IJCSE International Journal of Computer Sciences and Engineering Open Access
Research Paper Vol.-6, Issue-6, June 2018 E-ISSN: 2347-2693

Statistical Analysis on Global Temperature Anomalies

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Available online at: www.ijcseonline.org

Accepted: 08/Jun/2018, Published: 30/Jun/2018

Abstract- Temperature affects the smallest details of our daily life from what we wear to how we get to work to what we eat for lunch. Seldom can we go even a day without needing to know what the temperature is or will be. And we know that these days the temperature has been rising steadily around us and across the globe as well, thus we intended to make a study on Global temperature. The data set which we used in this paper is from the National Oceanic and Atmospheric Administration (NOAA). We have the Global temperature anomaly with respect to land and ocean from the year 1880 to 2017. Statistical techniques like Descriptive Statistics to summarize the data, Cluster Analysis to form clusters of the years that show similar kind of temperature variation, Correlation Analysis to understand the related variation between Land and Ocean temperature anomaly were carried out. Further Double Exponential Smoothing (Holt) model and ARIMA model is fitted to forecast the Land and Ocean temperature anomaly using the training set and there after the accuracy of the forecasted models has been compared by using Mean Absolute Error (MAE) and Mean Absolute Percent Error (MAPE). Finally, the model that has more accuracy is used to forecast the temperature anomaly for the year 2018 and 2019.

Keywords- Temperature anomaly, Chernoff face**,** Clusters**,** ARIMA and Holt model.

I. INTRODUCTION

Temperature is a physical quantity expressing hot and cold. Temperature is measured with a thermometer, historically calibrated in various temperature scales and units of measurement. The most commonly used scales are the Celsius scale, denoted in °C (informally, *degrees centigrade*), the Fahrenheit scale (°F), and the Kelvin scale. The Kelvin (K) is the unit of temperature in the International System of Units (SI), in which temperature is one of the seven fundamental base quantities. Temperature affects the smallest details of our daily life from what we wear to how we get to work to what we eat for lunch. Seldom can we go even a day without needing to know what the temperature is or will be. After all, few people would want to walk to work or school in a snow storm, or can enjoy a bowl of hot soup when it is upwards of 90 degrees outside. Therefore, temperature plays an important role and it is valuable to know what temperature is, how it is measured, and what implications it may have for society as a whole.

In the past few decades there are many research articles published on analysis of Global temperature (for example, [1,2,3]). Scientists use four major datasets of global temperature namely HadCRUT4 (produced by UK Met Office Hadley Centre and the University of East Anglia's Climatic Research Unit), GISTEMP (produced by the NASA Goddard Institute for Space Sciences (GISS)), MLOST (produced by National Oceanic and Atmospheric Administration (NOAA)) and JMA (produced by Japan Meteorological Agency). The global temperature records show the fluctuations of the temperature of the atmosphere and the oceans through various spans of time. The most detailed information exists since 1850, when methodical thermometer-based records began; these records are usually presented as temperature anomalies rather than an absolute temperature. **A temperature anomaly** is the difference from an average, or baseline temperature. The baseline temperature is typically computed by averaging 30 or more years of temperature data. A **positive anomaly** indicates the observed temperature was **warmer** than the baseline, while a **negative anomaly** indicates the observed temperature was **cooler** than the baseline. When calculating an average of absolute temperatures, things like station location or elevation will have an effect on the data (ex. higher elevations tend to be cooler than lower elevations and urban areas tend to be warmer than rural areas). However, when looking at anomalies, those factors are less critical.

How are these Global Temperatures Recorded?

To get a complete picture of Earth's temperature, scientists combine measurements from the air above land and the ocean surface collected by ships, buoys and sometimes satellites, too. The temperature at each land and ocean station is compared daily to what is 'normal' for that location and time, typically the long-term average over a 30-year period and hence the Daily temperature anomalies are obtains these are then averaged together over a whole month. These are, in turn, used to work out temperature anomalies from season-to-season and year-to-year. After working out the annual temperature anomalies for each land or ocean station, the next job for scientists is to divide the earth up into grid boxes. They work out the average temperature for each box by combining data from all the available stations. The smaller the grid boxes, the better the average temperature of the box will reflect the actual temperature at any given point, leading to a more accurate estimate global temperature when we add them all together. The aim of this paper is to study the pattern of Global temperature anomaly with respect to land and ocean for the year 1880 -2017 and then check if there is any relation between those anomalies. Further to provide a realistic forecast for the year 2018 and 2019 based on the latest available data.

Rest of the paper is organized as follows; Section II contains some of the related research works, Section III explains about the basic information of the data under study, Section IV summarizes the methodologies related to different techniques like Chernoff faces, Cluster Analysis and Time Series models. The various results found throughout the analysis were arranged systematically with necessary references in Section V and the major findings of the study and the conclusions notes were given in the last Section.

II.RELATED WORK

[1] uses univariate time series techniques to model the properties of a global mean temperature dataset in order to develop a parsimonious forecasting model for managerial decision-making over the short-term horizon. The statistical techniques include seasonal and non-seasonal unit root testing with and without structural breaks, as well as ARIMA and GARCH modeling. A forecasting evaluation showed that the chosen model performs well against rival models. The estimation results confirm the findings of a number of previous studies, namely that global mean temperatures increased significantly throughout the 20th century. The use of GARCH modeling also shows the presence of volatility clustering in the temperature data, and a positive association between volatility and global mean temperature. [2] analyzed daily mean surface air temperature data compiled by the Japan Meteorological Agency were considered, the original data of the temperatures were standardized using the mean values and variances of the estimated deterministic seasonal cycles. A parametric form of a non-stationary auto-regressive (AR) model to quantify the anomalies is considered, by applying it to the normalized data. The model is applied to high-pass filtered data to investigate the relation between the seasonal structure and a high-frequency variability in anomalies, which helps in determining the climatic influence on anomalies of surface air temperature in Japan. A research paper by [3] explains how Holt's exponential smoothing and Auto-Regressive Integrated Moving Average (ARIMA) model has been used to forecast zakat in Indonesia using zakat collection from 2009 to 2014, The accuracy of the two models is compared using mean absolute percentage error and mean square error. Results show that Holt's exponential smoothing best fits the zakat time series data and is therefore suitable for forecasting zakat.

III. ABOUT DATA

The data is obtained from National Oceanic and Atmospheric Administration i.e. NOAA's National Centres for Environmental Information .The data consists of Global temperature anomaly with respect to land and ocean for the year 1880 -2017 and land temperature of anomalies of some of the continents like Asia, Europe, Africa, North America, South America, Oceania from the year 1910 -2017. Global anomalies are with respect to the 20th century average and Continental anomalies are with respect to the 1910 to 2000 average**.** All computations of this work were carried out using **R (3.4.4)** software.

IV. METHODOLOGY

Cluster Analysis

Cluster analysis or clustering is the task of grouping a set of objects in such a way that objects in the same group. The basic objective in cluster analysis is to discover natural groupings of the items (or variables). It is the most important unsupervised learning problem. It deals with finding structure in a collection of unlabeled data. In turn, we must first develop a quantitative scale on which to measure the association (similarity) between objects. Unsupervised learning is the machine learning task of inferring a function to describe hidden structure from "unlabeled" data (a classification or categorization is not included in the observations). Similarity measures most efforts to produce a rather simple group structure from a complex data set require a measure of "closeness," or "similarity." There is often a great deal of subjectivity involved in the choice of a similarity measure. Important considerations include the nature of the variables (discrete, continuous, binary), scales of measurement (nominal, ordinal, interval, ratio), and subject matter knowledge. When items (units or cases) are clustered, proximity is usually indicated by some sort of distance. By contrast, variables are usually grouped on the basis of correlation coefficients or like measures of association [4].

Chernoff face

It is very important to visualize the data to common men to understand the data and its consequences. In this direction, the idea of Chernoff face which was invented by Herman Chernoff in 1973 plays an important role. It displays the data in the shape of a human face. The individual parts, such as eyes, ears, mouth and nose of face represent values of the variables by their shape, size, placement and orientation. The idea behind using faces is that humans easily recognize faces and notice small changes without difficulty [5].

Time Series Analysis

The main purpose of time series analysis to know the past, to understand the present and forecast the future. Thus it is essential to fit an appropriate model. Here we applied Auto-Regressive Integrated Moving Average (ARIMA) class models and Holt's exponential smoothing model to forecast the respective temperature anomaly for the year 2018 and 2019. First we divide the data into testing and training set. Training set consists of the respective temperature anomaly from the year 1880 to 2007 and training set consist observations from the year 2008 to 2017.

Autoregressive Moving Average (ARMA) Process:

Let $\{\varepsilon_t,\ t\geq 1\}$ is sequence of white noise with $E(\varepsilon_t)=0, V(\varepsilon_t)=\sigma^2$ The time series $\{X_t,\ t\geq 1\}$ is said to follow ARMA process of order (p,q) if it has the representation

$$X_t=\beta_1 X_{t-1}+\ldots\ldots\beta_p X_{t-p}+\varepsilon_t - \alpha_1\varepsilon_{t-1}-\ldots.-- \alpha_q\varepsilon_{t-q}$$

where $\beta_1, \beta_2 \ldots \beta_p$ are the parameters of AR process and $\alpha_1, \alpha_2 \ldots \alpha_q$ are the parameters of MA process.

Autoregressive Integrated moving average (ARIMA) Process:

Let $\{X_t, t \in I\}$ denotes the observed stationary time series. Let this series becomes stationary after d differences denote $Z_t=\partial^d (X_t)$.Where ∂= (1-B) and B is the backward shift operator .If Z_t follows ARMA (p, q) then X_t is said to follow ARIMA (p, d, q).

Using the Auto Correlation Function (ACF) and Partial Auto Correlation Function (PACF) we get an initial idea on what the underlying process is and what is its order i.e initial values for p, d and q [6, 7]. Further we have to assess the adequacy of fitted model by checking whether the model assumption is satisfied. The basic assumption is that the $\{\varepsilon_t\}$ is a white noise sequence. That is ε_t**'s** are uncorrelated random shocks with zero mean and constant variance. Theoretically, one can check this assumption using **Ljung Box test.** The null hypothesis of **Ljung–Box** test can be defined as,

H_0: Series under study is uncorrelated

H_1: Series under study is not uncorrelated

The test statistic is

$$Q= n(n+2) \sum_{k=1}^{h} \frac{\hat{\rho}_k^2}{n-k} \qquad (1)$$

In the classical time series set up it is common to assume that the white noise sequence ε_t is independently and identically distributed as Gaussian [6].To check the validity of this assumption we used **Shapiro Wilk test** for normality. The null hypothesis of the test can be defined as,

H_0**:** Sample $x_1 \ldots x_n$ came from a normally distributed population
H_1**:** Sample $x_1 \ldots x_n$ doesn't come from a normally distributed population.

The test statistic is:

$$W = \frac{\left(\sum_{i=1}^{n} a_i x_{(i)}\right)^2}{(x_i - \overline{x})^2} \qquad (2)$$

x_i -ith smallest value of x

a_i - Shapiro Wilk constant

To fit an ARIMA class model, we have to convert the non stationary time series data into stationary time series data. On the other hand, there are certain methods available where we can fit the model without converting the original series into stationary. One such method is *Exponential Smoothing* method. There are different models available on this exponential smoothing technique based on the nature of time series data. Since the data under study is a yearly data there may exists only trend component but not seasonal component, therefore double exponential smoothing (some papers like [3] referred as Hotl model) is very reliable. The mathematical representation of the Holt model is as follows.

$$S_t = \alpha y_{t-1} + (1-\alpha)S_{t-1}$$

$$b_t = \gamma(S_t - S_{t-1}) + (1-\gamma)b_{t-1} \qquad (3)$$

where α = the smoothing constant, a value from 0 to 1. When α is close to zero, smoothing happens more slowly. The best value for α is the one that results in the smallest mean squared error (MSE). There are various ways you can do this, but a popular method is the Levenberg–

Marquardt algorithm, t represents the time period. γ is a constant that is chosen with reference to α.

Forecast Performance Measures

There are several forecast performance measures available in the literature to check the accuracy of the fitted model .The forecast performance measures used in our project is The Mean Absolute Error (MAE) and The Mean Percentage Error (MPE). Suppose y_t is the actual value, f_t is the forecasted value, then $e_t=y_t-f_t$ is the forecast error and n is the size of the test set [8]. Then the mean absolute error and mean absolute percentage error is defined as,

$$MAE= \frac{1}{n}\sum_{i=1}^{n}|e_i|$$

$$MAPE= \frac{1}{n}\sum_{i=1}^{n}\left|\frac{e_i}{y_i}\right|$$

V. DESCRIPTIVE MEASURES AND VISUALIZATION OF DATA

Statistical analysis of any data begins from a look into summary statistics. The summary statistics of this data is presented in the Table 1.

Table1: Represents the descriptive statistics of Global temperature anomaly with respect to land and ocean

	LAND	OCEAN
Mean	0.064	0.048
Median	-0.05	-0.02
Kurtosis	3.179	2.552
Skewness	0.979	0.566

By looking at Table 1 we can observe that the distribution of land and ocean temperature anomaly is positively skewed. We can be also notice that the distribution of land temperature anomaly is heavier than normal distribution and ocean temperature anomaly is flatter than normal distribution.

To know the degree of relationship between Land and Ocean temperature anomaly we calculated the Pearson's Coefficient of Correlation and is found to be **0.9115.**This indicates that there exists a strong relationship between Land and Ocean Temperature anomaly.

Table2: Representing the variable for the corresponding year from 2003-2017

Variable	Year	Variable	Year
height of face	2003	height of hair	2011
width of face	2004	width of hair	2012
shape of face	2005	styling of hair	2013
height of mouth	2006	height of nose	2014
width of mouth	2007	width of nose	2015
curve of smile	2008	width of ears	2016
height of eyes	2009	height of ears	2017
width of eyes	2010		

Figure 1: Represents the Chernoff faces of Global temperature anomaly with respect to land and ocean from the year 2003 to 2017

From Figure1 the happiest and the most appealing face indicate low temperature anomaly and the face that doesn't seem to be much appealing indicates higher temperature anomaly. So lower the temperature anomaly greater is the size, structure of various Organs. Here is the list of certain observation from Figure 1

1.The height of face of Ocean is shorter than that of Land indicating temperature anomaly to be greater for Land than that of Ocean in year 2003.

2.The width of mouth of Ocean is greater than that of Land indicating temperature anomaly to be greater for Land than that of Ocean in year 2007.

3.The width of eyes of Ocean is greater than that of Land indicating temperature anomaly to be greater for Land than that of Ocean in year 2010.

4.The height of nose of Ocean is shorter than that of Land indicating temperature anomaly to be greater for Land than that of Ocean in year 2014.

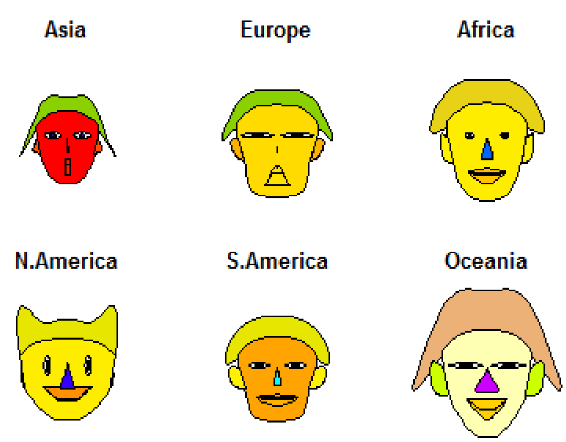

Figure 2: Represents the Chernoff faces of Continental temperature anomaly from the year 2003 to 2017

In similar way as for Land and Ocean temperature anomaly we obtained the Chernoff faces for Continental temperature anomaly for the year 2003 to 2017. From Figure 2 the happiest Face indicates the lowest temperature anomaly.

A conjecture of scientist is that, to know about the years that have similar temperature anomaly. To check this, cluster analysis is carried out on the Land and Ocean temperature anomalies of 21st Century by Ward's method of hierarchical clustering.

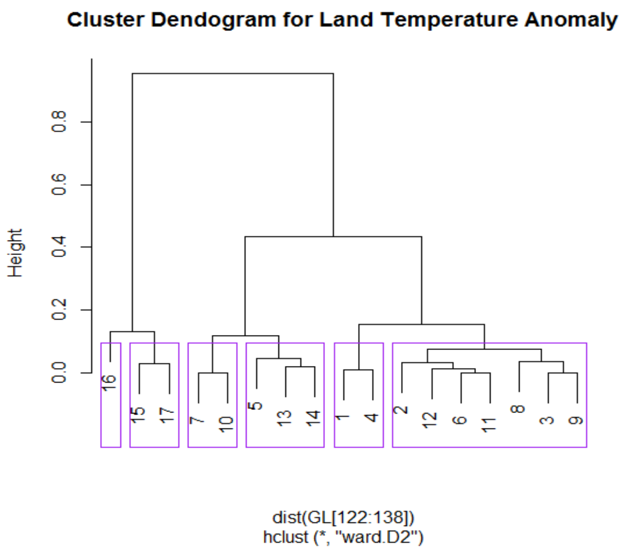

Figure 3: Represents the Dendrogram of Land temperature anomaly from the year 2000 to 2017

Table 3: Represents the Classification of years into different cluster

Cluster	1	2	3	4	5	6
Years	2016	2015 2017	2007 2010	2005 2013 2014	2001 2004	2002,2012 2006,2011 2008,2003 2009

From Figure 3, we can observe that year 2016 forms a separate cluster .Thus the Land temperature anomaly for 2016 is different from other years. We can also observe that 7years (out of 17years) form a single cluster indicating the similarity between those anomalies.

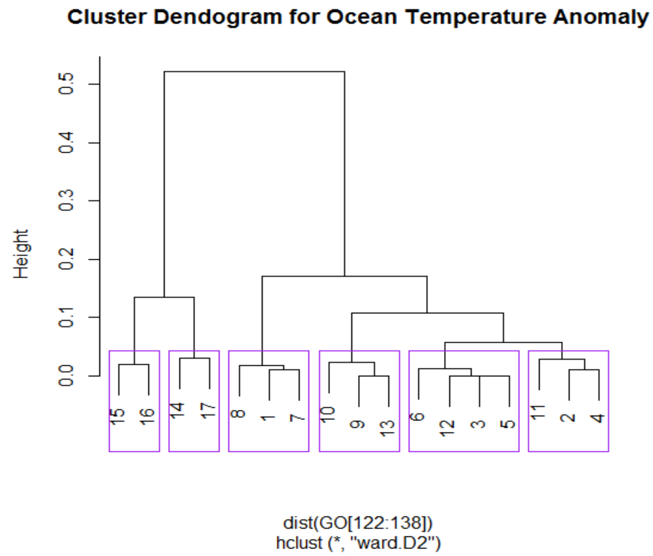

Figure 4: Represents the Dendrogram of Ocean temperature anomaly from the year 2000 to 2017

Table 4: Represents the Classification of years into different cluster

Cluster	1	2	3	4	5	6
Years	2015 2016	2014 2017	2008 2001 2007	2010 2009 2013	2006 2012 2003 2005	2011 2002 2004

From Figure 4, temperature anomaly with respect to ocean is spread almost equally over the different clusters. Hence no specific conclusion can be drawn.

Fitting ARIMA class models

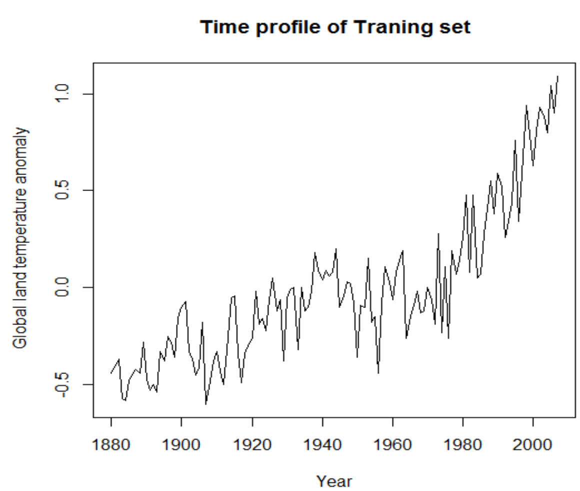

Figure 5: Represents the Time Profile of Training set

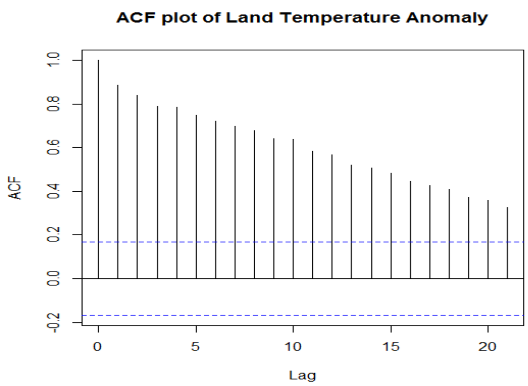

Figure6: Represents the ACF plot of Training set

Figure 5 and 6 shows clear upward trend in the data. Theoretically, one can check the presence of monotonic trend using Mann-Kendall test and computed value of this statistic is turned out to 0.665 with p-value =< 2.22e-16.Since p-value is less than level of significance (0.05) we accept the alternative hypothesis of presence of monotonic trend.

To fit ARIMA class model it is essential to transform the data under study to stationary series. We used variance difference method to bring the series into stationary. To verify the stationarity of the first difference series we use Augmented Dickey-Fuller (ADF) test. The computed value of Dickey-Fuller statistic is found to be -6.6973 with p-value = 0.01.Since p value is less than level of significance (0.05) so we reject null hypothesis and conclude that the differenced series is stationary series.

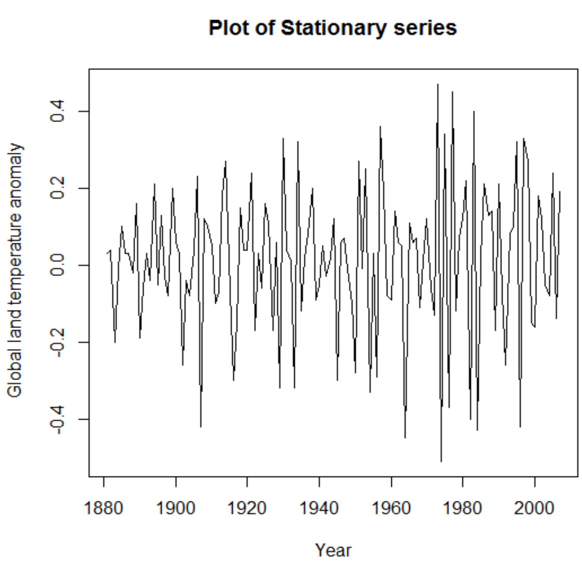

Figure 7: Represents the Plot of Stationary series

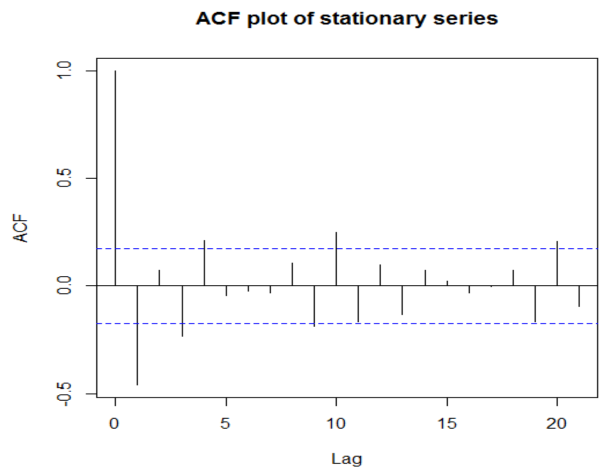

Figure8: Represents the ACF Plot of Stationary series

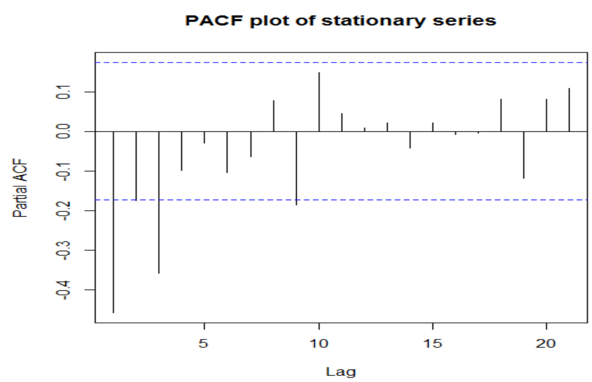

Figure9: Represents the PACF Plot of Stationary series

From the Figure 8 and 9 we identified that the orders for p=3, q=4 and since the first difference series turns out to be stationary we put d=1.This gives only an initial idea for order of the model to be fitted. Following table summarizes the results of diagnostic test procedures on residuals (Wilk's and Box p-values) and model information criteria (AIC) for some of the models among those that we tried. We choose the model with minimum AIC; however one should note that the accuracy of fitted model depends not only on AIC value but also on the assumptions of residuals.

Table 5: Represents the summary of the residuals of fitted models.

Model	AIC	Wilk's p-value	Box p-value
(3,1,1)	-2.6018	0.951	0.304
(2,1,2)	-2.5938	0.943	0.387
(0,1,1)	-2.6017	0.773	0.206
(2,1,1)	-2.5722	0.755	0.118
(2,1,3)	-2.6592	0.5942	0.5076

Among the different combination we tried, all the models have p-value's greater than 0.05 with respect Wilk's and Box test and hence we can conclude that residuals are uncorrelated and follows normal distribution. Further while observing the AIC values , ARIMA(3,1,1), ARIMA(0,1,1), ARIMA(2,1,3) seem to be the competing models. Among these three model, we have chosen ARIMA(0,1,1) it has minimum number of parameter.

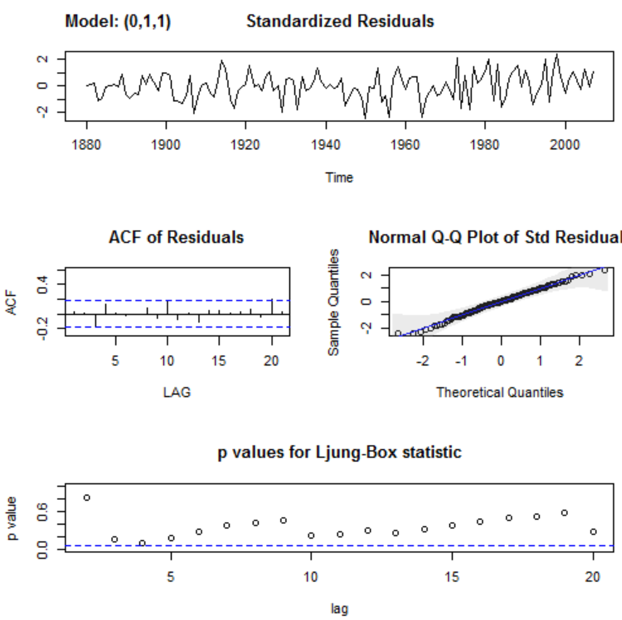

Figure10: Represents summary of residuals of ARIMA (0, 1, 1)

Table 6: Represents the summary of the Model Parameter for ARIMA (0, 1,1)

	Estimate	SE	t.value	p.value
MA1	-0.7049	0.0631	-11.1648	0.0060
Constant	0.0114	0.0043	2.6206	0.0099

Now, we use the model ARIMA (0, 1, 1) to forecast the land temperature anomaly for the year 2008 to 2017.

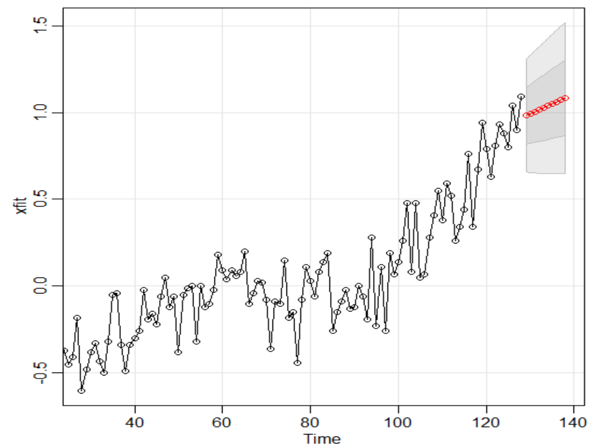

Figure 11: Represents Forecast plot using ARIMA (0, 1, 1) for the year 2008-2017

Holt Exponential Smoothing

The holt model consists of two smoothing parameters namely α and β (for level and trend) which can be either manually set or the function *HoltWinter()* with gamma being set to false will identify the optimal model parameters by minimizing the AIC and BIC values. Here gamma indicates the presence of seasonality, since the data under study has only trend component we use the *HoltWinter()* with gamma being set to false. We obtained the smoothing parameters as follows.

Alpha: 0.2618197

Beta: 0.07158208

Further we forecast using these smoothing parameters

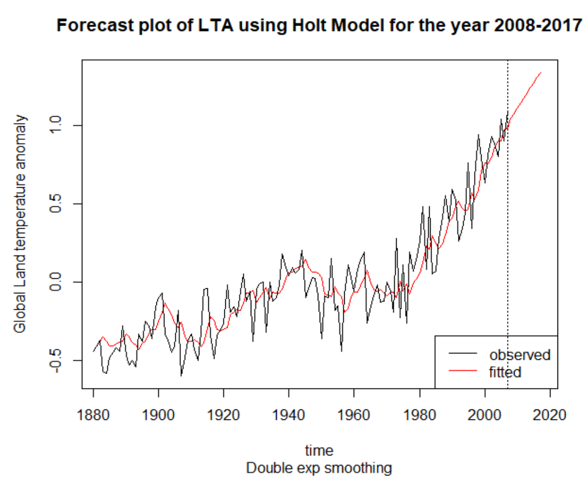

Figure12: Represents Forecast plot using Holt Model for the year 2008-2017

Now, we compare the Holt's exponential smoothing and ARIMA forecasting for the Land temperature anomaly from year 2008-2017

Table 7: Represents the comparison of Holt's exponential smoothing and ARIMA forecasting for Land Temperature Anomaly (LTA) for year 2008-2017

Year	Actual LTA	Forecast of LTA Holt's Model	Forecast of LTA ARIMA(0,1,1) Model
2008	0.85	1.0428	0.9825
2009	0.88	1.0755	0.9884
2010	1.09	1.1081	0.9994
2011	0.9	1.1408	1.0108
2012	0.91	1.1735	1.0222
2013	0.99	1.2062	1.0335
2014	1.01	1.2389	1.0449
2015	1.34	1.2715	1.0563
2016	1.44	1.3042	1.0676
2017	1.31	1.3369	1.0789
MAPE		**16.3374**	**13.3369**
MAE		**0.1587**	**0.1519**

From Table 7 we can clearly observe that the mean absolute percent error and mean absolute error for ARIMA (0, 1, 1) model is less when compared with Holt model .This indicates that ARIMA (0, 1, 1) is more suitable for forecasting the Land temperature Anomaly. Therefore we forecast land temperature anomaly for the 2018 and 2019 using ARIMA (0,1,1).

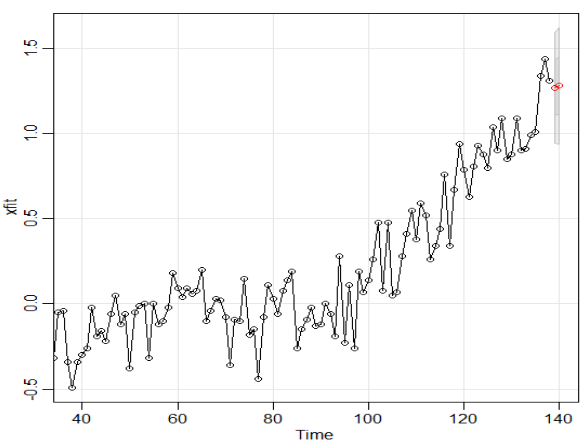

Figure13: Represents Forecast plot using ARIMA (0, 1, 1) for the year 2018- 2019

The forecasted value for the year 2018 is 1.2703 and that of 2019 is 1.2829.

In similar approach, we compared the Holt's exponential Smoothing and ARIMA forecasting for the Ocean temperature anomaly from year 2008-2017.

Table 8: Represents the comparison of Holt's exponential smoothing and ARIMA forecasting for Ocean temperature anomaly (OTA) from year 2008-2017

Year	Actual OTA	Forecast of OTA Holt's Model	Forecast of OTA ARIMA(1,1,1)Model
2008	0.42	0.4427	0.4409
2009	0.54	0.4503	0.4491
2010	0.56	0.4579	0.4559
2011	0.46	0.4656	0.4617
2012	0.51	0.4732	0.4669
2013	0.54	0.4808	0.4718
2014	0.64	0.4885	0.4764
2015	0.74	0.4961	0.4809
2016	0.76	0.5038	0.4853
2017	0.67	0.5114	0.4898
MAPE		**54.2996**	**55.0842**
MAE		**0.5949**	**0.6041**

From Table 8 we can clearly observe that the mean absolute percent error and mean absolute error for ARIMA (1, 1, 1) model is more when compared with Holt model .This indicates that Holt Model is more suitable for forecasting the Ocean temperature Anomaly for the 2018 and 2019.

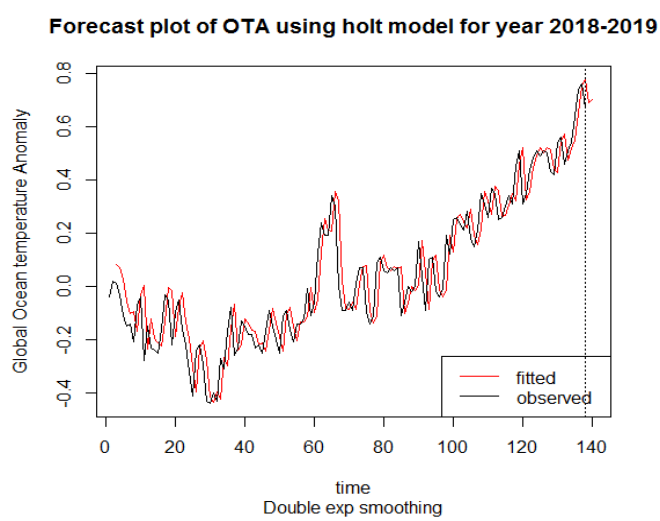

Figure 14: Represents Forecast plot using Holt Model for the year 2018- 2019

The forecasted value for the year 2018 is 0.6882 and that of 2019 is 0.7012.

VI. CONCLUSION

The coefficient of skewness calculated shows that the distribution of Land and Ocean temperature Anomaly are positively skewed. Further, from calculated coefficient of kurtosis it can be noticed that, distribution of land temperature anomaly is heavier than normal distribution and ocean temperature anomaly is flatter than normal distribution. Further we find that both land and ocean temperature anomaly vary together and there exists a strong relationship between them.

From Chernoff faces we observe that the Chernoff face on Ocean is happier and brighter and appealing when compared to that of the Chernoff face on Land which implies that the temperature is deviating more in land than in ocean.

We carried out cluster analysis on land and ocean temperature anomaly separately for the recent 17years to check the shift in its nature .With respect to land temperature anomaly we can observe that year 2016 forms a separate cluster .Thus the Land temperature anomaly for 2016 is different from other years. Further we also observe that 7 years (2002, 2003, 2006, 2008, 2009, 2011, 2012) form a separate cluster indicating the similarity between those anomalies. On the other hand temperature anomaly with respect to ocean is spread almost equally over the different clusters. Hence no specific conclusion can be drawn.

To shed light on nature of upcoming temperature anomaly, we compared ARIMA and Holt's exponential smoothing for both land and ocean temperature anomaly. For land temperature anomaly, we found that most suitable model is ARIMA (0, 1, 1) and for ocean temperature it turned out be Holt's model. Hence we used the respective Model to forecast the land and ocean temperature Anomaly for the year 2018 and 2019. We obtained the forecasted value of land temperature anomaly for the year 2018 is 0.6882 and that of 2019 is 0.7012. Also the forecasted value of ocean temperature anomaly for the year 2018 is 1.2703 and that of 2019 is 1.2829. Since these anomalies are positive; we expect *hot days* in the next two years.

When we observe the Chernoff faces on continental temperature anomaly, it shows that Oceania has the most appealing face and Asia has a really disturbing Chernoff face, which indicates that the temperature anomaly is more in Asia and least in Oceania when compared to other continents. *The methods used here to forecast temperature anomaly can also be implemented on continents.*

ACKNOWLEDGMENT

The authors would like to thank Prof. ISMAIL B. Chairman, Department of PG Studies and Research in Statistics, Mangalore University for his support.

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