Automation Detection of Change in EthiopiaGross Domestic Product (GDP) using Novel approach.

ABSTRACT

The main objective of this study is to use BFTSC (Break for Time Series Components) to identify the components of time series present in the Ethiopia Gross Domestic Product (GDP). This data is the GDP yearly data of Ethiopia Gross Domestic Product (GDP). The Gross fixed capital formation (% of GDP) was provided. The (Ethiopia GDP) data spanned for the period of twelve years. The GDP of Ethiopia is a secondary data obtained from the DataStream of Universiti Utara Malaysia Library. The weaknesses of BFAST (Break for Additive Seasonal and Trend) were examined by the extension of BFAST to BFTSC. BFTSC was created to capture the cyclical and irregular components that was not captured by BFAST technique. BFTSC is designed to present the image of all the 4 time series components. BFAST only identifies trend and seasonal components only. Empirical data of Ethiopia was employed to BFTSC and subsequently the next forecast was made. The simulated and real data findings suggested that BFTSC can provide a better time series components identification better than manual process and hence caution should be taken because Ethiopia GDP is sliding, less it got to ruin. Improvement in Ethiopia GDP is recommended.

***Keywords**: Ethiopia, Break for Time Series Components, Seasonal Data, Gross, Cyclical, Irregular components.*

1. INTRODUCTION

This study uses GFTSC (Group for time series components) to identify the components of time series present in the empirical data which is the GDP yearly data of Ethiopia GDP gross domestic product. GFTSC is considered to be more efficient in identifying all the components of time series statistics better than manual approach and BFAST. Jong, Verbesselt, Schaepman and Bruin (2012) recommended an approach of basic swing identification to spot time series *component. This approach was also used by (23) as the latest time series component recognition approach which is a technique that was first described and utilized by (33).*

The Economy of Ethiopia remained very traditional until the later 20th century, although Ethiopia—unlike most sub-Saharan countries—had maintained trade and contacts with the outside world for centuries. Since ancient times, Ethiopian traders exchanged gold, ivory, musk, and wild animal skins for salt and luxury goods, such as silk and velvet.By the late nineteenth century, coffee had become one of Ethiopia's more important cash crops. At that time, most trade flowed along two major trade routes, both of which terminated in the far southwest in the Kefa-Jimma region. From there, one route went north to Mitsiwa, via Gonder and Adwa, and the other along the Awash River valley to Harer then on to Berbera or Zeila on the Red Sea.Despite its many riches, Ethiopia never became a great trading nation. Most Ethiopians despised traders, preferring instead to emulate the country's warriors and priests. After establishing a foothold in the country, Greek, Armenian, and Arab traders became economic intermediaries between Ethiopia and the outside world. Arabs also settled in the interior and eventually dominated all commercial activity except petty trade (1,2).

Efforts to modernize and develop the economy in the final years of the monarchic period had relatively little success, and after the Ethiopian Revolution of 1974, nationalization, increased spending on the military and an unstable political climate did little to improve matters. A severe drought in much of the country in 1983-85 led to a disastrous famine. Only in the 1990s did the economy begin to improve, although in 2021 disputes, including open warfare, between the Tigray Region and the national government were still causing serious disruption.When their occupation of Ethiopia ended in 1941, the Italians left behind a country whose economic structure had changed little in centuries. Some improvement had taken place in communications, particularly in road building, and some limited attempts had been made to establish a few industries and to introduce commercial farming, particularly in Eritrea, which Italy had occupied since 1890. Only a small proportion of the population participated in the money economy, so trade at the time consisted of barter. Wage labor was limited, economic units were largely self-sufficient, foreign trade was negligible, and the market for manufactured goods was extremely small (3, 4, and 52).

During the late 1940s and 1950s, much of the economy remained unchanged. The government focused its development efforts on expanding the bureaucratic structure and ancillary services. Most farmers cultivated small plots of land or herded cattle. Traditional and primitive farming methods provided the population with a subsistence standard of living. In addition, many nomadic peoples in drier areas raised livestock and followed a life of seasonal movement. The agricultural sector grew slightly, and the industrial sector represented a small part of the total economy (5, 6, and 51).

By the early 1950s, Emperor Haile Selassie I (reigned 1930–74) had renewed calls for a transition from a subsistence economy to an agro-industrial economy. Ethiopia needed an infrastructure to exploit its resources, improved living conditions, and better health, education, communications, and other services. A key element of the emperor's new economic policy was centrally-administered development plans. Between 1945 and 1957, several technical missions, including one each from the United States, the Food and Agriculture Organization of the United Nations (FAO), and Yugoslavia, prepared a series of development plans. However, these plans failed to achieve any meaningful results, largely because basic statistical data were scarce and the government's administrative and technical capabilities were minimal (3, 4, 51).

In 1954–55 the government created the National Economic Council to coordinate the state's development plans. This agency, which was a policy-making body chaired by the emperor, devoted its attention to improving agricultural and industrial productivity, eradicating illiteracy and diseases, and improving living standards for all Ethiopians. The National Economic Council helped to prepare Ethiopia's first and second five-year plans.The first five-year plan (1957-61) sought to develop infrastructure to link isolated regions, particularly in transportation, construction, and communications. Another goal was an indigenous cadre of skilled and semiskilled personnel to work in processing industries to help reduce Ethiopia's dependence on imports. The plan also proposed to accelerate agricultural development by promoting commercial agricultural ventures. The second five-year plan (1962-67) began a 20-year program to change Ethiopia's predominantly agricultural economy to an agro-industrial one. The plan's objectives included diversification of production, introduction of modern processing methods, and expansion of the economy's productive capacity to increase the country's growth rate. The third five-year plan (1968-73) sought to raise manufacturing and agro-industrial performance. Unlike its predecessors, the third plan expressed the government's *willingness to expand educational opportunities and to improve peasant agriculture. Total investment for the first five-year plan reached 839.6 million birr, about 25 percent above the planned 674 million birr figure; total expenditure for the second five-year plan was 13 percent higher than the planned 1,694 million birr figure. The allocation for the third five-year plan was 3,115 million birr (3, 4, 51, and 52).*

During the first five-year plan, the gross national product (GNP) increased at a 3.2 percent annual rate as opposed to the projected figure of 3.7 percent, and growth in economic sectors such as agriculture, manufacturing, and mining failed to meet the plan's targets. Exports increased at a 3.5 percent annual rate during the first plan, whereas imports grew at a rate of 6.4 percent per annum, thus failing to correct the negative balance of trade that had existed since 1951.The second five-year plan and third five-year plan anticipated that the economy would grow at an annual rate of 4.3 percent and 6.0 percent, respectively. Officials also expected agriculture, manufacturing, and transportation and communications to grow at respective rates of 2.5, 27.3, and 6.7 percent annually during the second five-year plan and at respective rates of 2.9, 14.9, and 10.9 percent during the third five-year Plan. The Planning Commission never assessed the performance of these two plans, largely because of a shortage of qualified personnel (3, 4, 51, and 52).

Relative to its neighbors, Ethiopia's economic performance was mixed. Ethiopia's 4.4 percent average per capita GDP growth rate was higher than Sudan's 1.3 percent rate or Somalia's 1 percent rate. However, Kenya's GDP grew at an estimated 6 percent annual rate, and Uganda achieved a 5.6 percent growth rate during the same 1960–61 to 1972–73 period.[1]

By the early 1970s, Ethiopia's economy not only had started to grow but also had begun to diversify into areas such as manufacturing and services. However, these changes failed to improve the lives of most Ethiopians. About four-fifths of the population were subsistence farmers who lived in poverty because most of their meager production went to pay taxes, rents, debt payments, and bribes. On a broader level, from 1953 to 1974 the balance of trade registered annual deficits. The only exception was 1973, when a combination of unusually large receipts from the export of oilseeds and pulses and an unusually small increase in imports resulted in a favorable balance of payments of 454 million birr. With the country registering trade deficits, the government attempted to restrict imports and substitute locally *produced industrial goods to improve the balance of trade. However the unfavorable trade balance continued. As a result, foreign grants and loans financed much of the balance of payments deficit (3, 4, 51, and 52).*

The 1974 revolution resulted in the nationalization and restructuring of the Ethiopian economy. After the revolution, the country's economy went through four phases.Internal political upheaval, armed conflict, and radical institutional reform marked the 1974-78 period of the revolution. There was little economic growth; instead, the government's nationalization measures and the highly unstable political climate caused economic dislocation in sectors such as agriculture and manufacturing. Additionally, the military budget consumed a substantial portion of the nation's resources. As a result of these problems, GDP increased at an average annual rate of only 0.4 percent. Moreover, the current account deficit and the overall fiscal deficit widened, and the retail price index jumped, experiencing a 16.5 percent average annual increase. The basic economy during this time was dependent on the agriculture industry. Upwards of eighty percent of the population was directly or indirectly dependent upon agriculture for their livelihood (3,4,51,52).

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Consequently, GDP grew at an average annual rate of 5.7 percent. Benefiting from good weather, agricultural production increased at an average annual rate of 3.6 percent, and manufacturing increased at an average annual rate of 18.9 percent, as many manufacturers whose had shut down, particularly in Eritrea, reopened. The current account deficit and the overall fiscal deficit remained below 5 percent of GDP during this period.In the third phase (1980-85), the economy experienced a setback. Except for Ethiopian fiscal year (EFY) 1982–83, the growth of GDP declined.Manufacturing took a downturn as well, and agriculture reached a crisis stage. Four factors accounted for these developments. First, the 1984-85 drought affected almost all regions of the country,so the government committed scarce resources to famine relief and tabled long-term development projects. Consequently, the external accounts (as shown in the current account deficit and the debt service ratio) and the overall fiscal deficit worsened, despite international drought assistance totaling more than US$450 million. Close to eight million people became famine victims during the drought of the mid-1980s, and about 1 million died.[1] Second, the manufacturing sector stagnated as agricultural inputs declined. Many *industries exhausted their capacity to increase output as a result, they failed to meet rising demand for consumer goods. Third, the lack of foreign exchange and declining investment reversed the relatively high rate of growth in manufacturing of 1978–80. Finally, Ethiopia's large military establishment created a major burden on the economy. Defense expenditures during this time absorbed 40 to 50 percent of the government's current expenditures (51,52).*

In the fourth period (1985-90), the economy continued to stagnate, even though an improvement in the weather in EFY 1985–86 and EFY 1986–87, helped reverse the agricultural decline. The manufacturing sector also grew during this period, and GDP increased at an average annual rate of 5 percent. However, the lingering effects of the 1984-85 drought undercut these achievements and contributed to the economy's overall stagnation. During the 1985-90 period, the current account deficit and the overall fiscal deficit worsened to annual rates of 10.6 and 13.5 percent, respectively, and the debt service ratio continued to climb.Since 1991, the Ethiopian government has embarked on a program of economic reform, including privatization of state enterprises and rationalization of government regulation. While the process is still ongoing, the reforms have attracted much-needed foreign direct investment (51,52)..

In 2015, Ethiopia had 2,700 millionaires, a number that has more than doubled since 2007. Their fortunes were mainly made in niches of economic rents (banks, mines, etc.) without investing in structural or strategic sectors (industrial production, infrastructure, etc.) and in no way promote economic development or represent a source of competition for Western multinationals.The Ethiopian government is stepping up its efforts to attract foreign investors, particularly in the textile sector. They can now import machines without customs duties, and benefit from a tax exemption for ten years, rents much lower than market prices, and almost free water and electricity. Major brands have established themselves in the country, such as Decathlon, H&M and Huajian. These companies also benefit from a cheap labor force, with a monthly salary of around 35 euros. Finally, trade agreements between Ethiopia and the European Union allow them to export duty-free. There is huge economic reforms, starting from 2018, has been undertaken after the leadership of EPDRF-TPLF foll down and replaced by "Prosperity Party" leadership of Abiy Ahimed Ali (PHD)(51,52)..

The technique BFAST was for recognizing breaking points with the help of seasonal and trend decomposition using loess (STL), it facilitates the detection of trend change in a given information. The elementary standard of the BFAST technique is the splitting of time series into seasonal, trend and also remnants element by the approach for breaks detecting software in R studio core 2012 (10). In this paper GFTSC (Group for time series components) would be used to identify the components of time series present in the empirical data which is the GDP yearly data of Ethiopia GDP gross domestic product.

LITERATURE REVIEW

The technique BFAST had much lower RMSE and was more robust against noise, Hence BFAST is recommended as one of the best trend break detection. One of the limitation of CCDC with CV is that its algorithm was made complicated, unlike CCDC, CCDC with CV did not have a straightforward relationship between RMSE number of breaks and noise. CCDC with CV was also found to be less accurate (34). Another limitation of this technique is also in terms of noise, with increased noise, the technique was less likely to detect correct results and the likelihood of detecting at least one false break remained constant. The unique pattern shown by CCDC with CV suggests that it must also detect more breaks if there is very little noise (34,37).

EWMACD was built to focus on subtle changes, such as partial changes within pixels (Brooks, Wynne, Thomas, Blinn, Coulston, 2019). Just like CCDC and BFAST Monitor, EWMACD also detects condition (increasing/decreasing trend) the EWMA chart, to rapidly help in identification of time series component (38).

Zhu, Zhang, Yang, Aljaddani, Cohen, Qiu and Zhou (2020) developed a new univariate time series components identification method known as COntinuous Monitoring of Land Disturbance (COLD) using Landsat time series data. COLD can detect many time series component such as trend and seasonal. COLD can also detect land disturbance continuously as new pattern is collected and likewise provide historical land disturbance history. Evaluation of the trend detection ability and land disturbance, different kinds of data are utilized. The COLD algorithm was developed and calibrated based on all the lessons learned. The accuracy assessment shows that COLD results were accurate for detecting trend and seasonal as land disturbance with an *omission error of 27% and a commission error of 28%. The limitation of COLD was inability to detect time series components accurately with large noise (36).*

Zewdie et al. (2017) argues that the technique of BFAST can predict and analyse a topographical forest movement with the help of normalized difference vegetation index's branded as (NDVI). This was done by detecting and determining factors of arid area changes using (NDIV) data to monitor the variations (9,10,11,12,13,). Many scholars employ the use of BFAST in identifying trend in topographical data (26).

The extension of BFAST is an improved technique that identifies all-time series components. This new technique is known as GFTSC (Group for time series components). Many of the automated techniques of pattern detection are computer oriented. GFTSC is one of the first extension of BFAST in history which also focus more on computer approach strategy rather than theoretical approach strategy GFTSC technique considers every vital component of time series statistics. BFAST is known to be weak in identifying and breaking random variations, also very weak in applicability to other types of empirical data (21). The technique considers the extension and improvement of the BFAST to GFTSC.

GFTSC is made available into computer R package and can be used by anyone who wishes to be a beneficiary, for better identification and diagrammatic representation of the time series data to bridge the gap of time series components identification (21). GFTSC followed similar derivative steps like BFAST but in addition of cyclical and irregular components. GFTSC is the technique used in analyzing the generality of time series data by extracting the trend components and seasonal components, cyclical components and irregular components during time series decomposition but would not be discussed in this paper (discussed in 1,2,3,4,5). Given the general time series additive model as in equation (1.1) of the form:

$$Y_P = T_p + S_p + C_p + I_p \quad (1.1)$$

For identification of Y_P , S_p ,C_p , *and* I_p*(See the paper: 7,8,9,10, 23,24,25).*

BFAST identify trend, seasonal and random components (29,30,31,32,33).

Material and Methods

BFAST is the technique used in analyzing the generality of time series data by extracting the trend and seasonal pattern during time series decomposition. Given the general time series additive model of the form of equation 1.1 (27,28,36).

From equation (1.2) BFAST takes all other components relatively trend and seasonal component to be randomized (R_p) and the equation was expressed as

$Y_P = T_p + S_p + R_p$ *(1.2)*

The residual random consist of cyclical and irregular component (17,18,19,20,22).

To generate trend components using BFAST, we need a piecewise linear model approach.Suppose T_p is a piecewise linear model with an actual slope and intercept on q+1 segments broken with q breakpoints and P period; $p_1^{\neq}$,……….,$p_q^{\neq}$ then T_p can takes the form as follows

$T_p = \alpha_k + \beta_k P$

where $p_{k-1}^{\neq} < p \leq p_k^{\neq}$

and If k = 1,…..,q then $p_0^{\neq}$ = 0 and $p_{q+1}^{\neq}$ = n.

The slope of the change before the breakpoints while β_{k-1} and the slope of the breaks after the change breakpoints areβ_k. The intercept and the slop of the linear model α_k and β_k with time period p and it will be used to derive the magnitude and direction of change (1,2,3,4,5).

To generate seasonal components using BFAST, we need a simple harmonic model.

Thus, S_p can be represented by a simple harmonic model with j terms; j = 12….J and time t.

$$S_p = \sum_{j=1}^{J} \omega_{k,j} \, Sin \left(\frac{2\pi jt}{F} + \sigma_{K,j} \right) \quad (1.3)$$

where k = 1… q, $p_{k-1}^{\neq} < p \leq p_k^{\neq}$ and also $\omega_{k,j}$, $\sigma_{K,j}$ are the segment amplitude and F is the frequency (1,2,3).

To generate random components, any data that does not belong to trend nor seasonal is classified random R_p.

$$Y_P = \underbrace{\{\alpha_k + \beta_k P\}} + \underbrace{\left\{\sum_{j=1}^{J} \omega_{k,j}\ Sin\left(\frac{2\pi jt}{F} + \sigma_{K,j}\right)\right\}} + \underbrace{R_p} \quad (1.4)$$

$$Y_P = \quad T_p + \qquad S_p \qquad + \qquad R_p$$

The new technique called GFTSC considered splitting the random into cyclical components and irregular components which is an extension of BFAST. This was done through the inclusion of two new components.

To calculate cyclical components, center moving average is involved (14,15,16).

Derivation of cyclical code, let CMA be the center moving average of t objects, then CMA can be computed as follow

$$CMA = \sum_t^n \frac{Yt}{nt} \quad (1.5)$$

$$C_p = \frac{CMA}{\overset{\wedge}{CMA}} \quad (1.7)$$

After extracting the trend, seasonal and cyclical components, the left out components is called irregular components, the new equation becomes

$$Y_P = \underbrace{\{\alpha_k + \beta_k P\}} + \underbrace{\{\sum_{j=1}^{J} \omega_{k,j}\ Sin\ (\frac{2\pi jt}{F} + \sigma_{K,j}\ )\}} + \underbrace{\{\frac{CMA}{\overset{\wedge}{CMA}}\}} + \{\ \underbrace{I_p}\} \qquad (1.8)$$

$$Y_P = \quad T_p + \qquad S_p \qquad + \qquad C_p + \quad I_p$$

For identification of Y_P , S_p ,C_p , and I_p(See the paper: 5,6, 33).

The first stage in forecasting is to view the data and to examine all the components of time series present in that data in order to select the most appropriate forecasting technique. The Ethiopia GDP data components identification was carried out with the help of the new *technique called BFTSC. This new technique helps to have a clear image of the entire variations presents in the time series data (1, 2, 3, 4,).*

GFTSC (Group for time series components)

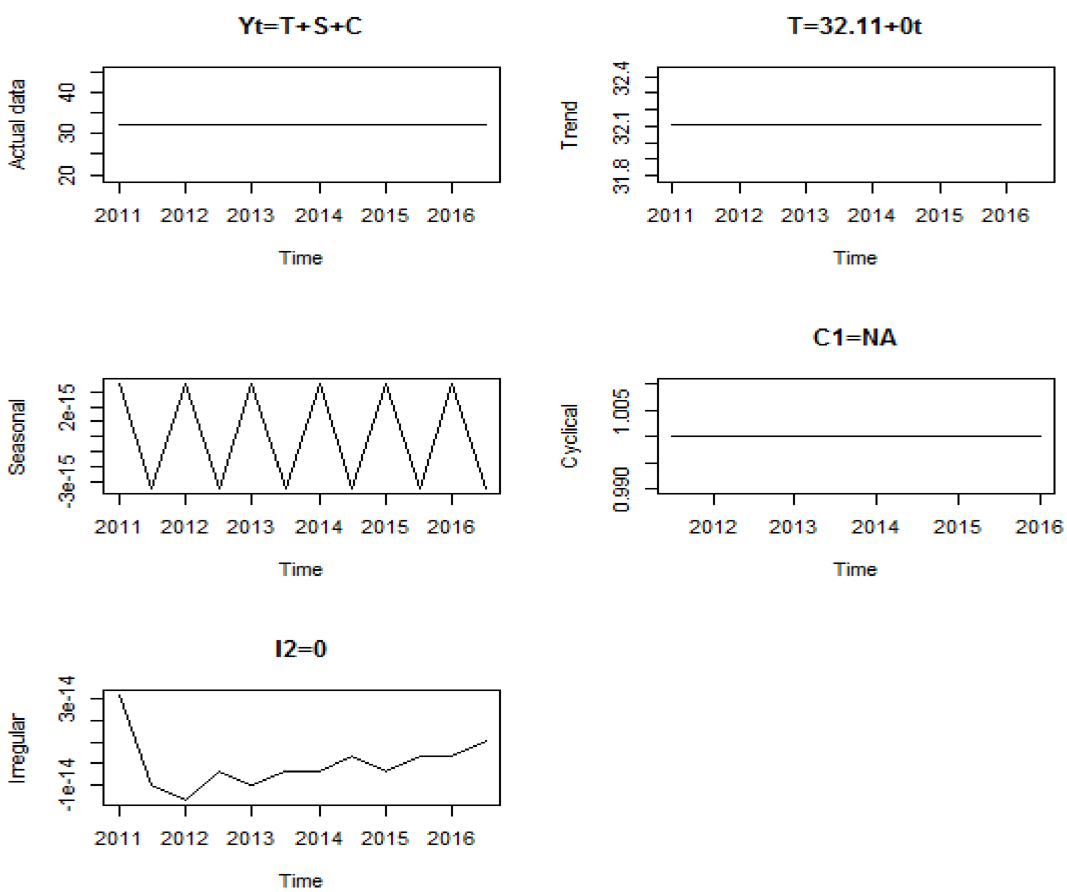

Figure 1. BFTSC for Colombia Gross Domestic Product (GDP).

Figure 1 reveals all the time series components hidden in the Ethiopia Gross Domestic Product (GDP) data for 12 Years, the image in the figure above indicate the presence of trend, seasonal, cyclical and irregular components. Only trend can be seen to be more obvious and it was stationary from 2011 to 2023.

Lifted from: Wikipedia, the free encyclopedia Development of GDP per capital

Figure 2. *Original Manual Ethiopia Gross Domestic Product (GDP) plot*

Figure 2. Thefree fitted value and the real data of the Ethiopia Gross Domestic Product (GDP) shows that the GDP had not really change in the recent years, it was stationary, the are able to maintain stable GDP. This reveal that for the next ten years period, theEthiopia Gross Domestic Product (GDP) remain stable, show no evidence of decline in Ethiopia Gross Domestic Product (GDP) data so the model can be applied for prediction of more years GDP of Ethiopia.Only trend can be seen to be more obvious and it was stationary from 2011 to 2023.

3. RESULT

Figure 1 and 2 reveals stationary GDP for Ethiopia, such that for the next ten years period, the Ethiopia Gross Domestic Product (GDP) remain stable, show no evidence of decline in Ethiopia Gross Domestic Product (GDP) data so the model can be applied for prediction of more years GDP of Ethiopia.Only trend can be seen to be more obvious and it was stationary from 2011 to 2023.

Based on the result in figure 1 and figure 2, there are no evidence of decline in Ethiopia GDP. ,The forecast data reveal smooth and steady movement in trend Ethiopia GDP. Hence no scientific evidence of GDP crash or ruin in the next five good years provided every other normal conditions id not obstructed. Never the less this should not be taken for levity but with all seriousness to make the Ethiopia GDP grow beyond prediction and beyond expectation. The forecast should not stop the country from improving and investing on the country GDP so as to have blossom reserve. Ethiopia should employ all other possible means of generating revenue (both internally and externally) for the country utilization.

GFTSC is the most appropriate for time series components identification. GFTSC is recommended as a good alternative to BFAST. This is because GFTSC identifies the four components of time series statistics which is one of the basic limitations of BFAST. Based on the forecast value for 2019 and 2020 , it reveal no scientific evidence of drop and crash in Ethiopia GDP so improvement can be establish to improve on the yearly quarterly Ethiopia GDP. The contribution of this study to the scientific community is that the GFTSC gives good results that improve the weaknesses of the existing BFAST. GFTSC forecast output is more reasonable for effective policy making.

Note: The data, BFTSC and GFTSC can be made available based on request from the original author of this paper Dr. Ajare Emmanuel. The data utilized in this study is available freely if the author is contacted. The BFTSC and GFTSC can be acquired with $10,000 from Dr Ajare Emmanuel. The forecast in this Ethiopia GDP can likewise be acquired with $1000 per year per forecast. This forecast is very good for economic development.

Discussion/Conclusion

The technique BFAST was for recognizing Breaks for Additive Seasonal and Trend (BFAST). This technique helps to recognize trend breaks enclosed by the series. The essential guide of the BFAST technique is the decomposition of time series component into seasonal, trends and miscellany elements with the technique for recognizing structural similarity and difference. Verbesselt et al. (2010) recommended that the technique of BFAST is for identifying *topographical pattern and also for improvement to be applied in other related disciplines (46.47,48,49).*

Jamali, Jönsson, Eklundh, Ardö, and Seaquist (2015) describe BFAST as not being capable of identifying topographical vegetation basic component perfectly, though satellite sensor image have made topographical vegetation data available for so many years but yet the detection of topographic trend and variation is not yet clearly defined. Chen (2006) suggested that, this may be due to the limited number of available trend and change detection techniques accessible, algorithm suitable in identifying and characterizing abrupt changes without sacrificing accuracy and efficiency (41,43,44,45).

Based on previous studies, BFAST is used for topographical green forest picture data at certain specific time. Introducing BFAST to time series data and how to implement BFAST on time series data which contain only one variable for each time is another form of challenge. BFAST is a technique that take in data and processed to extract each component point of the data, it would be reasonable to use BFAST for time series components identifications (32, 33,34).
BFAST approach give a very considerable outcome and was recommend as a modern instrument for statistics information decomposition and detections but could not separate random noise and is a customized additive decomposition method, from all indication observed so far, it reveal that BFAST need to be extended for the purpose of coping with other varieties of uses (27,28,29).

8. WEAKNESS AND FUTURE RESEARCH

The issue of how large is large and maximum sample size for Gross Domestic Product (GDP) data accepted by BFAST and BFTSC is yet to be addressed [28]. Likewise the issue of maximum sample size for Manual method of time series identification Gross Domestic Product (GDP) data data. BFTSC and BFAST are not being fully utilized addressed because it's a new automated time series identification technique and depends on the nature of individual research and interest. More automated and innovated time series components identifications is a welcome development. Model that can predict epidemic like flood, fire outbreak, earthquake etc should be encouraged. A special technique that can forecast irregular time series component automatically is a good and welcome innovation in forecasting field.

Ethics

This is the original manuscript; there will be no expectationof any ethical problems.

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