Segregate The Variability Climate Is Responsible For In Vegetation Loss Using Time Series Analsis.

Kalong Boniface And Fugah Seletey Mitchell

2022-08-11

```
\tableofcontents
\begin{flushleft}
    \section{CHAPTER ONE}
      \section{INTRODUCTION}
      All thing change, but how we respond to change is our responsibility, to  fare it or embrasse it.

      The purpose of this paper is to establish an understanding in time series analysis on remotely ser
      Galamsey("gather them and sell"),(OwusuNimo2018) is the term given by local Ghanaian for illegal s
      Another factor is that lack of job security.

      On November 13, 2009 a collapse occurred in an illegal, privately owned mine in Dompoase, in the A

      Illegal mining causes damage to the land and water supply(Ansah2017). In March 2017, the Minister

      Under current Ghanaian constitution, it is illegal to operate as galamseyer.That is to dig on land
      oxide or sulfide gold ore using liquid mercury.
      Between 20,000 to 50,000, including thousands from China are believed to be engaged in Galamsey in
      of large mining companies(Barenblitt2021). As a group, they are economically disad vantaged. Galar
      \subsection{Background of The Study}
      As Galamsey is considered an illegal activity, they operations are hidden to the eyes of the autho


      collection, now it possible to access imagery back to the 90's, allowing us to look at areas of in
      \subsection{Problem Statement}
      The Footprint of Galamsey is Spreading at a very faster rate, causing vegetation loss.Other factor
      \subsection{Research  Question}
      \subsubsection{Research Objectives}
      The purpose is to establish an understanding in time series analysis on remotely sensed data. We w
      \begin{itemize}
        \item  Perform time series analysis on satellite derived vegetation indices

        \item  Estimate the extent to which Galamsey causes vegetation loss

        \item  Dissociate or single out the variability climate is responsible for in vegetation loss
      \end{itemize}
      \subsection{Significance Of The  Study}
      \subsection{Scope of The  Study}

      \subsection{Limitation Of  The Study }
      Time series modeling aims to build an explanatory model of the data without over fitting the probl
      \subsection{ Organization  of  The  Study}
```

```
\section{CHAPTER  TWO}
\section{LITERATURE REVIEW}
\subsection{Theoretical Review}
This literature review will follow narrative approach to gain insight into research topic. A time se

\subsubsection{What is Time Series Analysis?}

Makridakis and hibon, in time series analysis researchers have conducted a competition named M-compe
\begin{itemize}
\item   Statistically sophisticated or complex methods do not necessarily provide more accurate fore
\item   The relative ranking of the performance of the various methods varies according to the accur
\item   The accuracy when various methods are being combined outperformed, on average, the individua
\item   The accuracy of the various methods depends upon the length of the forecasting horizon invol
\end{itemize}

The time series data is visualized and analyzed to find out mainly three things, trend, seasonality

\textbf{Trend:} It can be defined as the observation of increasing or decreasing pattern over a peri

\textbf{Seasonality:} It refers to a cyclic happening of events. A pattern which repeats itself afte

\textbf{Heteroscedasticity:} It is also known as level; it is defined as the non-constant variance f

Few methods do not perform well in forecasting if the data is seasonal, and few do not perform well

\subsubsection{Time Series Forecasting Using Stochastic Models}

The selection of a proper model is extremely important as it reflects the underlying structure of th
In general models for time series data can have many forms and represent different stochastic proces
\emph{Autoregressive (AR)} [6, 12, 23] and \emph{Moving Average (MA)} [6, 23] models. Combining thes
\textbf{ARIMA} model and its different variations are based on the famous Box-Jenkins principle [6,
Linear models have drawn much attention due to their relative simplicity in understanding and implem
\emph{Conditional Heteroskedasticity (ARCH)} [9, 28] model and its variations like \emph{Generalized
\\
\textbf{Exponential Smoothing Models:}\\
Time-series data relies on the assumption that the observation at a certain point of time depends on
To understand the methods and to evaluate different models, few concepts like stationarity and diffe
\textbf{Stationarity:}\\
Stationarity alludes to an irregular process that creates a time-series which has mean, and distribu

An MA(q) process is always stationary, irrespective of the values the MA parameters [23]. The condit
$ \theta (L) = 0 $ lie outside the unit circle, then the ARMA(p, q) process is invertible and can be
\textbf{Differencing:}\\
This concept is used to make trending and seasonal data stationary. Subtraction between current obse
\textbf{Autoregressive models (AR):}\\
\textbf{AR} work on a concept called lags which is defined as the forecast of a series is solely bas

Where ; \quad
$ y_{t}$  = Target ,\quad
$\omega$= Intercept,\quad
$\phi$= Coefficient,\quad
$Y _{t-1}$=Lagged target,\quad
$e_{t}$= Error\\
It depends only on one lag in the past and also called  \emph{AR model of order one} (Shibata, R., 
```

E. \textbf{Moving Average (MA):}
The moving average model forecasts a series based on the past error in the series called error lags
$ y_{t} = \omega + \theta e _{t-1}+ e_{t}$
\\
In (2), all the abbreviations are same to AR model formula except,   = Previous error
There arises a question as this method uses the error for the previous value but when it reaches to

F. \textbf{Comparing AR method with MA method}:

Let focus on the two methods which were used in the early years of time series forecasting and compa

In addition, paper written by (Baltagi, B.H. and Li, Q., 1995), Demonstrates the comparison of AR ar

The findings of both the paper were quite different but one cannot prove either of the model to be b

\textbf{Autocorrelation and Partial Autocorrelation Functions (ACF and PACF) }\\
To determine a proper model for a given time series data, it is necessary to carry out the ACF and P
μ is the mean of the time series, i.e. $ \mu = E\left[x_{t}\right] $. The autocovariance at lag
Another measure, known as the Partial Autucorrelation Function (PACF) is used to measure the correla

Normally, the stochastic process governing a time series is unknown and so it is not possible to det
As given in [23], the most appropriate sample estimate for the ACVF at lag k is \textbf{ACF} plot i
\textbf{Autoregressive Moving Average (ARMA) model:}\\

ARMA model is a combination of AR and MA models. The equation of the AR model of order one, when it

To determine the optimal value for p and q there are two ways:
\begin{itemize}
\item   Plotting patterns in correlation
\item   Automatic selection techniques
\end{itemize}
\textbf{ Plotting patterns in correlation: }

There are two functions used for plotting patterns in correlation:
\textbf{   Auto correlation factor (ACF):} It is the correlation between the observations at the cu
\textbf{   Partial auto correlation factor (PACF):} The correlation between the observations at two

\textbf{ Automatic selection techniques: }

There are three commonly used techniques for automatic selection of time series model:
\textbf{   Minimum info criteria (MINIC)}: This builds multiple combinations of models across a gri
\textbf{b) Squared canonical correlations (SCAN):} It looks at correlation matrix of the data, then
\textbf{c) The extended sample auto correlation function (ESACF):} As it is known that AR and MA ar
It completely depends on the individual to choose from either of the methods helping them to find th

H. \textbf{Autoregressive Integrated Moving average (ARIMA):}

To understand ARIMA model, we need to understand ARMA model as this is just an extension to ARMA mod

I. \textbf{Seasonal Autoregressive Integrated Moving Average (SARIMA):}

SARIMA models were introduced to handle seasonality in the data. Seasonality is different from stati
Where;
\begin{itemize}
\item   P = Number of seasonal AR terms.\item D = Number of seasonal differences. \item Q = Number o
\end{itemize}
 Removing seasonality will help the model to perform better but getting rid of seasonality in data

J. \textbf{Comparing ARIMA method with SARIMA method:}

In comparison to ARIMA and SARIMA, (Valipour, M., 2015) investigated it on long-term runoff forecast

(Wang, S., Li, C. and Lim, A., 2019) have used ARIMA and SARIMA models from the perspective of Linea

The findings from the (Valipour, M., 2015) have proven SARIMA to better however, their claim contrad

\subsubsection{ADVANTAGES AND DISADVANTAGES OF TIME SERIES FORECASTING}
\textbf{Advantages of time series forecasting:}
\begin{itemize}
\item   Time series forecasting is of high accuracy and simplicity.
\item   It can be used to analyze how the changes associated with the data point picked correlate w
\item   Statistical techniques have been developed to analyze time series in such a way that the fac
\item   It can give good output with less variables. As regression models fail with less variables,
\end{itemize}
\textbf{Disadvantages of time series forecasting:}
\begin{itemize}
    \item   Time series models can easily be overfitted, which lead to false results.
    \item   It works well with short term forecasting but does not work well with long term forecast
    \item   It is sensible to outliers, if the outliers are not handled properly then it could lead
    \item   The different elements that impact the fluctuations of a series cannot be fully adjusted
\end{itemize}

\subsubsection{Time Series Forecasting Using Support Vector Machines}
Concept of Support Vector Machines
Till now, we have studied about various stochastic and neural network methods for time
series modeling and forecasting. Despite of their own strengths and weaknesses, these methods are qu
Vapnik's SVM technique is based on the Structural Risk Minimization (SRM) principle
[24, 29, 30]. The objective of SVM is to find a decision rule with good generalization ability throu
Another important characteristic of SVM is that here the training process is equivalent to solving a
\subsubsection{Forecast Performance Measures }
While applying a particular model to some real or
simulated time series, first the raw data is divided into two parts, viz. the Training Set and Test
Set. The observations in the training set are used for constructing the desired model. Often a
small subpart of the training set is kept for validation purpose and is known as the Validation
Set. Sometimes a preprocessing is done by normalizing the data or taking logarithmic or other
transforms. One such famous technique is the Box-Cox Transformation [23]. Once a model is
constructed, it is used for generating forecasts. The test set observations are kept for verifying
how accurate the fitted model performed in forecasting these values. If necessary, an inverse
transformation is applied on the forecasted values to convert them in original scale. In order to
judge the forecasting accuracy of a particular model or for evaluating and comparing different
models, their relative performance on the test dataset is considered.
Due to the fundamental importance of time series forecasting in many practical situations,
proper care should be taken while selecting a particular model. For this reason, various

performance measures are proposed in literature [3, 7, 8, 9, 24, 27] to estimate forecast accuracy and to compare different models. These are also known as performance metrics [24]. Each of these measures is a function of the actual and forecasted values of the time series.

In this chapter we shall describe few important performance measures which are frequently used by researchers, with their salient features.

\textbf{Description of Various Forecast Performance Measures} \\
In each of the forthcoming definitions, $ y_{t} $ is the actual value, $ f_{t} $ is the forecasted

\textbf{The Mean Forecast Error (MFE) }\\
This measure is defined as [24] $ \displaystyle MFE = \frac{1}{n}\sum_{t=1}^{n}e_{t} $ The properti
\subsection{Empirical Review}
LULC data are records that documents to what extent a region is covered by wetlands, forests, agric
change in barren land changing into agricultural land continuously from 1984 to 2009.\\

Similarly, in [1] used the maximum likelihood algorithm (MLA) and Markov chain model (MCA) to study

Furthermore, in [10], They made used of the Maximum likelihood classification   (MLC), Change detec
vegetation, bare soil, cultivated land built-up and wetland/lowland.   Also, a significant increas

Also, [12] used Maximum Likelihood Classification and comparison method to study the \textbf{LULC}

Moreover, in [13] studied the \textbf{LULC} change in Duzce plain Turkey. Supervised classification
Also, a significant increase and a decrease of \textbf{LULC} were noticed between the years 1973, 1

Also, in [16] studied the 20 years spatiotemporal \textbf{LULC} in Hawalbagh block India, the super

Furthermore, in [17] study the \textbf{LULC} change of watershed in Pakistan from 1992 to 2012 usin

Also, in [18] study, both unsupervised (ISODATA) and supervised (MLA) methods were used for LULC cl
detection and Markov change analysis methods used to measure   the LULC changes and generate futur
changes were minimal.\\

Similarly, in [19] studied the LULC classification of Sawantwadi taluka, in India. The hybrid, para

Also, in [20] measured the LULC change in Seramban. In the study, Natural Breaks (Jenks) and Norma

Likewise, in [21] studied twenty-five years the spatiotemporal urban growth of Kuala Lumpur, using

Also, in [22] used NDVI method to study the LULC change of Sambas watershed, in Malaysia for the y

Also, in [23] studied the ten years LULC changes of Aluva taluk, in India from 2000 to 2010. Superv
LULC change of Kolong River basin of India in the years 1967-68 and 2014. The finding shows six LUL
increasing much in the year 2014 respectively.\\

Similarly, in [25] used supervised \emph{Maximum likelihood classification (MLC)}, and \emph{multi-
Moreover, in [26] studied 31 years \textbf{LULC} change in Beressa Watershed Ethiopia from 1984 to

```
using Erdas imagine and Change Detection methods were used in
\textbf{LULC} classification and change magnitude respectively. The finding shows six classes of \te

Furthermore, in [27] studied \textbf{LULC} changes in Udhaim river basin    in Iraq using Landsat TM

Likewise, in [28] study the \textbf{LULC} of Kan basin from 2000 to 2016.   Supervised classificatio

Moreover, in [29] study the \textbf{LULC} change of hotspot area in Pune    region using Landsat ima

Also, in [30] studied ten years \textbf{LULC} change and transformations
in Kanyakumari coast India. The study used supervised classification of (MLA) and Change Detection.

Also, in [31] study the \textbf{LULC} change in Tanguar Haor, Bangladesh. The study used supervised

Furthermore, in [32] used Google Earth and GIS Operation to study the LULC changes in Muar sub-distr
the year 2010 to 2015. The results show 6 \textbf{LULC} classes viz agriculture, barren land, built-

Also, in [33] studied the spatial-temporal \textbf{LULC} change in Astrakhan city, Russia, from the

Furthermore, in [35] studied the \textbf{LULC} change Khan-Kali watershed and Anas River from Gujara
land and riverine LULC.\\

Moreover, in [36] studied \textbf{LULC} classification in Okara, Pakistan.  The supervised classifi
```

```r
#if(!require("pacman")){install.packages("pacman")}
pacman::p_load(char = c('rgee','reticulate','raster','tidyverse',
                'dplyr','sf','mapview','mapeddit','caret','forcats','reticulate',
                'rgee', 'remotes', 'magrittr', 'tigris', 'tibble', 'stars', 'stars',
                'st', 'lubridate', 'imputeTS', 'leaflet', 'classInt', 'RColorBrewer',
                'ggplot2', 'googledrive', 'geojsonio', 'ggpubr','cartogram'),
               install = F, update = F, character.only = T)
```

```
## Warning in pacman::p_load(char = c("rgee", "reticulate", "raster", "tidyverse", : Failed to install/l
## tidyverse, mapeddit
```

```r
library(rgee)

library(reticulate)
#ee_install()
ee_check()

ee_Initialize("kalong",drive = TRUE) # initialize GEE,
#this will have you log in to Google Drive
```

```r
library('sf')
# Load shape file

#setwd("C:/Users/Guy/Documents/GitHub/Artisanal-Mining-In-Ghana-Galamsey/New Regions")
aoi <- read_sf('Ghana shp file/GHA/gadm41_GHA_1.shp')
aoi <- st_transform(aoi, st_crs(4326))
aoi.ee <- st_bbox(aoi) %>%
st_as_sfc() %>%
sf_as_ee() #Converts it to an Earth Engine Object
```

These functions return the QA value from MODIS imagery and apply a quality Mask, returning quality masked EVI values, this technique was adapted from one presented by Cesar Aybar (one of the rgee authors) here.

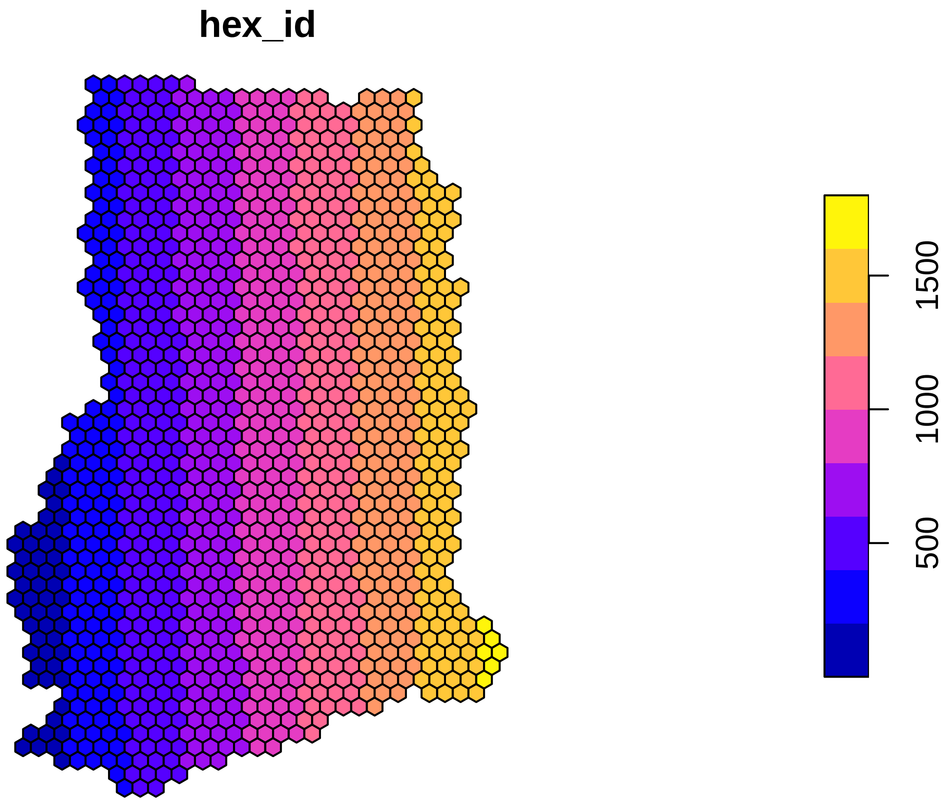
```
getQABits <- function(image, qa) {
  # Convert binary (character) to decimal (little endian)
  qa <- sum(2^(which(rev(unlist(strsplit(as.character(qa), "")) == 1))-1))
  # Return a mask band image, giving the qa value.
  image$bitwiseAnd(qa)$lt(1)
}

mod.clean <- function(img) {
  # Extract the NDVI band
  ndvi_values <- img$select("EVI")
  # Extract the quality band
  ndvi_qa <- img$select("SummaryQA")
  # Select pixels to mask
  quality_mask <- getQABits(ndvi_qa, "11")
  # Mask pixels with value zero.
  ndvi_values$updateMask(quality_mask)$divide(ee$Image$constant(10000)) #0.0001 is the MODIS Scale Fact
}

modis.evi <- ee$ImageCollection("MODIS/006/MOD13Q1")$filter(ee$Filter$date('2000-01-01','2022-01-01'))$m
```

Now we will create a hexagonal grid over the study area

```
library(tibble)
aoi.proj <- st_transform(aoi, st_crs(2392))
hex <- st_make_grid(x = aoi.proj, cellsize = 17280, square = FALSE) %>%
st_sf() %>%
rowid_to_column('hex_id')
hex <- hex[aoi.proj,]
plot(hex)
```



Now we will use the grid created above to extract the mean EVI values within each cell for the years 2000-2020.

Which we are going to perform a time series analysis on the data within each grid cell. But first, we will work through the procedure one step at a time.

```
#converting the data to a transposed data frame
tsv <- data.frame(evi = t(evi.df[i, 2:ncol(evi.df)]))
colnames(tsv) <- c("evi")
#write.csv(tsv,"Data/tsv.csv")
head(tsv) #let's take a look
```

```
##                  evi
## 2001-01-17 0.3103816
## 2001-03-22 0.6017811
## 2001-04-23 0.5585050
## 2002-01-17 0.3728227
## 2002-02-02 0.4369971
## 2002-04-07 0.5701539
```

CHAPTER THREE

METHODOLOGY

Data from a time series is a set of observations made in a particular order over a period of time. There is a chance for correlation between observations because time series data points are gathered at close intervals. To help machine learning classifiers work with time series data, we provide several new tools. We first contend that local features or patterns in time series can be found and combined to address challenges involving time-series categorization. Then, a method to discover patterns that are helpful for classification is suggested. We combine these patterns to create computable categorization rules. In order to mask low-quality pixels, we will first collect Sentinel 2 data from Google Earth Engine in order to choose NDVI and EVI values.

```
Instead of analyzing the imagery directly, we will summarize the mean NDVI and EVI values. This wil

\subsection{Research Design}
In this study, the submission used a quantitative approach. Instead of using subjective judgment, fi
\subsection{Specification of the Model}
\subsubsection{Data Representation}
\subsubsection{The Analysis Of Variance (ANOVA) Method}
\subsubsection{The Empirical * Theory model}
\subsubsection{Assumptions }
```

```r
#We want to get an idea of the number of entries with no EVI value
na.cnt <- length(tsv[is.na(tsv)])
evi.trend$na.cnt[i] <- na.cnt
td <- tsv %>%
  mutate(month = month(as.Date(rownames(tsv))), year = year(as.Date(rownames(tsv)))) %>%
  group_by(year, month) %>%
  summarise(mean_evi = mean(evi, na.rm = T), .groups = "keep") %>%
  as.data.frame()
head(td)
```

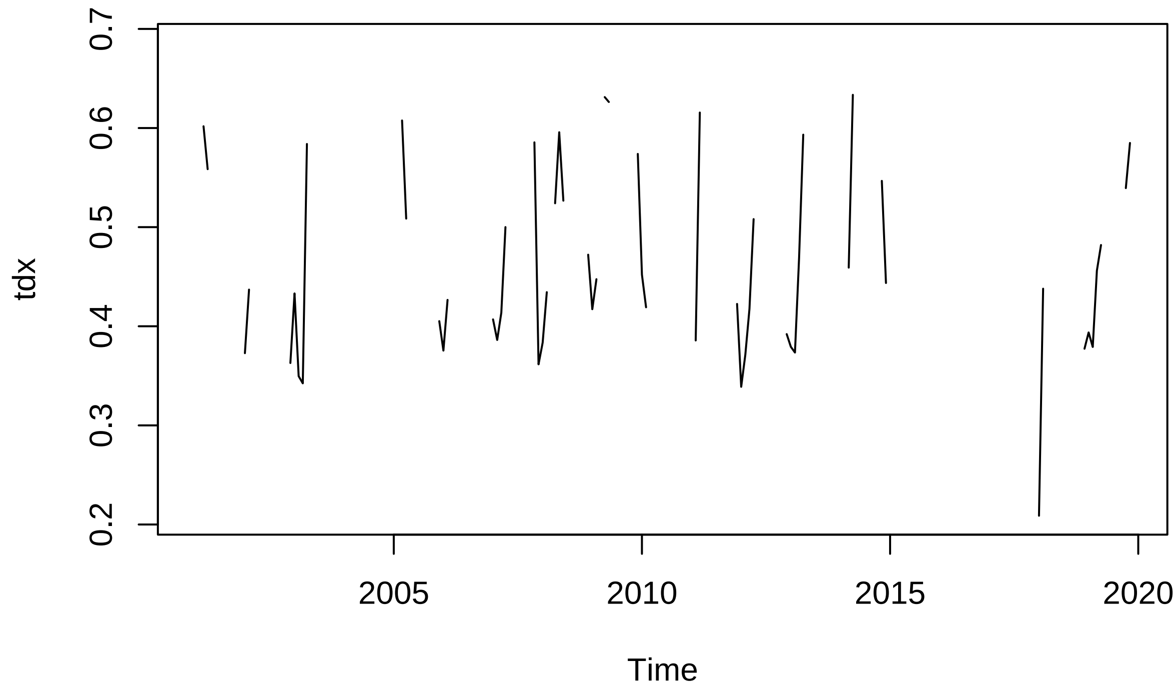
```
##   year month  mean_evi
## 1 2001     1 0.3103816
## 2 2001     3 0.6017811
## 3 2001     4 0.5585050
## 4 2002     1 0.3728227
## 5 2002     2 0.4369971
## 6 2002     4 0.6160278
```

That looks better! Unfortunately though, there are a number of dates which don't have any evi value at all, let's figure out which ones these are.

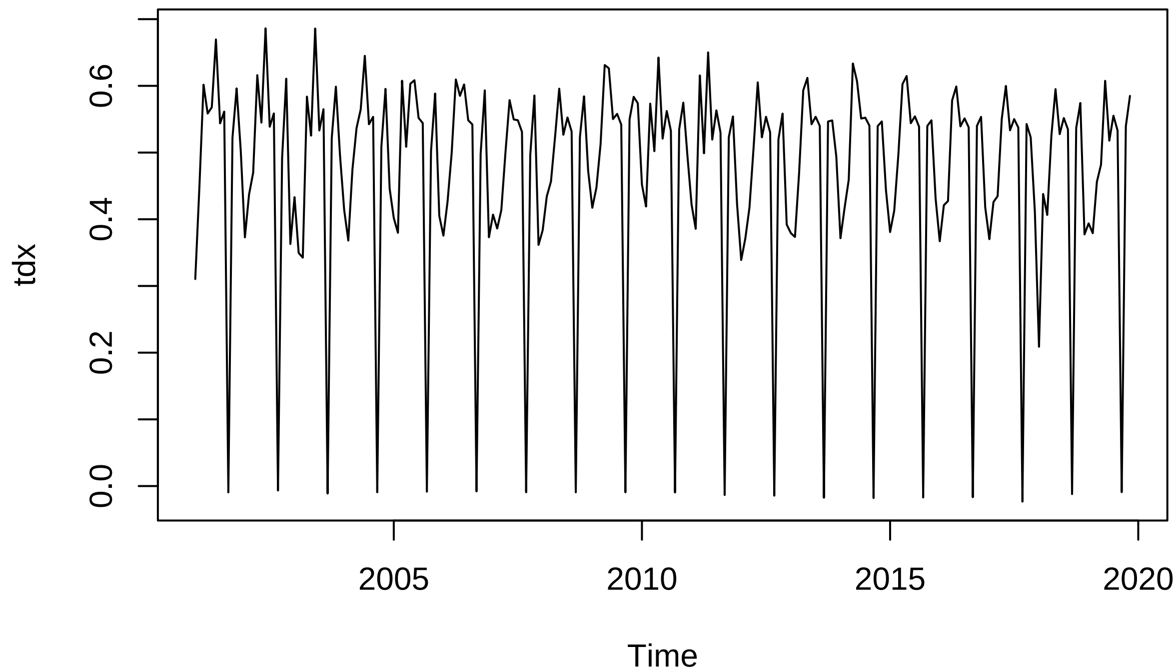
```r
dx$mean_evi <- NA
tdx <- rbind(td, dx) %>%
  arrange(date)
write.csv(tdx,"Data/tdx.csv")
tdx <- read.csv("Data/tdx.csv")
head(tdx)
```

```
##     X year month  mean_evi       date
## 1   1 2001     1 0.3103816 2001-01-01
## 2 216 2001     2        NA 2001-02-01
## 3   2 2001     3 0.6017811 2001-03-01
## 4   3 2001     4 0.5585050 2001-04-01
## 5 510 2001     5        NA 2001-05-01
## 6 610 2001     6        NA 2001-06-01
```

```r
na.cnt <- length(tdx[is.na(tdx)])
# Convert data to time series.
tdx <- ts(data = tdx$mean_evi, start = c(2001, 1), end = c(2019, 11), frequency = 12)
plot(tdx)
```

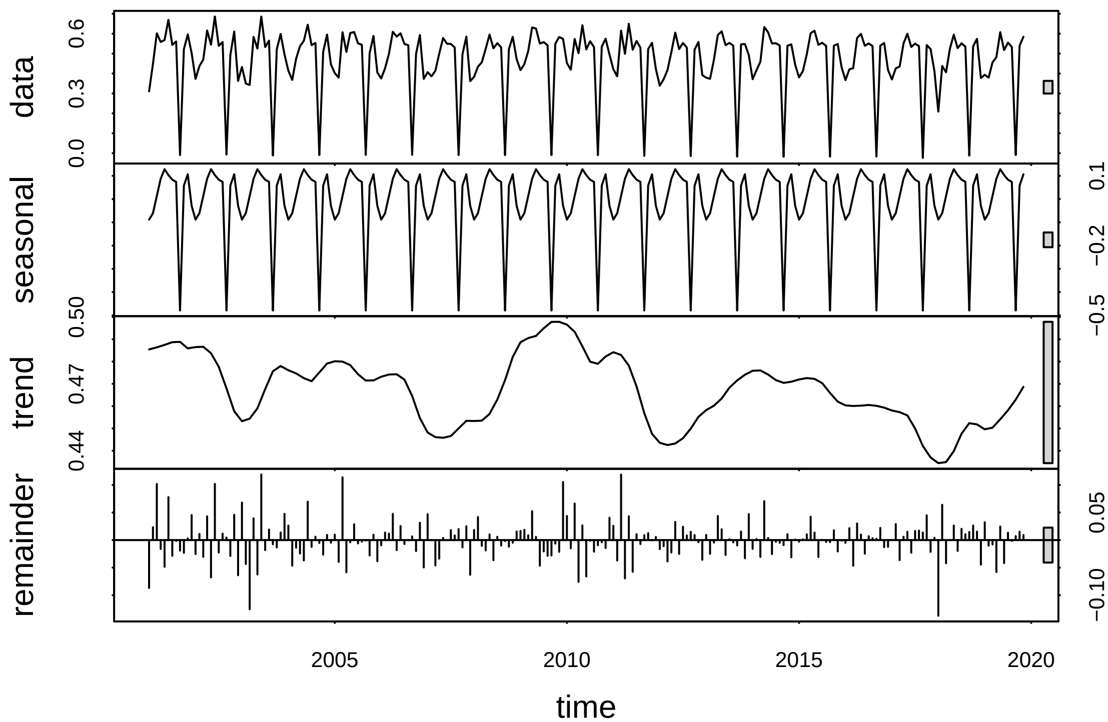



```
library(imputeTS)
tdx <- if(na.cnt > 0){imputeTS::na_kalman(tdx, model = "auto.arima", smooth = T)} else {
    tdx
}
plot(tdx)
```




```r
new_tdx <- write.csv(tdx,"Data/new_tdx.csv")
```

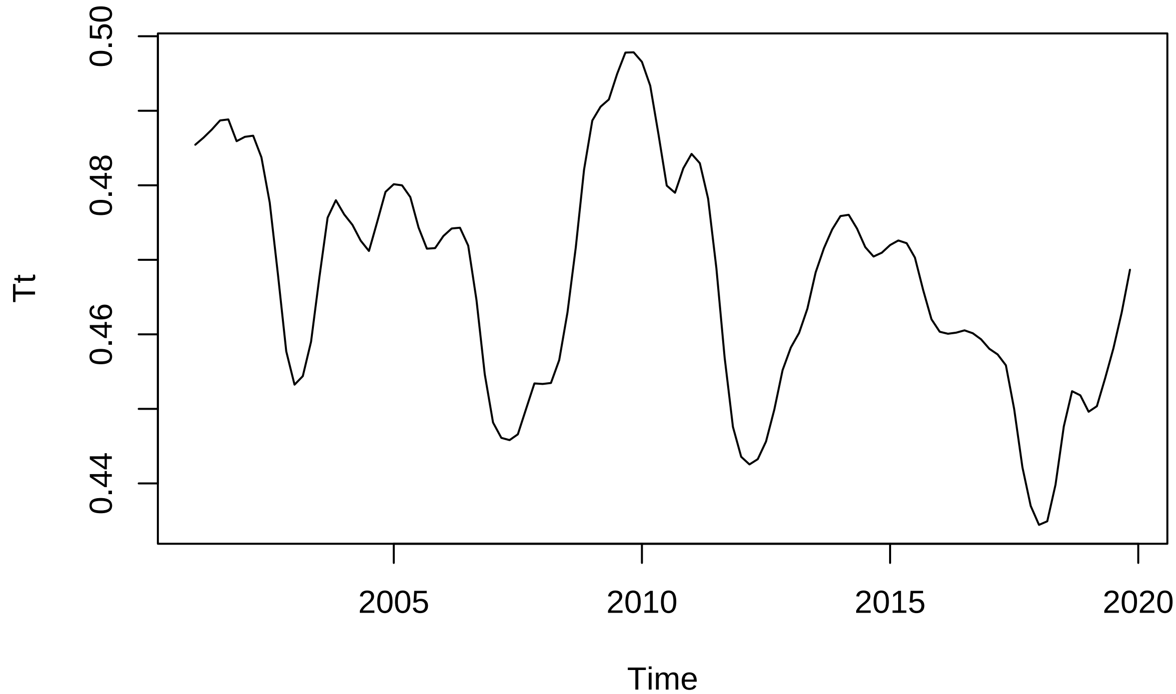
```r
tdx.dcp <- stl(tdx, s.window = 'periodic')
plot(tdx.dcp)
```



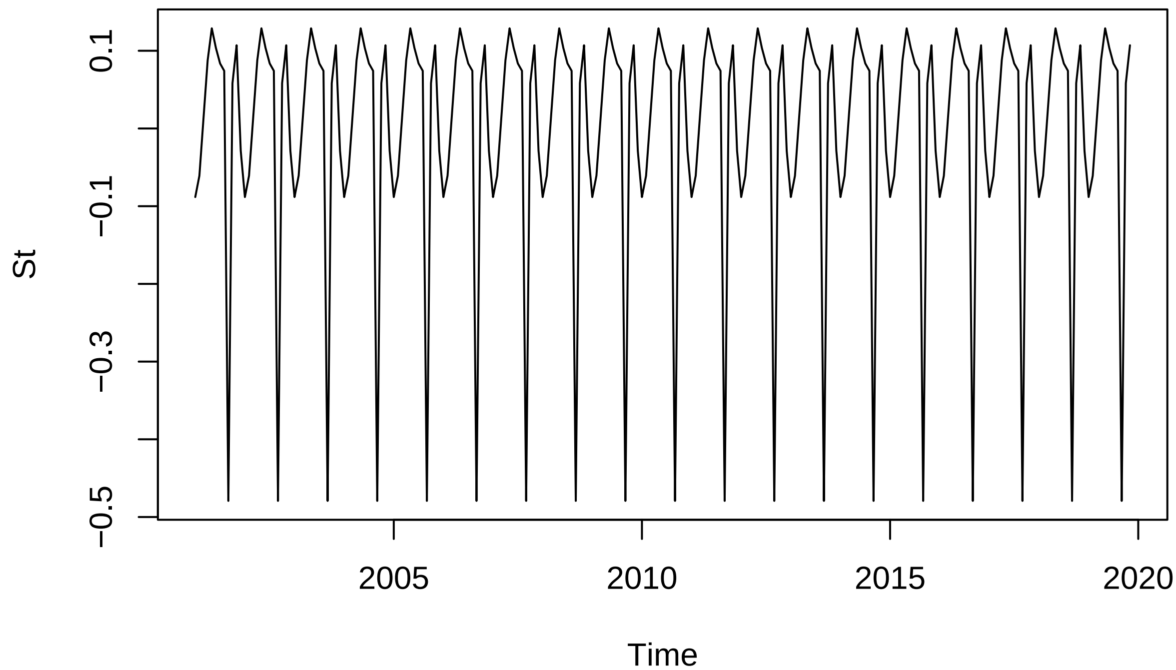

```r
library(forecast)
```

```
## Warning: package 'forecast' was built under R version 4.1.3
```

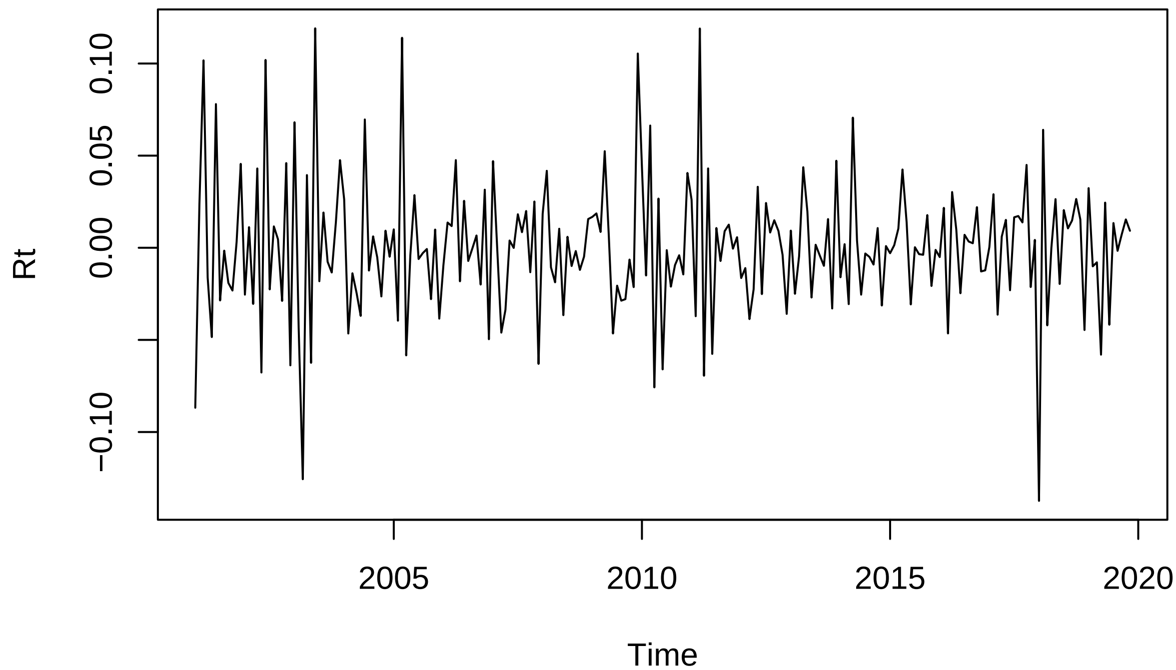
```r
Tt <- trendcycle(tdx.dcp)
St <- seasonal(tdx.dcp)
Rt <- remainder(tdx.dcp)
plot(Tt)
```




```
plot(St)
```




```
plot(Rt)
```



Stationarity When investigating a time series, one of the first things to check before building an ARIMA model is to check that the series is stationary. That is, it needs to be determined that the time series is constant in mean and variance are constant and not dependent on time.

Here, we will look at a couple methods for checking stationarity. If the time series is provided with seasonality, a trend, or a change point in the mean or variance, then the influences need to be removed or accounted for. # Augmented Dickey–Fuller (ADF) t-statistic test for unit root Another test we can conduct is the Augmented Dickey–Fuller (ADF) t-statistic test to find if the series has a unit root (a series with a trend line will have a unit root and result in a large p-value).

```
library(tseries)
```

```
##
## Attaching package: 'tseries'

## The following object is masked from 'package:imputeTS':
##
##     na.remove
```

```
adf.test(Rt)
```

```
##
##  Augmented Dickey-Fuller Test
##
## data:  Rt
## Dickey-Fuller = -8.639, Lag order = 6, p-value = 0.01
## alternative hypothesis: stationary
```

```
adf.test(Tt)
```

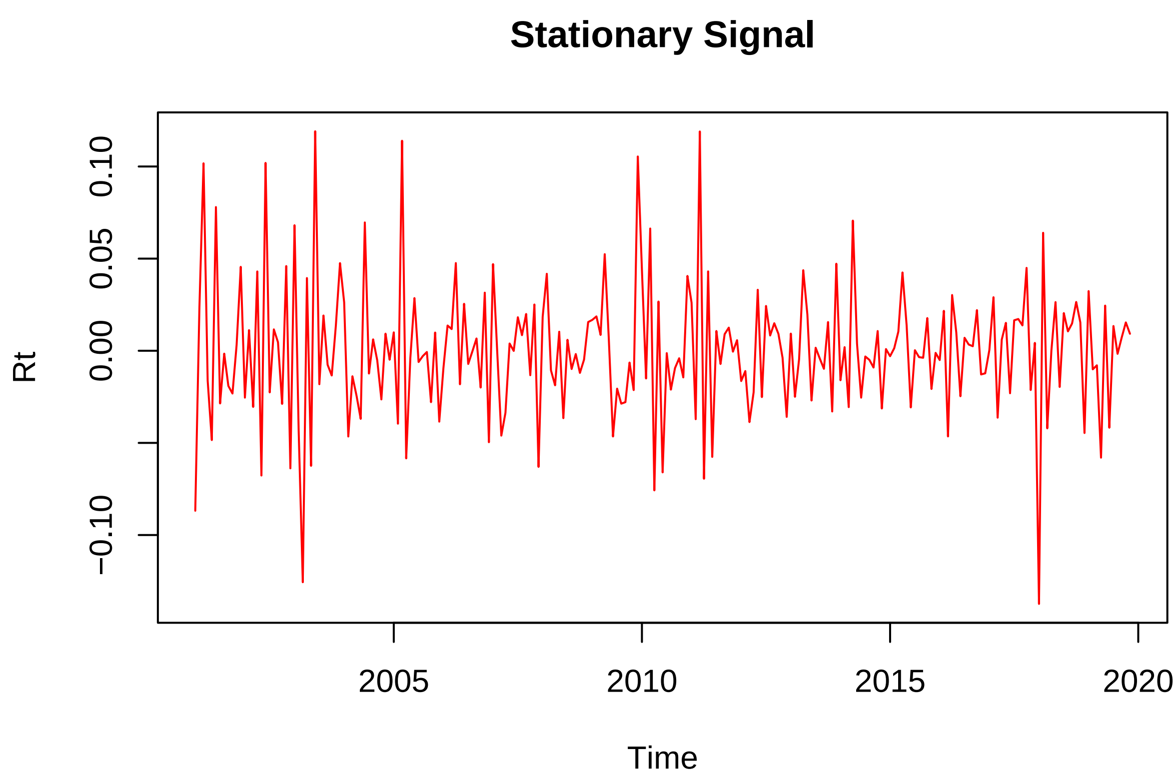
```
##
##  Augmented Dickey-Fuller Test
##
## data:  Tt
## Dickey-Fuller = -3.4545, Lag order = 6, p-value = 0.04798
## alternative hypothesis: stationary
```

```
adf.test(tdx)
```

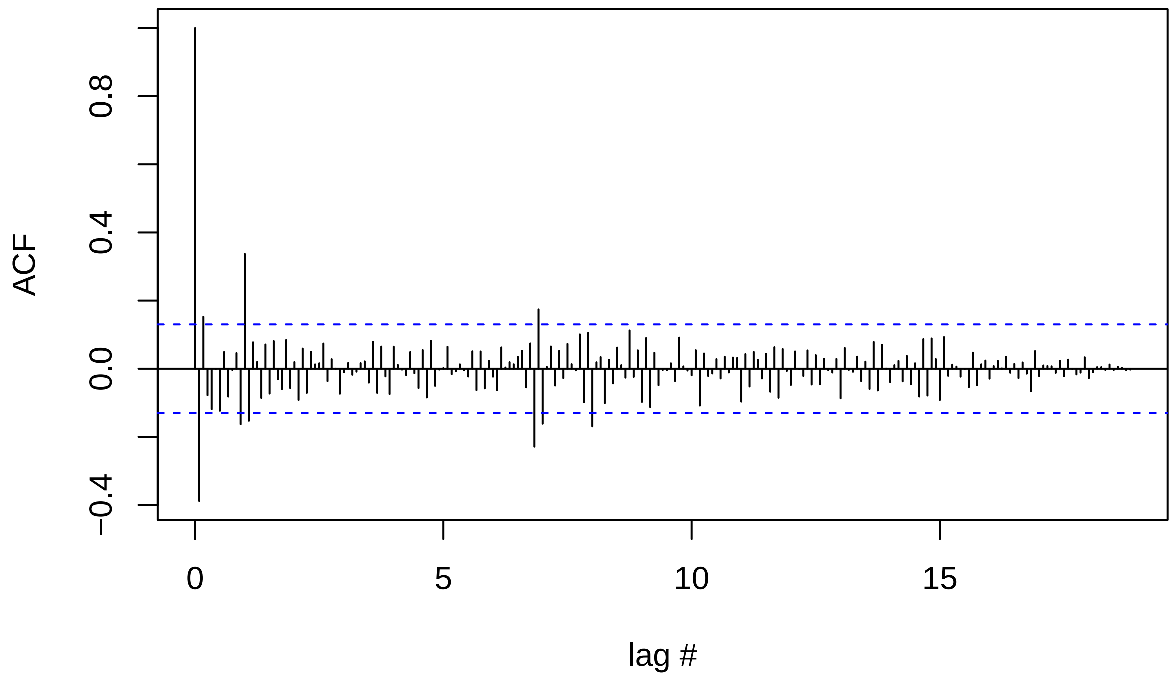
```
##
##  Augmented Dickey-Fuller Test
##
## data:  tdx
## Dickey-Fuller = -8.2685, Lag order = 6, p-value = 0.01
## alternative hypothesis: stationary
```

#Autocorrelation Function (ACF) Identify if correlation at different time lags goes to 0

```
plot.new()
frame()
# The Stationary Signal and ACF
plot(Rt,col= "red", main = "Stationary Signal")
```

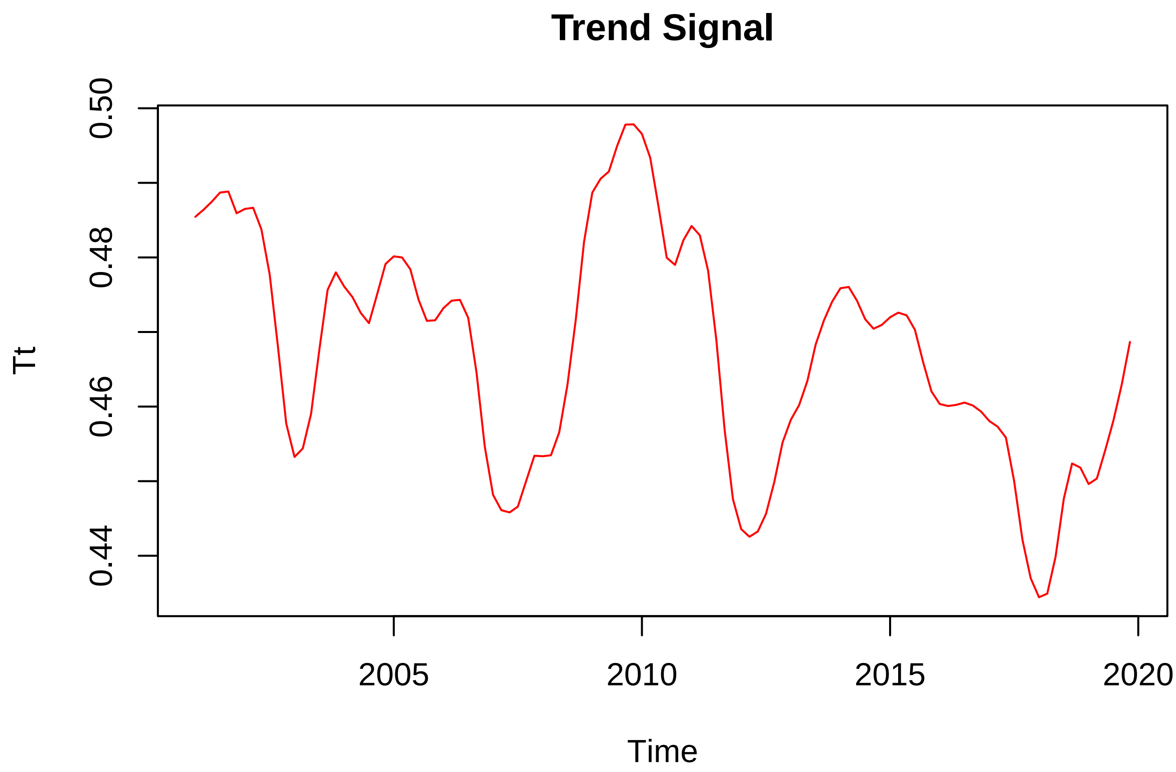



```
acf(Rt, lag.max = length(Rt),
    xlab = "lag #", ylab = 'ACF', main = '')
```

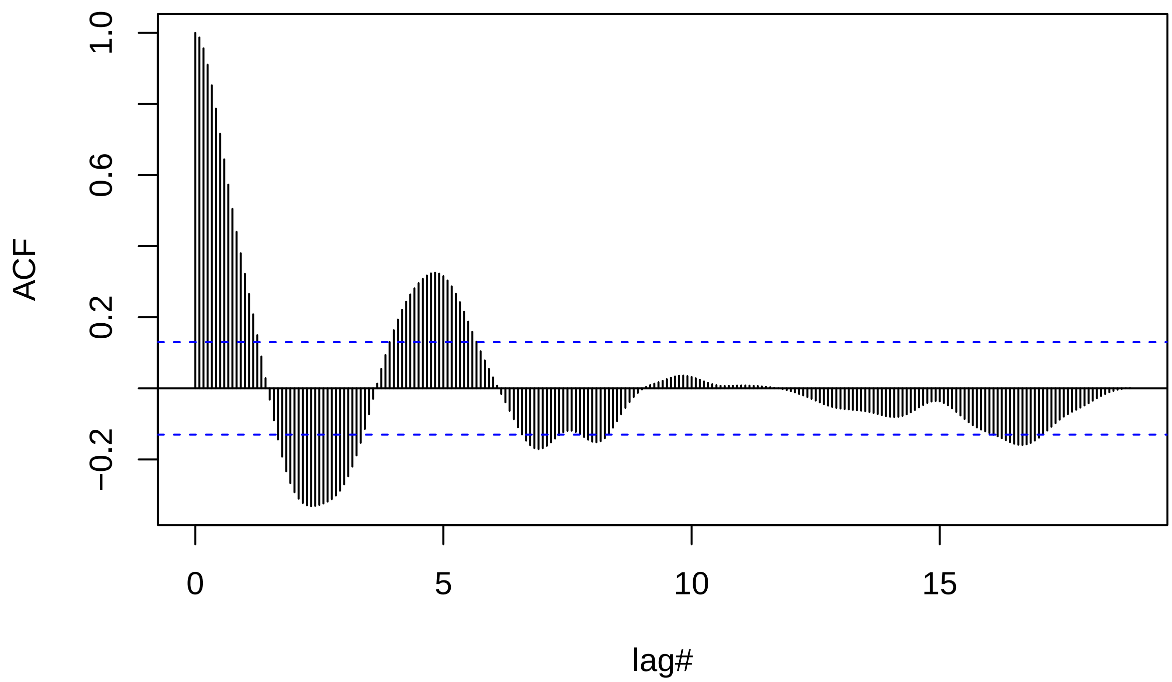



```
#The Trend Signal anf ACF

plot(Tt,col= "red",main = "Trend Signal")
```



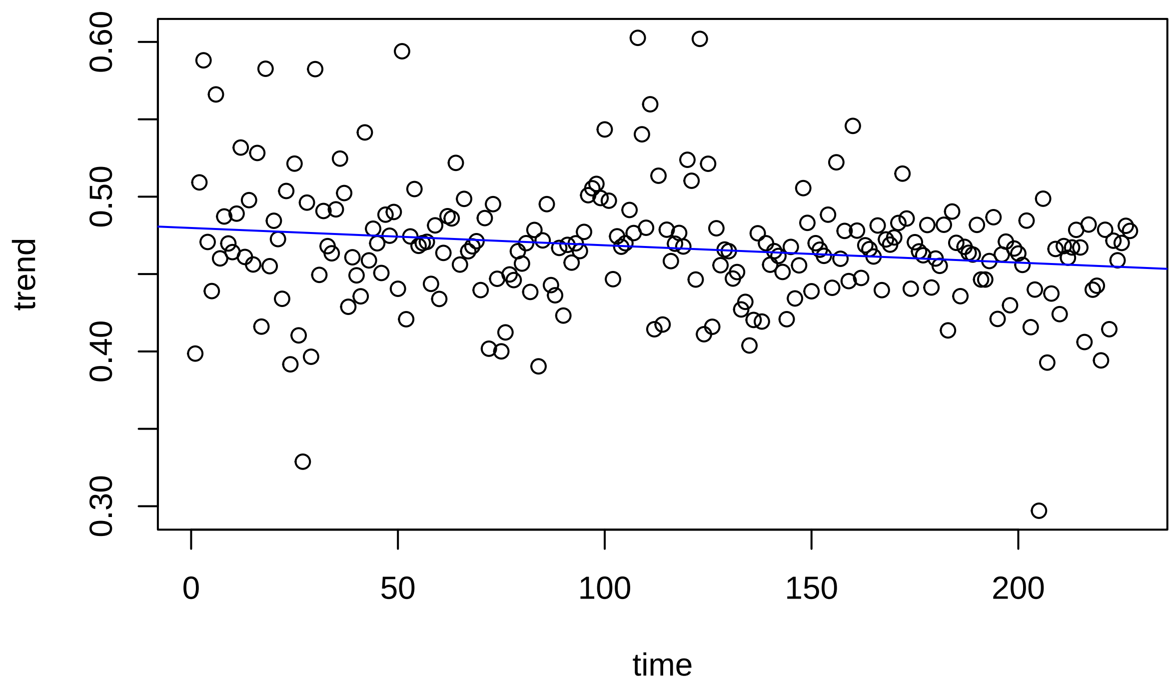

```
acf(Tt, lag.max = length(Tt),
    xlab = "lag#", ylab = "ACF", main = '')
```



It is noteworthy that the stationary signal (top left) generates few significant lags that are larger than the ACF's confidence interval (blue dotted line, bottom left). In contrast, practically all delays in the time series with a trend (top right) surpass the ACF's confidence range (bottom right). Qualitatively, we can observe and infer from the ACFs that the signal on the left is steady (due to the lags that die out) whereas the signal on the right is not (since later lags exceed the confidence interval).

```
tdx.ns <- data.frame(time = c(1:length(tdx)), trend = tdx - tdx.dcp$time.series[,1])
summary <- summary(lm(formula = trend ~ time, data = tdx.ns))
```

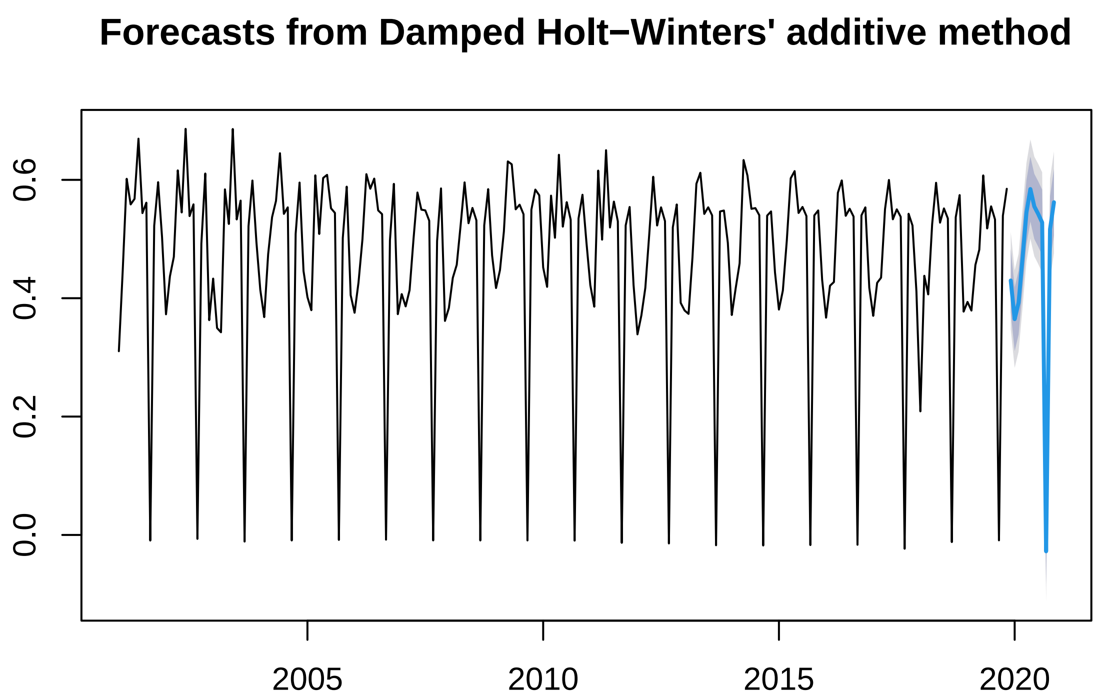
```
plot(tdx.ns)
abline(a = summary$coefficients[1,1], b = summary$coefficients[2,1], col = 'blue')
```




```r
# Count of na values to dataframe
# Calculating Trend and Seasonal Strength
evi.trend$NA_Values[i] <- na.cnt
evi.trend$Trend[i] <- summary$coefficients[2,1]
evi.trend$Trend_Strength[i] <- round(max(0,1-(var(Rt)/var(Tt+Rt))),1)
evi.trend$Seasonal_Strength[i] <- round(max(0,1-(var(Rt)/var(St+Rt))),1)
evi.trend$P_value[i] <- summary$coefficients[2,4]
evi.trend$R_Squared[i] <- summary$r.squared
evi.trend$Standard_Error[i] <- summary$sigma
evi.trend[i,]
```

```
##   hex_id na.cnt NA_Values       Trend     P_value  R_Squared Standard_Error
## 1     34      0       152 -0.00011184 0.005928196 0.03316554     0.03974499
##   Trend_Strength Seasonal_Strength
## 1            0.2                 1
```

```r
plot(evi.hw <- forecast::hw(y = tdx, h = 12, damped = T))
```




```r
#ggdensity(tdx, x = "tmie",y = "trend",fill = "#0073C2FF",color ="#0073C2FF",add = "mean",rug = TRUE)
```

```
    \section{CHAPTER  FIVE}
    \section{CONCLUSIONS AND RECOMMENDATIONS}
    \subsubsection{Summary}
        Broadly speaking, in this study we have presented a state-of-the-art of the following popular ti
    \begin{itemize}
        \item  The Box-Jenkins or ARIMA models for linear time series forecasting.
        \item Some non-linear stochastic models, such as NMA, ARCH.
        \item SVM based forecasting models; LS-SVM and DLS-SVM.
    \end{itemize}
    \subsubsection{ Conclusions}
    It has been seen that, the proper selection of the model orders (in case of ARIMA), the number of in

    We have considered a few important performance measures for evaluating the accuracy of forecasting m
    Our satisfactory understanding about the considered forecasting models and their successful implemen
    \subsubsection{Recommendations}
    Time series forecasting is a fast growing area of research and as such provides many scope for futur
    Together with other analysis in time series forecasting, we have thought to find an efficient combin
```

References

\end{flushleft} ““