Statistical model for the analysis of temperature: case study the 1895 - 2014 serie for Florida state

Modelo para el análisis de valores de temperatura: caso de estudio serie 1895-2014 del estado de Florida, EUA

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Abstract

This study applied experimental design to mean annual, mean maximum and mean minimum temperatures of Florida State, U. S. A. Considerations are: 1. Testing various continuous probability distributions, to identify the best one, to avoid experimental errors using the statistics Anderson-Darling (A-D) and P-value. The results showed the normal distribution was the best. 2. Calculations of descriptive statistical for the mean annual, mean maximum and mean minimum temperatures. The results showed very little experimental errors. 3. Constructing normal probability plotting positions to calculate return periods and probabilities of occurrence. 4. Construction of time-series analysis and its subjectivist validation, to assess annual temperature trends. The results showed upward trends for the mean annual, mean maximum and mean minimum temperatures. 5. Establishing a reliable database temperature framework for Florida State, to be used by researchers in meteorology, environmental engineering, hydrology, civil engineering, agriculture, etc.

Keywords: Experimental design, normal probability plotting positions and time-series analysis.

Resumen

Este estudio aplicó diseño experimental a las temperaturas promedio anuales, medias máximas y medias mínimas del estado de Florida, EUA. Las consideraciones son: 1. Análisis de varias distribuciones de probabilidad continua, para identificar la óptima, para evitar errores experimentales usando la estadística Anderson-Darling (A-D) y valor de p. Los resultados mostraron la distribución normal como la mejor. 2. Cálculos de estadísticas descriptivas de la temperatura media anual, media máxima y media mínima. Los resultados mostraron muy pocos errores experimentales. 3. Construcción de posiciones gráficas de probabilidad normal para calcular periodos de retorno y probabilidades de ocurrencia. 4. Estructuración de análisis de series de tiempo y su validación subjetivista, para analizar las tendencias de temperaturas anuales. Los resultados mostraron directrices alcistas de las temperaturas, para las medias anuales, medias máximas y medias mínimas. 5. Establecimiento de una infraestructura de datos de temperaturas para el estado de Florida, EUA para ser usados por investigadores en meteorología ingeniería ambiental, hidrología, ingeniería civil, agricultura, etc.

Palabras clave: diseño experimental, posiciones gráficas de probabilidad normal y análisis de series de tiempo.

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Introduction

Atmospheric observing systems were established in support of economically relevant activities such a food production, transportation, hidrometeorological and weather forecasting and lost prevention. More recently, long data-series are the base for tendency analysis in the detection of global warming and urban heat islands.

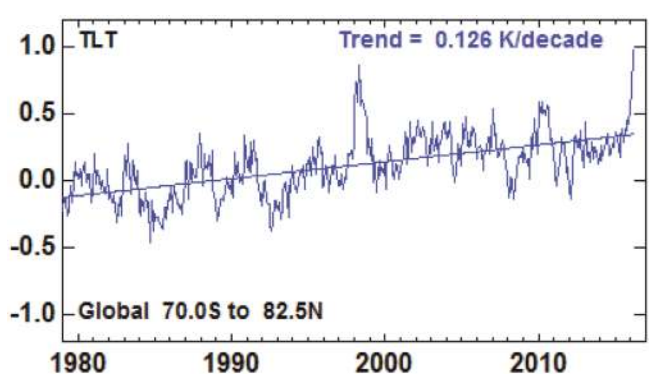
Unfortunately, certain practices that may be of little significance in an operational environment, such as relocating a station or shifting its observation time, may have a profound impact on the integrity of the historical record (Vose and Mathhew 2004). As a result, data from most existing networks needs adjustments to account for historical variations in observing practice as recognized by experts and the World Meteorological Organization (Panel on Climate Observing Systems Status 1999; Peterson *et al*. 1998). Even after the careful application of statistical adjustments, it is often not possible to address many critical aspects of climate variability and change (Karl *et al*. 1995). This situation has lead to increasingly frequent calls for the deployment of new observing systems and statistical techniques to test the validity os long data-series.

The objective of this study was the application of statistical functions to a 118-year sample of temperature data of the State of Florida, U.S.A., for period 1895-2014. The study applied experimental design techniques to identify and control background experimental errors to assure the optimization of the results. To do so, the study calculated descriptive statistics and cumulative and density probabilities aimed to check for the symmetry of the data to preclude experimental errors. Another objective was the application of a screening process to identify the most appropriate continuous probability distribution, to control experimental errors aimed at improving the results. Another directive was the establishments of normal probability plotting positions to calculate periods of return and probabilities of occurrence, for any desired temperature. Another goal was the structuring of time series statistical graphical models to predict temperature trends for wide-state Florida. Finally, the ultimate goal was the establishing of a reliable database temperature framework for Florida State, to be used by researchers in meteorology, environmental engineering, hydrology, civil engineering, agriculture, etc.

Insofar as the application of continuous probability distributions, there are several revisions done on the subject. For example, Quevedo (2012), in his book of hydrology, applied experimental design techniques, to identify the most appropriate probability function, as the normal, lognormal, gamma, Weibull, Gumbel, and so on, to minimize the experimental error, thus, to optimize de results. Additionally, Quevedo *et al*. (2014) used an analogous procedure, in a study on precipitation values of El Paso, Texas, aimed to minimize the background noise, thus to enhance the results.

Another source of information on temperatures trends is provided by the organization Remote Sensing Systems, which discusses measurement methods for upper air temperatures and temperature measurements in the lower troposphere. In (Figure 1) below shows the graph of globally averaged temperature anomaly time series for the Lower Tropospheric Temperature (TLT). The plot shows the warming of the troposphere over the last 3 decades, which has been attributed to human-caused global warming.

Figure 1. Figure showing globally averaged temperature anomaly time series for the Lower Tropospheric Temperature (TLT). The plot shows the warming trends of the troposphere over the last 3 decades, which has been attributed to anthropogenic-caused global warming. Source: Remote Sensing Systems (http://www.remss.com/measurements/upper-air-temperature).



These concerns had been fully documented by the IPCC as well as the relentless increment of recognized effects of climate change in all human and no-human vital systems (IPCC 2007). Costal communities as those in Florida, California, Tabasco and others are becoming more vulnerable to the rise of sea leavel, wildfires, heat waves and droughts. Currently, one of the mos comprehensive long-term temperature and precipitation data for the continental US states is the one provided by NOAA´s U. S. Climate database suitable for statistical models.

Materials and methods

The methodology consisted in the processing of a sample data of mean annual, mean maximum and mean minimum temperatures values for the period of 1895 to 2014 for the State of Florida, U.S.A. To accomplish such goal, the study applied several statistical functions, as descriptive statistics, and boxplot diagrams (though not shown here explicitly), to check for the symmetry of the data and the possible identification of outliers that could give to experimental errors. The study also calculated cumulative and density probabilities, to check for the symmetry and skewness of the data. The method attempted different probability graphs using the temperature values to determine the best probability distribution that fits the data, thus eliminating experimental errors. The Minitab computer program was used to do this task, because it determines the best continuous probability distribution based on the value of the Anderson-Darling goodness of fit test and the P-value, in order to control background noise. Also, the procedure arranged normal probability plotting positions to calculate periods of return and probabilities of occurrence. Finally, the process constructed time series graphical trend analyses for the prediction of mean annual temperatures and minimum and maximum annual temperatures.

This being so, this research used the temperature values shown in (Table 1) below, which displays the time, in years, from 1895 to 2014, the mean annual temperatures, the mean annual maximum temperatures and the mean minimum annual temperatures, expressed in degrees Fahrenheit (°F).

Similarly, this research prepared a summary of descriptive statistics that included the mean, the median, the standard deviation, the variance, the skewness and the maximum and minimum values. This was done to check for the symmetry of the data, to identify and control the possibility of experimental errors. Tables 2, 2a and 2b beneath show a summary of descriptive statistics using the data of Table 1.

Table 2. Table showing the values of the mean, standard deviation, median, minimum and maximum values, range. Skewness and kurtosis corresponding to the mean annual temperatures for the State of Florida.

Mean	St. Dev.	Median	Min	Max	Range	Skewness	Kurtosis
70.243	0.8909	70.2	68	72.5	4.5	0.025729	-0.10403

Table 2a. Table showing the values of the mean, standard deviation, median, minimum and maximum values, range, skewness and kurtosis corresponding to the mean minimum annual temperatures for the State of Florida.

Mean	St. Dev.	Median	Min	Max	Range	Skewness	Kurtosis
59.42	1.044	59.4	56.8	62.2	5.4	-0.03825	-0.0455

Table 2b. Table showing the values of the mean, standard deviation, median, minimum and maximum values, range, skewness and kurtosis corresponding to the mean maximum annual temperatures for the State of Florida.

Mean	St. Dev.	Median	Min	Max	Range	Skewness	Kurtosis
80.948	0.8958	81	79	83.6	4.6	0.030062	-0.1844

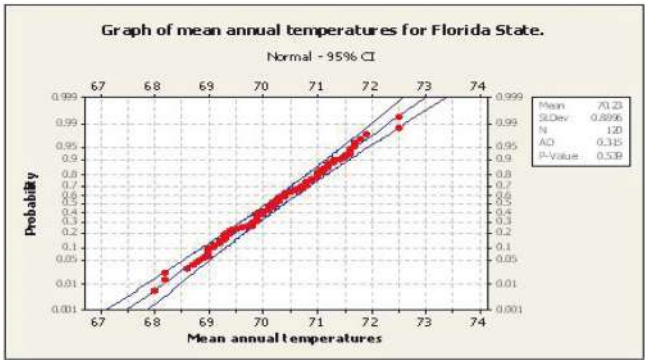
Later on, the methodology applied several continuous probability distributions, by going through a trial-and-error procedure to identify the most appropriate probability function, as the normal, lognormal, gamma, Weibull, Gumbel, and so on. This was done basing the criterion on the smallest values of the Anderson-Darling (A-D) goodness-of fit test, and on the P-value. This procedure was done to eliminate a possible source of experimental errors (which it did). For example: Figure 2. Below shows the graph of the mean annual temperatures values using the data of Table 1.

Table 1. Table showing the mean annual temperatures, the mean annual maximum temperatures and the mean minimum annual temperatures, expressed in degrees Fahrenheit (°F), for period 1895 to 2014.

Time	Mean ann. temp.	Mean max. ann. temp.	Mean min. ann. temp.	Time Cont.	Cont.	Cont.	Cont.
1895	68.7	79.1	58.4	1955	70.2	81.4	59
1896	69.9	80.3	59.6	1956	69.9	81.2	58.6
1897	70.4	80.7	60.2	1957	71	81.3	60.7
1898	70.1	80.8	59.4	1958	69	79.2	58.7
1899	70.4	80.9	59.8	1959	70.6	80.5	60.7
1900	69.9	80.2	59.6	1960	69.3	80	58.6
1901	68	79	57	1961	70	81.2	58.9
1902	69.9	80.7	59.1	1962	69.9	81	58.7
1903	69	79.6	58.4	1963	69.2	80.2	58.3
1904	69.3	80.4	58.1	1964	70.1	80.4	59.7
1905	70.1	80.4	59.7	1965	70.2	80.8	59.6
1906	69.7	79.9	59.4	1966	69	79.4	58.7
1907	70.5	81.7	59.4	1967	70.2	81.4	59
1908	70.3	81.2	59.4	1968	68.6	79.9	57.3
1909	70.2	81.2	59.2	1969	69	79.5	58.5
1910	68.2	79.6	56.8	1970	69.4	80.3	58.6
1911	71.3	82	60.5	1971	70.4	81.6	59.3
1912	70	79.9	60.1	1972	71	81.6	60.3
1913	70	80.6	59.4	1973	70.3	80.9	59.7
1914	69.1	79.6	58.5	1974	70.9	82	59.8
1915	69.1	79.6	58.6	1975	71.2	82	60.4
1916	69.6	80.5	58.7	1976	69	80	58
1917	68.8	80	57.6	1977	69.4	80.6	58.3
1918	69.8	80.4	59.3	1978	69.8	80.5	59
1919	70.4	80.6	60.1	1979	69.9	80.5	59.2
1920	69.8	79.3	58.5	1980	69.9	80.8	59.1
1921	71	82	60	1981	69.3	81	57.5
1922	71.1	81.3	60.8	1982	71.5	81.9	61.1
1923	70.1	80.5	59.6	1983	69.3	79.6	58.9
1924	69.4	79.9	58.8	1984	70	80.8	59.2
1925	70.4	81.1	59.8	1985	70.8	81.6	60
1926	69.3	80	58.6	1986	71.5	82.1	60.8
1927	71.1	82.4	59.8	1987	70.2	80.8	59.5
1928	69.3	80	58.6	1988	69.7	80.6	58.8
1929	70.7	81.1	60.3	1989	71	82	60
1930	69.2	79.4	59	1990	72.5	83.6	61.4
1931	69.9	80.7	59	1991	71.8	81.9	61.7
1932	71	81.6	60.4	1992	70.3	80.6	59.9
1933	70.9	81.6	60.1	1993	70.3	81	59.6
1934	69.8	80.6	59	1994	71.6	81.5	61.5
1935	69.8	80.7	58.9	1995	70.8	81.2	60.5
1936	70.1	80.6	59.6	1996	69.9	80.7	59
1937	69.8	80.3	59.4	1997	71.1	81.6	60.7
1938	70.2	81.3	59.1	1998	72.5	82.8	62.2
1939	70.6	81.6	59.6	1999	71.2	82.2	60.1
1940	68.2	79.2	57.2	2000	70.6	82.1	59.1
1941	69.9	80.5	59.2	2001	70.9	81.7	60.1
1942	69.4	80.7	58.1	2002	71.3	81.8	60.8
1943	69.5	81.1	57.9	2003	70.9	81.2	60.6
1944	70.2	81.4	58.9	2004	70.8	81.4	60.3
1945	70.7	81.7	59.8	2005	70.8	81	60.7
1946	71.2	81.7	60.8	2006	71.4	82.5	60.3
1947	70.3	80.4	60.3	2007	71.8	82.4	61.1
1948	71.6	82	61.2	2008	70.8	81.5	60.2
1949	71.6	82.3	60.9	2009	71.2	81.7	60.7
1950	70.3	81.4	59.1	2010	69.2	80.1	58.3
1951	70.4	81.5	59.2	2011	71.7	82.8	60.6
1952	70.3	81.2	59.4	2012	71.9	82.4	61.4
1953	70.8	81.2	60.5	2013	71.7	81.8	61.6
1954	70.1	81.3	59	2014	70.7	81.2	60.2

Source: NOAA-National Oceanic and Atmospheric Administration.

Figure 2. The normal probability graph of the mean annual temperatures for Florida State, with the goodness of fit test of the Anderson-Darling value of 0.315 and a P-Value of 0.539.



Similarly,

Figure 3. Below shows the plot of the mean maximum annual temperatures (left figure) and underneath depicts the mean minimum annual temperatures.

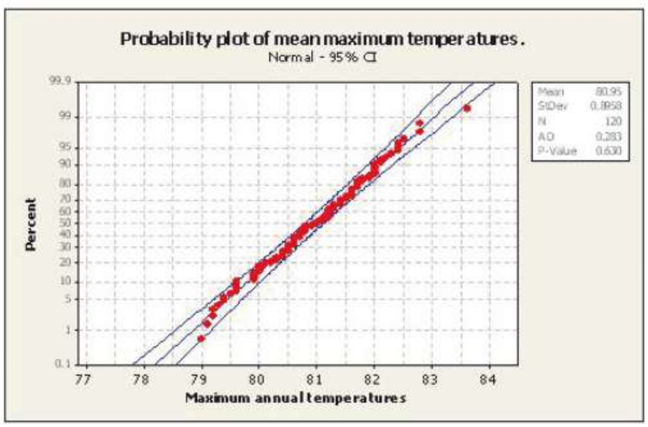
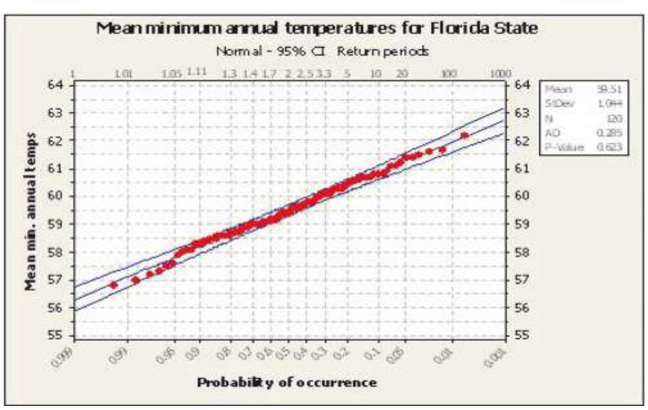


Figure 4. Left: the normal probability plot for the mean maximum annual temperatures, with the goodness of fit test of the Anderson-Darling value of 0.283 and a P-Value of 0.630. Right: the normal probability plot for the mean minimum annual temperatures, with the goodness of fit test of the Anderson-Darling value of 0.285 and a P-Value of 0.623.



Normal distribution. The methodology selected the normal distribution, as the tool to process the data. In this way, the probability density function of a random normal variable X, with μ equal to 0 (where $-\infty < \mu < \infty$) and standard deviation σ equal to 1 is:

$$\mathbf{f(x; \mu, \sigma)} = \frac{\mathbf{1}}{(\mathbf{2\pi})^{\mathbf{0.5}}\,\boldsymbol{\sigma}} \mathbf{exp} - (\mathbf{0.5}) \left[\frac{(\mathbf{x-\mu})}{\boldsymbol{\sigma}}\right]^{\mathbf{2}} \quad (1)$$

$$-\infty < x < \infty$$

Where the parameter μ is the mean of the normal distribution and where σ is the standard deviation and its variance is σ^2.

However, if μ = 0 and σ = 1, the distribution is called the normal standard distribution as shown below:

$$\mathrm{f(x)} = \frac{\exp-(0.5\,x^2)}{(2\pi)^{0.5}} \quad (1a)$$

Analogously, the cumulative normal distribution is the integral of:

$$P(x_1 < X < x_2) = \int_{x_1}^{x_2} N(x; \mu, \sigma)\, dx \quad (2)$$

$$= \frac{1}{(2\pi)0.5\,\sigma} \int_{x_1}^{x_2} \exp - (0.5) \left[\frac{x-\mu)}{\sigma}\right]^2 dx \quad (2a)$$

Since it is difficult to resolve mathematically the integral without recurring to numeric methods, it is necessary to consult the table of the normal distribution to make transformations, that is:

$$Z = \frac{X - \mu}{\sigma} \quad (3)$$

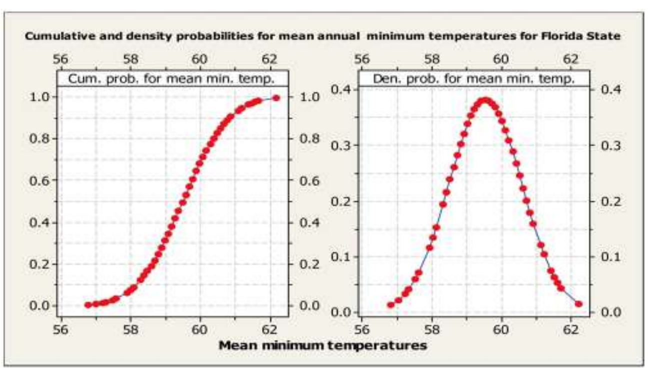
Or its statistics $$z = \left(\frac{x - \overline{X}}{s}\right) \quad (3a)$$

Later on, the methodology included a box plot diagram to identify outliers. This statistical method identifies what is called outliers or unusually large or small observations that can cause variability of the data, thus of experimental error or noise that can degrade the response variable. Though not shown here, the box plot diagrams did identify one outlier of one mean maximum annual temperature, which corresponded to a value of 83.6 ^{o}F that occurred in 1990 (see Table 1). Nonetheless, this extreme value had little effect on the experimental error.

The methodology's next step consisted in the calculation of the mean annual, mean minimum and mean maximum cumulative and density probabilities (though the values not shown here, explicitly, but only their corresponding graphs) and their graphical analysis to estimate temperature probabilities and to check for the symmetry (or skewness) of the distributions of temperatures. In this instance, Figure 5 below shows this situation. Similarly, the methodology constructed graphs for the cumulative and density probabilities for the maximum temperatures, as displayed in Figure 6 below.

Consistently, the procedures constructed the graphs for the minimum cumulative and density probabilities, as exposed in Figure 7.

Figure 5. Graph showing the cumulative and density probabilities for mean annual temperatures for Florida State. The left curve shows the cumulative probabilities and the right graph shows the density probabilities.



The next step consisted in structuring normal probability plotting positions for the mean annual; mean maximum and mean minimum temperatures, for the purpose of estimating periods of return and probabilities of occurrence, for each one of those three categories. For example, Figure 8 shows normal probability plotting position for the mean annual temperatures.

Figure 6. Graph showing the cumulative and density probabilities for mean annual maximum temperatures of Florida State. The left curve shows the cumulative probabilities and the right graph shows the density probabilities.

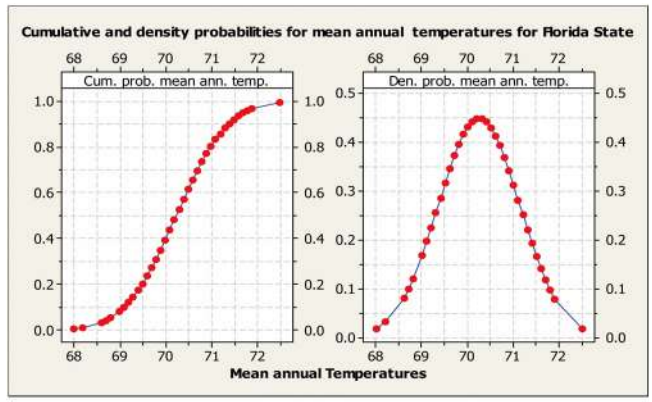
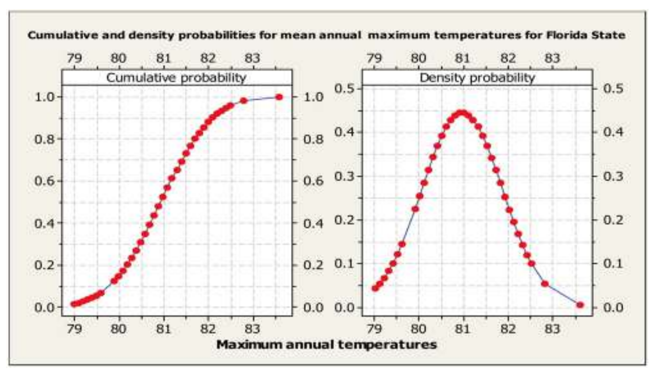


Figure 7. Graph showing the cumulative and density probabilities for mean minimum annual temperatures for Florida State. The left curve shows the cumulative probabilities and the right graph shows the density probabilities.



Similarly, Figure 9 shows the normal probability plotting position for mean minimum annual temperatures. Correspondingly, Figure 10 beneath shows the normal probability plotting position for mean maximum annual temperatures. Likewise, the methodology built a time-series graphical analysis and its residual subjectivist validation, to assess annual temperature trends for state-wide Florida. Figure 11 below depicts this situation.

Further, the residual subjectivist complementary plot validation of the time series linear trend model of Figure 11 is shown in Figure 11a.

Figure 8. Graph showing the normal probability plotting position of mean annual temperatures, as a function of periods of return and their probabilities of occurrences.

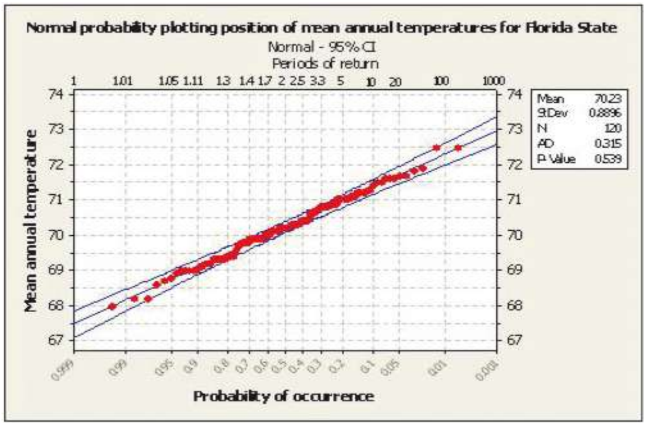
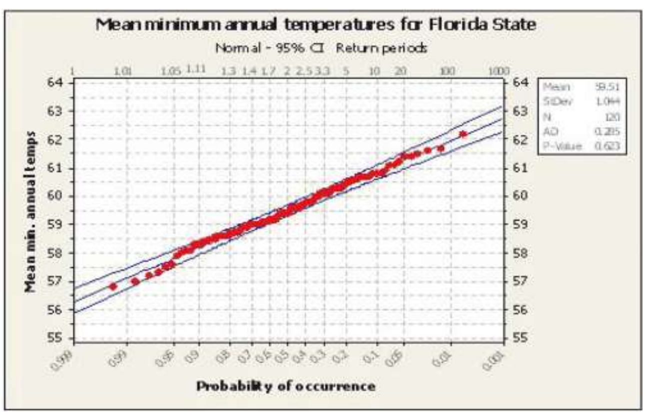


Figure 9. Graph showing the normal probability plotting position for mean minimum annual temperatures, as a function of periods of return and their related probabilities of occurrences.



Additionally, Figure 12 underneath shows the graph of the mean maximum linear trend model and its accuracy criteria of MAPE, MSD and MAD. Still, the corresponding residual subjectivist plot validation for the mean maximum temperatures of Figure 12 is shown in Figure 12a.

Figure 10. Graph showing the normal probability plotting position for the mean maximum annual temperatures, as a function of periods of return and their associated probabilities of occurrences.

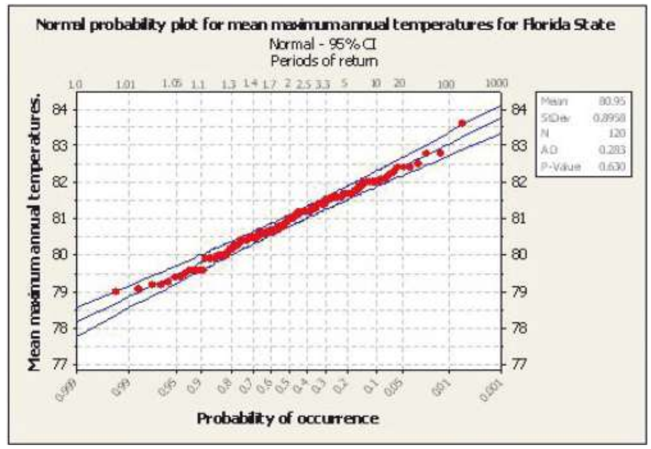


Figure 11. Graph showing the linear trend model for the mean annual temperature values of the State of Florida. This graph includes the linear trend model and MAPE, MAD and MSD accuracy measures.

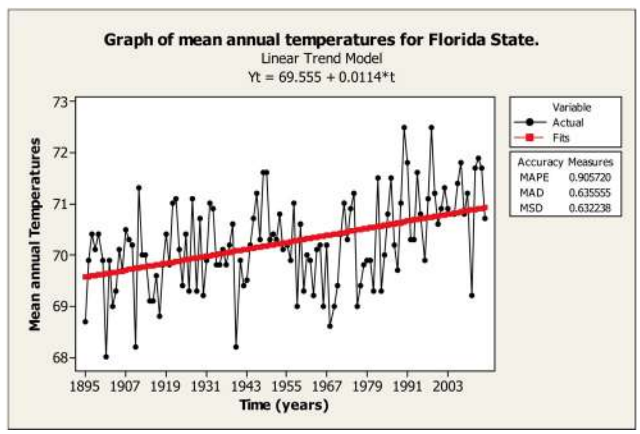


Figure 11a. Graph showing the residual plots for the mean annual temperatures, which includes the normal probability plot, the residual fitted values plot, the histogram and residual observation order plot.

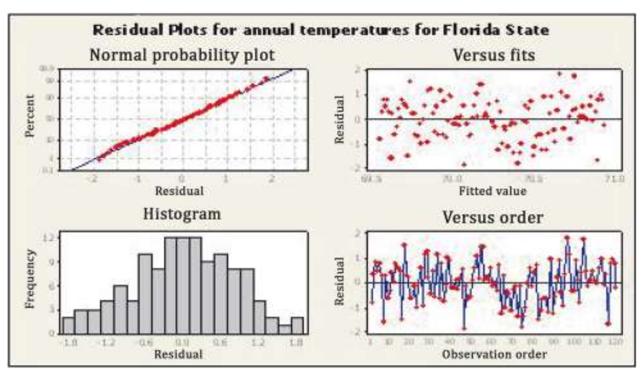


Figure 12. Graph showing the linear trend model for the mean annual maximum temperature values of the State of Florida. This graph includes the linear trend model and the values of MAPE, MAD and MSD accuracy measures.

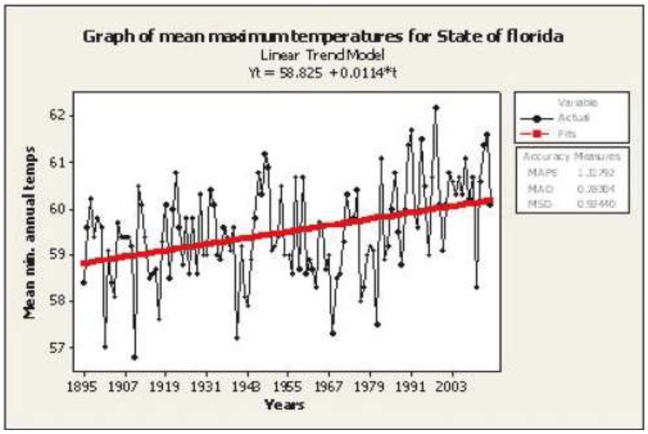


Figure 12a. Graph showing the residual plots for the mean annual maximum temperatures, which includes the normal probability plot, the residual fitted values plot, the histogram and residual observation order plot.

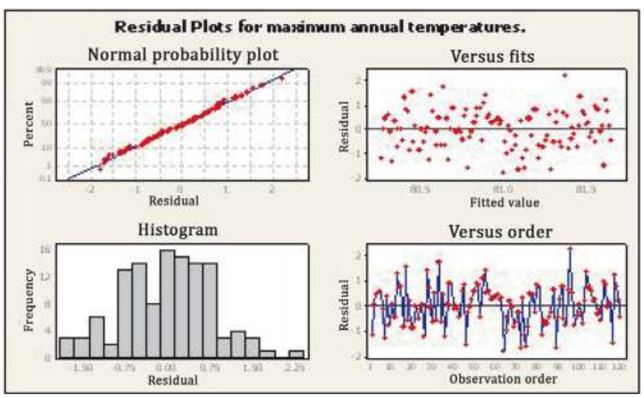


Figure 13. Graph showing the linear trend model for the mean minimum annual temperature values of the State of Florida. This graph includes the value of MAPE, MAD and MSD accuracy measures.

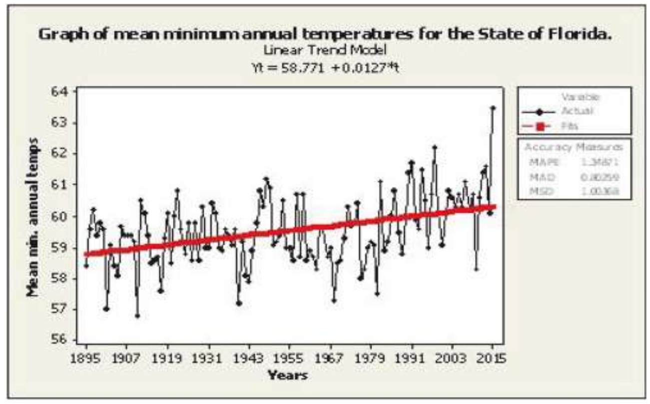
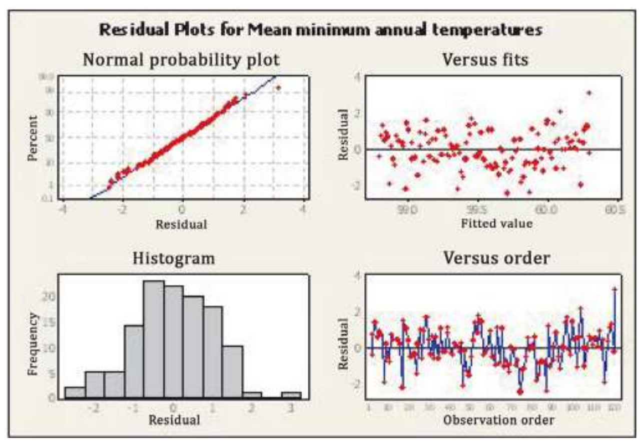


Figure 13a. Graph showing the residual plots for the mean minimum annual temperatures, which includes the normal probability plot, the residual fitted values plot, the histogram and residual observation order plot.



Similarly, Figure 13 shows the graph of the mean minimum linear trend model and its accuracy diagnostic criteria of MAPE, MSD AND MAD. Finally, Figure 13a below shows the residual subjective plots of the mean minimum temperatures that complement the results of Figure 13.

Results and discussions

Table 1 shows the mean annual temperatures values, mean annual maximum and mean minimum temperatures values expressed in degrees Fahrenheit (°F), for the period 1895 to 2014, for the State of Florida. The National Oceanic and Atmospheric Administration National Centers apportioned this information for Environmental information (https:www.ncdc.noaa.gov/cag/).

This research chose the data of temperature values of the State of Florida, because of its availability and precision. By examining Table 1, there was onlyone outlier value corresponding to the mean annual maximum value of 83.6 °F, which occurred in 1990. Aside from that, Tables 2, 2a and 2b show the values of the mean, standard deviation, median, minimum and maximum values, range, skewness and kurtosis corresponding to the mean annual, mean minimum and mean maximum annual temperatures. For example, by analyzing Table 2, which depicts the descriptive statistics for the mean annual temperatures, the values of the mean and the median are almost identical. Moreover, the relation between the mean annual value of 70.243 and the value of standard deviation of 0.8909 are very different. Likewise, the values of the skewness and kurtosis are very close to zero. These observations preclude the possibility of experimental errors that could degrade the trustworthiness of the pursued results. Similarly, by analyzing the results of Table 2a, the mean maximum value is almost the same as the median value. Too, the skewness value is close to zero. Also the value of the kurtosis of -0.1844 suggests a platikurtic (flat) distribution probably attributed to the extreme value of 83.6 ºF. For the same reason, the results of Table 2b show more symmetric values as Table 2. From the experimental design standpoint, all these observations suggest a good symmetry of the distributions of the temperatures and the absence of serious experimental errors that could compromise the predictive capability of the statistical models of this research.

Insofar as the screening process to select the best continuous probability distribution for the mean annual temperatures, the results showed the normal probability function, as the best one. This is shown in Figure 2 with an A-D equal to 0.315 and a P value of 0.539. Likewise, Figure 3 shows the normal probability plot corresponding to the mean annual maximum temperatures, with an A-D value of 0.283 and a P value of 0.630. Equally, Figure 4 shows the normal probability plot of the mean minimum annual temperature values. In this graph the ensuing goodness of fit test of the Anderson-Darling values of 0.285 and the P-value of 0.623 were the lowest values recorded, after testing several continuous probability distributions, as the lognormal, Weibull, Gamma, etc. Besides, the usefulness of the normal probability graphs is that these graphs are useful to calculate any probability (by interpolation) associated with any temperature, with a good degree of precision.

Insofar as the results of the calculations of the cumulative and density probabilities, Figures 5, 6 and 7 show the results. For example, Figure 5 shows the graphs of the cumulative and density probabilities for the mean annual temperatures. By analyzing the density probability curve, the symmetry is almost perfect; conditions that exclude experimental errors. Similarly, Figure 6 shows the cumulative and density probabilities for the mean annual maximum temperatures. By analyzing the right-hand density probability curve, it is a little skewed to the right due to the extreme value of 83.6, which occurred in 1990. Inasmuch as, Figure 7 which shows the cumulative and density probabilities for the mean annual minimum temperatures, it is seen that the symmetry of these values is almost perfect barring the existence of experimental errors that could degrade de outcomes.

About the results related to the construction of the probability plotting positions, these graphs are useful to calculate periods of return and their associated probabilities of occurrence. These probability-plotting positions are displayed in Figures 8, 9 and 10. For example, Figure 8 shows the normal probability plotting position for the mean annual temperatures, with their respective periods of return and probabilities of occurrence. Likewise, Figure 9 shows the normal probability plotting position for the mean minimum annual temperatures, with their respective periods of return and probabilities of occurrence. Lastly, Figure 10 shows the normal probability plotting position for the mean maximum annual temperatures. These graphs can be used to calculate any desired temperature and its associated period of return and probability of occurrence. For example, by analyzing Figure 8, if it is desired to calculate a period of return for a mean annual temperature of 71 ºF, its corresponding period of return is about 5 years, with a probability of occurrence of .2 and so on. Similarly, with Figure 9, if it is desired to calculate a mean minimum value of 62 ºF, its corresponding period of return is 100 years and the probability of occurrence is 0.01 and so on. Alike, with Figure 10, if it is desired to calculate a mean maximum annual temperature of 83 ºF, its period of return is 100 years and its associated probability would be .01 and so on.

Finally, about the use of the graphs of time series, its primary goal is forecasting temperature tendencies. In this particular scientific work, the major objective of these analyses is to assess annual temperature trends, as exposed in Figures 11, 12 and 13. As seen in all these figures, the resulting trend is always upward for the mean annual, mean minimum and mean maximum annual temperatures. For example, Figure 11 displays a linear trend model for the mean annual temperature. This figure includes the adjusted linear trend equation of Y_t = 69.55 + 0.0114(t). Here, if it is desired to calculate a mean annual temperature for any year, just substitute the corresponding year index in the trend equation and that will give the forecast. Moreover, this graph includes the statistics MAPE, MAD and MSD accuracy measures. In this instance, the acronym MAPE stands for Mean Absolute Percentage and measures the precision of the adjusted values in the time series analyses, which in this case, was equal to .9057. This means there is about a 0.9 percent error in the predictive capability using the adjusted linear trend model. Likewise, the acronym MAD stands Mean Absolute Deviation, which in this case was equal to 0.6355. This statistics measures the precision of the adjusted time series values and helps conceptualize the amount of error. Moreover, the resulting value of MSD, which stands for Mean Square Deviation, was equal to 0.6202. This statistics is used in the measurement of precision. In general, the lower the values of MAPE, MAD and MSD, the better off the accuracy of the prediction being pursued. About the subjectivist evaluation of Figure 11, Figure 11a depicts the normal probability plots, the fits, the histograms and the observation order plot using the residuals. All these four residual graphs serve to evaluate the utility of the linear trend model. The results of these graphs suggest the linear trend models fits the data in all cases. For example, in the normal probability plot all the points are very close to the least square line, which means there is little variation in the data values. Likewise, the graph of the fitted values shows approximately the same number of positive and negative residual values. The histogram of the residual values looks very symmetric and close to normality and so on.

About the resulting structure of a time-series graphical analyses and its subjectivist validation for the mean annual maximum temperatures of Figure 12, the trend equation is calculated as Y_t = 58.825 + 0.0114t. This equation can be used as a tool to predict futures mean maximum annual temperatures. The values of the statistics for the mean annual maximum temperatures were recorded as MAPE = 1.387, MAD = 0.783 and MSD = 0.904. In this instance the value of MAPE =1.387 measured the precision of the adjusted values, as percentage. The complementary subjectivist evaluation of Figure 12, that is, Figure 12a shows this situation. Again, by analyzing the residual normal probability plot, the great majority of the data points are very close to the fitted line. Also, the graph of the fitted values show about the same number of positive and negative values and so on.

Regarding the resulting built a time-series graphical analyses and its subjectivist validation for the mean minimum annual (Figure 13), the calculated linear trend model equation is Yt = 58.771 + 0.0127t. This equation can be used to predict future mean minimum annual temperatures. Additionally, the values of the statistics for the mean minimum annual temperatures were recorded as MAPE = 1.387, MAD = 0.8029 and MSD = 1.004. In this instance, the value of MAPE =1.387 measured the precision of the adjusted values, as percentage. The subjective evaluation of time-series graphical analyses for this temperature category is shown in Figure 13a. The results suggest the linear trend models fits the data in all cases. For example, in the normal probability plot the great majority of all the points are very close to the least square line which means there is little variation in the values, thus, little experimental errors. Likewise, the graph of the fitted values shows approximately the same number of positive and negative residual values. Besides, the histogram of the residual values looks pretty close to normality and so on.

Conclusions

This study is a unique instructive method, because it applies a deep experimental design scheme, to control experimental errors, thus, to yield more precise temperature results in the evaluation of global warming trends and their consequential climatic distortions.

Further, the methodology and the results obtained in this paper suggest that, before one attempts to processes any temperature data, it is required to check its symmetry by the use of descriptive statistics, to identify the possibility of experimental errors that can degrade the results. Besides, of utmost importance is the identification of the best continuous probability distribution that fits the data, to minimize background experimental errors (by choosing the right distribution). Too, the calculations of cumulative and density probabilities are two-fold, because they can be used to calculate cumulative or density probabilities for each one of the three categories of temperatures used. Moreover, these graphs can serve to visually check the symmetry of the data.

Congruently, the use of probability plotting positions is important to assess global warming trends, periods of return and probabilities of occurrence of heat waves that can affect the health and welfare of people. Alternatively, farmers could find useful applications of probability plotting positions to project farming yields and future planning and so on. Similar interrogations are derived by using probability-plotting positions for minimum temperature events. This is because these probability-plotting positions can be used to observe historical changes of extreme maximum or minimum values on short and long terms. In addition, these probability-plotting positions are of paramount importance for planning purposes and contingency situations.

Further, the use of time series linear trend models can be used to monitor the underway global warming increases. Besides, time series forecasting can be used to predict future trend temperature values based on previously observed standards. In fact, in this research, the results of the upward trends of the mean annual, mean annual maximum and mean annual minimum, demonstrate that global warming is underway, at least in the Florida State.

On the other hand, by applying an objective and subjective intellectualism, extreme temperature events are going to be more and more common, due to the undiscriminating burning of fossil fuels (because the world economy is tied up to the oil industry). These situations are generating artificial greenhouse gases, which are causing the anthropogenic global warming and their consequential effects on the climate, the economy, on health, on socio-political systems and on the distortions of geographic, regional or local temperature patterns. To challenge these present and future adverse situations, leaders of all world nations will have to come with more strict environmental policies and economic and political strategies to reduce fossil fuels consumption and to the use of alternative sources of clean energy. This responsibility will be crucial, so to protect the public and the well-being of future generations.

As a final point, it is concluded that this forward-looking method aimed to assess temperature values, is very reliable due to the profound experimental design statistical efforts done on its development and to the use of trustworthy temperature data apportioned by NOAA. In fact, it is asserted that the main intention of this experimental design research is to establish a dependable and precise framework of temperature values for Florida State. That is, a dependable database that can be used by investigators doing research in environmental engineering, meteorology, agriculture, civil engineering, experimental designs and so on.

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