Advances and Applications in Mathematical Sciences
Volume 18, Issue 9, July 2019, Pages 885-892

A DIAGNOSTIC APPROACH TO ANALYSE THE CHARACTERISTICS OF TROPICAL CYCLONE USING HIGH PERFORMANCE COMPUTING

SURAJ ARAVIND BOLLAPRAGADA and KRISHNA PRASAD MHM

Department of CSE
University College of Engineering Kakinada
Jawaharlal Nehru Technological University Kakinada
Andhra Pradesh, India
E-mail: surajaravind.b@gmail.com
Krishnaprasad.mhm@gmail.com

Abstract

Tropical Cyclones are natural phenomena that occur over oceans on a regular basis. If unprepared they bring lot of destruction leading to human and property loss. Careful analysis of the cyclones will give information related to global weather. This paper studies and adopts some popular techniques employed in analyzing some characteristics of cyclones like Tropical Cyclone Precipitation (TCP), Accumulated Cyclone Energy (ACE), Power Dissipation Index (PDI) and Sea Surface Temperature (SST). These characteristics help in understanding the whole of cyclone from genesis to land fall. The existing methods used to analyze the characteristics can be modified to suit to areas related to High Performance Computing (HPC), Big Data Analytics (BDA) and Deep Learning.

1. Introduction

Over the past 150 years lot of work is carried out regarding data assimilation of tropical cyclones (TCs) that occurred in all basins. Many agencies related to forecasting cyclones store TC data collected from satellites, aircrafts, ships, buoys and weather stations for analysis purposes. This data is used by researchers to study and analyse the behavior of cyclones from genesis to land fall. This also leads to understanding the distribution, frequency and intensity of TCs. The data is available in different formats like Hurricane Database (HURDAT), spreadsheet tables, various ASCII formats

2010 Mathematics Subject Classification: 68Q01.
Keywords: Tropical Cyclone; High Performance Computing; Big Data Analytics; Deep Learning.
Received November 19, 2018; Accepted January 20, 2019

etc., with a level of uncertainty. Attempts have been made to bring all this data into a common format [1]. As the data spans over Spatio-temporal domains, trajectory clustering techniques help in analysis [2]. Characteristics of TCs like TCP, ACE, PDI and SST are considered for analysis and suitable techniques are adopted for obtaining results.

1.1. Characteristics of TCs

We studied the four popular TC characteristics – TCP, ACE, PDI and SST. Each one of them is defined as follows:

Tropical Cyclone Precipitation (TCP): American Meteorological Society defined TCP as "Liquid or solid aqueous particles that originate in the atmosphere and fall on earth's surface due to gravity". The unit of measurement is mm or inches of liquid water depth that has fallen at a given point over a specified point of time.

Accumulated Cyclone Energy (ACE): is a measure of the destructive potential of individual TCs and overall TC season. It is calculated as the square of maximum sustained wind speeds every 6hrs, scaled by a factor of 10^4 for usability.

Power Dissipation Index (PDI): is defined as the sum of maximum one-minute sustained wind speed cubed, at 6-hourly intervals, for all periods when the cyclone is at least of tropical storm length.

Sea Surface Temperature (SST): is the temperature of the water close to the ocean surface.

Each one of the above characteristic helps in the analysis of the TC to the best extent possible. The above characteristic data collected from different sources over the last 50 years offers valuable information about behavior of TCs due to climate changes.

1.2. TC Basins

All Weather forecasting agencies identify seven TC basins spread through the World. They are Eastern Pacific (EP), North Atlantic (NA), Western North Pacific (WP), Southern Indian Ocean (SI), Northern Indian Ocean (NI), South Pacific (SP) and South Atlantic (SA).

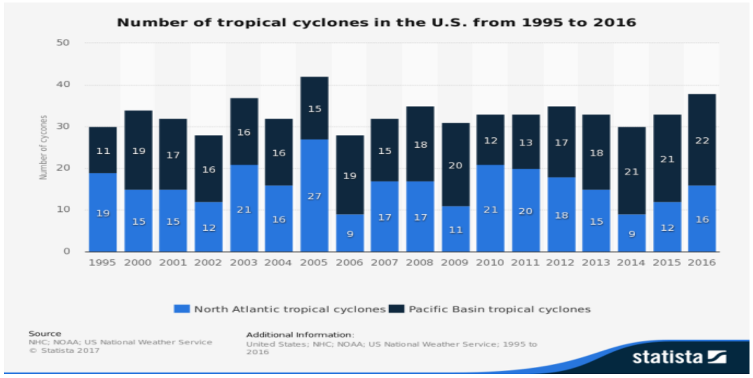

Figure 1. Number of TCs in US during 1995-2016 in both Atlantic and Pacific basins Courtesy-Statista

2. Tropical Cyclone Precipitation Analysis

The precipitation distribution is important from several points of view like management of water for agriculture and generation of hydel power, control of flood and drought situations. The Precipitation datasets used in the results are taken from Global Precipitation Climatology Project (GPCP) [3]. The resolution of the data is 2.5° latitude X 2.5° longitude grid. Figure 2 shows the monthly precipitation for September 2017 calculated by GPCC visualizer. This specific month was chosen as Hurricane Irma hit the coastal region of North America during 30 Aug to 12 Sep 2017. One could see the higher precipitation levels indicated with blue and pink colors.

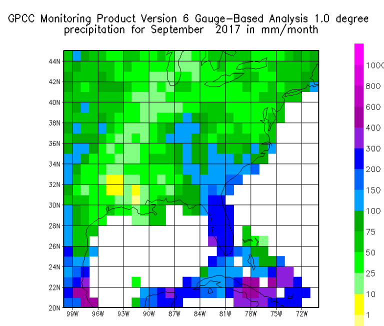

Figure 2. GPCC Visualizer indicating monthly precipitation for September 2017 for North America.

The precipitation data can be obtained from sources like geosynchronous Infra-Red based estimates, microwave scattering estimates over land, rain gauges etc. Due to huge volume of data gathered by these sources, algorithms that run on HPC is the need of the hour. In the algorithm GPM Combined Radar-Radiometer Precipitation [4], hybrid ensemble Kalman filter (EnKF) is used multiple times. The architecture of this algorithm is adopted from a rich heritage of algorithms that were developed for the Tropical Rainfall Measuring Mission (TRMM). The documentation of the algorithm quotes that the computational requirements of various routines add significant latency to the combined algorithm processing and suggested to use HPC.

2.1. Pseudo code of Proposed Algorithm

Step 1. Collect input from Dual Precipitation Radar (DPR) consisting of calibrated reflectivities at Ku and Ka band.

Step 2. Data collected in Step 1 is combined with GPM Microwave Imager (GMI) brightness temperature data to obtain DPR foot prints.

Step 3. DPR foot print locations identify possible rain regions.

3. Accumulated Cyclone Energy

ACE incorporates the TC genesis frequency, life span and intensity. Hence the ACE value in a particular basin can be used as a measure of overall TC activity. As ACE is the cumulative total of the square of maximum surface wind speed, a small increase in mean TC intensity could have a substantial increase in ACE. ACE helps in categorizing a TC. An empirical statistical analysis was proposed in [5]. With this analysis they could identify the factors responsible for the positive trends and decadal anomalies in ACE in the North Atlantic during 1995-2012. A similar analysis is needed in other basins to identify the contributing factors. A revised Accumulated Cyclone Energy Index (RACE) was proposed in [6]. In this RACE is computed by averaging the mean wind energy over a circular area based on the modified Rankine Vortex structure as shown below.

$$k_{mrv} = \frac{v_{\max}^2}{r_c^2}\left[\frac{1}{2} + \frac{r_c^{(2-2\alpha)} - 1}{(1-\alpha)}\right], \quad (1)$$

where $v_{\max}$ indicates maximum sustained wind, r_c denotes the cut-off radius within which the wind energy is estimated, α denotes the decaying tendency of wind outside the radius of maximum tangential wind. This study provides an alternative means for describing total TC activity. Suitable studies are needed to reveal any correlation between ACE and other parameters.

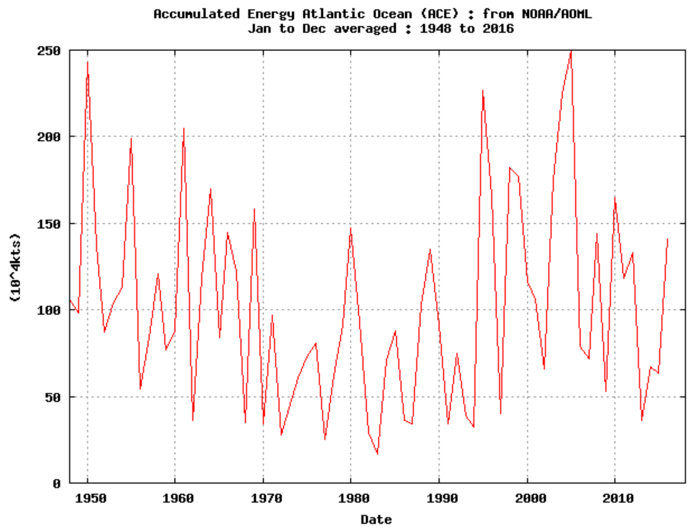

Figure 3. Accumulated Cyclone Energy of Atlantic Ocean during 1948 - 2016 Courtesy-NOAA .

4. Power Dissipation Index

[7] examined the changes in the lifetime, intensity, and annual frequency of the TCs in contributing to the changes in the annual accumulated PDI. Kendall-Tau significance test was employed to find linear trends. Figure 4 and Figure 5 show the relationship between PDI and SST. One could observe the gradual increase in both these values leading to more devastating TCs in recent years.

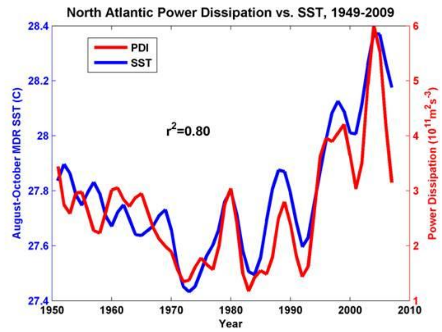

Figure 5. North Atlantic Storm Maximum Power Dissipation vs SST during 1870-2009 Courtesy-Kerry Emanuel, Massachusetts Institute of Technology (MIT).

ACE and PDI together are referred to as Storm Activity Index (SAI) and written in general form

$$\sum_{0}^{N} \sum_{0}^{t} V_{\max}^{n}, \tag{2}$$

where $V_{\max}$ is the maximum sustained wind speed of the TCs and n is an integer. The two Σ denote the summations over the lifetime (t) of each TC at 6-hour increments and for all the TCs (N) that occurred each year in a specific basin. With $n = 2$ it refers annual ACE and with $n = 3$ accumulated PDI is referred. As ACE and PDI are correlated, HPC techniques can be employed for better accuracy.

5. Sea Surface Temperature

Shaltout and Omstedt [8] analyzed the Mediterranean SSTs and their response to global change using 1/4 degree gridded Advanced Very High Resolution Radiometer (AVHRR) during 1982-2012. The data analyzed in this paper indicate significant annual warming and spatial variation in annual average SST. The daily SST relative to each grid (i, j) was analyzed using Fourier analysis of a periodic function:

$$f_{i,j}(t) = a_{i,j} \cos(2\pi t/T) + b_{ij} \sin(2\pi t/T) = A \cos(2\pi t/T + v_{i,j}), \tag{3}$$

where a and b are the Fourier coefficients, T is the One year period, t is the time, A is the amplitude $(a^2 + b^2)^{1/2}$ and v is $\tan^{-1}(b/a)$. The paper also identified significant relationships between SST and the atmospheric parameters Total Cloud Cover (TCC), Sea Level Pressure (SLP), precipitation. [9] collected data from publicly available NOAA database for SST, wind speed and direction over a period of 26 years (1988 to 2013). This database is robust, combining observations from satellite sensors interpolated with sensors on ships and buoys. Prediction of SST over different basins assists in better analysis of tropical cyclone. Deep Learning can assist in this.

6. Conclusion

With studies in the major areas of tropical cyclone parameters, one could understand that lot of work is concentrated towards Atlantic and Pacific basins. But with global warming there is considerable increase in SST in all basins which is one of the favorable factors for the formation of TCs. More suitable models are required to analyze the behavior of TCs in preferably all basins by taking considerable historical data from satellites, in-situ measurements etc. High performance computing (HPC) techniques can be used for better analysis and Deep Learning can be employed for better prediction. Big Data Analytics is a suitable technique for analyzing huge amount of data.

References

[1] K. R. Knapp, M. C. Kruk, D. H. Levinson, H. J. Diamond and C. J. Neumann, The International Best Track Archive For Climate Stewardship (IBTrACS) Unifying Tropical Cyclone Data, *Bull. Am. Meteorol. Soc.* 91(3) (2010), 363-376.

[2] H. Munaga, L. Ieronutti and L. Chittaro, CAST: A Novel Trajectory Clustering and Visualization Tool for Spatio-Temporal Data, in Proceedings of the First International Conference on Intelligent Human Computer Interaction, 2009.

[3] R. F. Adler *et al.*, The Version-2 Global Precipitation Climatology Project (GPCP) Monthly Precipitation Analysis (1979–Present), J. Hydrometeorol. 4(6) (2003), 1147-1167.

[4] H. M. William and S. Oslon, GPM Combined Radar-Radiometer Precipitation Algorithm, 2010.

[5] H. Murakami, T. Li and P. C. Hsu, Contributing factors to the recent high level of Accumulated Cyclone Energy (ACE) and Power Dissipation Index (PDI) in the North Atlantic, J. Clim. 27(8), 3023-3034.

[6] J. Y. Yu, C. Chou and P. G. Chiu, A revised Accumulated Cyclone Energy Index, Geophys. Res. Lett. 36(14) (2009), 1-5.

[7] L. Wu, B. Wang and S. A. Braun, Implications of Tropical Cyclone Power Dissipation Index, Encycl. Atmos. Sci., vol. 4, no. December 2007, p. 1549–1555., 2001.

[8] M. Shaltout and A. Omstedt, Recent Sea Surface Temperature trends and future scenarios for the Mediterranean Sea, Oceanologia 56(3) (2014), 411-443.

[9] P. C. Goela, C. Cordeiro, S. Danchenko, J. Icely, S. Cristina and A. Newton, Time Series analysis of data for Sea Surface Temperature and upwelling components from the Southwest coast of Portugal, J. Mar. Syst. 163 (2016), 12-22.