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DETECTION OF A LOCAL CLIMATE CHANGE

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1. INTRODUCTION.

The main purpose of this work is to propose a statistical test to detect when a significant climate change occurs. The test is very simple and efficient and consists of removing the autocorrelation structure of the process and determines when the fingerprint of the process exhibits a significant change. The major contribution of this work is to introduce a tool to determine without ambiguity when a local climate change occurs. The local climate change will be a relative change depending on the baseline or the reference point. However, when the change is extremely large then the baseline may not affect the detection time.

Climate is the accumulation of seasonal weather events over long periods of time and over a particular place. The response of anthropogenic changes in climate forcing factors occurs against the natural forcing climate variability (Feldstein, 2002). Climate variability which is not forced by external factors is known as internal climate variability and occurs at all times from weeks to centuries. External factors that force climate variations are due to natural and anthropogenic causes, such as solar radiation, volcanic eruption, and increasing concentration of greenhouse gases (Barnett, et al., 1999). Climate change detection is the procedure to determine when an observed climate behavior differs significantly from the internal natural variability.

Climate change can be detected by studying the time series behavior of climate indicators. The Intergovernmental Panel on Climate Change (IPCC) classified the indicators as: concentration, weather, biological, physical and economical indicators. Examples are the time series of CO_2, O_3, air temperature, rainfall, sea level, artic ice, etc. A climate indicator is a sequence of observations that have been collected for long period of time. The climate in a particular region of the world can be represented by a stationary process, which is characterized by having an internal natural variability and its joint probability density function is invariant with time. However, if the probability distribution changes with time it implies that external factors cause the mean and the autocovariance functions to change with time. Therefore to detect a climate change is equivalent to determining when the process changes from being a stationary to a nonstationary process.

Most of the meteorological variables and climate indicators exhibit strong autocorrelation structure and therefore the conventional statistical tests provide misleading results because they are based on the assumption that the underlying time series are formed by a sequence of independent variables (Ramirez, and Sastri, 1997). For instance the usual t, F and Chi-square tests do not work for most of the climate indicator variables.

The proposed algorithm was used to detect whether or not the hurricane activity in the North Atlantic basin exhibits a behavior that is significantly different from a baseline hurricane activity. The algorithm was also used to determine whether or not the main Caribbean islands exhibit a significant change in the air surface temperature. The algorithm identified a significant change in the hurricane activity and in the surface air temperature of the islands and consequently it can be stated that a climate change has occurred in the Caribbean basin. It was also noted that the detected climate change is in harmony with the observations of global warming.

The remainder part of this paper is organized as follows: the second section presents a description of the data sets used. The third section describes the proposed detection algorithm. The fourth section presents climate change detection results. The fifth section presents a simulation exercise to validate the detection algorithm and the final section presents some conclusions.

2. DATA.

Three types of data were used in this study: air temperature in the North Hemisphere, air temperature in the main Caribbean islands and the hurricane activity in the North Atlantic basin.

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2.1. *Temperature in the North Hemisphere.*

This data set was acquired from Goddard Institute for space Studies (GISS) at the following web site http://data.giss.nasa.gov/gistemp/. This data includes anomalies of surface temperature in the North Hemisphere from 1880 to 2004. This data set was documented by Hansen, and Ruedy, (1999). Figure 1 shows the anomalies of the air temperature in the North Hemisphere.

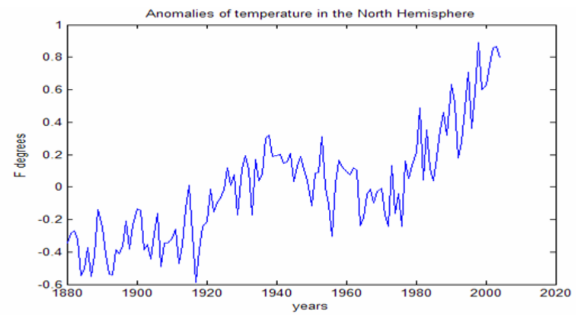

Figure 1. Annual anomalies of surface temperature in the North Hemisphere.

2.2. *Air temperature on the main Caribbean islands.*

Puerto Rico (PR) is one of the well instrumented Caribbean islands and includes a large amount of weather stations that belong to the national cooperative network. The Cooperative Observed Network (the Coop Network) is a nationwide weather and climate monitoring network of volunteer citizens and institutions that observe and report weather information on a regular basis. Information from Coop stations can be obtained from the following web site: http://www.dnr.state.sc.us/pls/cirrus/ cirrus.login. PR has 124 coop stations, six of them have information since the beginning of the 20th Century, and a large number of stations have been providing information since 1955 to the present. Thus, the selected data sets include 56 stations that have precipitation data and out of them 39 exhibit air temperature (minimum, maximum and mean). In addition to this data set, 15 weather stations were included that belong to the Global Historical Climatology Network (GHCN) which is a comprehensive global surface baseline climate data for monitoring and detecting climate change. This network recorded air temperature, precipitation, and pressure on a monthly basis. Thus the air temperature for PR was computed by using 54 stations. The total studied stations for Puerto Rico are presented in Figure 2.

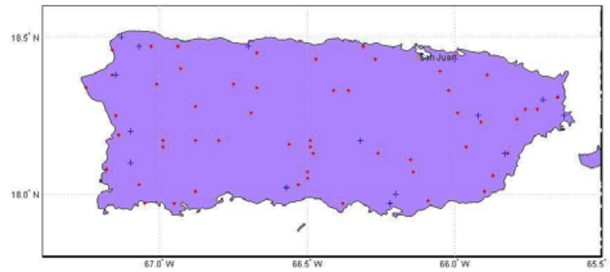

Figure 2: The location of the Global Historical Climatology Network stations are given in blue cross and the coop stations are exhibited with red dots.

Data for the remaining Caribbean islands are very limited and difficult to obtain. Information from weather stations was obtained from the GHCN. The available stations for each country are the following: Cuba has 14, Dominic Republic 28, Haiti 1, and Jamaica 5 stations. Stations for Cuba and PR include minimum, maximum, and average temperatures. However, for other islands the data is limited to only monthly averages. Usually, the data sets have time series from 1960 to 1980, i.e., each time series exhibits significant amount of missing values. Therefore, a regression approach was used to reconstruct the times series. The reconstruction task is tedious and time consuming. Thus, stations that exhibit the most complete time series were selected to perform the preliminarily data reconstruction exercise. Atmospheric reanalysis data was used to conduct the data reconstruction. Reanalysis data was obtained from the National Centers for Environmental Prediction (NCEP). Most of the meteorological data collected over the globe arrives at NCEP, where environmental scientists analyze this information and generate a wide variety of environmental guidance information. This effort involves the recovery of land surface, ship, rawinsonde, aircraft, satellite and other data (Kalnay, et al., 1996). The NCEP data is given in 2.5 degrees spatial resolution with 27 vertical levels. Information from the surface level and the closest NCEP grid points to a given island were used to estimate the air temperature. The blue cross on Figures 3 to 5, show the location of the stations, the red dots indicate the location of the selected station for reconstruction and the green dots indicate the location of the NCEP grid points used for estimation. Monthly anomalies were computed and organized in annual and quarterly time series: December, January and February (DJF), March, April and May (MAM), June July and August (JJA), and September, October and November (SON). Also the difference between the maximum and the minimum air temperature were computed.

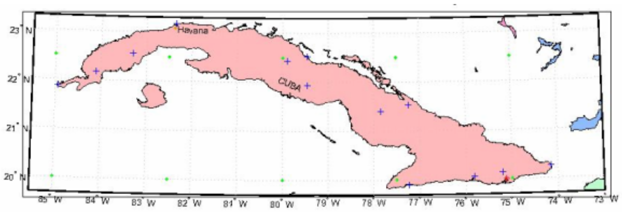

Figure 3. Location of the stations in Cuba.

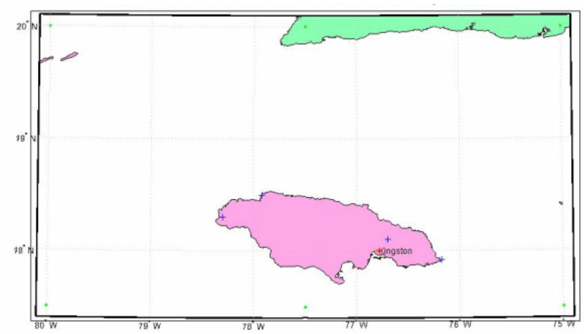

Figure 4. Location of stations in Jamaica.

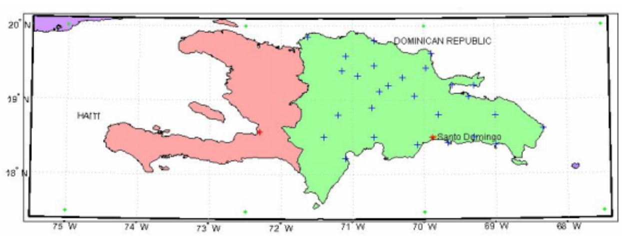

Figure 5. Location of stations in Haiti and Domincan Republic.

The NCEP data is given every six hours and is used to estimate the monthly average of air temperature. The NCEP data provides information at: 0, 6, 16, and 18 universal times. Observations at 6 and 18 times were used to estimate the minimum and maximum air temperature, respectively. The average of the four daily observations was used to estimate the mean daily air temperature and these time series were used to estimate the monthly air temperatures.

2.3. *Tropical storms and hurricanes.*

The North Atlantic basin (including the North Atlantic Ocean, the Caribbean sea, and the Golf of Mexico) exhibits interannual and interdecadal variability of tropical cyclone activity. Tropical storms and hurricanes that have occurred since 1886 to present are exhibited in Figure 6. These data were obtained from the National Hurricane Center.

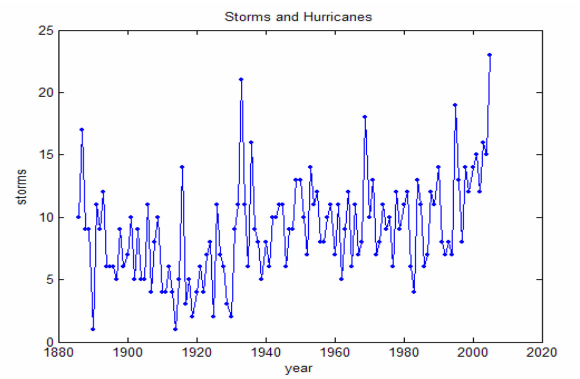

Figure 6. Hurricane and tropical storms in the North Atlantic basin (information available at the National Hurricane Center).

3. CHANGE DETECTION TEST

The proposed detection algorithm consists of removing the autocorrelation structure of a climate indicator and determines whether or not the mean and/or the autocorrelation function of the process changes over time. The algorithm consists of determining when the process changes from being a stationary to nonstationary stage and includes five major steps: (1) collect the largest sequence of a climate indicator; (2) divide the data sets in two parts: the baseline and the testing sequence; (3) identify an autoregressive moving average model to the baseline; (4) computing the autoregressive moving average (ARMA) finger print; and (5) use a sequential hypothesis testing procedure to determine whether or not the mean of the process has changed. The sequential test also includes determining whether or not the autocorrelation structure changes over time.

3.1. *Sequence of a climate indicator.*

It is assumed that climate properties of a given part of the world are expressed by a sequence of a climate indicator. A climate indicator can be expressed as a time series of air temperature, sea level, pressure, etc. It is required that the selected time series has no missing values and were obtained at equal time intervals. It is desirable that the time series will be large enough to identify the autocorrelation structure and left a significant part of the series in the testing side. The minimum length of the time sequence must be 50 observations.

3.2. *Dividing the time series.*

The time series will be divided into two parts. The first part will be called the baseline and the second part will be called the testing part. The baseline will be used as a reference point to measure the change with respect to the baseline. The baseline must be at least 30 observations i.e. to be able to identify a time series model. The baseline will be located on the left and the testing part on the right hand side of the series. Typically, the baseline may be located at the beginning of the series; however, it could be placed in almost any part of the series as long as enough testing observations are available. The testing part will be at least 20 observations and will be used to measure whether or not there exists a significant change with respect to the baseline. It should be noted that the change detection test will be relative and always will depend on the selected baseline. The baseline and the testing sequence can be expressed as follows:

Baseline sequence: x_t for $t = 1,2,\cdots,m$

Testing sequence: x_t for $t = m+1, m+2,\cdots,n$

For $m \geq 30$ and $n - m \geq 20$

Where x_t represents the anomalies of the underlying climate indicator at time *t*; m is sample size of the baseline, and n is the total number of available observations of the climate indicator.

3.3. *Identify an ARMA model.*

Most of the climate indicators and meteorological variables are a sequence of autocorrelated time series. For instance, the baseline of anomalies of air temperature, sea level pressure, sun radiation CO_3, and O_3 are autocorrelated processes and can be represented by an ARMA model. The baseline will be tested first to determine whether or not the baseline is an autocorrelated or a white noise process. If the underlying process is a white noise the ARMA model is not required. On the other hand, if the baseline is autocorrelated then it will be used to identify an ARMA model. It should be noted that the baseline must be a stationary process. Stationary in the sense that the mean and the autocorrelation function will not change over time. This assumption is satisfied because the climate with internal natural variability will exhibit a process with constant mean and autocorrelation function independent of time. The main purpose of identifying an ARMA model is to remove the autocorrelation structure. The identification of an ARMA model can be easily accomplished by using the methodology described in several time series textbooks (Box and Jenkins 1976). An ARMA model is developed by using the historical observations to estimate the current observation. This process is known as the autoregression. If the deviation of the estimated from the observations is small the model will be called autoregressive model. On the other hand, and if a significant deviation occurs in the estimation the errors and the historical observations are used to estimate the current observation and this model is called autoregressive moving average model. Several statistical software are available to perform an automatic identification of the ARMA model: for instance: Statgraphics, ITMS2000. Other alternative is to use Matlab which includes the system identification toolbox that provides an excellent tool to identify the ARMA model. A typical representation of an ARMA model is as follows:

$$x_t = \frac{\theta_1 B + \theta_2 B^2 + \cdots + \theta_q B^q}{\phi_1 B - \phi_2 B^2 + \cdots + \phi_p B^p} a_t \qquad (1)$$

$$\text{for} \quad t = 1,2,\cdots,m$$

Where x_t and m as defined previously; θ's and ϕ's are the parameters of the moving average and the autoregressive components of the model, respectively. The values of p and q define the order of the two polynomials; B is the back shift operator; a_t is a sequence of independent random variables with mean equal to zero and a standard deviation equal to one. It should be noted that x_t is the anomalies of the climate indicator, i.e., the periodicity component is already removed and the baseline is likely to be a stationary process.

3.4 *Computing the ARMA finger print.*

The ARMA fingerprint is the sequence created by the difference at each point in time between the estimated from the ARMA model and the observed value. The ARMA fingerprint can be computed as follows:

$$f_t = x_t - \hat{x}_t \quad \text{for} \quad t = 1,2,\cdots,n \qquad (2)$$

$$\hat{x}_t = \frac{\hat{\theta}_1 B + \hat{\theta}_2 B^2 + \cdots + \hat{\theta}_q B^q}{\hat{\phi}_1 B - \hat{\phi}_2 B^2 + \cdots + \hat{\phi}_p B^p} \hat{a}_t \qquad (3)$$

Where f_t is the ARMA fingerprint; $\hat{a}_t$ the residuals for the baseline sequence; $\hat{\theta}$'s and $\hat{\phi}$'s are parameter estimates that must be computed with the baseline sequence and must be unchanged for $t = 1,2,\cdots,n$. Again the ideal software to perform this calculation is Matlab.

Thus, if no change has occurred in the underlying process then the fingerprint will reduce to residual values $(f_t = \hat{a}_t)$, and will behave as a white noise sequence. However, if the process exhibits a significant change, the ARMA model will show a unique characteristic which will be exhibited either in the mean or in the autocovariance function of the given sequence and this special sequence will be called the ARMA fingerprint. Thus, if a significant change occurs in the mean of the process, the ARMA fingerprint will also exhibit a significant change in the mean. On the other hand, if change occurs in the second moment of the process, the fingerprint will exhibit significant change in the autocorrelation function (Ramirez, and Sastri, 1997).

3.5. *Sequential hypothesis testing.*

If the climate indicator was forced by external forces, its ARMA fingerprint will present a trend in the mean or a significant change in the autocorrelation structure. Thus to detect these changes two sequential tests are needed. Since the climate changes are represented by a small variation either in the mean or in the autocovariance, the tests must be very sensitive. In addition since the decision of the hypothesis testing is at each point in time, the exponentially weighted moving average (EWMA) and the transient detection test are adopted to detect the climate change. EWMA test was proposed by Roberts (1959) and the transient test was proposed by Ramirez and Sastri (1997). In this study only the EWMA test is implemented, the transient test will be applied in a future work.

The exponential weighted moving average test can be expressed as follows:

$$z_t = \lambda f_t + (1-\lambda) z_{t-1} \qquad (4)$$

A significant increment occurs in the mean at time t if $z_t > U_t$ and a significant decrement occurs in the mean at time t if $z_t < L_t$, where

$$U_t = \mu + M\sigma\sqrt{\frac{\lambda}{2-\lambda}\left[1-(1-\lambda)^{2t}\right]}, \qquad (5)$$

$$L_t = \mu - M\sigma\sqrt{\frac{\lambda}{2-\lambda}\left[1-(1-\lambda)^{2t}\right]} \qquad (6)$$

for $t = 1,2,\ldots,n$

Where f_t is the ARMA fingerprint at time t, μ and σ are the mean and the standard deviation of the baseline sequence of f_t for t=1,2,…,m; z_t is the exponentially weighted moving average of the fingerprint, and the initial value of z_t can be estimated by the average of the fingerprint during the baseline (t=1,2,…,m); λ is a weighted constant and varies between zero and one. However, to have better results it is recommended to take the value of 0.2. and M is constant that change depending on λ. Thus, for $\lambda = 0.2$ $M = 3$.

The EWMA test was adopted because has been shown to be an efficient test to detect a small shift in the mean and is a robust test in the senses that is not affected by moderate deviations from the Gaussian process and because is not affected by weakly autocorrelated time series. Cumulative sum (CUSUM) test can also be used to detected climate change (Page 1954). However, since the implementation EWMA is easier than the CUSUM and detection results are about the same the EWMA test is recommended. An excellent discussion of the implementation of these tests can be found in Montgomery, (2001)

4. CLIMATE CHANGE RESULTS

Essentially three climatic indicators were studied and results are presented in the following order: surface temperature in the North Hemisphere, air temperature in the Caribbean islands, and hurricane activity in the North Atlantic.

4.1. *Change detected in the North Hemisphere*.

Anomalies of the surface temperature in the North Hemisphere are presented in Figure 1. This series include 125 years of information (1980 – 2004). The baseline was explored with from the first 30 up to 110 years with increments of 10. This exploration was conducted to determine consistency on the change detection time. Table one shows that the detection time occurred on years 1995 and 1998. However, there are five baselines that indicate a change occurred in 1995 and all the baseline indicate that a change occurred in 1988. Therfere, there is an agreement that there is a significan change in the anomalies in the North Hemisphere. Thus, the baseline could be 30, 40, 60 or a 110. For purpose of illustration of the performances of the test the size of the baseline was fixed to 60, i.e., *m=60*. Thus, the baseline is formed by the sequence of anomalies from 1880 to 1939.

Table 1. Baseline for the surface temperature in North Atlantic.

Size of the baseline	Detection time
30	1998
40	1998
50	1995,and 1998
60	1998
70	1995,and 1998
80	1995,and 1998
90	1995,and 1998
100	1995,and 1998
110	1998

Figure 7 and 8 show the autocorrelation and the partial autocorrelation functions, which indicates that the baseline behaves as an autoregressive process of order one. This is due to the fact that the autocorrelation function shows a sinusoidal decay and also the partial autocorrelation function shows that only its first lag is significant. These are the typical characteristics of an autoregressive process of order one, AR(1).

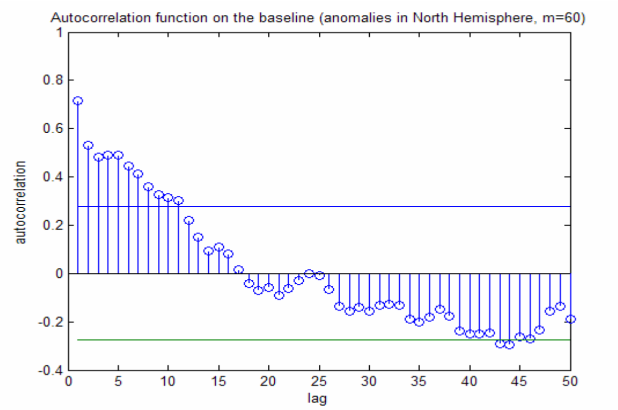

Figure 7. Autocorrelation of the baseline.

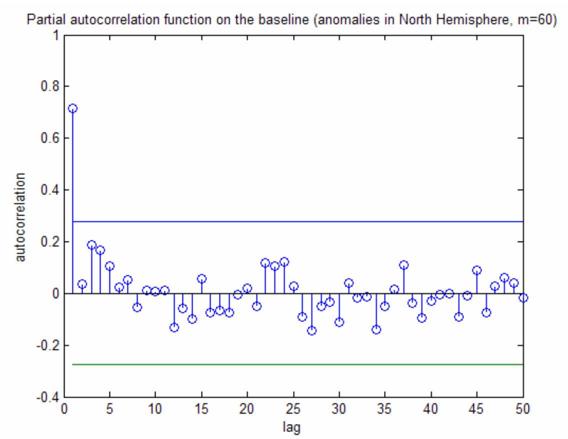

Figure 8. Partial autocorrelation function of the baseline.

A loss function was minimized to determine the optimal estimate of the parameter of the AR(1) model. The estimation procedure arrived to the following value $\hat{\phi}_1 = 0.8497$ and the minimum value of the loss function was 0.0258. Figure 9 shows the behavior of the AR(1) finger print. The first m values of the fingerprint behave as a white noise process and the finger print from observation m+1, m+2,…, n exhibits a strong autocorrelation behavior, indicating that a change is embedded in the fingerprint. Figure 10 shows the sequential hypothesis testing results. When a point falls between the red lines it indicates that there is no evidence to reject the hypothesis that a significant change has occurred at a specific point in time. On the other hand, if a point falls outside of the red lines it indicates that a significant change has occurred at that particular time. The level of significance was set equals to 5%.

Figure 10 shows that a significant change occurred in 1998. This figure also shows that the change becomes evident in 1998; however, the trend of this change started in about 1970. It should be noted that the test does not detect immediately the change unless the change is extremely large as is explained in the next section.

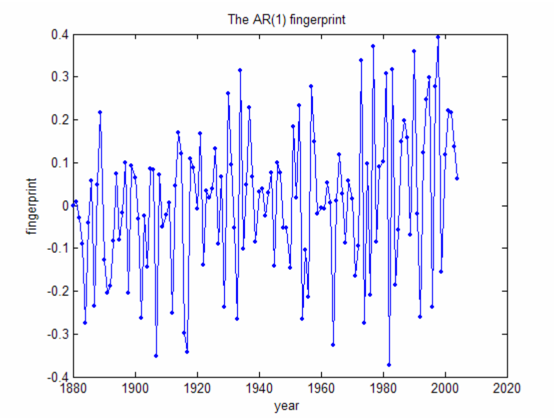

Figure 9. The AR(1) finger print.

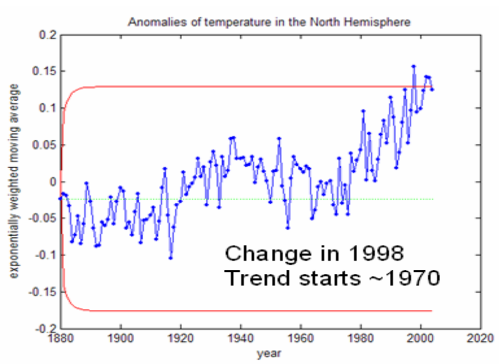

Figure 10. Climate change detection with anomalies of the air temperature in the North Hemisphere.

4.2. *Change detected in the Caribbean islands.*

The detection test was also implemented into the four major Caribbean islands. It was that observed the strongest climate indicator was the gradient temperature, i.e., the annual differences between the average of the maximum and the average of the minimum air temperature. The mean of this difference were also computed and subtracted form the difference to obtain the annual anomaly of the gradient temperature. This calculation was possible only for Puerto Rico and for Cuba, because of the data availability. The rest of the islands, only the annual average was possible to reconstruct. An autoregressive model of order one AR(1) was identified for the gradient temperature for both islands: Puerto Rico and Cuba. Figure 11 shows the EWMA test for the gradient temperature indicating that a significant change occured in Puerto Rico in 1998, and possible this change started in 1995. Figure 12 also shows the EWMA test of the gradient temperature for Cuba indicating that a significant change occurred in 2000, and possible this change started in 1995 because of the trend of the EWMA fingerprint.

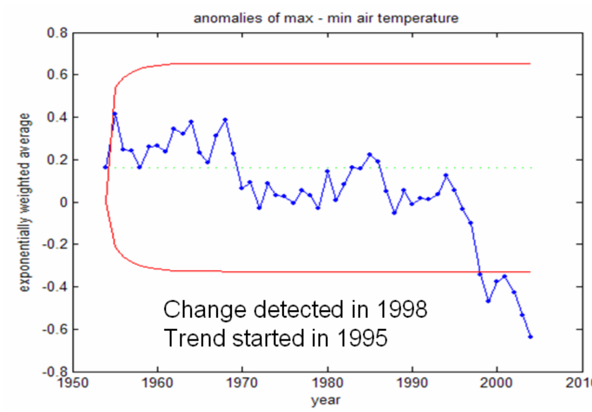

Figure 11. Change detected in Puerto Rico using the gradient temperature.

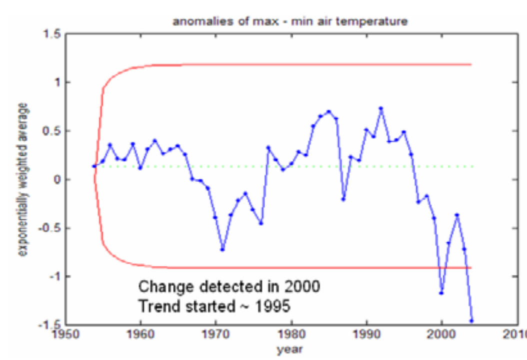

Figure 12. Climate change detected in Cuba in 2000

The anomalies of the mean temperature for these islands also show an autoregressive behavior of order one. Figures 13-15 show the EWMA test for Dominican Republic, Haiti and Jamaica respectively. These tests were based on the AR(1) fingerprint of the annual average of air temperatures. Data reconstruction was accomplished using the daily NCEP reanalysis data as explained in section 2. These figures are in agreement and show that a significant change occurred in these countries at the same time. The detected change occurred in 1998 and the most probably starting point was in 1995. Therefore, the Caribbean climate change is in agreement with the global climate change detected in the North Hemispheric.

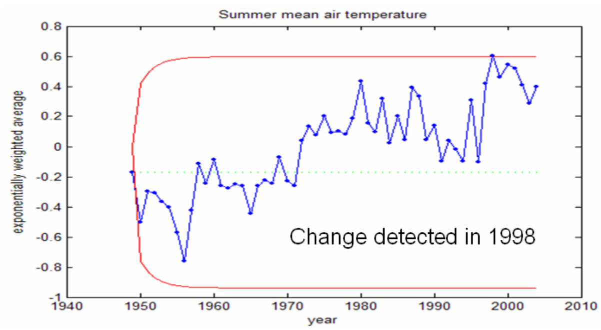

Figure 13. Change detected in Dominican Republic.

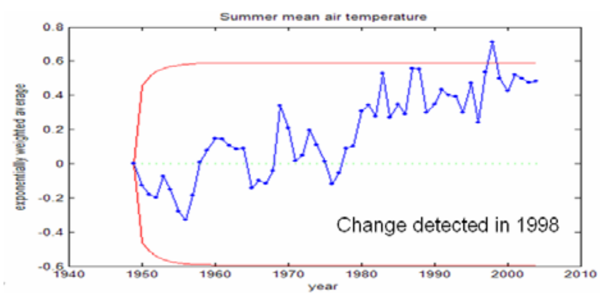

Figure 14. Change detected in Haiti.

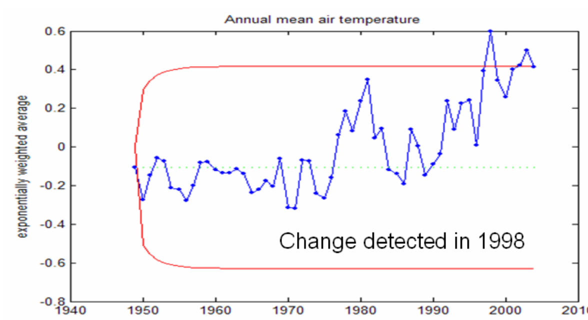

Figure 15. Change detected in Jamaica.

4.3. *Change detected in the Hurricane Activity*.

The hurricane activity in the North Atlantic was studied to identify whether or not there is a significant change. The hurricanes activity was organized as follows: The storms that reached the category of hurricane, the tropical storms that do not become a hurricane and the total number of named storms. It should be noted that the hurricanes behaves as s sequence of independent random variables. Therefore, the ARMA model was not needed, e.i., the fingerprint is a white noise and the original information was processed. The available historical information started in 1886. However, the reliable information started in 1944 (Goldember, et al., 2001). Thus the performed analysis was limited the period of 1944 to 2005.

In order to identify consistency on detection, different baselines were explored. Although different baselines were used, the detection time was the same. Therefore, a significant change in the number of tropical storm has been detected in 2002. The detection procedure is consistent and any of the baselines can be used to perform the detection test. Figure 16 shows the EWMA test pointing out that a significant number of tropical storms occurred in 2002 and the possible starting time was in 2000.

Table 2. Number of tropical storms

Size of baseline	Change detection time
20	2002
30	2002
40	2002
50	2003

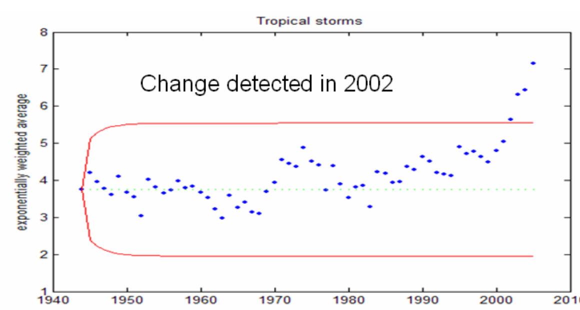

Figure 16. Tropical storms in the North Atlantic

Different sizes of baselines were used to detect a change in the number of hurricanes and also the different baselines generate a single detection time. Therefore a significant increment in the number of hurricanes occurred in 2005. However, the fingerprint indicates that the actual increment started about 1995, as is shown in Figure 17.

Table 3. Number of hurricanes.

Size of baseline	Change detection time
25	2005
30	2005
35	2005
40	2005
45	2005
50	2005

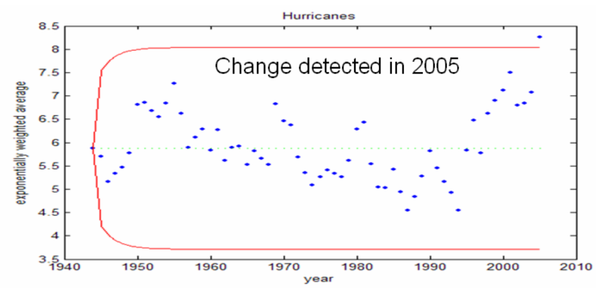

Figure 17. Change detected on the number of Hurricanes.

When tropical storms and hurricanes are combined the change becomes evident in 2001. However the trend in the fingerprint indicates that the change started about 1995. Therefore, the change in the hurricane activity started in 1995, which is also in agreement with the global climate change that started in 1995.

Table 4. Number of tropical storms and hurricanes

Size of baseline	Change detection time
20	2001
25	2001
30	2003
35	2001
40	2001
45	2001
50	2001

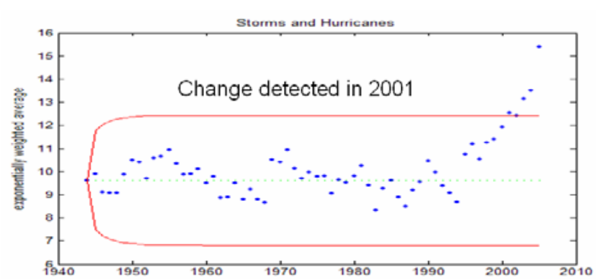

Figure 18. Change detected on tropical storms and hurricanes.

5. SIMULATION RESULTS

The fingerprint is tested throughout the sequential test to determine if there is enough evidences to declare a change. In a hypothesis testing two types of errors can occur. It should be noted that there will be no errors if the entire population is known. However, in the real life the only available information a single sample of the process, and consequently the sampling will generate two types of errors. Error type I is the incorrect decision of indicating that there is a change when in reality no change has occurred. The error type II consist on point that there is not a change when in reality a change has occurred. The probability that a type one error occurs is called the significant level and typically is assigned a value in the range between 2.5% to 10% and the magnitude of this risk is established by the designer of the hypothesis test. The probability that the error type II occurs is called beta and it depends on the magnitude of the climate change and the natural variability of the climate indicator. If the occurred climate change is relatively large with respect to the variability of the process then the beta size will be small. On the other hand if the occurred climate change is relatively small with respect to the variability of the process then the beta size will be very large. For practical purposes it would be desirable to have a strong test that exhibits a small alpha and beta values. A test with a small beta value is the one that exhibits a small average run length (ARL).

A Monte Carlo simulation technique was used to represent the annual anomalies of the air temperature. Since the anomalies of the air temperature in the Norh Hemisphere and in the Caribbean islands behave as an autoregressive process of order one, 200 years were of anomalies of air temperature were simulated. A shift in the mean of the synthetic series was imposed to measure whether or not the sequential test detects the change. Two parameters are controlled in the simulation: the size of the change, and the time when the shift occurs. The magnitude of the change is a multiple of the variance of the noise in the baseline. The shift in the mean was imposed at the following point in time 80, 90,…, 190. The exercise was repeated 50 times with a different seed number random generator. The AR(1) fingerprint was processed by the EWMA sequential test. Thus for each set of random numbers, and for a specific increment and a point of shift the following statistics were computed: the number of times that a change was detected, the probability of detection, the time delay to detect a change and its average which is called the average run length (ARL), the number of false alarms, the probability of a false alarm occurs. It should be noted that the ARL depends on the variability of the process, the amount of the mean shift and seed numbers.

Figure 19 shows a simulation of an AR(1). A shit in the mean occurs at time 120 and the minim required increment to perform the first detection was $\Delta = 1.25\sigma$. The detection occurs at time 122, i.e., a time delay of 2 units of time. Figure 20 shows also a simulation of an AR(1) and the shift in the mean occurs at time 150. The minim required increment to perform the first detection was $\Delta = 3\sigma$. The detection occurs at time 158 with a delay of 2 units of time. This exercise shows that if the change occurs when the process exhibits large values the delay to detect a change is small and also the required shift in the mean is small. On the other hand, if the shift in the mean is imposed when the process exhibits is smallest values then the delay to detect a change is larger and the required minimum size of the shift to detect a change is larger.

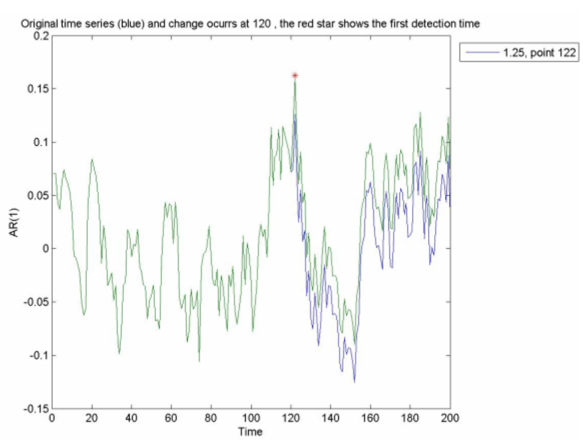

Figure 19. The change occurs at 120 and was detected at time 122. The minimum increment to perform the first detection was $\Delta = 1.25\sigma$

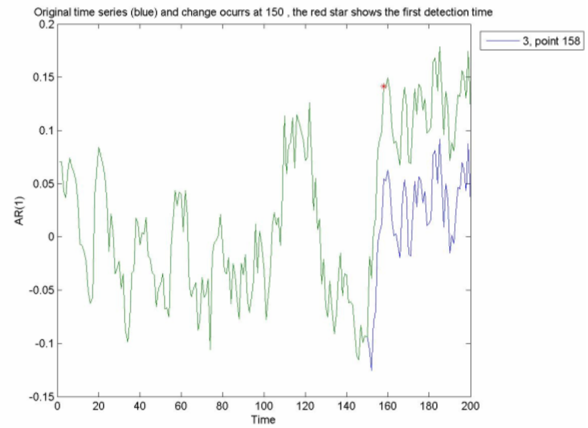

Figure 20. Change occurs at 150 and was detected at time 150. The minimum increment to perform the first detection was $\Delta = 3\sigma$.

Table 5. Simulation results.

Specifications	Average Δ	Average ARL	Average %of detection	Average %of false alarm
the first detection	1.62	19.11	15.17	4.67
5 ≤ Detec. ≤ 10	1.75	12.24	8.33	0.00
11 ≤ Detec. ≤ 20	2.07	16.54	16.67	8.33
21 ≤ Detec. ≤ 30	2.42	12.72	25.00	1.33
31 ≤ Detec. ≤ 40	3.28	9.26	33.33	0.93
41 ≤ Detec. ≤ 50	2.66	19.84	45.10	6.13
51 ≤ Detec. ≤ 60	3.03	19.82	58.33	0.67
61 ≤ Detec. ≤ 70	3.23	20.59	66.67	1.89
71≤ Detec. ≤ 80	3.30	19.14	75.00	2.60
81 ≤ Detec. ≤ 90	3.78	19.22	83.33	2.45
91 ≤ Detec. ≤ 100	4.21	16.34	92.91	1.06
100% detection	4.79	13.90	100.00	1.06
ARL=1	6.36	1.00	77.78	0.19

Simulation results are summarized as follows. The average minim increment to perform the first detection was 1.64σ, average run length is 18.97, the average probability of detection associated to this increment is 0.16 and average false alarm is 0.04.

6. CONCLUSIONS.

A global climate change was detected in 1998; however, the trend of the finger print suggests that in 1995 the changes in the climate produced by external factors become greater than the internal natural variability. Three of the main islands also show evidences that a climate change occurred in 1998 and the staring time was 1995. The total number of tropical storms and hurricanes exhibit an increasing hurricane activity in 2001 and the most probable starting time of this change was also in 1995. In summary the Caribbean climate change becomes evident in 1998 and this change started in 1995. The local Caribbean climate change is also in harmony with the global climate change, detected by the anomalies of the North Hemisphere was evident in 1998; however,

An algorithm is proposed to detect a climate change. The algorithm is simple and efficient. The detection strategy consist on identifying the autocorrelation structure of a given climate indicator and the autocorrelation structure is removed to determine the ARMA fingerprint and a sequential hypothesis testing is incorporated based on the exponentially weighted moving average of the finger print. It has been observed that the proposed algorithm determines with a 95 confidence interval when a climate change is likely to occur. This test provides the possibility of determining whether or not a given climate change is a result of internal natural variability or whether or not the underlying climate change is caused by external factors, and consequently the external factors must be investigated to mitigate the drastic and future consequences.

The proposed detection test was implemented and the following changes were detected: The anomalies of the air temperature in the North Hemisphere exhibits a significant change that started about 1970 and show strong evidences that an increment of air temperature in the North Hemisphere occurred in 1998. The major Caribbean islands also exhibit a significant increment in the air temperature, with the exception of Cuba that exhibits a change in 2002. A significant increment in the number of hurricanes, and this increment was identified in 2002. There is also strong evidences that the number of tropical storms that do not reach the hurricane stage exhibit a significant change that occurred in 2005 and the total number of tropical storms and hurricanes exhibit a significant change that occurred in 2001.

The local climate change will be a relative change depending on the baseline or the reference point. However, when the change is extremely large the base line may not affect the detection time.

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