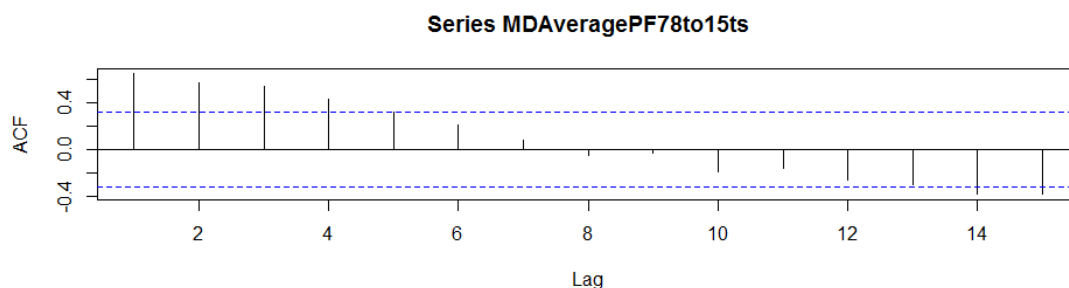
1455 Calculated differences needed for stationary via KPSS: 1

1456 `cat("\n")`


```

1457 Box.test(NCAveragePF78to15ts, type = "Ljung-Box")
1458
1459     Box-Ljung test
1460
1461 data:  NCAveragePF78to15ts
1462 X-squared = 33.028, df = 1, p-value = 9.084e-09
1463
1464 adf.test(NCAveragePF78to15ts, alternative = "stationary")
1465
1466     Augmented Dickey-Fuller Test
1467
1468 data:  NCAveragePF78to15ts
1469 Dickey-Fuller = -1.0784, Lag order = 3, p-value = 0.913
1470 alternative hypothesis: stationary
1471
1472 adf.test(diff(NCAveragePF78to15ts), alternative = "stationary")
1473
1474     Augmented Dickey-Fuller Test
1475
1476 data:  diff(NCAveragePF78to15ts)
1477 Dickey-Fuller = -3.6576, Lag order = 3, p-value = 0.04226
1478 alternative hypothesis: stationary
1479
1480 kpss.test(NCAveragePF78to15ts)
1481
1482     KPSS Test for Level Stationarity
1483
1484 data:  NCAveragePF78to15ts
1485 KPSS Level = 1.7308, Truncation lag parameter = 1, p-value = 0.01
1486
1487 kpss.test(diff(NCAveragePF78to15ts))
1488
1489     KPSS Test for Level Stationarity
1490
1491 data:  diff(NCAveragePF78to15ts)
1492 KPSS Level = 0.11765, Truncation lag parameter = 1, p-value = 0.1
1493
1494 acf(MDAveragePF78to15ts)

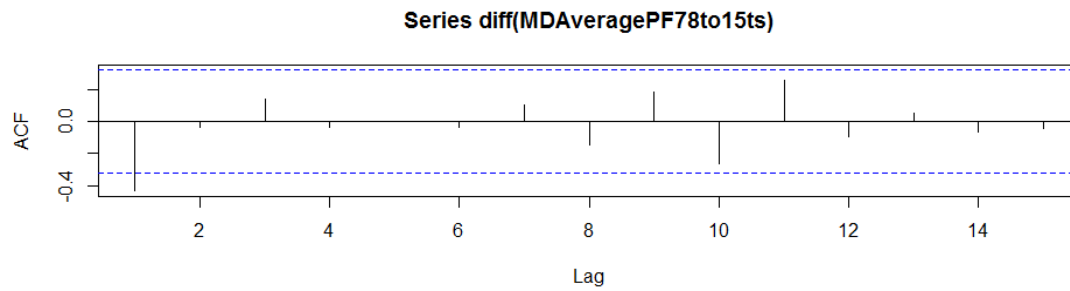
```



```

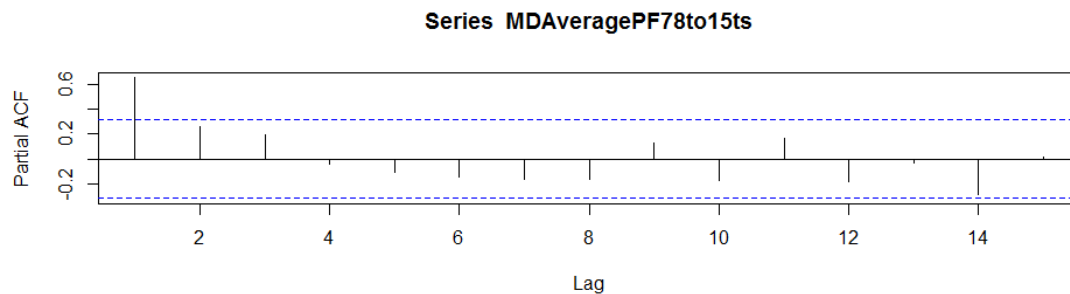
1490
1491 acf(diff(MDAveragePF78to15ts))

```



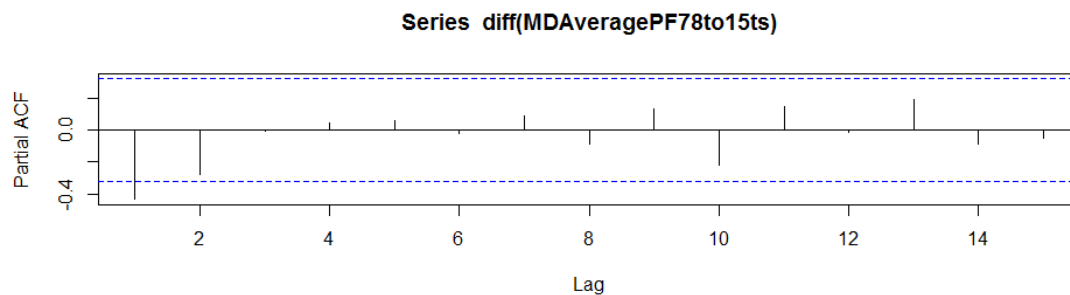
1492

1493 `pacf(MDAveragePF78to15ts)`



1494

1495 `pacf(diff(MDAveragePF78to15ts))`



1496

1497 **Northern Mockingbird Averages**

1498 `cat("Calculated differences needed for stationary via KPSS: ",`
 1499 `ndiffs(NMAveragePF78to15ts, alpha=0.05, test="kpss"))`

1500 Calculated differences needed for stationary via KPSS: 1

1501 `cat("\n")`

1502 `Box.test(NMAveragePF78to15ts, type = "Ljung-Box")`

1503
 1504 Box-Ljung test

1506 data: NMAveragePF78to15ts
 1507 X-squared = 30.5, df = 1, p-value = 3.338e-08

1508 `adf.test(NMAveragePF78to15ts, alternative = "stationary")`

1509
 1510 Augmented Dickey-Fuller Test

1511 data: NMAveragePF78to15ts

```

1513 Dickey-Fuller = -1.4304, Lag order = 3, p-value = 0.7959
1514 alternative hypothesis: stationary

1515 adf.test(diff(NMAveragePF78to15ts), alternative = "stationary")

1516
1517     Augmented Dickey-Fuller Test
1518
1519 data: diff(NMAveragePF78to15ts)
1520 Dickey-Fuller = -3.9083, Lag order = 3, p-value = 0.02408
1521 alternative hypothesis: stationary

1522 kpss.test(NMAveragePF78to15ts)

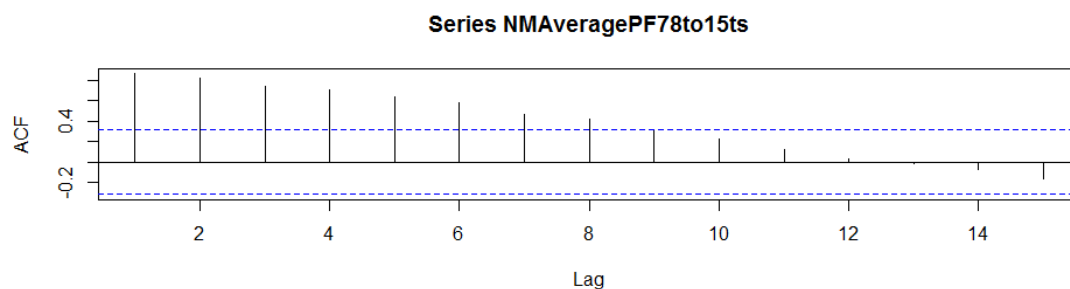
1523
1524     KPSS Test for Level Stationarity
1525
1526 data: NMAveragePF78to15ts
1527 KPSS Level = 1.8095, Truncation lag parameter = 1, p-value = 0.01

1528 kpss.test(diff(NMAveragePF78to15ts))

1529
1530     KPSS Test for Level Stationarity
1531
1532 data: diff(NMAveragePF78to15ts)
1533 KPSS Level = 0.062417, Truncation lag parameter = 1, p-value = 0.1

1534 acf(NMAveragePF78to15ts)

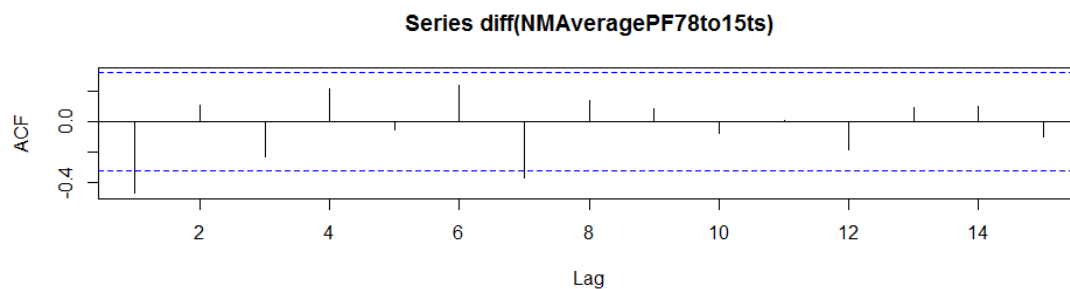
```



```

1535
1536 acf(diff(NMAveragePF78to15ts))

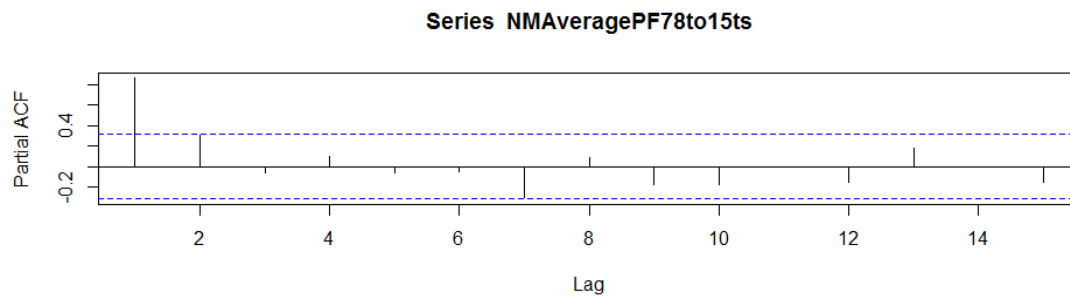
```



```

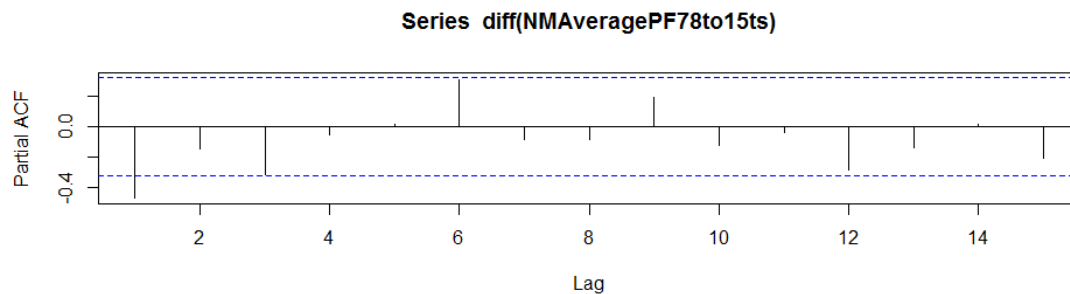
1537
1538 pacf(NMAveragePF78to15ts)

```



1539

1540 `pacf(diff(NMAveragePF78to15ts))`



1541

1542 **Blue Jay Trend Index**

1543 `cat("Calculated differences needed for stationary via KPSS: ",`
 1544 `ndiffs(BJIndexPF78to13ts, alpha=0.05, test="kpss"))`

1545 Calculated differences needed for stationary via KPSS: 1

1546 `cat("\n")`

1547 `Box.test(BJIndexPF78to13ts, type = "Ljung-Box")`

1548

1549 Box-Ljung test

1550

1551 data: BJIndexPF78to13ts

1552 X-squared = 29.779, df = 1, p-value = 4.842e-08

1553 `adf.test(BJIndexPF78to13ts, alternative = "stationary")`

1554

1555 Augmented Dickey-Fuller Test

1556

1557 data: BJIndexPF78to13ts

1558 Dickey-Fuller = -1.9107, Lag order = 3, p-value = 0.6079

1559 alternative hypothesis: stationary

1560 `adf.test(diff(BJIndexPF78to13ts), alternative = "stationary")`

1561

1562 Augmented Dickey-Fuller Test

1563

1564 data: diff(BJIndexPF78to13ts)

1565 Dickey-Fuller = -3.8106, Lag order = 3, p-value = 0.03143

1566 alternative hypothesis: stationary

1567 `kpss.test(BJIndexPF78to13ts)`

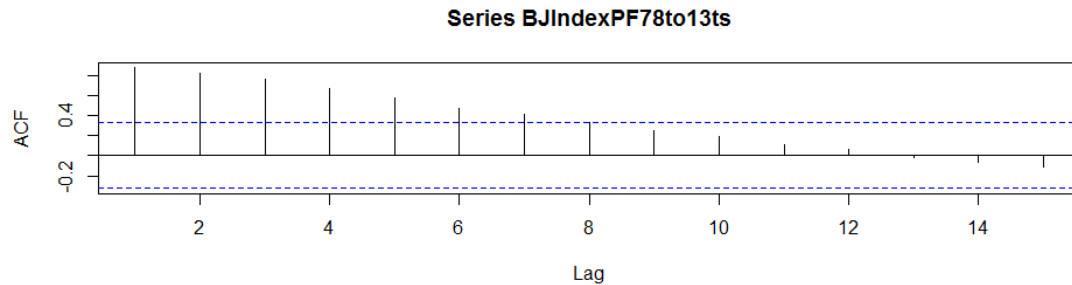
1568

1569 KPSS Test for Level Stationarity

```

1570
1571 data: BJIndexPF78to13ts
1572 KPSS Level = 1.8122, Truncation lag parameter = 1, p-value = 0.01
1573
1574 kpss.test(diff(BJIndexPF78to13ts))
1575
1576 KPSS Test for Level Stationarity
1577 data: diff(BJIndexPF78to13ts)
1578 KPSS Level = 0.055263, Truncation lag parameter = 1, p-value = 0.1
1579
1580 acf(BJIndexPF78to13ts)

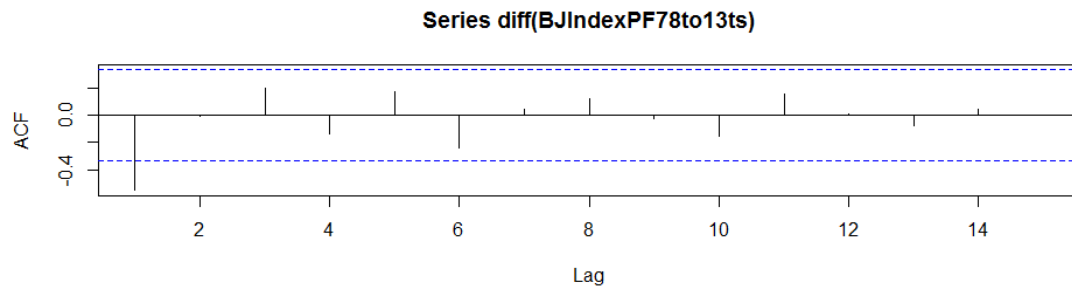
```



```

1580
1581 acf(diff(BJIndexPF78to13ts))

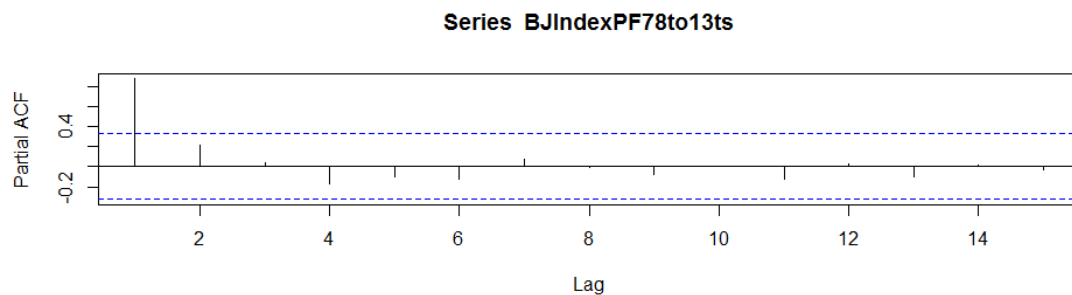
```



```

1582
1583 pacf(BJIndexPF78to13ts)

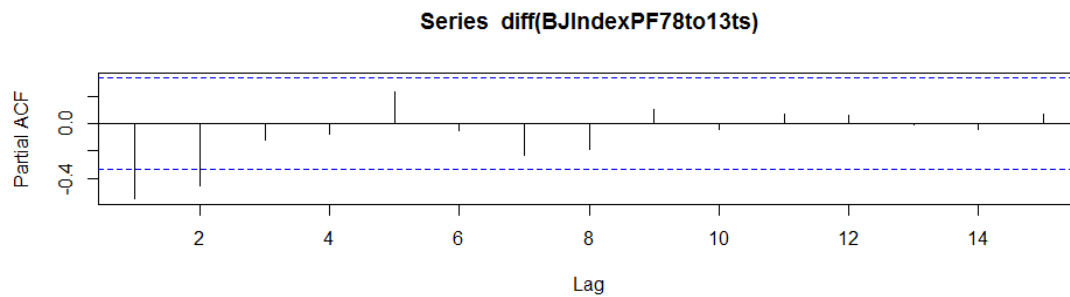
```



```

1584
1585 pacf(diff(BJIndexPF78to13ts))

```



1586

1587 Common Grackle Trend Index

```
1588 cat("Calculated differences needed for stationary via KPSS: ",
1589     ndiffs(CGIndexPF78to13ts, alpha=0.05, test="kpss"))
```

1590 Calculated differences needed for stationary via KPSS: 1

```
1591 cat("\n")
```

```
1592 Box.test(CGIndexPF78to13ts, type = "Ljung-Box")
```

1593
1594 Box-Ljung test

1595 data: CGIndexPF78to13ts
1596 X-squared = 33.512, df = 1, p-value = 7.083e-09

```
1598 adf.test(CGIndexPF78to13ts, alternative = "stationary")
```

1599
1600 Augmented Dickey-Fuller Test

1601 data: CGIndexPF78to13ts
1602 Dickey-Fuller = -1.9966, Lag order = 3, p-value = 0.5745
1603 alternative hypothesis: stationary

```
1605 adf.test(diff(CGIndexPF78to13ts), alternative = "stationary")
```

1606
1607 Augmented Dickey-Fuller Test

1608 data: diff(CGIndexPF78to13ts)
1609 Dickey-Fuller = -3.6539, Lag order = 3, p-value = 0.04323
1610 alternative hypothesis: stationary

```
1612 kpss.test(CGIndexPF78to13ts)
```

1613
1614 KPSS Test for Level Stationarity

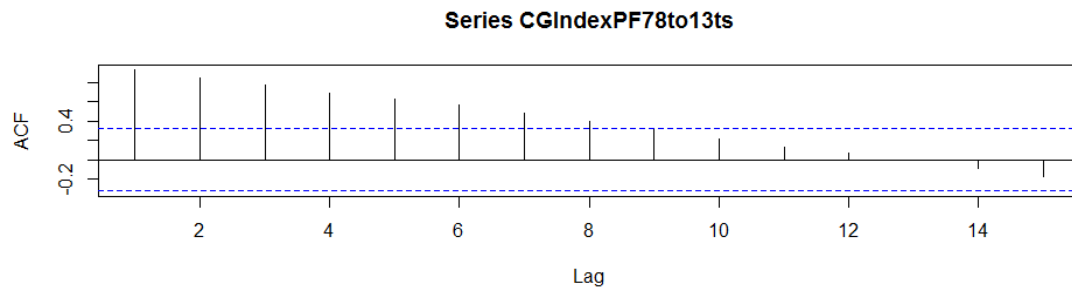
1615 data: CGIndexPF78to13ts
1616 KPSS Level = 1.8122, Truncation lag parameter = 1, p-value = 0.01

```
1618 kpss.test(diff(CGIndexPF78to13ts))
```

1619
1620 KPSS Test for Level Stationarity

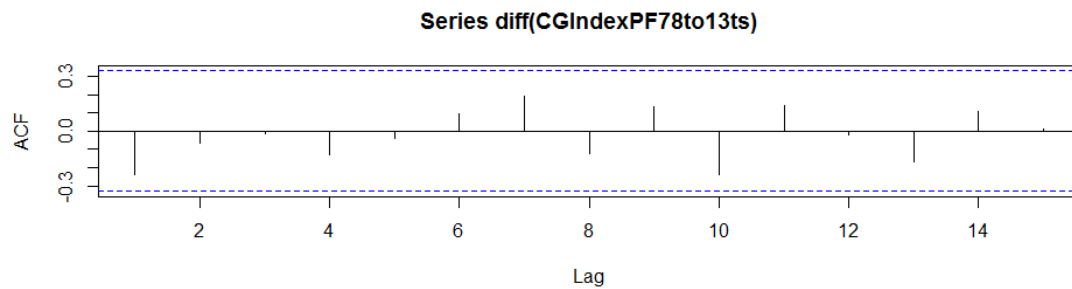
1621 data: diff(CGIndexPF78to13ts)
1622 KPSS Level = 0.080284, Truncation lag parameter = 1, p-value = 0.1

```
1624 acf(CGIndexPF78to13ts)
```



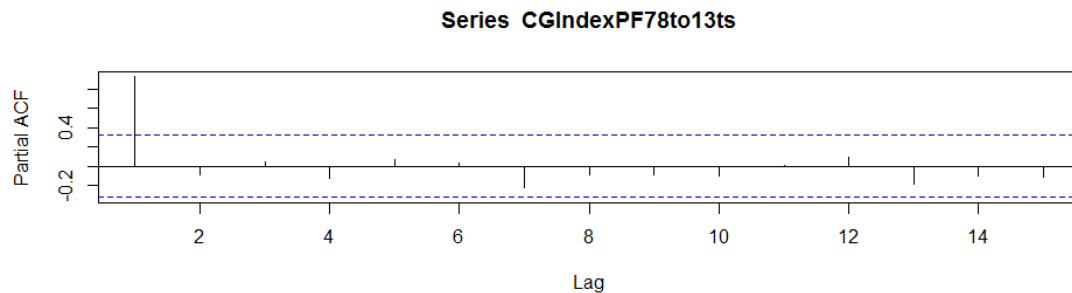
1625

1626 `acf(diff(CGIndexPF78to13ts))`



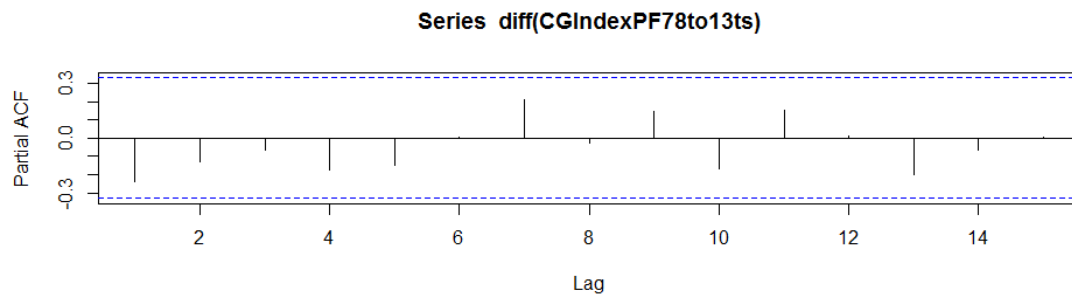
1627

1628 `pacf(CGIndexPF78to13ts)`



1629

1630 `pacf(diff(CGIndexPF78to13ts))`



1631

1632 **Mourning Dove Trend Index**

1633 `cat("Calculated differences needed for stationary via KPSS: ",`
 1634 `ndiffs(MDIndexPF78to13ts, alpha=0.05, test="kpss"))`

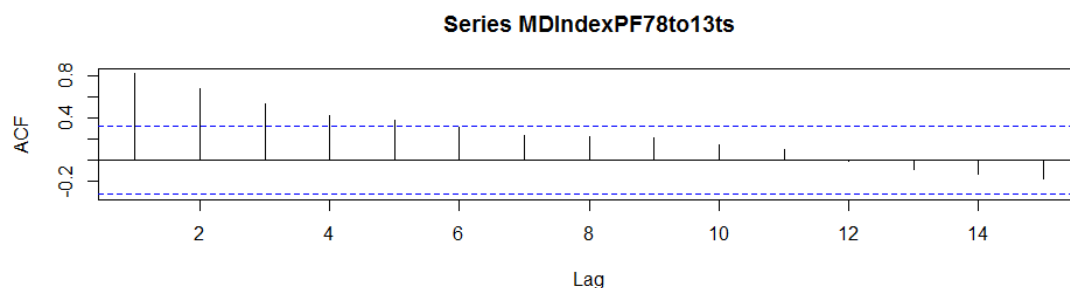
1635 Calculated differences needed for stationary via KPSS: 1

1636 `cat("\n")`

```

1637 Box.test(MDIndexPF78to13ts, type = "Ljung-Box")
1638
1639     Box-Ljung test
1640
1641 data: MDIndexPF78to13ts
1642 X-squared = 26.173, df = 1, p-value = 3.122e-07
1643
1644 adf.test(MDIndexPF78to13ts, alternative = "stationary")
1645
1646     Augmented Dickey-Fuller Test
1647
1648 data: MDIndexPF78to13ts
1649 Dickey-Fuller = -2.3474, Lag order = 3, p-value = 0.438
1649 alternative hypothesis: stationary
1650
1651 adf.test(diff(MDIndexPF78to13ts), alternative = "stationary")
1652
1653     Augmented Dickey-Fuller Test
1654
1655 data: diff(MDIndexPF78to13ts)
1656 Dickey-Fuller = -3.0753, Lag order = 3, p-value = 0.1556
1656 alternative hypothesis: stationary
1657
1658 kpss.test(MDIndexPF78to13ts)
1659
1660     KPSS Test for Level Stationarity
1661
1662 data: MDIndexPF78to13ts
1663 KPSS Level = 1.4472, Truncation lag parameter = 1, p-value = 0.01
1664
1665 kpss.test(diff(MDIndexPF78to13ts))
1666
1667     KPSS Test for Level Stationarity
1668
1669 data: diff(MDIndexPF78to13ts)
1670 KPSS Level = 0.055945, Truncation lag parameter = 1, p-value = 0.1
1671
1672 acf(MDIndexPF78to13ts)

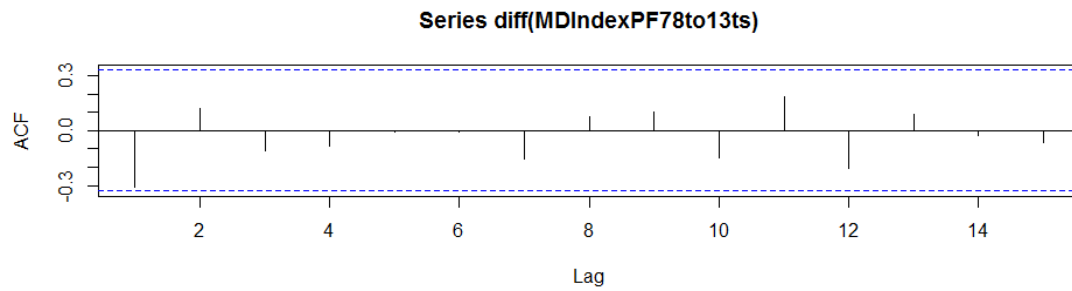
```



```

1670
1671 acf(diff(MDIndexPF78to13ts))

```

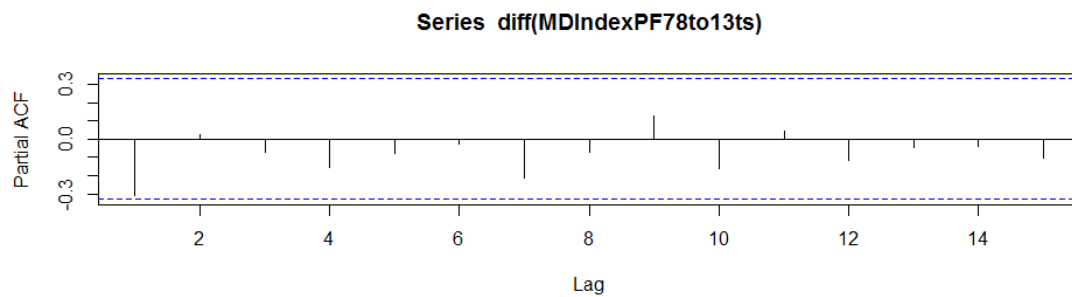
1672

1673 `pacf(MDIndexPF78to13ts)`



1674

1675 `pacf(diff(MDIndexPF78to13ts))`



1676

1677 **Northern Cardinal Trend Index**

1678 `cat("Calculated differences needed for stationary via KPSS: ",`
 1679 `ndiffs(NCIndexPF78to13ts, alpha=0.05, test="kpss"))`

1680 Calculated differences needed for stationary via KPSS: 1

1681 `cat("\n")`

1682 `Box.test(NCIndexPF78to13ts, type = "Ljung-Box")`

1683

1684 Box-Ljung test

1685

1686 data: NCIndexPF78to13ts

1687 X-squared = 8.9004, df = 1, p-value = 0.002851

1688 `adf.test(NCIndexPF78to13ts, alternative = "stationary")`

1689

1690 Augmented Dickey-Fuller Test

1691

1692 data: NCIndexPF78to13ts

```

1693 Dickey-Fuller = -2.5638, Lag order = 3, p-value = 0.3538
1694 alternative hypothesis: stationary

1695 adf.test(diff(NCIndexPF78to13ts), alternative = "stationary")

1696
1697     Augmented Dickey-Fuller Test
1698
1699 data: diff(NCIndexPF78to13ts)
1700 Dickey-Fuller = -4.017, Lag order = 3, p-value = 0.02047
1701 alternative hypothesis: stationary

1702 kpss.test(NCIndexPF78to13ts)

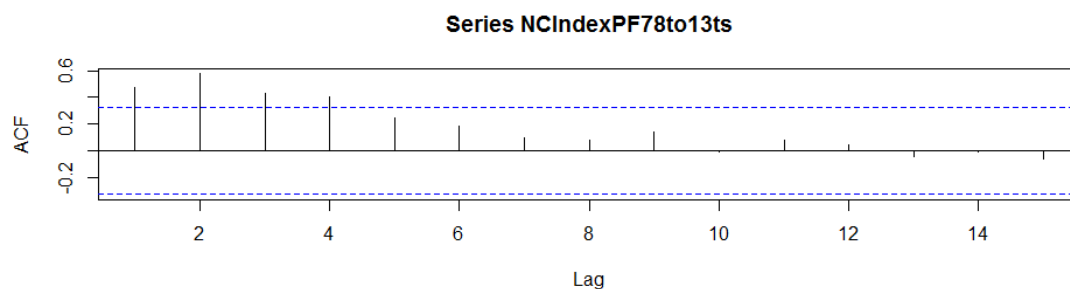
1703
1704     KPSS Test for Level Stationarity
1705
1706 data: NCIndexPF78to13ts
1707 KPSS Level = 1.3542, Truncation lag parameter = 1, p-value = 0.01

1708 kpss.test(diff(NCIndexPF78to13ts))

1709
1710     KPSS Test for Level Stationarity
1711
1712 data: diff(NCIndexPF78to13ts)
1713 KPSS Level = 0.065347, Truncation lag parameter = 1, p-value = 0.1

1714 acf(NCIndexPF78to13ts)

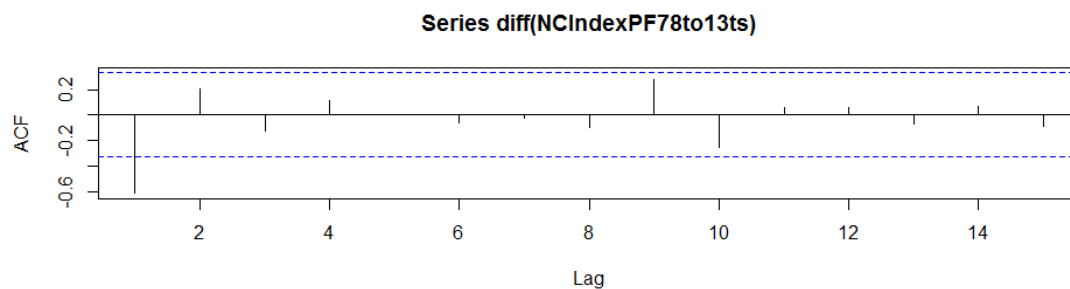
```



```

1715
1716 acf(diff(NCIndexPF78to13ts))

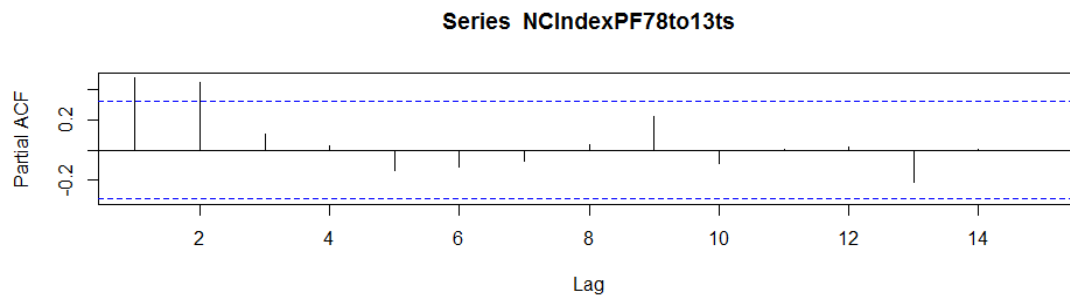
```



```

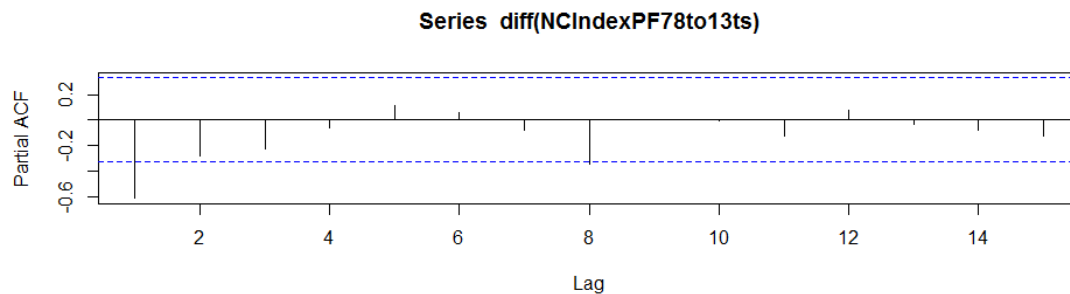
1717
1718 pacf(NCIndexPF78to13ts)

```



1719

1720 `pacf(diff(NCIndexPF78to13ts))`



1721

1722 **Northern Mockingbird Trend Index**

1723 `cat("Calculated differences needed for stationary via KPSS: ",`
 1724 `ndiffs(NMIndexPF78to13ts, alpha=0.05, test="kpss"))`

1725 Calculated differences needed for stationary via KPSS: 1

1726 `cat("\n")`

1727 `Box.test(NMIndexPF78to13ts, type = "Ljung-Box")`

1728

1729 Box-Ljung test

1730

1731 data: NMIndexPF78to13ts

1732 X-squared = 32.588, df = 1, p-value = 1.139e-08

1733 `adf.test(NMIndexPF78to13ts, alternative = "stationary")`

1734

1735 Augmented Dickey-Fuller Test

1736

1737 data: NMIndexPF78to13ts

1738 Dickey-Fuller = -2.7806, Lag order = 3, p-value = 0.2694

1739 alternative hypothesis: stationary

1740 `adf.test(diff(NMIndexPF78to13ts), alternative = "stationary")`

1741

1742 Augmented Dickey-Fuller Test

1743

1744 data: diff(NMIndexPF78to13ts)

1745 Dickey-Fuller = -3.0466, Lag order = 3, p-value = 0.1667

1746 alternative hypothesis: stationary

1747 `kpss.test(NMIndexPF78to13ts)`

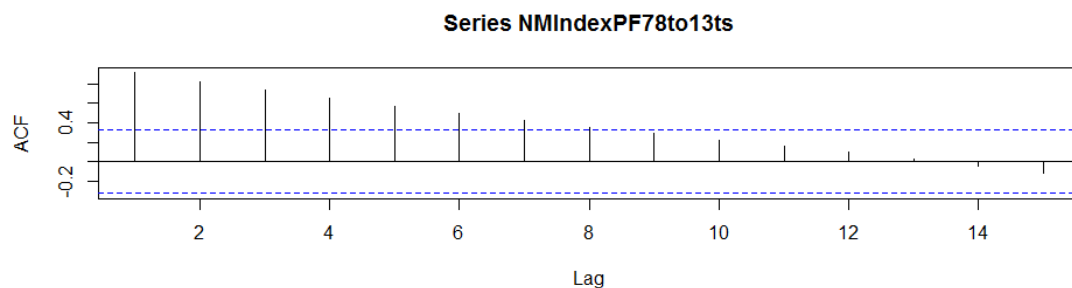
1748

1749 KPSS Test for Level Stationarity

```

1750
1751 data: NMIndexPF78to13ts
1752 KPSS Level = 1.852, Truncation lag parameter = 1, p-value = 0.01
1753
1754 kpss.test(diff(NMIndexPF78to13ts))
1755
1756 KPSS Test for Level Stationarity
1757 data: diff(NMIndexPF78to13ts)
1758 KPSS Level = 0.18858, Truncation lag parameter = 1, p-value = 0.1
1759
1760 acf(NMIndexPF78to13ts)

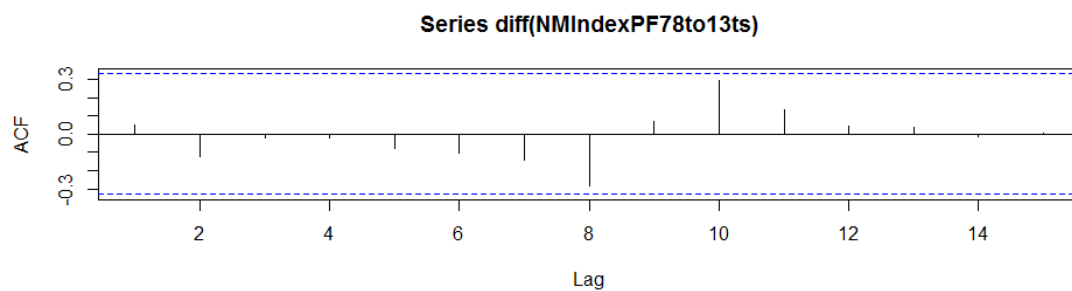
```



```

1760
1761 acf(diff(NMIndexPF78to13ts))

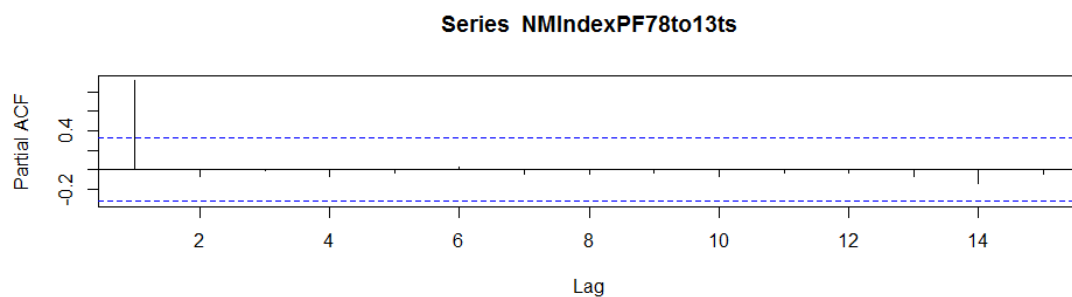
```



```

1762
1763 pacf(NMIndexPF78to13ts)

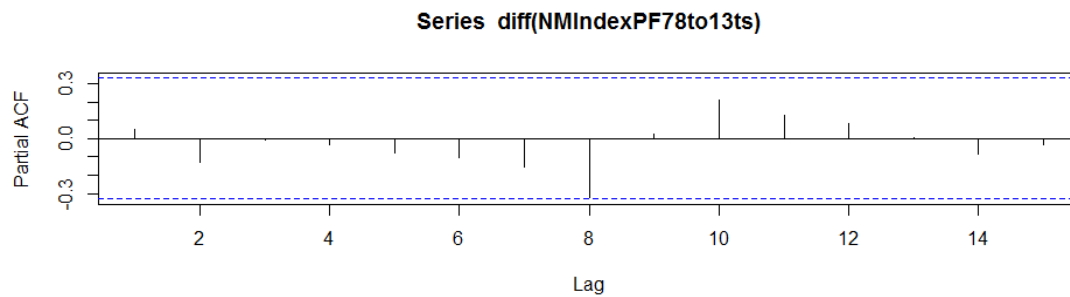
```



```

1764
1765 pacf(diff(NMIndexPF78to13ts))

```



1766

1767 Transmission Data Differences

1768 Flavivirus

```
1769 cat("Calculated differences needed for stationary via KPSS: ",
1770     ndiffs(log(SCFlaviPF78to15ts+1), alpha=0.05, test="kpss"))
```

1771 Calculated differences needed for stationary via KPSS: 0

```
1772 cat("\n")
```

```
1773 Box.test(log(SCFlaviPF78to15ts+1), type = "Ljung-Box")
```

1774

Box-Ljung test

1775

data: log(SCFlaviPF78to15ts + 1)

1776 X-squared = 2.29, df = 1, p-value = 0.1302

```
1777 adf.test(log(SCFlaviPF78to15ts+1), alternative = "stationary")
```

1778

Augmented Dickey-Fuller Test

1779

data: log(SCFlaviPF78to15ts + 1)

1780 Dickey-Fuller = -2.9759, Lag order = 3, p-value = 0.1919

1781 alternative hypothesis: stationary

```
1782 adf.test(diff(log(SCFlaviPF78to15ts+1)), alternative = "stationary")
```

1783

Augmented Dickey-Fuller Test

1784

data: diff(log(SCFlaviPF78to15ts + 1))

1785 Dickey-Fuller = -4.0073, Lag order = 3, p-value = 0.02032

1786 alternative hypothesis: stationary

```
1787 kpss.test(log(SCFlaviPF78to15ts+1))
```

1788

KPSS Test for Level Stationarity

1789

data: log(SCFlaviPF78to15ts + 1)

1790 KPSS Level = 0.3425, Truncation lag parameter = 1, p-value = 0.1

```
1791 kpss.test(diff(log(SCFlaviPF78to15ts+1)))
```

1792

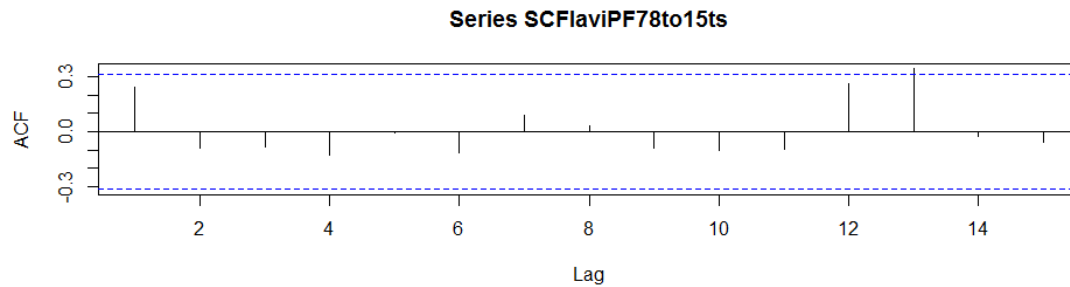
KPSS Test for Level Stationarity

1793

data: diff(log(SCFlaviPF78to15ts + 1))

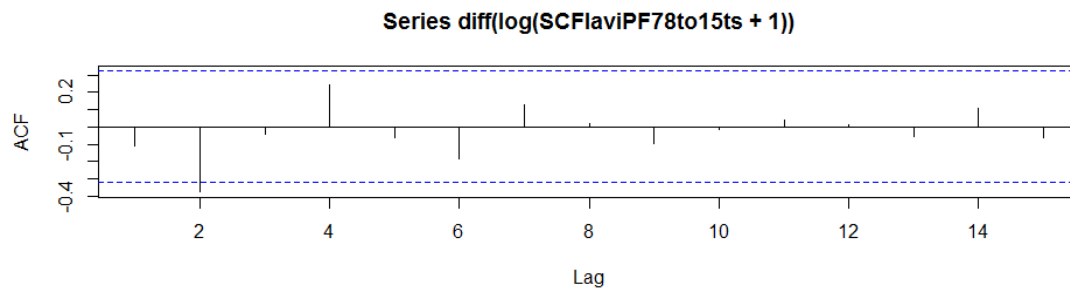
1794 KPSS Level = 0.06706, Truncation lag parameter = 1, p-value = 0.1

1805 `acf(SCFlaviPF78to15ts)`



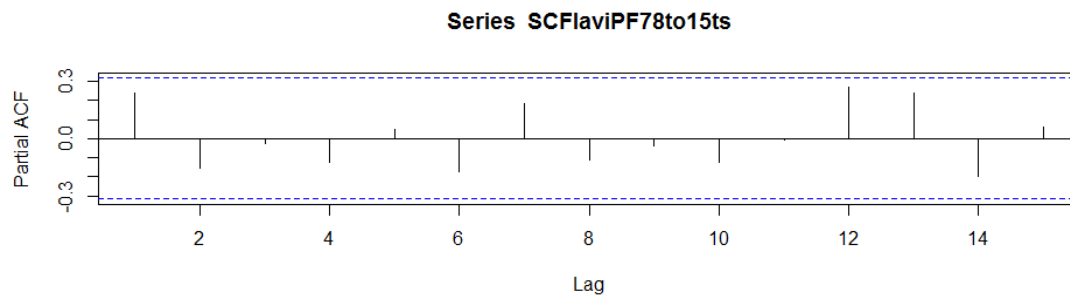
1806

1807 `acf(diff(log(SCFlaviPF78to15ts+1)))`



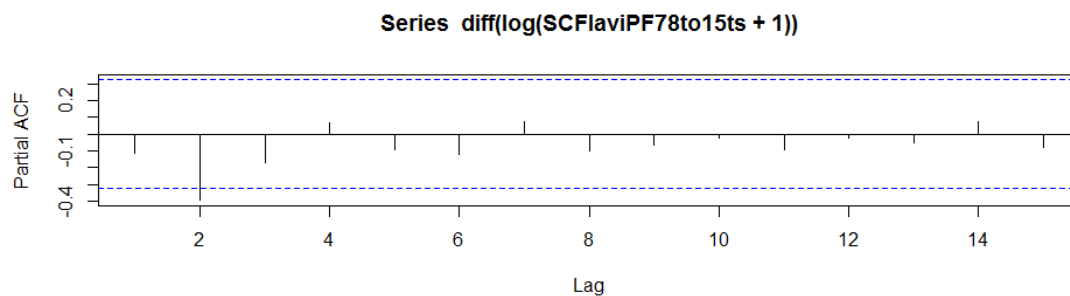
1808

1809 `pacf(SCFlaviPF78to15ts)`



1810

1811 `pacf(diff(log(SCFlaviPF78to15ts+1)))`



1812

1813 **SLE**

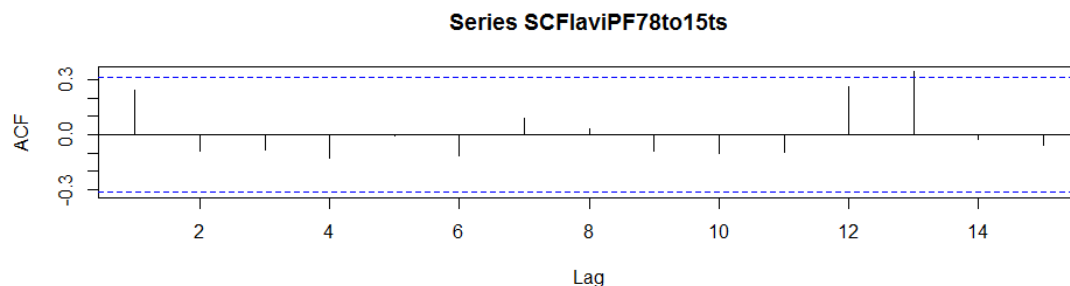
1814 `cat("Calculated differences needed for stationary via KPSS: ",`
1815 `ndiffs(log(SCFlaviPF78to15ts+1), alpha=0.05, test="kpss"))`

1816 Calculated differences needed for stationary via KPSS: 0

```

1817 cat("\n")
1818 Box.test(log(SCFlaviPF78to15ts+1), type = "Ljung-Box")
1819
1820     Box-Ljung test
1821
1822 data: log(SCFlaviPF78to15ts + 1)
1823 X-squared = 2.29, df = 1, p-value = 0.1302
1824
1825 adf.test(log(SCFlaviPF78to15ts+1), alternative = "stationary")
1826
1827     Augmented Dickey-Fuller Test
1828
1829 data: log(SCFlaviPF78to15ts + 1)
1829 Dickey-Fuller = -2.9759, Lag order = 3, p-value = 0.1919
1830 alternative hypothesis: stationary
1831
1832 adf.test(diff(log(SCFlaviPF78to15ts+1)), alternative = "stationary")
1833
1834     Augmented Dickey-Fuller Test
1835
1836 data: diff(log(SCFlaviPF78to15ts + 1))
1836 Dickey-Fuller = -4.0073, Lag order = 3, p-value = 0.02032
1837 alternative hypothesis: stationary
1838
1839 kpss.test(log(SCFlaviPF78to15ts+1))
1840
1841     KPSS Test for Level Stationarity
1842
1843 data: log(SCFlaviPF78to15ts + 1)
1843 KPSS Level = 0.3425, Truncation lag parameter = 1, p-value = 0.1
1844
1845 kpss.test(diff(log(SCFlaviPF78to15ts+1)))
1846
1847     KPSS Test for Level Stationarity
1848
1849 data: diff(log(SCFlaviPF78to15ts + 1))
1849 KPSS Level = 0.06706, Truncation lag parameter = 1, p-value = 0.1
1850
1851 acf(SCFlaviPF78to15ts)

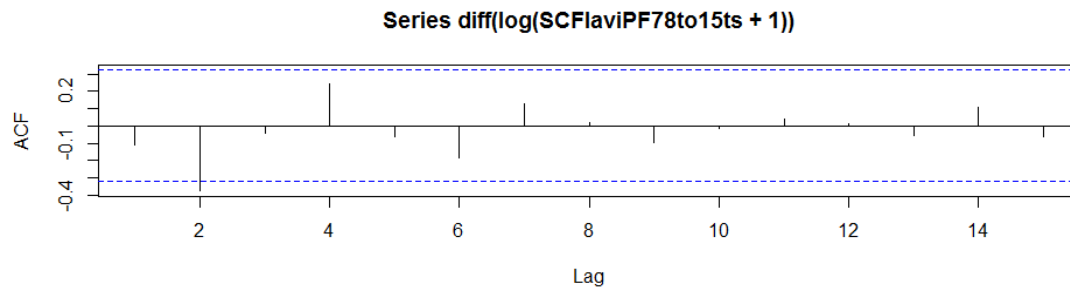
```



```

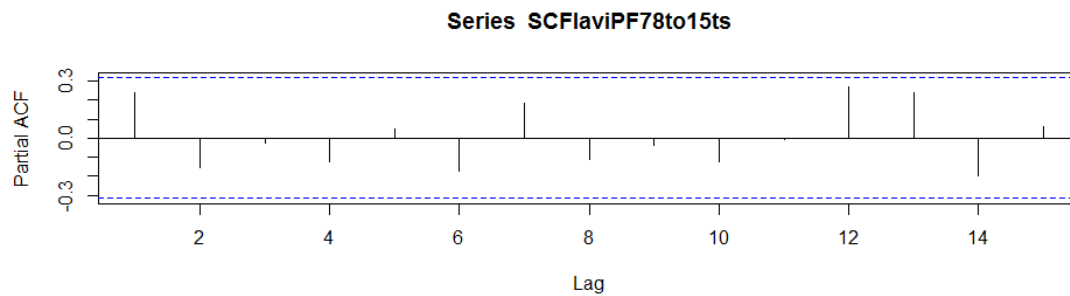
1851
1852 acf(diff(log(SCFlaviPF78to15ts+1)))

```



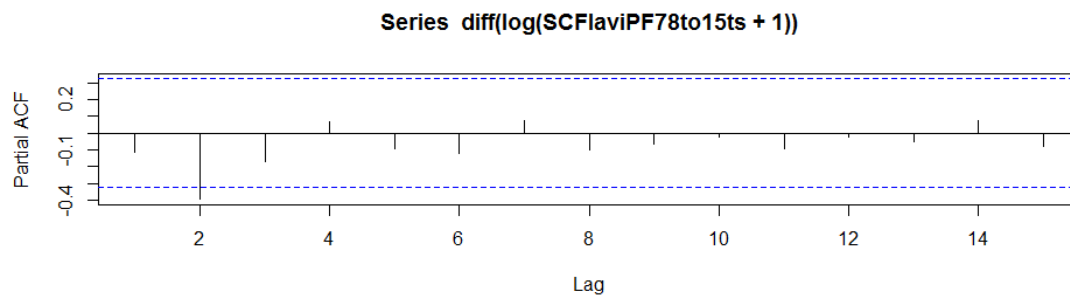
1853

1854 `pacf(SCFlaviPF78to15ts)`



1855

1856 `pacf(diff(log(SCFlaviPF78to15ts+1)))`



1857

1858 **WN**

1859 `cat("Calculated differences needed for stationary via KPSS: ",`
 1860 `ndiffs(log(SCWNPF01to15ts+1), alpha=0.05, test="kpss"))`

1861 Calculated differences needed for stationary via KPSS: 0

1862 `cat("\n")`

1863 `Box.test(log(SCWNPF01to15ts+1), type = "Ljung-Box")`

1864

1865 Box-Ljung test

1866

1867 data: log(SCWNPF01to15ts + 1)

1868 X-squared = 4.8561, df = 1, p-value = 0.02755

1869 `adf.test(log(SCWNPF01to15ts+1), alternative = "stationary")`

1870

1871 Augmented Dickey-Fuller Test

1872

1873 data: log(SCWNPF01to15ts + 1)


```

1874 Dickey-Fuller = -2.4577, Lag order = 2, p-value = 0.398
1875 alternative hypothesis: stationary

1876 adf.test(diff(log(SCWNPF01to15ts+1)), alternative = "stationary")

1877
1878     Augmented Dickey-Fuller Test
1879
1880 data: diff(log(SCWNPF01to15ts + 1))
1881 Dickey-Fuller = -1.8499, Lag order = 2, p-value = 0.6296
1882 alternative hypothesis: stationary

1883 kpss.test(log(SCWNPF01to15ts+1))

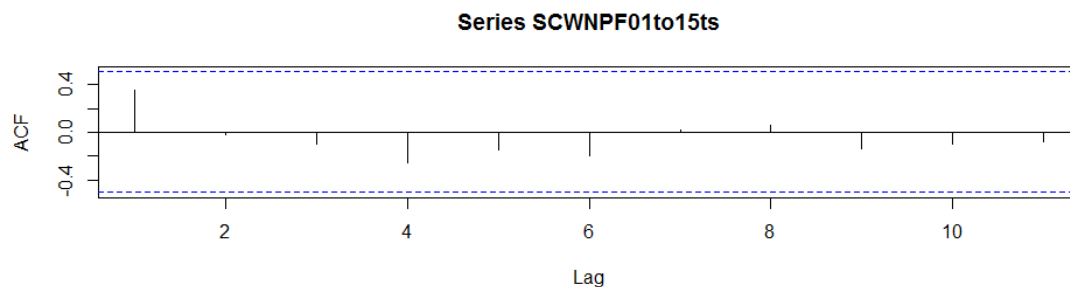
1884
1885     KPSS Test for Level Stationarity
1886
1887 data: log(SCWNPF01to15ts + 1)
1888 KPSS Level = 0.20022, Truncation lag parameter = 0, p-value = 0.1

1889 kpss.test(diff(log(SCWNPF01to15ts+1)))

1890
1891     KPSS Test for Level Stationarity
1892
1893 data: diff(log(SCWNPF01to15ts + 1))
1894 KPSS Level = 0.088582, Truncation lag parameter = 0, p-value = 0.1

1895 acf(SCWNPF01to15ts)

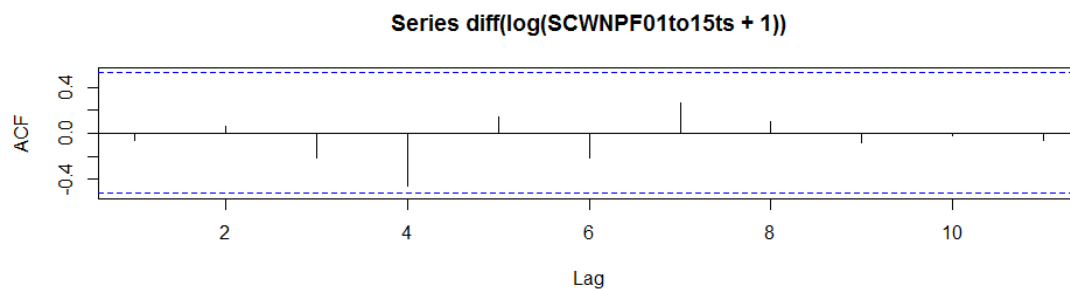
```



```

1896
1897 acf(diff(log(SCWNPF01to15ts+1)))

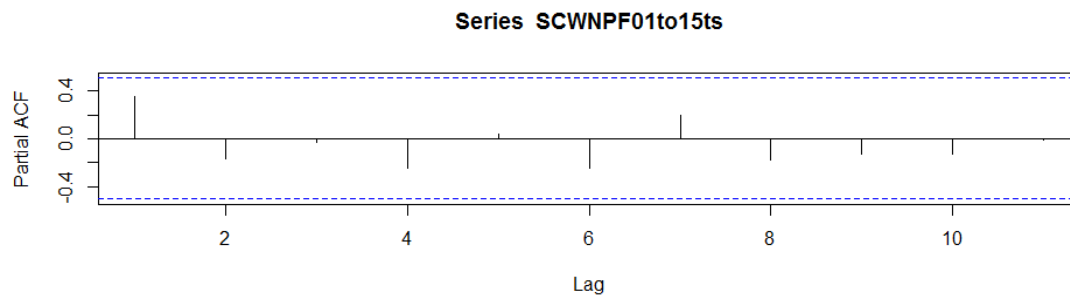
```



```

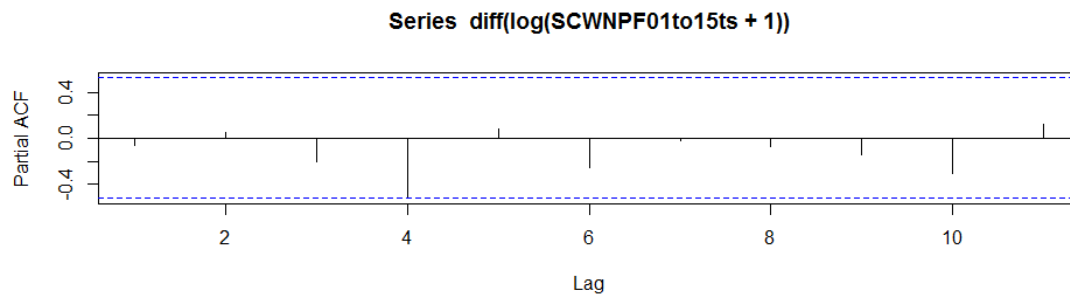
1898
1899 pacf(SCWNPF01to15ts)

```



1900

1901 `pacf(diff(log(SCWNPF01to15ts+1)))`



1902

1903 Model Fitting

1904 ARIMA models are fit using `auto.arima` function in the `forecast` package. Fitted models are then used to prewhiten data
 1905 in the Analysis phase. Models only need to be fitted to the BBS data.

1906 BBS Models

1907 Blue Jay Averages

1908 `fitbj <- auto.arima(BJAveragePF78to15ts, seasonal = FALSE, trace = TRUE)`

```

1909
1910 ARIMA(2,1,2) with drift          : Inf
1911 ARIMA(0,1,0) with drift          : 214.8543
1912 ARIMA(1,1,0) with drift          : 212.9345
1913 ARIMA(0,1,1) with drift          : 209.5992
1914 ARIMA(0,1,0)                    : 212.6157
1915 ARIMA(1,1,1) with drift          : Inf
1916 ARIMA(0,1,2) with drift          : 211.2073
1917 ARIMA(1,1,2) with drift          : Inf
1918 ARIMA(0,1,1)                    : 207.2474
1919 ARIMA(1,1,1)                    : 208.8307
1920 ARIMA(0,1,2)                    : 208.7959
1921 ARIMA(1,1,2)                    : Inf
1922

```

1923 Best model: ARIMA(0,1,1)

1924 `fitbj`

1925 Series: BJAveragePF78to15ts
 1926 ARIMA(0,1,1)

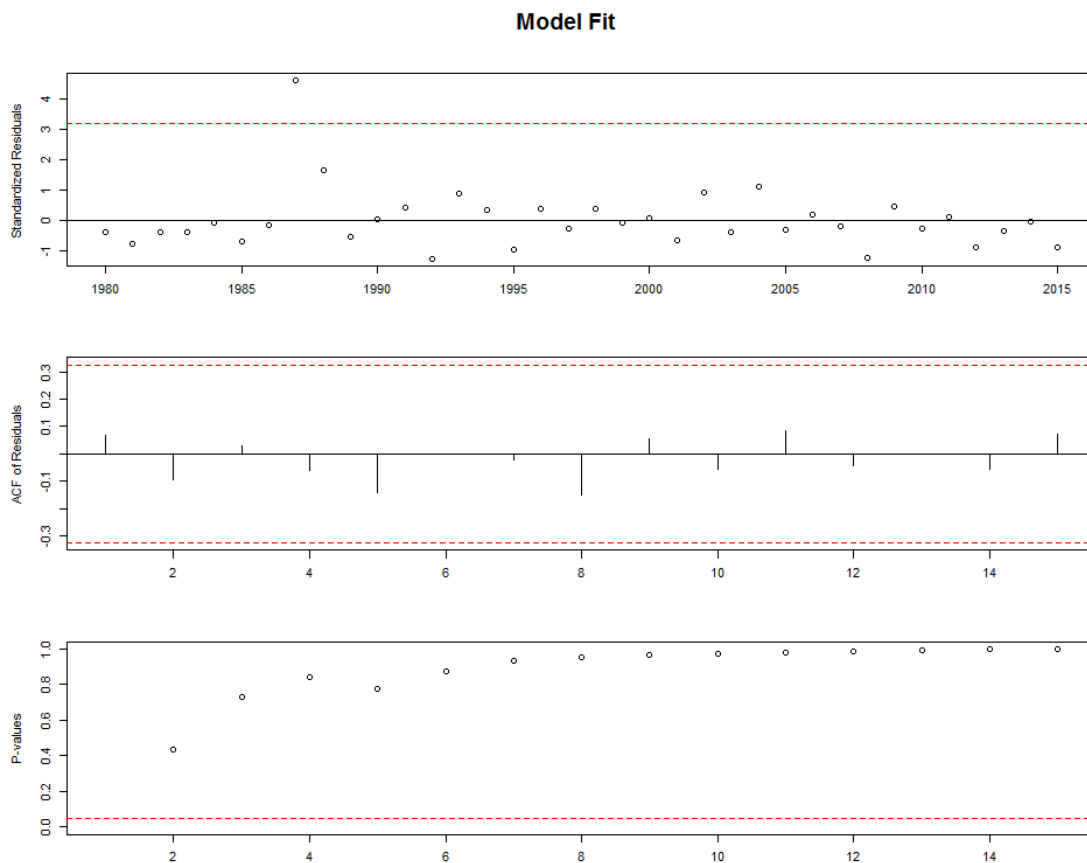
```

1927
1928 Coefficients:
1929     ma1
1930  -0.5587
1931 s.e.   0.1725
1932

```

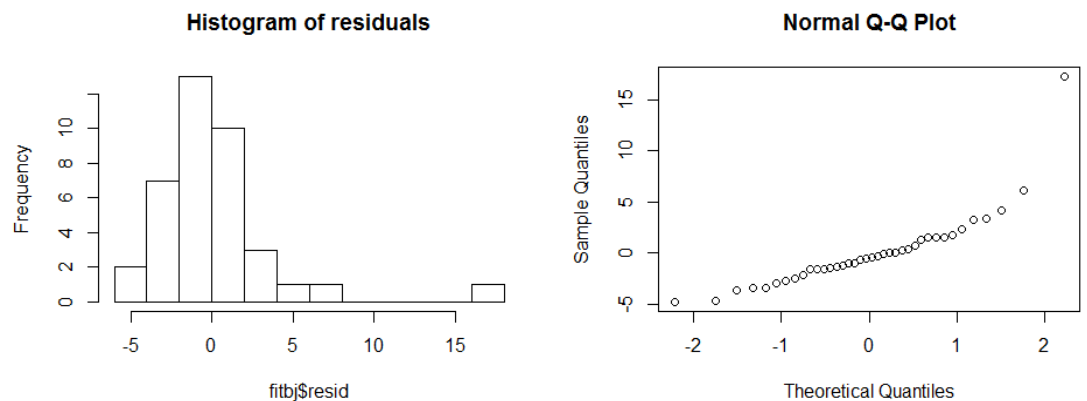
```
1933 sigma^2 estimated as 13.95: log likelihood=-101.45
1934 AIC=206.89 AICc=207.25 BIC=210.12
```

```
1935 par(oma=c(0,0,2,0))
1936 tsdiag(Arima(BJAveragePF78to15ts, model=fitbj))
1937 title("Model Fit", outer = TRUE)
```



```
1938
```

```
1939 par(mfrow=c(1,2))
1940 hist(fitbj$resid, nclass="FD", main="Histogram of residuals")
1941 qqnorm(fitbj$resid)
```



```
1942
```

```
1943 Box.test(fitbj$resid, type = "Ljung-Box")
```

```
1944
1945 Box-Ljung test
1946
```

```

1947 data: fitbj$resid
1948 X-squared = 0.14372, df = 1, p-value = 0.7046

1949 Common Grackle Averages
1950 fitcg=auto.arima(CGAveragePF78to15ts, seasonal=FALSE, trace=TRUE)

1951
1952 ARIMA(2,1,2) with drift : 295.9334
1953 ARIMA(0,1,0) with drift : 295.6592
1954 ARIMA(1,1,0) with drift : 293.196
1955 ARIMA(0,1,1) with drift : 289.3978
1956 ARIMA(0,1,0) : 293.425
1957 ARIMA(1,1,1) with drift : 291.8666
1958 ARIMA(0,1,2) with drift : 291.808
1959 ARIMA(1,1,2) with drift : 294.0616
1960 ARIMA(0,1,1) : 287.0651
1961 ARIMA(1,1,1) : 289.395
1962 ARIMA(0,1,2) : 289.3463
1963 ARIMA(1,1,2) : 291.4329
1964
1965 Best model: ARIMA(0,1,1)

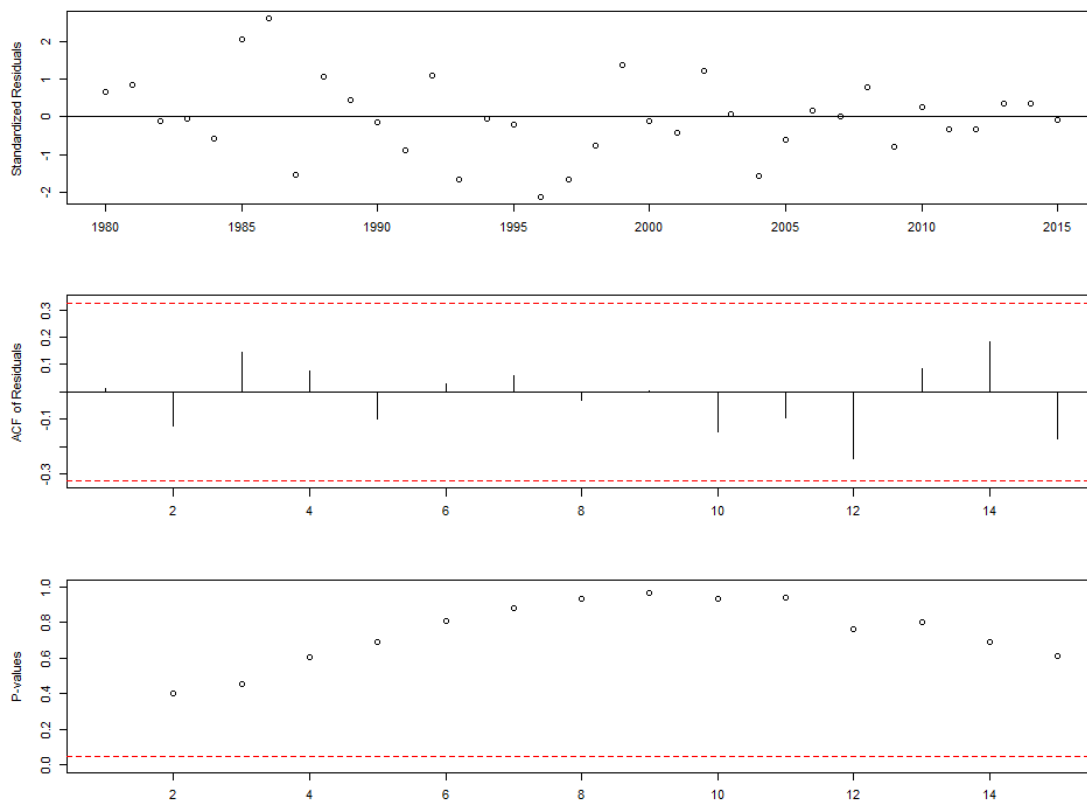
1966 fitcg

1967 Series: CGAveragePF78to15ts
1968 ARIMA(0,1,1)
1969
1970 Coefficients:
1971      ma1
1972    -0.5297
1973 s.e.    0.1371
1974
1975 sigma^2 estimated as 120.8: log likelihood=-141.36
1976 AIC=286.71 AICc=287.07 BIC=289.93

1977 par(oma=c(0,0,2,0))
1978 tsdiag(Arima(CGAveragePF78to15ts, model=fitcg))
1979 title("Model Fit", outer = TRUE)

```

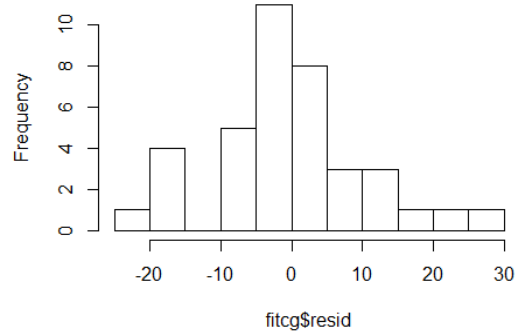
Model Fit



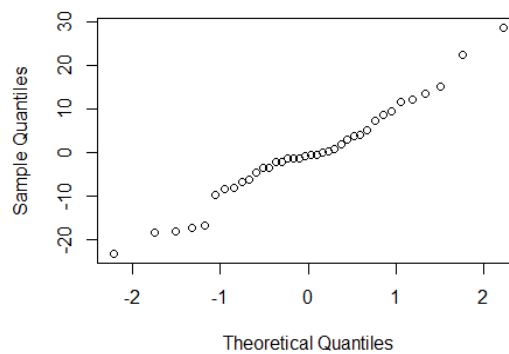
1980

```
1981 par(mfrow=c(1,2))
1982 hist(fitcg$resid, nclass="FD", main="Histogram of residuals")
1983 qqnorm(fitcg$resid)
```

Histogram of residuals



Normal Q-Q Plot



1984

```
1985 Box.test(fitcg$resid, type = "Ljung-Box")
```

```
1986
1987     Box-Ljung test
```

```
1988
1989 data: fitcg$resid
1990 X-squared = 0.0023868, df = 1, p-value = 0.961
```

Mourning Dove Averages

```
1992 fitmd=auto.arima(MDAveragePF78to15ts, seasonal=FALSE, trace=TRUE)
```

```

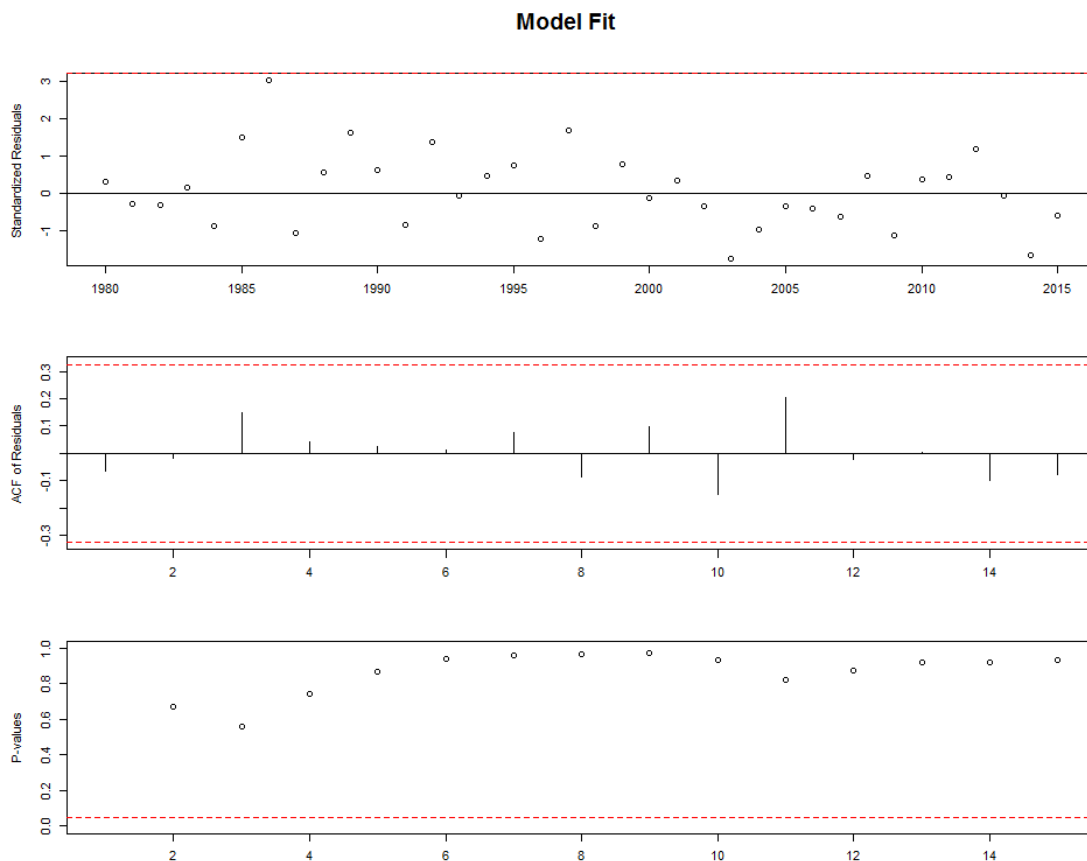
1993
1994 ARIMA(2,1,2) with drift : 255.5328
1995 ARIMA(0,1,0) with drift : 255.9683
1996 ARIMA(1,1,0) with drift : 250.7897
1997 ARIMA(0,1,1) with drift : 248.8007
1998 ARIMA(0,1,0) : 253.7423
1999 ARIMA(1,1,1) with drift : 251.1112
2000 ARIMA(0,1,2) with drift : 250.9443
2001 ARIMA(1,1,2) with drift : 253.1824
2002 ARIMA(0,1,1) : 246.5557
2003 ARIMA(1,1,1) : 248.6943
2004 ARIMA(0,1,2) : 248.5024
2005 ARIMA(1,1,2) : 250.5361
2006
2007 Best model: ARIMA(0,1,1)

2008 fitmd

2009 Series: MDAveragePF78to15ts
2010 ARIMA(0,1,1)
2011
2012 Coefficients:
2013      ma1
2014      -0.4929
2015 s.e.    0.1254
2016
2017 sigma^2 estimated as 40.47: log likelihood=-121.1
2018 AIC=246.2 AICc=246.56 BIC=249.42

2019 par(oma=c(0,0,2,0))
2020 tsdiag(Arima(MDAveragePF78to15ts, model=fitmd))
2021 title("Model Fit", outer = TRUE)

```

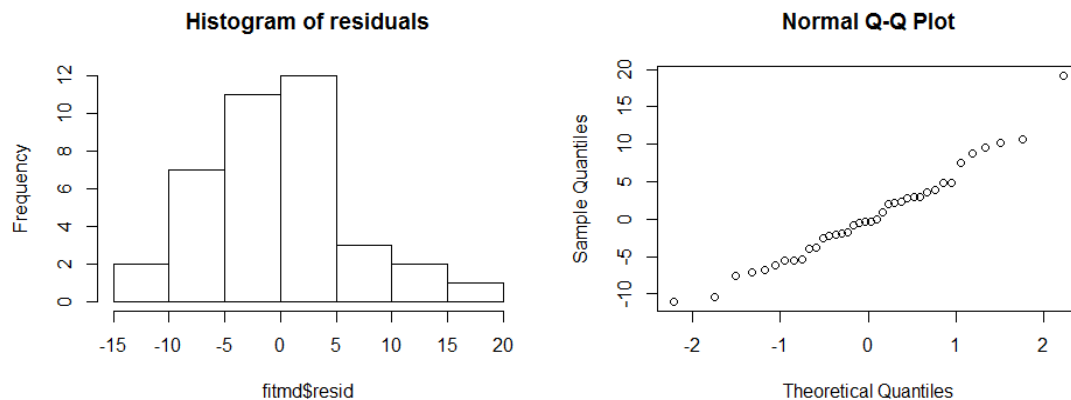


2022

```

2023 par(mfrow=c(1,2))
2024 hist(fitmd$resid, nclass="FD", main="Histogram of residuals")
2025 qqnorm(fitmd$resid)

```



```

2026
2027 Box.test(fitmd$resid, type = "Ljung-Box")
2028
2029     Box-Ljung test
2030
2031 data:  fitmd$resid
2032 X-squared = 0.17061, df = 1, p-value = 0.6796

```

2033 Northern Cardinal Averages

```

2034 fitnc=auto.arima(NCAveragePF78to15ts, seasonal=FALSE, trace=TRUE)

```

```

2035
2036 ARIMA(2,1,2) with drift      : Inf
2037 ARIMA(0,1,0) with drift     : 231.5002
2038 ARIMA(1,1,0) with drift     : 232.7511
2039 ARIMA(0,1,1) with drift     : 232.1039
2040 ARIMA(0,1,0)                : 229.5898
2041 ARIMA(1,1,1) with drift     : Inf
2042
2043 Best model: ARIMA(0,1,0)
2044
2045 fitnc
2046
2047 Series: NCAveragePF78to15ts
2048 ARIMA(0,1,0)
2049
2050 sigma^2 estimated as 27.39: log likelihood=-113.74
2051 AIC=229.48  AICc=229.59  BIC=231.09

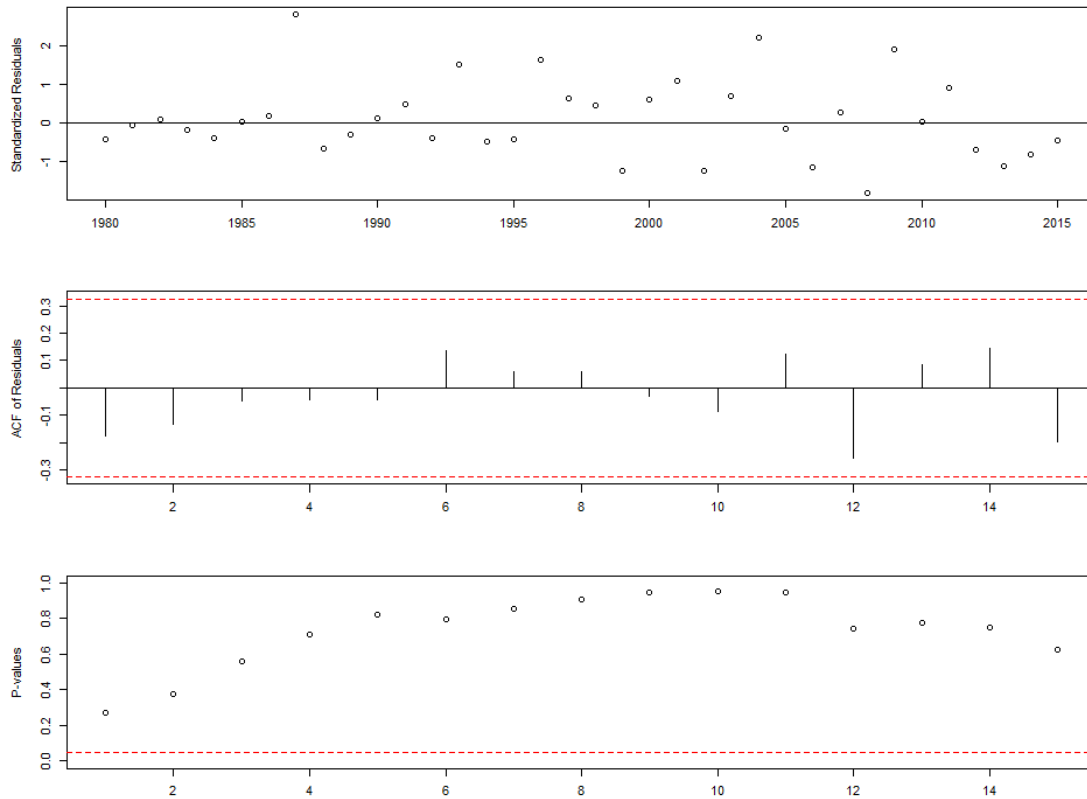
```

```

2050 par(oma=c(0,0,2,0))
2051 tsdiag(Arima(NCAveragePF78to15ts, model=fitnc))
2052 title("Model Fit", outer = TRUE)

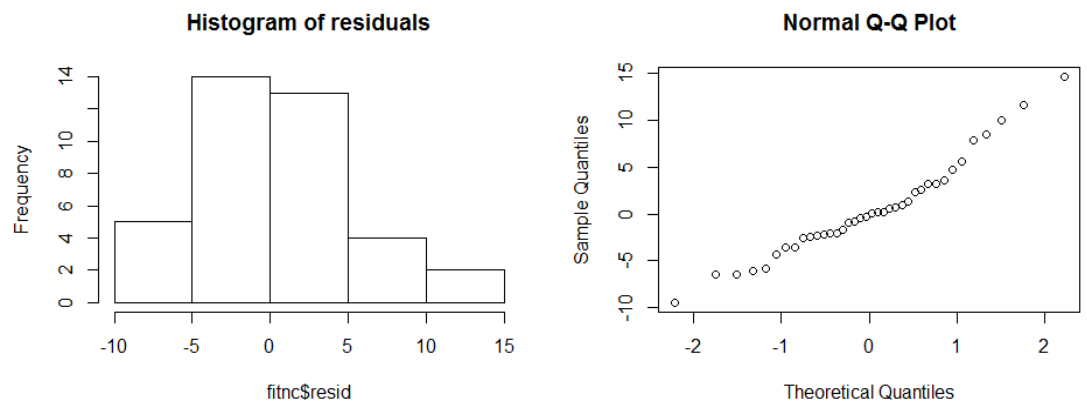
```

Model Fit



2053

```
2054 par(mfrow=c(1,2))
2055 hist(fitnc$resid, nclass="FD", main="Histogram of residuals")
2056 qqnorm(fitnc$resid)
```



2057

```
2058 Box.test(fitnc$resid, type = "Ljung-Box")
```

2059

2060 Box-Ljung test

2061

2062 data: fitnc\$resid

2063 X-squared = 1.243, df = 1, p-value = 0.2649

2064 Northern Mockingbird Averages

```
2065 fitnm=auto.arima(NMAveragePF78to15ts, seasonal=FALSE, trace=TRUE)
```



```

2066
2067 ARIMA(2,1,2) with drift      : 343.1423
2068 ARIMA(0,1,0) with drift     : 345.482
2069 ARIMA(1,1,0) with drift     : 338.8013
2070 ARIMA(0,1,1) with drift     : 336.1272
2071 ARIMA(0,1,0)                : 343.8001
2072 ARIMA(1,1,1) with drift     : 338.5844
2073 ARIMA(0,1,2) with drift     : 338.5816
2074 ARIMA(1,1,2) with drift     : Inf
2075 ARIMA(0,1,1)                : 337.3919
2076
2077 Best model: ARIMA(0,1,1) with drift

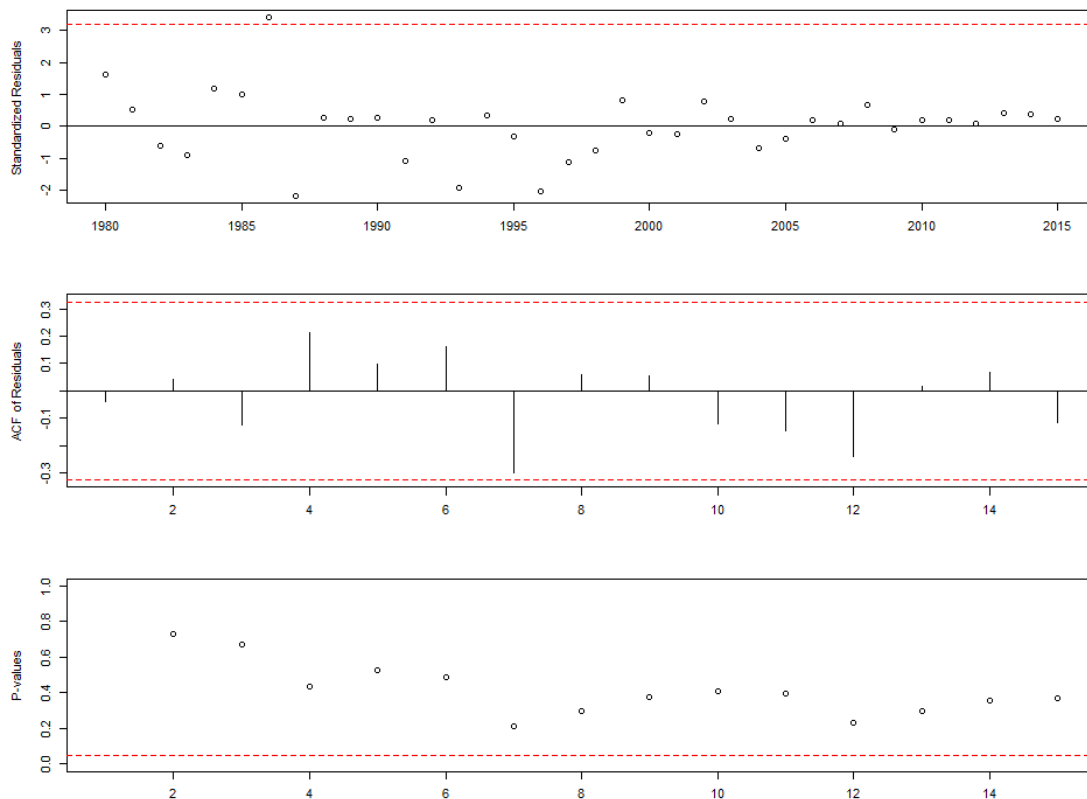
2078 fitnm

2079 Series: NMAveragePF78to15ts
2080 ARIMA(0,1,1) with drift
2081
2082 Coefficients:
2083      ma1      drift
2084    -0.5898   -3.3783
2085    s.e.   0.1289    1.4587
2086
2087 sigma^2 estimated as 425.5:  log likelihood=-164.7
2088 AIC=335.4   AICc=336.13   BIC=340.23

2089 par(oma=c(0,0,2,0))
2090 tsdiag(Arima(NMAveragePF78to15ts, model=fitnm))
2091 title("Model Fit", outer = TRUE)

```

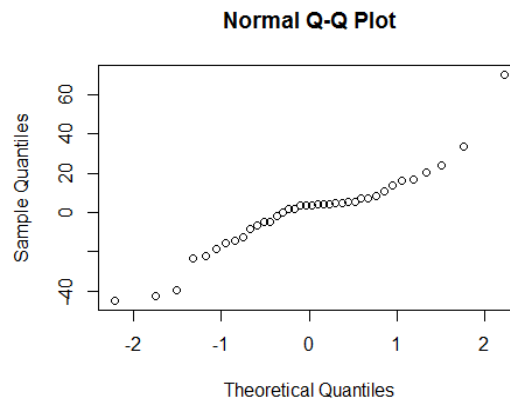
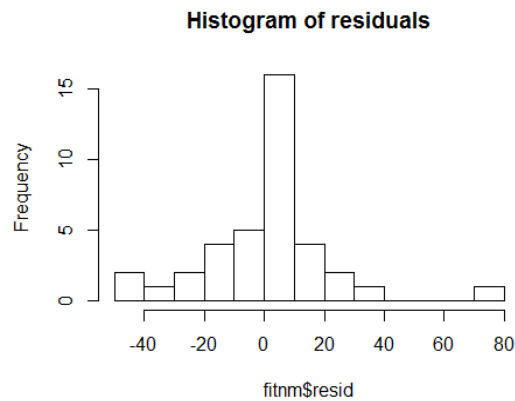
Model Fit



```

2092
2093 par(mfrow=c(1,2))
2094 hist(fitnm$resid, nclass="FD", main="Histogram of residuals")
2095 qqnorm(fitnm$resid)

```



2096

2097 `Box.test(fitm$resid, type = "Ljung-Box")`

2098

Box-Ljung test

2099

2100 data: fitm\$resid

2101 X-squared = 0.038131, df = 1, p-value = 0.8452

2103 **Blue Jay Trend Index**

2104 `fitbjindex <- auto.arima(BJIndexPF78to13ts, seasonal = FALSE, trace = TRUE)`

2105

```
ARIMA(2,1,2) with drift      : Inf
ARIMA(0,1,0) with drift     : 90.43102
ARIMA(1,1,0) with drift     : 79.79555
ARIMA(0,1,1) with drift     : 72.04334
ARIMA(0,1,0)                : 89.46693
ARIMA(1,1,1) with drift     : 73.65549
ARIMA(0,1,2) with drift     : Inf
ARIMA(1,1,2) with drift     : Inf
ARIMA(0,1,1)                : 82.34281
```

2115

Best model: ARIMA(0,1,1) with drift

2117

fitbjindex

2118 Series: BJIndexPF78to13ts

2119 ARIMA(0,1,1) with drift

2120

Coefficients:

2122 ma1 drift

2123 -0.8432 -0.1913

2124 s.e. 0.1499 0.0204

2125

2126 sigma^2 estimated as 0.3648: log likelihood=-32.63

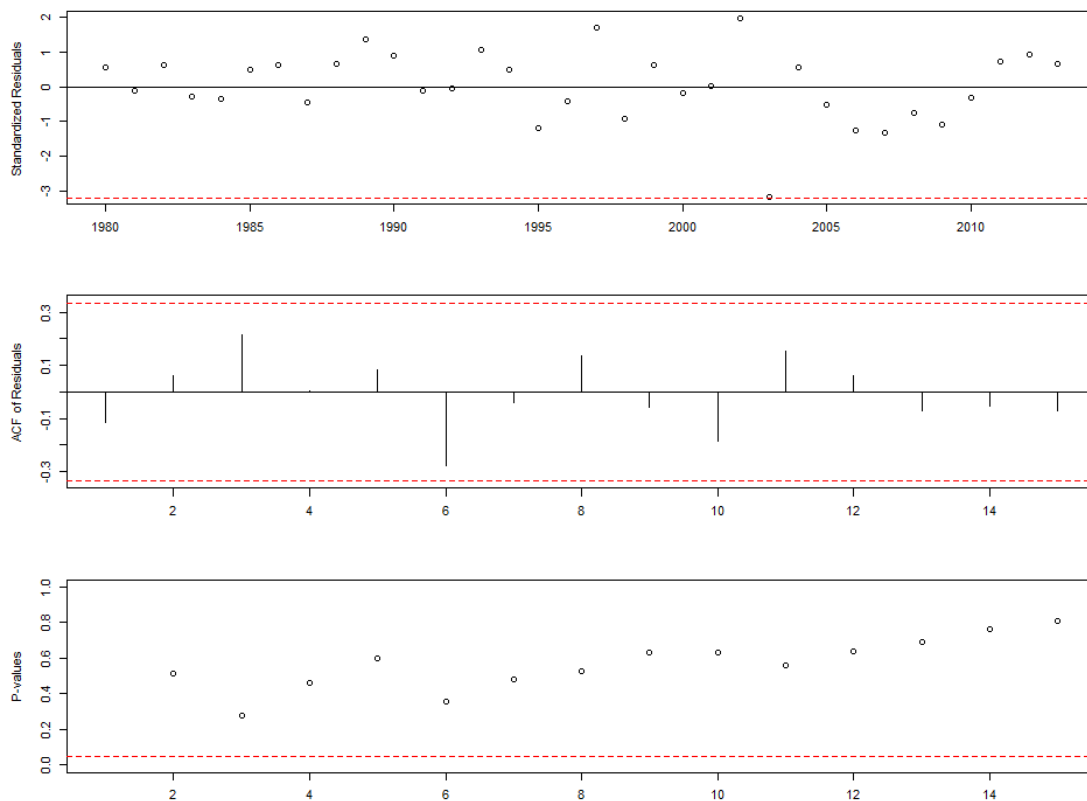
2127 AIC=71.27 AICc=72.04 BIC=75.94

2128 `par(oma=c(0,0,2,0))`

2129 `tsdiag(Arima(BJIndexPF78to13ts, model=fitbjindex))`

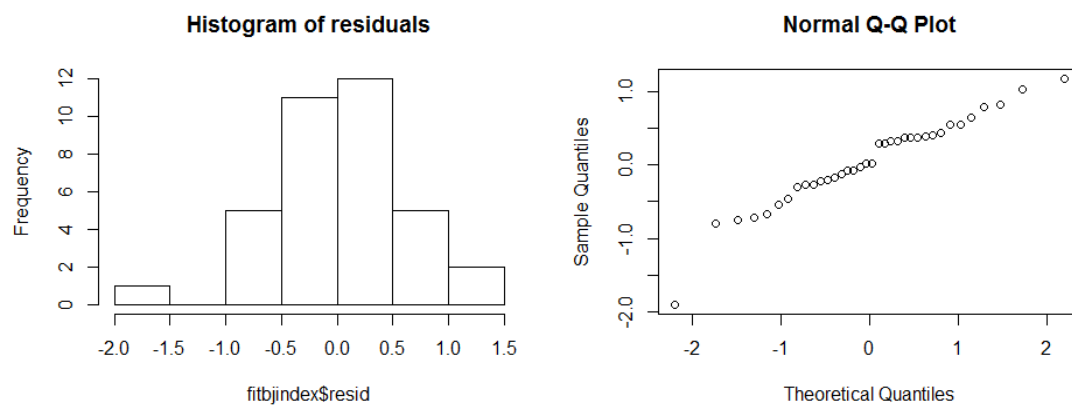
2130 `title("Model Fit", outer = TRUE)`

Model Fit



2131

```
2132 par(mfrow=c(1,2))
2133 hist(fitbjindex$resid, nclass="FD", main="Histogram of residuals")
2134 qqnorm(fitbjindex$resid)
```



2135

```
2136 Box.test(fitbjindex$resid, type = "Ljung-Box")
```

```
2137
2138     Box-Ljung test
```

```
2139
2140 data: fitbjindex$resid
2141 X-squared = 0.33475, df = 1, p-value = 0.5629
```

2142 **Common Grackle Trend Index**

```
2143 fitcgindex <- auto.arima(CGIndexPF78to13ts, seasonal = FALSE, trace = TRUE)
```

```

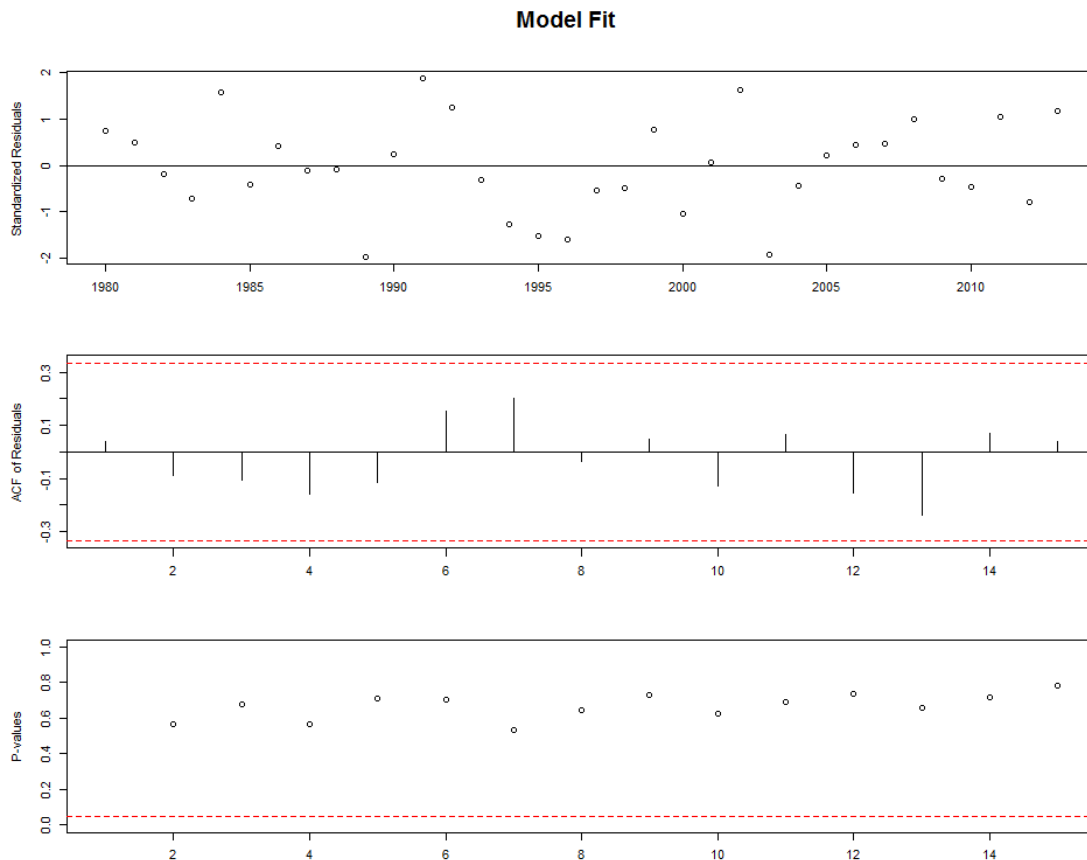
2144
2145 ARIMA(2,1,2) with drift      : Inf
2146 ARIMA(0,1,0) with drift     : 191.9144
2147 ARIMA(1,1,0) with drift     : 192.0968
2148 ARIMA(0,1,1) with drift     : 191.2062
2149 ARIMA(0,1,0)                : 191.9284
2150 ARIMA(1,1,1) with drift     : Inf
2151 ARIMA(0,1,2) with drift     : 192.9716
2152 ARIMA(1,1,2) with drift     : Inf
2153 ARIMA(0,1,1)                : 193.4492
2154
2155 Best model: ARIMA(0,1,1) with drift

2156 fitcindex

2157 Series: CGIndexPF78to13ts
2158 ARIMA(0,1,1) with drift
2159
2160 Coefficients:
2161      ma1      drift
2162    -0.3834  -1.0107
2163 s.e.   0.2171   0.3617
2164
2165 sigma^2 estimated as 11.33: log likelihood=-92.22
2166 AIC=190.43  AICc=191.21  BIC=195.1

2167 par(oma=c(0,0,2,0))
2168 tsdiag(Arima(CGIndexPF78to13ts, model=fitcindex))
2169 title("Model Fit", outer = TRUE)

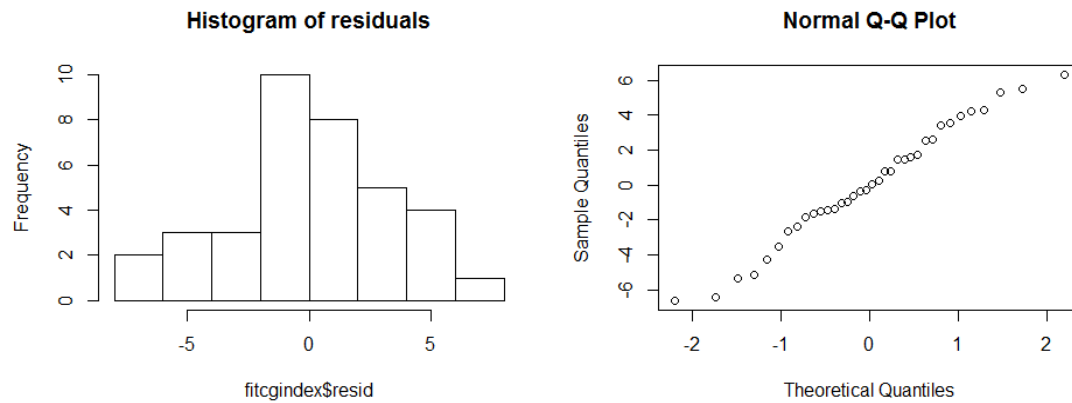
```



```

2170
2171 par(mfrow=c(1,2))
2172 hist(fitcindex$resid, nclass="FD", main="Histogram of residuals")
2173 qqnorm(fitcindex$resid)

```



2174

```
2175 Box.test(fitcindex$resid, type = "Ljung-Box")
```

2176

Box-Ljung test

2177

2178 data: fitcindex\$resid

2179 X-squared = 0.17067, df = 1, p-value = 0.6795

2181 Mourning Dove Trend Index

```
2182 fitmdindex=auto.arima(MDIndexPF78to13ts, seasonal=FALSE, trace=TRUE)
```

2183

```
2184 ARIMA(2,1,2) with drift      : Inf
2185 ARIMA(0,1,0) with drift     : 204.8869
2186 ARIMA(1,1,0) with drift     : 203.7522
2187 ARIMA(0,1,1) with drift     : 204.0641
2188 ARIMA(0,1,0)                : 203.9318
2189 ARIMA(2,1,0) with drift     : 206.2612
2190 ARIMA(1,1,1) with drift     : 206.2448
2191 ARIMA(2,1,1) with drift     : 208.9777
2192 ARIMA(1,1,0)                : 203.8543
```

2193

Best model: ARIMA(1,1,0) with drift

2194

fitmdindex

2196 Series: MDIndexPF78to13ts

2197 ARIMA(1,1,0) with drift

2198

Coefficients:

```
2200      ar1  drift
```

```
2201    -0.3104  0.8647
```

```
2202 s.e.   0.1604  0.5236
```

2203

2204 sigma^2 estimated as 16.24: log likelihood=-98.49

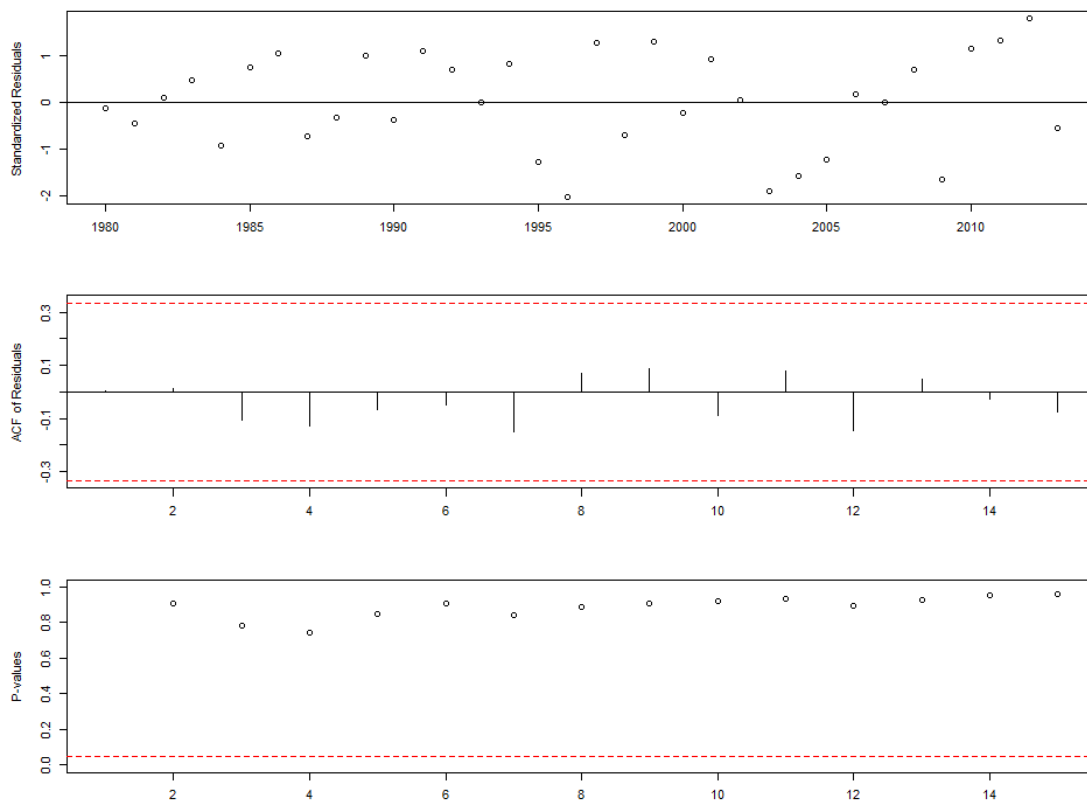
2205 AIC=202.98 AICc=203.75 BIC=207.64

```
2206 par(oma=c(0,0,2,0))
```

```
2207 tsdiag(Arima(MDIndexPF78to13ts, model=fitmdindex))
```

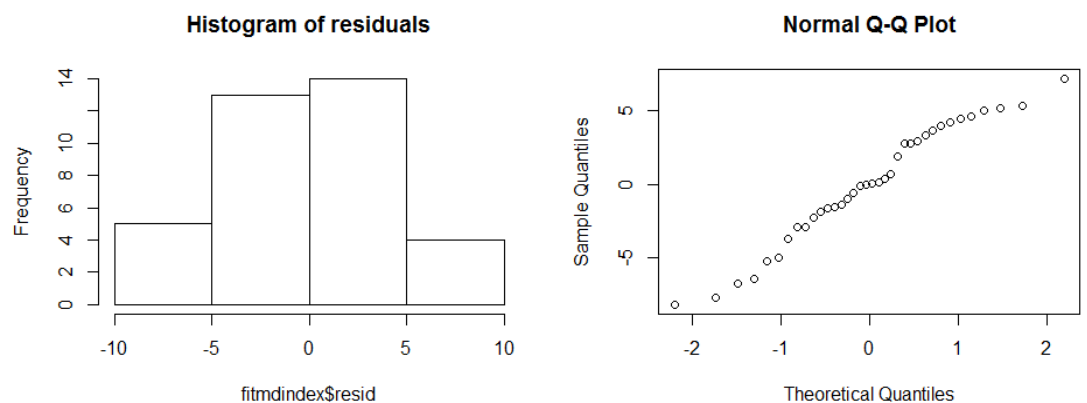
```
2208 title("Model Fit", outer = TRUE)
```

Model Fit



2209

```
2210 par(mfrow=c(1,2))
2211 hist(fitmdindex$resid, nclass="FD", main="Histogram of residuals")
2212 qqnorm(fitmdindex$resid)
```



2213

```
2214 Box.test(fitmdindex$resid, type = "Ljung-Box")
```

```
2215
2216     Box-Ljung test
```

```
2217
2218 data: fitmdindex$resid
2219 X-squared = 0.00069059, df = 1, p-value = 0.979
```

2220 Northern Cardinal Trend Index

```
2221 fitncindex=auto.arima(NCIndexPF78to13ts, seasonal=FALSE, trace=TRUE)
```

```

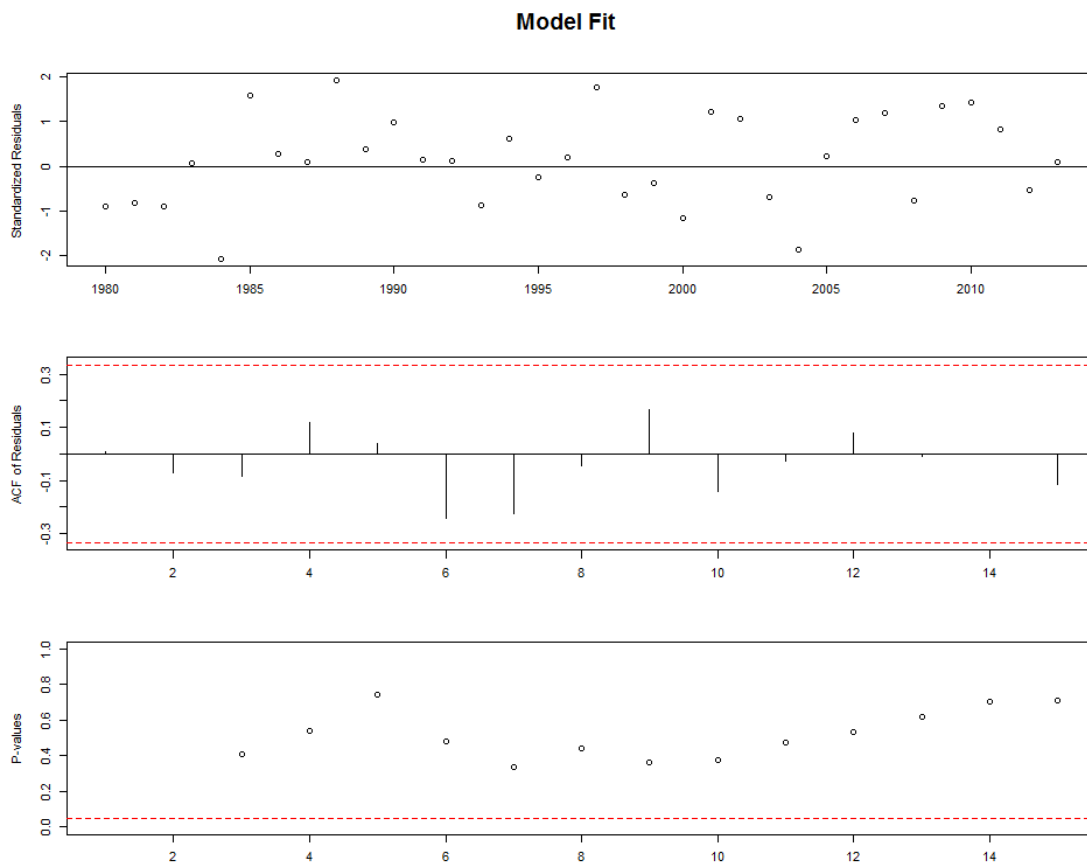
2222
2223     ARIMA(2,1,2) with drift           : Inf
2224     ARIMA(0,1,0) with drift           : 144.83
2225     ARIMA(1,1,0) with drift           : 130.5015
2226     ARIMA(0,1,1) with drift           : Inf
2227     ARIMA(0,1,0)                       : 142.7413
2228     ARIMA(2,1,0) with drift           : 130.4979
2229     ARIMA(2,1,1) with drift           : Inf
2230     ARIMA(3,1,1) with drift           : 134.4352
2231     ARIMA(2,1,0)                       : 128.7578
2232     ARIMA(1,1,0)                       : 128.5575
2233     ARIMA(1,1,1)                       : 128.1251
2234     ARIMA(2,1,2)                       : 132.0186
2235     ARIMA(1,1,1) with drift           : 129.1125
2236     ARIMA(0,1,1)                       : 128.048
2237     ARIMA(0,1,2)                       : 127.4672
2238     ARIMA(1,1,3)                       : 132.2656
2239     ARIMA(0,1,2) with drift           : 129.1828
2240     ARIMA(1,1,2)                       : 129.6167
2241     ARIMA(0,1,3)                       : 129.5481
2242
2243     Best model: ARIMA(0,1,2)

2244     fitncindex

2245     Series: NCIndexPF78to13ts
2246     ARIMA(0,1,2)
2247
2248     Coefficients:
2249             ma1      ma2
2250      -0.8566   0.3766
2251     s.e.    0.1848   0.2356
2252
2253     sigma^2 estimated as 1.8:  log likelihood=-60.35
2254     AIC=126.69   AICc=127.47   BIC=131.36

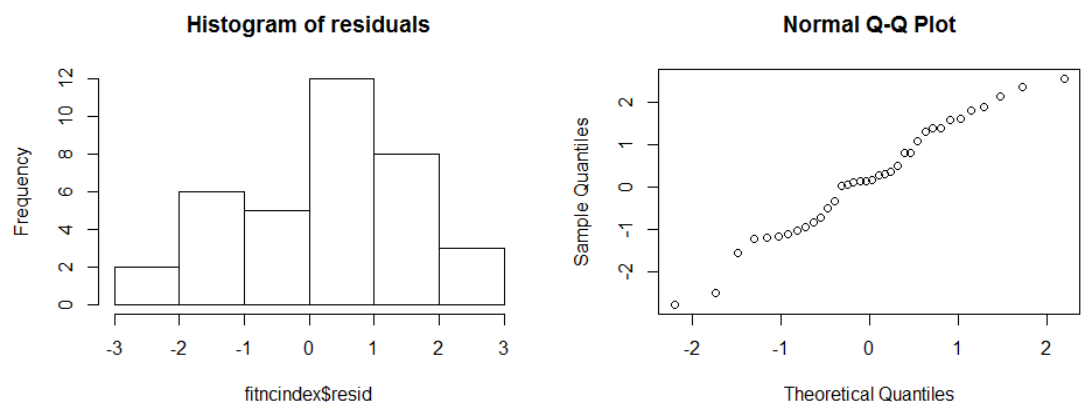
2255     par(oma=c(0,0,2,0))
2256     tsdiag(Arima(NCIndexPF78to13ts, model=fitncindex))
2257     title("Model Fit", outer = TRUE)

```



2258

```
2259 par(mfrow=c(1,2))
2260 hist(fitncindex$resid, nclass="FD", main="Histogram of residuals")
2261 qqnorm(fitncindex$resid)
```



2262

```
2263 Box.test(fitncindex$resid, type = "Ljung-Box")
```

2264

2265 Box-Ljung test

2266

2267 data: fitncindex\$resid

2268 X-squared = 0.0017779, df = 1, p-value = 0.9664

2269 **Northern Mockingbird Trend Index**

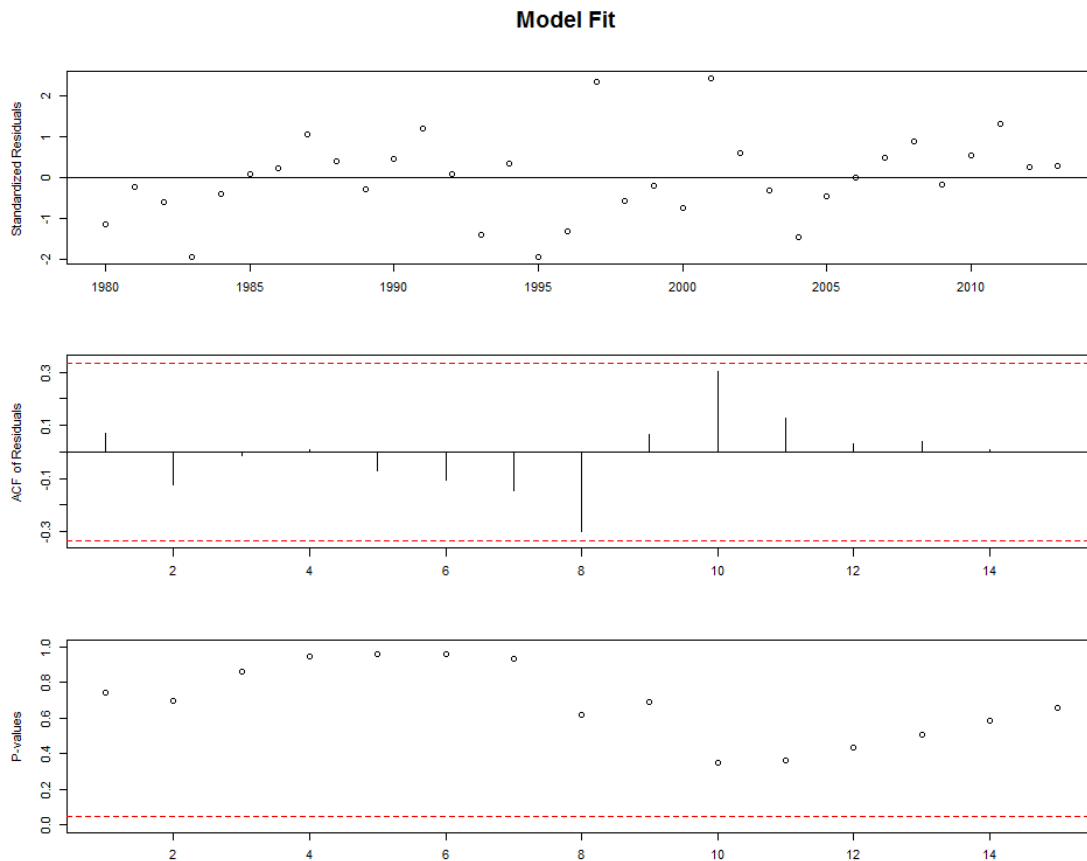
```
2270 fitnmindex=auto.arima(NMIndexPF78to13ts, seasonal=FALSE, trace=TRUE)
```



```

2271
2272 ARIMA(2,1,2) with drift      : Inf
2273 ARIMA(0,1,0) with drift     : 133.8833
2274 ARIMA(1,1,0) with drift     : 136.187
2275 ARIMA(0,1,1) with drift     : 136.1553
2276 ARIMA(0,1,0)                : 153.1394
2277 ARIMA(1,1,1) with drift     : 138.4137
2278
2279 Best model: ARIMA(0,1,0) with drift
2280
2281 fitnminindex
2282
2281 Series: NMIndexPF78to13ts
2282 ARIMA(0,1,0) with drift
2283
2284 Coefficients:
2285     drift
2286    -1.4180
2287 s.e.    0.2602
2288
2289 sigma^2 estimated as 2.369: log likelihood=-64.75
2290 AIC=133.51  AICc=133.88  BIC=136.62
2291
2292 par(oma=c(0,0,2,0))
2293 tsdiag(Arima(NMIndexPF78to13ts, model=fitnminindex))
2294 title("Model Fit", outer = TRUE)

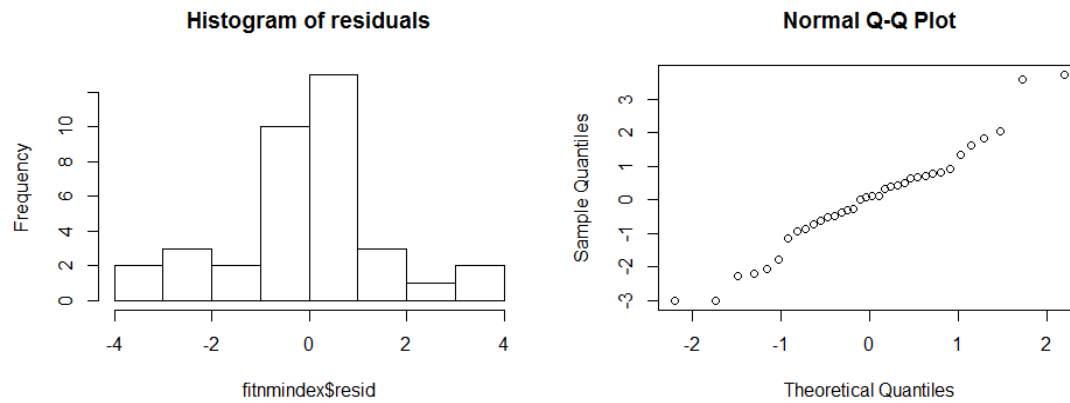
```



```

2294
2295 par(mfrow=c(1,2))
2296 hist(fitnminindex$resid, nclass="FD", main="Histogram of residuals")
2297 qqnorm(fitnminindex$resid)

```



2298

```
2299 Box.test(fitnmindex$resid, type = "Ljung-Box")
```

2300

```
2301     Box-Ljung test
```

2302

```
2303 data: fitnmindex$resid
```

```
2304 X-squared = 0.11188, df = 1, p-value = 0.738
```

2305 Transmission Models

2306 Transmission data does not need to be fitted with a models. Models only need to be fitted to the BBS data. BBS data
2307 models are then fitted to the Transmission data to prewhiten.

2308 Analysis

2309 ARIMA models fitted to the BBS data are used to prewhiten both the BBS and Transmission data prior to a Cross
2310 Correlation Function being calculated for the residuals at each time lag. Significant lags are then checked for Granger
2311 Causality.

2312 Cross Correlations

2313 Blue Jay Averages x SLE Sentinel Chicken Seroconversions

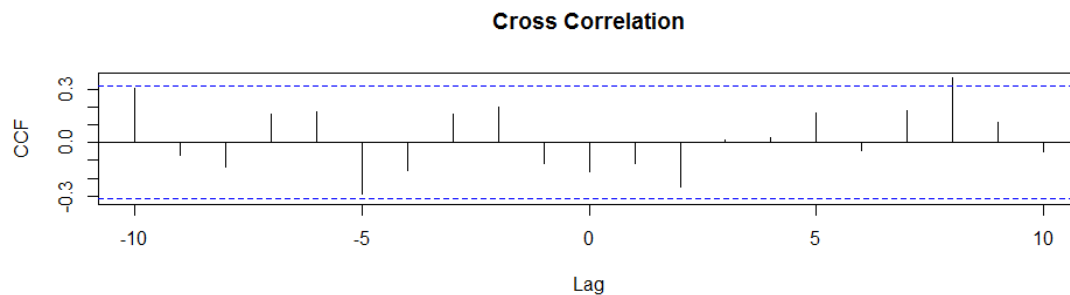
```
2314 resbj<-resid(Arima(BJAveragePF78to15ts, model=fitbj))
```

```
2315 resscbj<-resid(Arima(log(SCSLEPF78to15ts+1), model=fitbj))
```

```
2316 cat("\n")
```

```
2317 ccf(resbj, resscbj, lag.max = 10, type = "correlation", plot = TRUE,
```

```
2318     ylab="CCF", main = "Cross Correlation")
```



2319

2320 Common Grackle Averages x SLE Sentinel Chicken Seroconversions

```
2321 rescg<-resid(Arima(CGAveragePF78to15ts, model=fitcg))
```

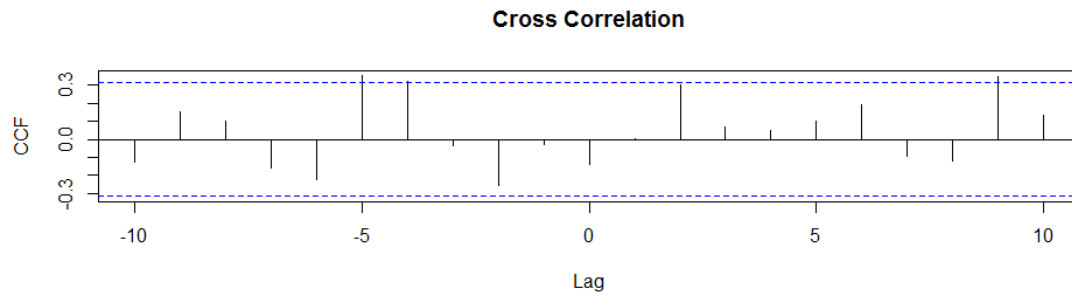
```
2322 resscg<-resid(Arima(log(SCSLEPF78to15ts+1), model=fitcg))
```

```
2323 cat("\n")
```

```

2324 ccf(rescsg, resscsg, lag.max = 10, type = "correlation", plot = TRUE,
2325     ylab="CCF", main = "Cross Correlation")

```



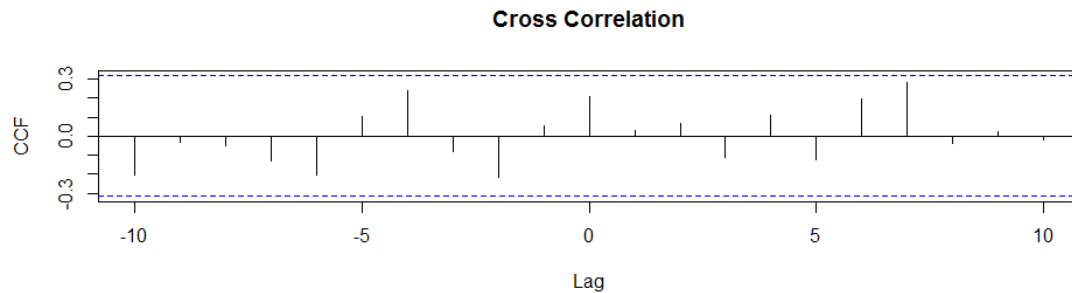
2326

2327 Mourning Dove Averages x SLE Sentinel Chicken Seroconversions

```

2328 resmd<-resid(Arima(MDAveragePF78to15ts, model=fitmd))
2329 resscmd<-resid(Arima(log(SCSLEPF78to15ts+1), model=fitmd))
2330 cat("\n")
2331 ccf(resmd, resscmd, lag.max = 10, type = "correlation", plot = TRUE,
2332     ylab="CCF", main = "Cross Correlation")

```



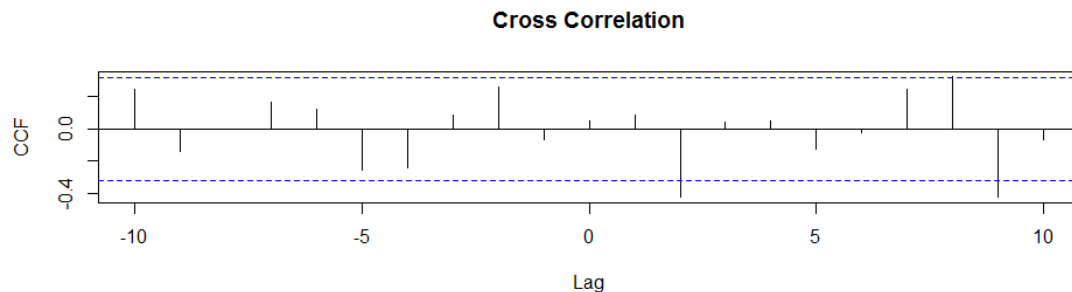
2333

2334 Northern Cardinal Averages x SLE Sentinel Chicken Seroconversions

```

2335 resnc<-resid(Arima(NCAveragePF78to15ts, model=fitnc))
2336 resscnc<-resid(Arima(log(SCSLEPF78to15ts+1), model=fitnc))
2337 cat("\n")
2338 ccf(resnc, resscnc, lag.max = 10, type = "correlation", plot = TRUE,
2339     ylab="CCF", main = "Cross Correlation")

```



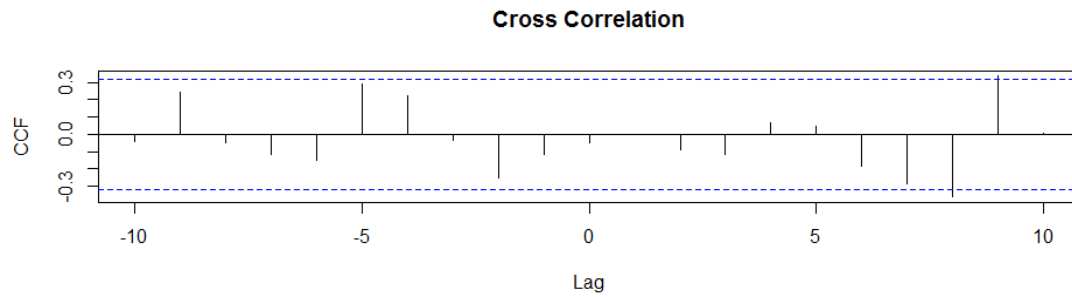
2340

2341 Northern Mockingbird Averages x SLE Sentinel Chicken Seroconversions

```

2342 resnm<-resid(Arima(NMAveragePF78to15ts, model=fitnm))
2343 resscnm<-resid(Arima(log(SCSLEPF78to15ts+1), model=fitnm))
2344 cat("\n")
2345 ccf(resnm, resscnm, lag.max = 10, type = "correlation", plot = TRUE,
2346     ylab="CCF", main = "Cross Correlation")

```

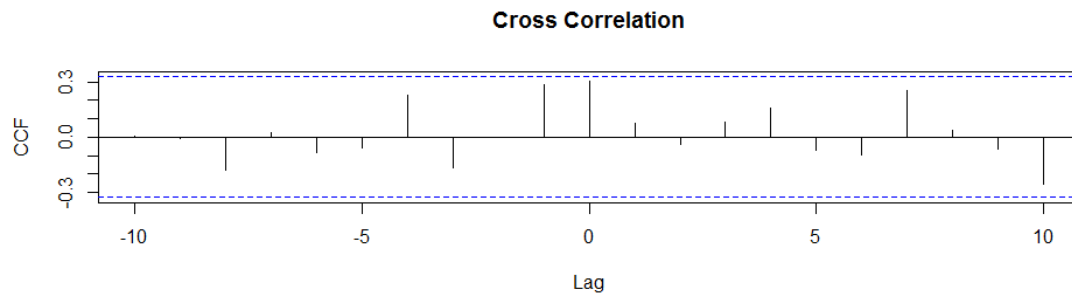


2347

2348 **Blue Jay Index x SLE Sentinel Chicken Seroconversions**

```
2349 resbjj<-resid(Arima(BJIndexPF78to13ts, model=fitbjj))
2350 resscbjj<-resid(Arima(log(SCSLEPF78to13ts+1), model=fitbjj))
2351 cat("\n")
```

```
2352 ccf(resbjj, resscbjj, lag.max = 10, type = "correlation", plot = TRUE,
2353     ylab="CCF", main = "Cross Correlation")
```

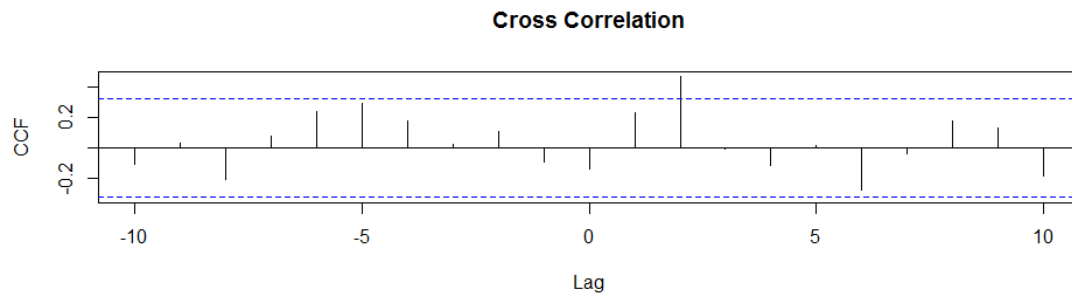


2354

2355 **Common Grackle Index x SLE Sentinel Chicken Seroconversions**

```
2356 rescgi<-resid(Arima(CGIndexPF78to13ts, model=fitcg))
2357 resscgi<-resid(Arima(log(SCSLEPF78to13ts+1), model=fitcg))
2358 cat("\n")
```

```
2359 ccf(rescgi, resscgi, lag.max = 10, type = "correlation", plot = TRUE,
2360     ylab="CCF", main = "Cross Correlation")
```

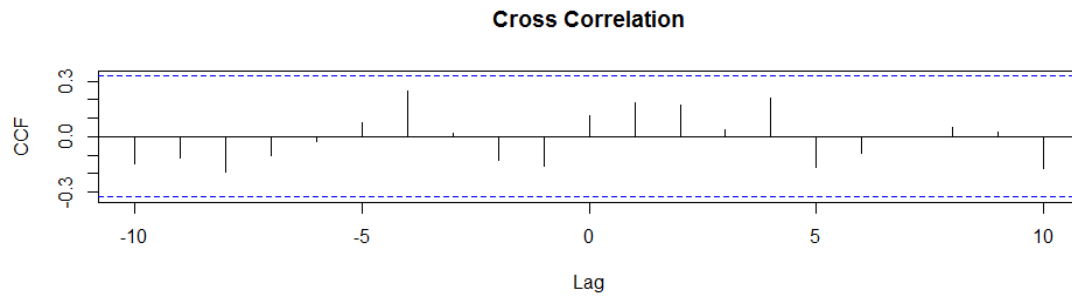


2361

2362 **Mourning Dove Index x SLE Sentinel Chicken Seroconversions**

```
2363 resmdi<-resid(Arima(MDIndexPF78to13ts, model=fitmd))
2364 resscmdi<-resid(Arima(log(SCSLEPF78to13ts+1), model=fitmd))
2365 cat("\n")
```

```
2366 ccf(resmdi, resscmdi, lag.max = 10, type = "correlation", plot = TRUE,
2367     ylab="CCF", main = "Cross Correlation")
```

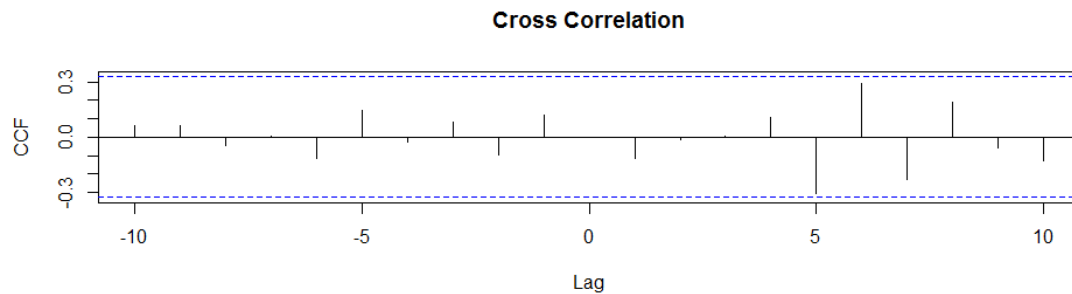


2368

2369 Northern Cardinal Index x SLE Sentinel Chicken Seroconversions

```
2370 resnci<-resid(Arima(NCIndexPF78to13ts, model=fitnc))
2371 resscnci<-resid(Arima(log(SCSLEPF78to13ts+1), model=fitnc))
2372 cat("\n")

2373 ccf(resnci, resscnci, lag.max = 10, type = "correlation", plot = TRUE,
2374     ylab="CCF", main = "Cross Correlation")
```

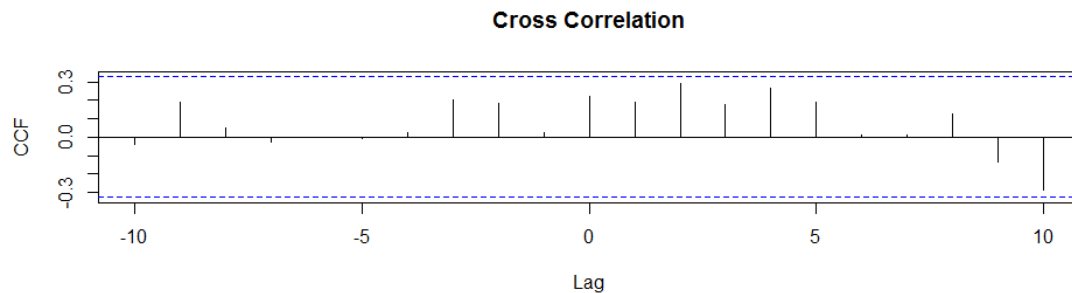


2375

2376 Northern Mockingbird Index x SLE Sentinel Chicken Seroconversions

```
2377 resnmi<-resid(Arima(NMIndexPF78to13ts, model=fitnm))
2378 resscnmi<-resid(Arima(log(SCSLEPF78to13ts+1), model=fitnm))
2379 cat("\n")

2380 ccf(resnmi, resscnmi, lag.max = 10, type = "correlation", plot = TRUE,
2381     ylab="CCF", main = "Cross Correlation")
```



2382

2383 Granger Causality

2384 Blue Jay Average x SLE Sentinel Chicken Seroconversions

```
2385 grangertest(BJAveragePF78to15ts, log(SCSLEPF78to13ts+1), 8)

2386 Granger causality test
2387
2388 Model 1: log(SCSLEPF78to13ts + 1) ~ Lags(log(SCSLEPF78to13ts + 1), 1:8) + Lags(BJAveragePF78to15ts, 1
2389 :8)
2390 Model 2: log(SCSLEPF78to13ts + 1) ~ Lags(log(SCSLEPF78to13ts + 1), 1:8)
```

```

2391   Res.Df Df      F Pr(>F)
2392   1      11
2393   2      19 -8 1.2515  0.356

2394 Common Grackle Average x SLE Sentinel Chicken Seroconversions
2395   grangertest(log(SCSLEPF78to15ts+1), CGAveragePF78to15ts, 4)

2396 Granger causality test
2397
2398 Model 1: CGAveragePF78to15ts ~ Lags(CGAveragePF78to15ts, 1:4) + Lags(log(SCSLEPF78to15ts + 1), 1:4)
2399 Model 2: CGAveragePF78to15ts ~ Lags(CGAveragePF78to15ts, 1:4)
2400   Res.Df Df      F Pr(>F)
2401   1      25
2402   2      29 -4 1.0351 0.4088

2403   grangertest(log(SCSLEPF78to15ts+1), CGAveragePF78to15ts, 5)

2404 Granger causality test
2405
2406 Model 1: CGAveragePF78to15ts ~ Lags(CGAveragePF78to15ts, 1:5) + Lags(log(SCSLEPF78to15ts + 1), 1:5)
2407 Model 2: CGAveragePF78to15ts ~ Lags(CGAveragePF78to15ts, 1:5)
2408   Res.Df Df      F Pr(>F)
2409   1      22
2410   2      27 -5 0.9435 0.4727

2411   grangertest(CGAveragePF78to15ts, log(SCSLEPF78to13ts+1), 9)

2412 Granger causality test
2413
2414 Model 1: log(SCSLEPF78to13ts + 1) ~ Lags(log(SCSLEPF78to13ts + 1), 1:9) + Lags(CGAveragePF78to15ts, 1
2415 :9)
2416 Model 2: log(SCSLEPF78to13ts + 1) ~ Lags(log(SCSLEPF78to13ts + 1), 1:9)
2417   Res.Df Df      F Pr(>F)
2418   1       8
2419   2      17 -9 2.0696 0.1595

2420 Mourning Dove Average x SLE Sentinel Chicken Seroconversions
2421 # No Cross Correlations to test

2422 Northern Cardinal Average x SLE Sentinel Chicken Seroconversions
2423   grangertest(NCAveragePF78to15ts, log(SCSLEPF78to15ts+1), 2)

2424 Granger causality test
2425
2426 Model 1: log(SCSLEPF78to15ts + 1) ~ Lags(log(SCSLEPF78to15ts + 1), 1:2) + Lags(NCAveragePF78to15ts, 1
2427 :2)
2428 Model 2: log(SCSLEPF78to15ts + 1) ~ Lags(log(SCSLEPF78to15ts + 1), 1:2)
2429   Res.Df Df      F Pr(>F)
2430   1      31
2431   2      33 -2 1.3774 0.2672

2432   grangertest(NCAveragePF78to15ts, log(SCSLEPF78to15ts+1), 8)

2433 Granger causality test
2434
2435 Model 1: log(SCSLEPF78to15ts + 1) ~ Lags(log(SCSLEPF78to15ts + 1), 1:8) + Lags(NCAveragePF78to15ts, 1
2436 :8)
2437 Model 2: log(SCSLEPF78to15ts + 1) ~ Lags(log(SCSLEPF78to15ts + 1), 1:8)
2438   Res.Df Df      F Pr(>F)
2439   1      13
2440   2      21 -8 0.9963 0.4819

2441   grangertest(NCAveragePF78to15ts, log(SCSLEPF78to15ts+1), 9)

```

```

2442 Granger causality test
2443
2444 Model 1: log(SCSLEPF78to15ts + 1) ~ Lags(log(SCSLEPF78to15ts + 1), 1:9) + Lags(NCAveragePF78to15ts, 1
2445 :9)
2446 Model 2: log(SCSLEPF78to15ts + 1) ~ Lags(log(SCSLEPF78to15ts + 1), 1:9)
2447   Res.Df Df      F Pr(>F)
2448   1      10
2449   2      19 -9 1.2534 0.363

2450 Northern Mockingbird Average x SLE Sentinel Chicken Seroconversions
2451   grangertest(NMAveragePF78to15ts, log(SCSLEPF78to15ts+1), 8)

2452 Granger causality test
2453
2454 Model 1: log(SCSLEPF78to15ts + 1) ~ Lags(log(SCSLEPF78to15ts + 1), 1:8) + Lags(NMAveragePF78to15ts, 1
2455 :8)
2456 Model 2: log(SCSLEPF78to15ts + 1) ~ Lags(log(SCSLEPF78to15ts + 1), 1:8)
2457   Res.Df Df      F Pr(>F)
2458   1      13
2459   2      21 -8 1.3004 0.3234

2460   grangertest(NMAveragePF78to15ts, log(SCSLEPF78to15ts+1), 9)

2461 Granger causality test
2462
2463 Model 1: log(SCSLEPF78to15ts + 1) ~ Lags(log(SCSLEPF78to15ts + 1), 1:9) + Lags(NMAveragePF78to15ts, 1
2464 :9)
2465 Model 2: log(SCSLEPF78to15ts + 1) ~ Lags(log(SCSLEPF78to15ts + 1), 1:9)
2466   Res.Df Df      F Pr(>F)
2467   1      10
2468   2      19 -9 3.3928 0.0352 *
2469 ---
2470 Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

2471 Blue Jay Index x SLE Sentinel Chicken Seroconversions
2472 # No Cross Correlations to test

2473 Common Grackle Index x SLE Sentinel Chicken Seroconversions
2474   grangertest(CGIndexPF78to13ts, log(SCSLEPF78to13ts+1), 2)

2475 Granger causality test
2476
2477 Model 1: log(SCSLEPF78to13ts + 1) ~ Lags(log(SCSLEPF78to13ts + 1), 1:2) + Lags(CGIndexPF78to13ts, 1:2
2478 )
2479 Model 2: log(SCSLEPF78to13ts + 1) ~ Lags(log(SCSLEPF78to13ts + 1), 1:2)
2480   Res.Df Df      F Pr(>F)
2481   1      29
2482   2      31 -2 2.3419 0.1141

2483 Mourning Dove Index x SLE Sentinel Chicken Seroconversions
2484 # No Cross Correlations to test

2485 Northern Cardinal Index x SLE Sentinel Chicken Seroconversions
2486 # No Cross Correlations to test

2487 Northern Mockingbird Index x SLE Sentinel Chicken Seroconversions
2488 # No Cross Correlations to test

2489

```