ISSN 2722-2039

Pettitt and Bayesian Change Point Detections in The Price of Kerosene in The Southwestern Region of Nigeria

Adedayo A. Adepoju [a,1,*], Anihunlopo A. Oludunni [b,2], Tayo P. Ogundunmade [b,3]

[a] Department of Statistics, University of Ibadan, Ibadan, Nigeria
[b] Laboratory for Interdisciplinary Statistical Analysis, Department of Statistics, University of Ibadan, Ibadan, Nigeria
[1] pojuday@yahoo.com , [2]dunnalice16@gmail.com, [3]ogundunmadetayo@yahoo.com
* corresponding author

ARTICLE INFO

Article history
Received January 15, 2022
Revised March 7, 2022
Accepted June 10, 2022

Keywords
change-point
bayesian analysis
pettitt analysis
kerosene
mann kendall trend

ABSTRACT

Kerosene is known to be one of the useful substances in crude oil. It is considered to be a useful household substance. It is a combustible hydrocarbon liquid widely used as fuel in industry and households. Over the years, it has been shown that there is an upward trend in the price of kerosene which has affected its use negatively. It would be of interest to investigate the change points in the price of kerosene in the six states of the southwestern region of Nigeria between 2015 and 2021. Mann Kendall trend test was used to determine the trends in the data. The Mann Kendall trend analysis showed a significant upward trend with their p-values less than 0.05 for all the States. Furthermore, Bayesian and Pettitt approaches were employed to detect change points in the price of Kerosene in the six states (Ekiti, Lagos, Ogun, Ondo, Osun and Oyo) of the southwestern region of Nigeria. The Pettitt method showed a single shift in each of the States while the Bayesian approach showed multiple shifts in each State. Both methods give the change point with dates while the Bayesian also provides the posterior means for the change points.

1. Introduction

Kerosene is a burnable hydrocarbon liquid for the most part used as a fuel in industry and families. It is known to be a light fuel oil that is gotten by refining petroleum, used especially in fly engines and local warming boilers, paraffin oil. Light fuel has been the huge treatment office thing for a long while until the presence of the electric light which incited mind blowing decline in its a motivation for lighting. Because of its financial achievability and the effortlessness of availability, Kerosene has continued to be used worldwide for quite a while with local livelihoods. In any case over 70% of light oil use all over the planet, observational evidence has revealed that for certain families, the decision over kerosene use and the force of its usage are educated by such innumerable factors. (Maiyoh et al., 2015).

Oyekale et al (2012), discussed the Assessment of rural families cooking energy decision during kerosene appropriation in Nigeria: A contextual investigation of Oluyole Local Government Area of Oyo State. They looked at the interest for various cooking energy sources when execution of kerosene endowment and confirmed that of fuel wood/charcoal. Their results uncovered that the extent of families that relied upon kerosene expanded from 49.2% before the sponsorship to 60.83% after the endowment. Likewise 16.67 and 14.17% of the respondents gathered kindling when the subsidy, separately. Danlami (2017) dealt with an Intensity of Household Kerosene use in Bauchi State, Nigeria. Tobit model was assessed to look at the effect of the family's financial and segment attributes on the power of the utilization of lamp fuel and utilization. The outcome demonstrated that degree old enough of the family head, residing in the metropolitan areas of Bauchi State, cost of kindling and pay, essentially affect the power of family utilization of lamp fuel. His result demonstrated that degree old enough of the family head, residing in the metropolitan areas of Bauchi State, cost of kindling and pay, fundamentally affect the force of family utilization of lamp fuel. Then again, cost of lamp fuel and neighborhood wellspring of lighting were found to contrarily affect the force of family lamp oil use in Bauchi State. Audu (2013) portrayed Nigeria as a rich country in mask prompting high neediness rate and joblessness especially in provincial regions. Numerous Nigerians are living underneath neediness level and as such can't bear the cost of the expense of lamp fuel, which is presently a fundamental ware and more costly than petroleum. For example, petroleum is being sold for one hundred and 67 naira (N167) per liter, comparable amount of lamp oil sells at 400 (N400) in most filling stations the nation over. This makes most Nigerians to rely upon "nature" for energizes, subsequently high pace of fuel-wood utilization, prompting unreasonable extraction and consumption as a rule. The purpose of this work is to use the Bayesian and Pettitt method to detect change points in the price of Kerosene for the six States in the Southwestern region of Nigeria. The rest of the paper is structured as follow: section 2 presents the materials and methods, section 3, data analysis and results while section 4 presents the conclusion.

2. Materials and Methods

In this section, the discussed on the data used. The considered test and methods were also discussed. These methods are the Mann-Kendal trend test, Pettitt change point analysis and the Bayesian method of change point.

2.1 Data Description

The data for this research work were collected from the National Household Kerosene Price Watch on average cost per litre paid by customers for National Household Kerosene in Nigeria. Kerosene price data for six southwestern states were collected which spanned from 2015 and 2021. These states includes Ekiti, Lagos, Ogun, Ondo, Osun and Oyo.

2.2 Mann-Kendall Trend Test

Mann-Kendall pattern test is broadly used to recognize patterns in time series information. In the Mann-Kendall pattern test, the invalid theory (H0) of information in a period series are autonomous and indistinguishably disseminated irregular factors was tried against the speculation (H1) of a pattern in the series. Factual boundary (S0) is characterized as

$$S_0 = \sum_{k=1}^{n-1} \sum_{j=k+1}^{n} \operatorname{sgn}(x_j - x_k) \tag{1}$$

where n is the length of the series, $k = 1, 2, \ldots, n - 1$, $j = 2, 3, \ldots, n$, and

$$\operatorname{sgn}(x_j - x_k) = \begin{cases} 1, & (x_j - x_k) > 0, \\ 0, & (x_j - x_k) = 0, \\ -1, & (x_j - x_k) < 0. \end{cases} \tag{2}$$

It has been proven that when $n \geq 8$, S_0 follows approximately the normal distribution with 0 mean and the variance as

$$Var(S_0) = \frac{[n(n-1)(2n+5)]}{18} \tag{3}$$

Standardizes statistic Z can be calculated as

$$Z = \begin{cases} \dfrac{S_0 - 1}{\sqrt{Var(S_0)}}, S_0 > 0, \\ 0, \qquad\qquad S_0 = 0, \\ \dfrac{S_0 + 1}{\sqrt{Var(S_0)}}, S_0 < 0. \end{cases} \tag{4}$$

Negative Z value denotes downward trend and positive Z value shows upward trend. The trend is significant at the 95% confidence level $|Z| > 1.96$ and vice versa.

2.3 Pettitt Change Point Analysis

Sudden changes in the mean or fluctuation of a period series can cause nonstationarity in the series. To recognize potential movements, standard change-point strategies have been applied to different time series information. One kind of homogeneity (no change-point) test is the Pettitt test (Pettitt, 1974), which is a nonparametric test, which means that there is no assumption on the underlying distribution.

To play out two-tailed hypothesis test on the area boundary (mean), the Pettitt test measurement is determined as

$$D_{ij} = \begin{cases} -1, & x_i < x_j, \\ 0, & x_i = x_j \\ 1, & x_i > x_j \end{cases} \tag{5}$$

where x_i and x_j relate to the extent of variable viable and x_i precedes x_j in time. For assessment over the whole sample (T years), these D statistics are joined as follows:

$$U_{t,T} = \sum_{i=1}^{t} \sum_{j=t+1}^{T} D_{ij} \tag{6}$$

The statistic U_t is identical to a Mann-Whitney measurement for testing that the two samples $X_1, \ldots, X_t$ and $X_{t+1}, \ldots, X_T$ come from a similar populace. The test measurement is assessed for all potential upsides of t going from 1 to T. The most plausible year of a change-point happening is assessed utilizing a two-tailed test on this statistic:

$$K_T = max|U_{t,T}| \tag{7}$$

If the statistic K_T is significantly not the same as 0, a change-point happens in the year t comparing direct on schedule for which the biggest outright worth of $U_{t,T}$, is gotten. The probability of a change in a year where $|U_{t,T}|$ is the most extreme is assessed by

$$p = 2\ exp\left(\frac{-6K_T^2}{T^3 + T^2}\right) \tag{8}$$

Given a specific importance level α, if P < α, the null hypothesis is rejected and infer that X_t is a huge change point at level α. The two critical levels (α = 0.05 and α = 0.10) are utilized in this work.

2.4 Bayesian Method of Change Point

According to Waheed B. Y. etal (2017), the Bayesian way to deal with change point issue consider the prior information, the model accepted and observed data to form prior distribution to display the information into posterior distribution to demonstrate related investigation. The Bayesian methodology in this study depends on single shifting model distribution and the obscure change point.

As opposed to the traditional methodology, the Bayesian strategies consider the the parameter of the model as random variables represented by a statistical distribution (prior distribution) rather than fixed values.

The Bayesian strategies license the incorporation of statistical analysis through the prior distribution with the latest data in light of the perceptions into a posterior distribution. The analysis included getting the mean worth when the change, how much the change and the variety in perceptions. This study examined two related issues, that of the discovery and assessment of the change point.

Assume that there is a succession of independent normal random variables, $y_1, y_2, \dots, y_n$. These are seen alongside time. This succession is said to have a change at a time point τ frequently called a change point if $\mu_1 \neq \mu_2$

$$Y_i \sim \begin{cases} \aleph(\mu_1, \sigma^2), & i = 1,2,\dots,\tau \\ \aleph(\mu_2, \sigma^2), & i = \tau+1, \tau+2 \dots, T \end{cases} \qquad (M_1)$$

where $\aleph(\mu, \sigma^2)$ represents normal distribution with the density function given below

$$f(\mu, \sigma^2) = \frac{1}{\sigma\sqrt{2\sigma}} exp\left\{-\frac{(y-\mu_r)^2}{2\sigma^2}\right\}, \quad y \in \mathbb{R} \qquad (9)$$

The parameters $\mu_1, \mu_2, and\ \sigma^2$ represent the change point, the mean when the unexpected change and the variance of the series respectively. The prior distribution of are thought to be a similar normal distribution given in the equation next:

$$p(\theta) = p(\sigma^2)p(\mu_1|\sigma^2)p(\mu_2|\sigma^2)p(\tau|M_1)$$

$$= \begin{cases} \mu_1 \,|\, \sigma^2 \sim \aleph(\phi_1, \sigma^2 k_1) \\ \mu_2 \,|\, \sigma^2 \sim \aleph(\phi_2, \sigma^2 k_2) \\ \sigma^2 \sim IG\left(\frac{v_0}{2}, \frac{v_0 \sigma_0^2}{2}\right) \end{cases} \qquad (10)$$

The studies on change point issues have continuously being partitioned into two sections. The initial segment is to detect the presence of changes, and that means to test the no-change of model by Eq. 3

$$Y_i \sim \aleph(\mu_1, \sigma^2), \quad i = 1,2,\dots,T \qquad (11)$$

against the change model (1) using the Bayes factor or the posterior probability.

The likelihood function resulting from T observations $y = (y_1, y_2, \dots, y_\tau)$ generated model M_1 can be written as

$$p(y|\mu_1, \mu_2, \sigma^2) = \prod_{i=1}^{\tau} \aleph(\mu_1, \sigma^2) \prod_{i=\tau+1}^{T} \aleph(\mu_2, \sigma^2)$$

$$= \left(\frac{1}{2\pi\sigma^2}\right)^{\left(\frac{T}{2}\right)} exp\left\{-\frac{\tau}{2\sigma^2}[s_1^2 + (\bar{y}_\tau - \mu_1)^2]\right\}$$

$$\times exp\left\{-\frac{T-\tau}{2\sigma^2}[s_2^2 + (\bar{y}_{T-\tau} - \mu_2)^2]\right\} \qquad (12)$$

where

$$\bar{y}_\tau = \sum_{i=1}^{\tau} \frac{y_i}{\tau}, \qquad \bar{y}_{T-\tau} = \sum_{i=\tau+1}^{T} \frac{y_i}{T-\tau},$$

$$s_1^2 = \sum_{i=1}^{\tau} \frac{(y_i - \bar{y}_\tau)^2}{\tau}, \qquad s_2^2 = \sum_{i=\tau+1}^{T} \frac{(y_i - \bar{y}_{T-\tau})^2}{T-\tau}$$

The likelihood (12) has the construction of a product of two normal distributions with one inverted gamma distribution for fixed τ which proposes a specially normal – inverted gamma distribution type to address prior knowledge about μ and σ^2. Accepting for model M_1 prior independence between τ and different parameters μ_1, μ_2, σ^2 and that $p(\tau \mid M_1)$ is any discrete distribution on the set {1, 2, - - - . T-1} prompts joint prior parameter p.d.f.

$$p(\mu_1, \mu_2, \sigma^2, \tau | M_1) = \aleph(\mu_1 \mid \phi_1, k_1\sigma^2)\, \aleph(\mu_2 | \phi_2, k_2\sigma^2) IG\left(\sigma^2 \mid \left(\frac{v_0}{2}\right), \left(\frac{v_0\sigma_0^2}{2}\right)\right) \times p(\tau \mid M_1)$$

$$= \aleph\aleph IG\left(\mu_1, \mu_2, \sigma^2 \mid \phi_1, \phi_2, k_1, k_2, \left(\frac{v_0}{2}\right), \left(\frac{v_0\sigma_0^2}{2}\right)\right) p(\tau \mid M_1) \tag{13}$$

In view of conjugate properties (Berger, 1985), under , the conditional joint posterior distribution $p(\mu_1, \mu_2, \sigma^2 \mid \tau, y, M_1)$ given τ and the observed data y likewise has a place with the class of normal – inverted gamma distributions however with updated parameters $\phi_1', \phi_2', k_1', k_2', \frac{v_n}{2}, \frac{v_n\sigma_n^2}{2}$.

Because of conjugate properties (Berger, 1985), under M_1, the conditional joint posterior distribution $p(\mu_1, \mu_2, \sigma^2 \mid \tau, y, M_1)$ given τ and the observed data y also belongs to the class of normal – inverted gamma distributions but with updated parameters $\phi_1', \phi_2', k_1', k_2', \frac{v_n}{2}, \frac{v_n\sigma_n^2}{2}$. All the more exactly,

$$p(\mu_1, \mu_2, \sigma^2 \mid \tau, y, M_1) = \aleph\aleph IG\left(\mu_1, \mu_2, \sigma^2 \mid \phi_1', \phi_2', k_1', k_2', \frac{v_n}{2}, \frac{v_n\sigma_n^2}{2}\right) \tag{14}$$

Where,

$$\phi_1' = (1 - k_1'\tau)\phi_1 + k_1'\tau\bar{y}_\tau \ , \quad \phi_2' = \left(1 - k_2'(T-\tau)\right)\phi_2 + k_2'(T-\tau)\bar{y}_{T-\tau}$$

$$k_1' = \frac{k_1}{(1+\tau k_1)} \ , \quad k_2' = \frac{k_2}{(1+(T-\tau)k_2)} \ ,$$

$$\sigma_n^2 = \frac{1}{v_n}\begin{pmatrix} v_0\sigma_0^2 + (\tau-1)s_1^2 + (1-\tau k_1')(\bar{y}_\tau - \phi_1)^2 + (T-\tau-1)s_2^2 \\ +(1-(T-\tau)k_2') + (\bar{y}_{T-\tau} - \phi_2)^2 \end{pmatrix},$$

$$v_n = v_0 + T$$

The prior predictive density can be expressed as

$$p(y \mid \tau, M_1) = \left(\frac{1}{2\pi}\right)^{\frac{T}{2}} \sqrt{\frac{k_1'k_2'}{k_1k_2}} \frac{\left(\frac{v_0\sigma_0^2}{2}\right)^{\frac{v_0}{2}}}{\left(\frac{v_n\sigma_n^2}{2}\right)^{\frac{v_n}{2}}} \frac{\Gamma\left(\frac{v_n}{2}\right)}{\Gamma\left(\frac{v_0}{2}\right)} \tag{15}$$

In this case, is obscure and its is unknown and its marginal posterior distribution $p(\tau \mid y, M_1)$ must be determined. Involving Bayes theorem and the prior density in Eq. (15), the marginal density of the change point τ = 1, 2, … , T-1 under model M_1 apparently is

$$p(\tau \mid y, M_1) = \frac{p(y \mid \tau, M_1)p(\tau \mid M_1)}{\sum_{\tau=1}^{T-1} p(y \mid \tau, M_1)p(\tau \mid M_1)}$$

$$\propto p(\tau \mid M_1)\sqrt{k_1'k_2'}\left(\frac{v_n\sigma_n^2}{2}\right)^{\frac{v_n}{2}} \tag{16}$$

This condition is discrete and gives the back posterior probability of shift event in the mean level expecting a change happened with sureness.

The computation in this strategy may not be communicated in a basic structure yet can be assessed utilizing Monte Carlo Chain approach.

3. Data Analysis and Results

Table 1 shows the descriptive statistics of the price of Kerosene for the southwestern states under study. The average value of the price of kerosene recorded for the states, the minimum and maximum values of prices for each location are displayed.

Table 1. Descriptive statistics

	Ekiti	*Lagos*	*Ogun*	*Ondo*	*Osun*	*Oyo*
Mean	293.1245	295.9941	297.9263	294.5641	291.9637	280.1544
Standard Error	6.495952	7.089051	6.376604	6.233299	7.183092	6.246633
Median	305	296.88	315.28	309.3	300	288.02
Mode	333.33	266.67	330.21	320.51	275	307.27
Standard Deviation	54.73586	59.7334	53.73022	52.52271	60.52581	52.63506
Sample Variance	2996.015	3568.079	2886.937	2758.635	3663.373	2770.45
Kurtosis	0.571521	0.112553	0.283359	0.391368	0.875484	0.835695
Skewness	-0.42123	-0.26816	-0.83147	-0.61982	-0.4935	-0.59501
Range	277.7	295.26	260.09	251.26	324.29	280.55
Minimum	167.54	160.3	165.35	172.81	140	142.78
Maximum	445.24	455.56	425.44	424.07	464.29	423.33
Sum	20811.84	21015.58	21152.77	20914.05	20729.42	19890.96
Count	71	71	71	71	71	71

The total number of data analyzed was seventy-one (71). Oyo State has the lowest mean price of kerosene in the six States of the southwestern region of Nigeria between 2015 and 2021 with mean of ₦280.1544 and standard deviation value of ₦52.63506. The standard deviation for the States indicates that the data point is close to the mean. The Kurtosis shows that the distribution is platykurtic and the skewness shows that it is negatively skewed i.e., the data is skewed to the left.

3.1 Trends of Price of Kerosene for Southwestern States

The results below show the trend price of kerosene for six Southwestern states in Nigeria. Mann Kendall statistic test Z values are recorded for the indexes at the 95% confidence level significant.

Table 2. Mann Kendall trend analysis for price of Kerosene

Location	Available data	Z-statistic	P-value
Oyo	2015-2021	9.502237	0.041227
Ogun	2015-2021	2.48551	0.044723
Osun	2015-2021	2.75082	0.008264
Ondo	2015-2021	1.54190	0.03855
Lagos	2015-2021	1.36459	0.016446
Ekiti	2015-2021	0.24475	0.017237

Table 2 shows the Mann Kendall trend analysis for price of kerosene for different southwestern states in Nigeria. For Oyo, a Z-statistic value of 9.502237 indicating an upward trend and a p-value of 0.041227 therefore significant was produced. The result for Ogun State showed a Z-statistic value of 2.48551 indicating a upward trend and a p-value of 0.044723 therefore significant. Osun State also produced a Z-statistic value of 2.75082 indicating a upward trend and a P-value of 0.008264 therefore significant. For Ondo State, a Z-statistic value of 1.5419 indicating a upward trend and a p-value of 0.03855 therefore significant was produced. For Lagos State, a Z-statistic value of 1.36459 indicating an upward trend and a P-value of 0.016446 therefore significant was also produced. Lastly for Ekiti State, with a Z-statistic value of 0.24475 indicating an upward trend and a p-value of 0.017237 significant. All the states showed an upward trend. The *p-value* for all the States showed that there is a monotonic trend in the price of Kerosene.

3.2 Change - Point Detection Using Pettitt Analysis

Change point analysis indicates different results for the different States under study. The general observations for all the six States indicate an increasing trend for all the states producing a significant p-values.

Table 3. Change point analysis in annual price of Kerosene for Southwestern States

	Changepoint-Pettitt						
Location	Shift year	Mean regime 1	Mean regime 2	Change %	Change Direction	P-value	Remark
Oyo	2018(9)	0.06633	0.73344	79.977	upward	2.115e-08	S
Ogun	2018(8)	0.325373	0.37186	5.350789	upward	1.164e-08	S
Osun	2018(8)	0.04186	0.07310	2.87567	upward	3.678e-08	S
Ondo	2018(8)	0.20713	0.91843	68.86963	upward	4.517e-08	S
Lagos	2017(4)	0.082218	0.16047	24.26923	upward	2.268e-08	S
Ekiti	2017(3)	0.160714	0.81005	64.1659	Upward	1.414e-07	S

*S means significance

Table 3 shows the Pettitt change point analysis in annual price of Kerosene for Southwestern States. Annual price amount for the common period indicated a significant upward shift at all stations. The result also shows the change point dates in each of the States; April 2017 for Lagos, March 2017 for Ekiti, August 2018 for Ogun, Ondo, and Osun and September 2018 for Oyo.

3.3 Bayesian Change Point Results

Table 4 shows the result for the change point in the data on the price of kerosene using the Bayesian approach. The table shows the posterior probability, posterior mean and the respective corresponding prices at each change points. The values in parentheses simply refers to the months i.e. 1- January, 2-Febrauary and till the last month 12-December. This applies to all the Tables.

Table 4. Bayesian Change Point (bcp) summary for Ekiti

Year	Probability	Posterior Mean	Corresponding Price
2015(11)	0.996	187.5	187.50
2015(12)	0.994	280.5	280.70
2016(5)	1.000	197.9	187.50
2016(12)	1.000	263.2	249.17
2017(2)	1.00	425.1	412.50
2017(7)	1.000	300.4	292.50
2017(10)	0.848	241.3	250.00
2018(7)	0.740	281.5	281.37
2018(10)	0.900	323.8	339.22
2019(3)	0.830	289.6	296.84
2021(3)	0.852	333.1	333.33

Table 5. Bayesian Change Point (bcp) summary for Lagos

Year	Probability	Posterior Mean	Corresponding Price
2016(6)	1.000	195.6	160.30
2016(12)	1.000	285.9	250.00
2017(2)	1.000	427.2	455.56
2019(4)	0.936	281.3	272.02

Table 6. Bayesian Change Point (bcp) summary for Ogun

Year	Probability	Posterior Mean	Corresponding Price
2015(10)	0.100	206.6	200.00
2016(6)	1.000	183.2	165.35
2016(11)	0.856	315.1	327.92
2016(12)	0.816	257.5	246.67
2017(1)	0.998	320.1	324.44
2017(2)	1.000	423.7	425.44

Table 7. Bayesian Change Point (bcp) summary for Ondo

Year	Probability	Posterior Mean	Corresponding Price
2016(4)	1.000	206.3	209.17
2016(5)	0.998	351.7	352.58
2016(11)	1.000	282.0	285.71
2017(2)	1.000	413.1	424.07
2017(7)	0.830	291.2	291.67
2017(11)	0.984	243.3	229.16
2018(8)	0.600	288.0	290.83

Table 8. Bayesian Change Point (bcp) summary for Osun

Year	Probability	Posterior Mean	Corresponding Price
2015(11)	0.976	179.2	176.85
2015(12)	0.962	268.2	270.18
2016(1)	1.000	185.6	182.92
2016(2)	1.000	353.8	354.76
2016(4)	0.990	154.1	140.00
2016(5)	0.988	264.4	264.83
2016(6)	1.000	156.4	153.79
2016(12)	1.000	278.7	275.00
2017(2)	1.000	422.6	412.04
2017(7)	0.950	281.2	286.67
2017(8)	0.864	206.0	197.92
2018(8)	0.852	273.4	270.93

Table 9. Bayesian Change Point (bcp) summary for Oyo

Year	Probability	Posterior Mean	Corresponding Price
2016(1)	0.936	186.2	167.95
2016(2)	0.916	273.4	279.17
2016(3)	0.962	164.6	196.16
2016(5)	0.964	267.0	269.72
2016(6)	0.996	155.3	150.00
2016(12)	1.000	264.2	243.75
2017(2)	1.000	401.6	423.33
2017(9)	0.686	259.3	253.43
2018(9)	0.614	272.7	277.25

3.4 Discussion

This work is based on change point detection in the data on the price of Kerosene in the six states (Ekiti, Lagos, Ogun, Ondo, Osun and Oyo) of the southwestern region of Nigeria. In detecting change point in the price of Kerosene in these states, a trend test was carried out using Mann Kendall trend test. The trend test shows an upward trend and it was significant for all the six states. Also, Bayesian and Pettitt methods were used to detect where the changes are located in the data set.

Table 4 shows the Bayesian change point result for Ekiti State. The result shows that change occurred in the price of Kerosene in Ekiti in these months/years: November and December 2015, May and December 2016, February, July and October 2017, July and October 2018, March 2019 and March 2021. Table 5 shows the Bayesian change point result for Lagos State. The result shows that change occurred on the data for the price of Kerosene in Lagos in these months/years: June and December 2016, February 2017 and April 2019. Table 6 shows the Bayesian change point result for Ogun State. The result shows that change occurred in the price of Kerosene in Ogun in these months/years: October 2015, June, November and December 2016, January and February 2017. Table 7 shows the Bayesian change point result for Ondo State. The result shows that change occurred in the price of Kerosene in Ondo in these months/years: April, May and November 2016, February, July and November 2017 and August 2018. Table 8 shows the Bayesian change point result for Osun State. The result shows that change occurred in the price of Kerosene in Osun in these months/years: November and December 2015, January, February, April, May, June, and December 2016, February, July and August 2017 and August 2018. Table 9 shows the Bayesian change point result for Oyo State. The result shows that change occurred in the price of Kerosene in Oyo in these months/years: January, February, March, May, June and December 2016, February and September 2017 and September 2018.

The Bayesian method detects changes in means and also gives the posterior probabilities and posterior means for each of the States. The Pettitt method also detects a single change point in each State including the change point dates.

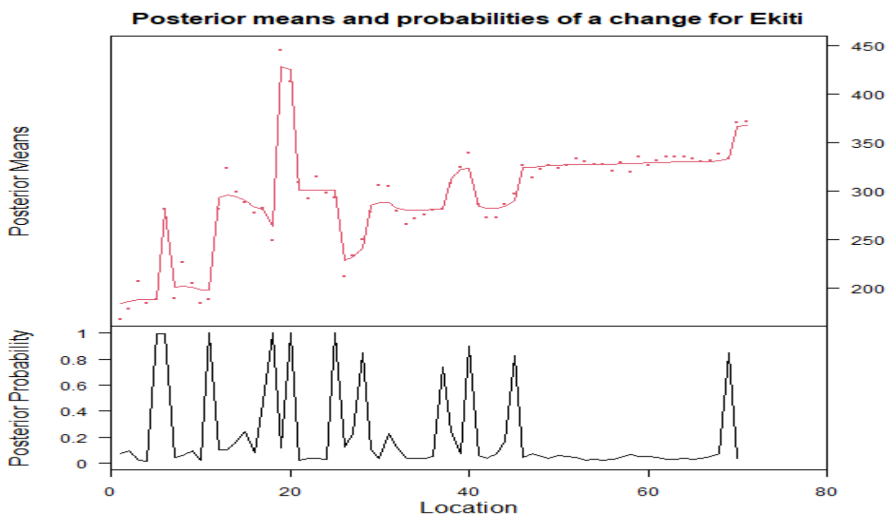

Figure 1. Plot of Probability and Posterior means for Ekiti

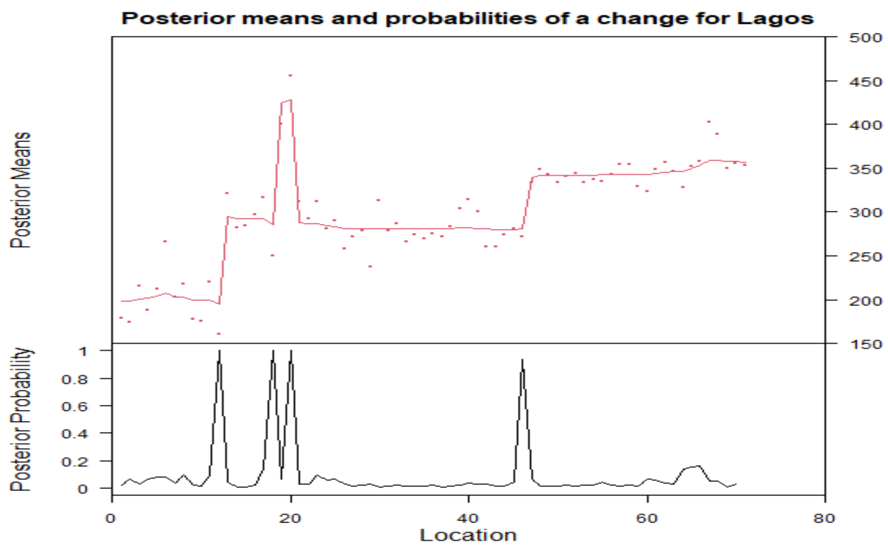

Figure 2. Plot of Probability and Posterior means for Lagos

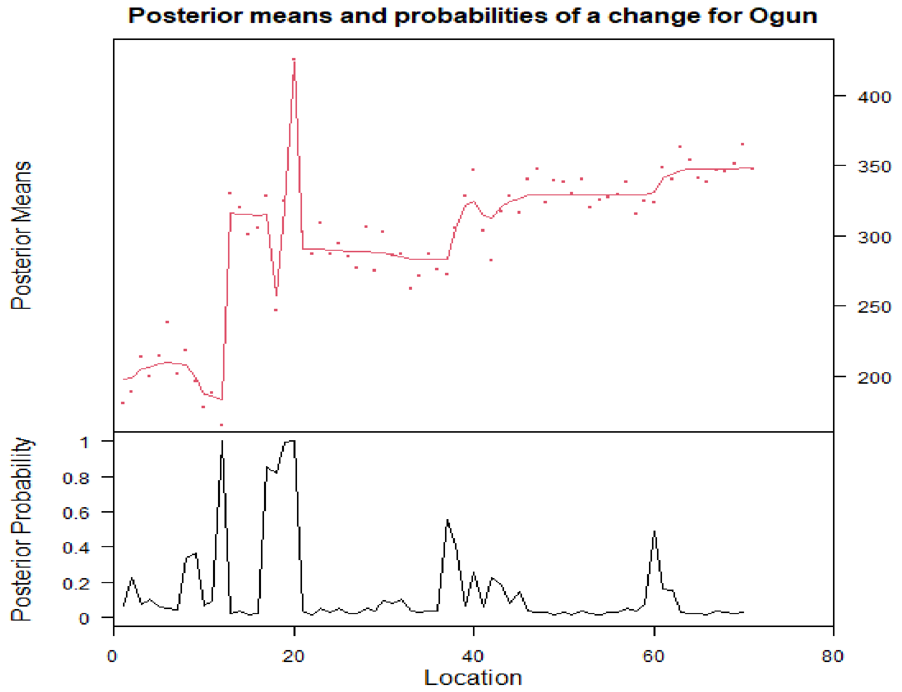

Figure 3. Plot of Probability and Posterior means for Ogun

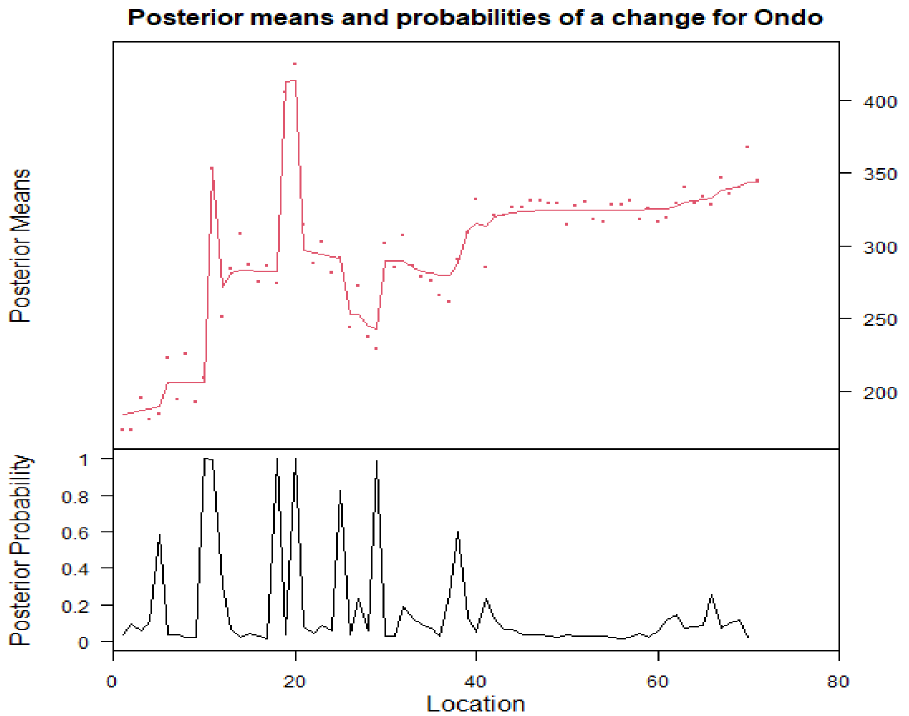

Figure 4. Plot of Probability and Posterior means for Ondo

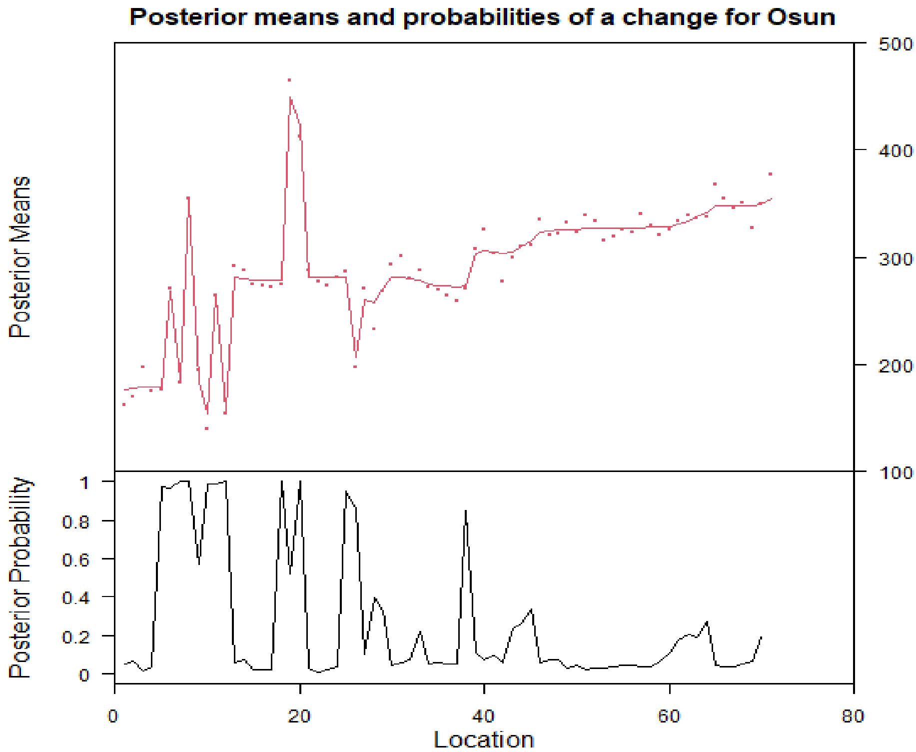

Figure 5. Plot of Probability and Posterior means for Osun

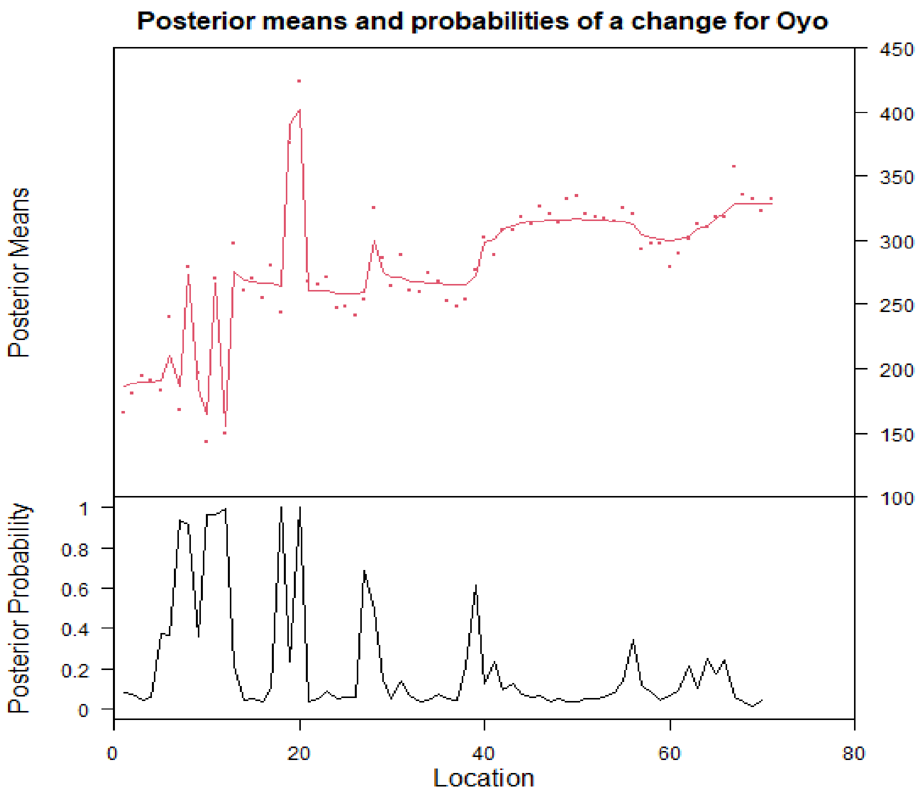

Figure 6. Plot of Probability and Posterior means for Oyo

4. Conclusion

The results of the analyses revealed that the price of kerosene for the southwestern states showed a consistent upward trends. Pettitt analysis showed the change point dates for the price of kerosene for the states. Changepoint occurred in September 2018 for Oyo State, August 2018 for Ogun, Osun and Ondo States, April 2017 for Lagos State and March 2017 for Ekiti State.

Bayesian approach also produced the probability values and posterior means for the change point dates. Bayesian change point results obtained showed that in Ekiti, change in price occurred in November and December of 2015, June and December in 2016, July and October in 2017 and 2018 and March in 2019 and 2021. For Lagos, change points in the price of Kerosene occurred in June and December in 2016, February in 2017 and April in 2019. For Ogun State, change points occurred in October 2015, June, November and December 2016, January and February 2017. For Ondo State, change points occur in April, May and November2016, February, July and November 2017, August 2018. For Osun State, change points occur in January, February, April, May, June and December 2016, February, July and August 2017 and August 2018. Lastly for Oyo State, change point occurred in January, February, March, May, June and December 2016, February 2017 and September 2018. Bayesian approach detected more change points than the Pettitt analysis.

References

[1] Audu, E.B. (2013). Fuel Wood Consumption and Desertification in Nigeria. International Journal of Science and Technology. Vol. 3, 2013.

[2] Berger, J.O. (1985). Statistical Decisions Theory and Bayesian Analysis. Springer, New York.

[3] Danlami, A.H. (2017). An Intensity of Household Kerosene Use in Bauchi State, Nigeria: A Tobit Analysis. Nigerian Jour. of Management Technology & Development, Vol 8(2), 2017.

[4] Maiyoh, G. K., Njoroge, R. W. & Tuei, V. C. (2015) Effects and mechanisms of kerosene userelated toxicity, Environmental Toxicology and Pharmacology, http://dx.doi.org/10.1016/j.etap.2015.05.010

[5] Oyekale, A. S., Dare, A. M. and Olugbire, O. O. (2012). Assessment of rural households cooking energy choice during kerosene subsidy in Nigeria: A case study of Oluyole Local Government Area of Oyo State. African Journal Of Agricultural Research, Vol.7(39), 5405-5411, 2012.

[6] Pettitt, A. N. (1979). A non-parametric approach to the change point problem. Applied Statistics, vol. 28, no. 2, pp. 126–135, 1979.

[7] Waheed B., Kazeem O.O. and Adegoke T.M.(2017). Bayesian change-point modelling of Hydrometeorological data in nigeria. 1ST International AnnualConference Of Nigeria Statistical Society, held at University of Ibadan.