Moving Mean and Moving Variance Over Sliding Window of Time-Series Data to Detect Climate Changes

A thesis to be submitted in partial fulfillment of the requirements for the degree

of

Bachelor of Science in Computer Science and Engineering

by

Md. Shanewaz Akib
ID: 2016-3-60-050

Syeda Tahnita Nooren
ID: 2016-3-60-047

Istiaq Ahamed Shuvo
ID: 2016-3-60-016

Under the supervision of

Dr. Mohammad Rezwanul Huq

DEPT. OF COMPUTER SCIENCE AND ENGINEERING

EAST WEST UNIVERSITY

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DECLARATION

Project Title	Moving Mean and Moving Variance Over Sliding Window of Time-Series Data to Detect Climate Changes
Authors	*Md. Shanewaz Akib*, *Syeda Tahnita Nooren*, and *Istiaq Ahamed Shuvo*
Student IDs	ID: 2016-3-60-050, ID: 2016-3-60-047, and ID: 2016-3-60-016
Supervisor	Dr. Mohammad Rezwanul Huq

We, hereby, declare that the work presented in this thesis is the outcome of the investigation performed by us under the supervision of **Dr. Mohammad Rezwanul Huq**, Associate Professor, Dept. of Computer Science and Engineering, East West University, Dhaka, Bangladesh. We also declare that no part of this thesis has been or is being submitted elsewhere for the award of any degree or diploma.

Md. Shanewaz Akib
ID: 2016-3-60-050
(Signature)

Countersigned

Syeda Tahnita Nooren
ID: 2016-3-60-047
(Signature)

Dr. Mohammad Rezwanul Huq
Associate Professor
(Supervisor)

Istiaq Ahamed Shuvo
ID: 2016-3-60-016
(Signature)

Date: July 1, 2021

Dept. of Computer Science and Engineering
East West University
Dhaka, Bangladesh.

LETTER OF ACCEPTANCE

This is to certify that the a thesis entitled **Moving Mean and Moving Variance Over Sliding Window of Time-Series Data to Detect Climate Changes**, submitted by **Md. Shanewaz Akib** (*ID: 2016-3-60-050*), **Syeda Tahnita Nooren** (*ID: 2016-3-60-047*), and **Istiaq Ahamed Shuvo** (*ID: 2016-3-60-016*) are undergraduate students of the **Dept. of Computer Science and Engineering** has been examined. Upon recommendation by the examination committee, we hereby accord our approval of it as the presented work and submitted report fulfill the requirements for its acceptance in partial fulfillment for the degree of *Bachelor of Science in Computer Science and Engineering*.

Dr. Mohammad Rezwanul Huq
Associate Professor

Dept. of Computer Science and Engineering
East West University
Dhaka, Bangladesh

Dr. Taskeed Jabid
Chairperson, Associate Professor

Dept. of Computer Science and Engineering
East West University
Dhaka, Bangladesh

Date: July 1, 2021

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Sincerely -
Md. Shanewaz Akib,
Syeda Tahnita Nooren, and
Istiaq Ahamed Shuvo

Dept. of Computer Science and Engineering
East West University
Dhaka, Bangladesh.

ABSTRACT

Write abstract here

Keywords: keyword1, keyword2

ABBREVIATIONS

AHSS	Advanced High Strength Steel
BOCD	Bayesian Online Changepoint Detection

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1
Introduction

1.1 Introduction

Over the last two decades, detection and attribution of climate change has gotten a lot of attention because it seeks to determine whether recent observed changes are consistent with internal climate variability alone, or with the expected response to various combinations of external forcing and internal variability [1]. Climate change is defined as a change in global and regional climate trends. Climate change is currently one of the most significant issues facing the country. We now see a variety of erratic behavior in the global environment, including frequent natural disasters and heat waves. It is a controversial issue that isn't limited to any particular set of people, but rather affects everyone on a local and global scale. Climate change has a significant impact on Bangladesh, and Bangladesh is one of the most vulnerable countries to the effects of global climate change in the future decades, according to the German Watch Global Climate Risk Index [2]. Bangladesh was selected as one of the ten most affected countries during the last two decades, based on their average weighted ranking (CRI score) and specific results for the four variables studied [3].

These changes will endanger Bangladesh's tremendous progress in employment generation and reducing poverty over the last two decades, making the MDGs harder to accomplish [4]. Climate change is already putting a strain on our physical and environmental resources, as well as our human capabilities and economic activity. In the detection of climate change, statistical method is crucial. To track climate change, techniques much like moving average and moving variance over a sliding window of time series data are needed. Our goal in this study is to develop a climate change detection system using statistical approaches for monitoring climate change.

1.2 Research and Region of Research: Dhaka, Bangladesh

Dhaka, the capital of Bangladesh and one of the world's largest megacities, and one of the fastest growing cities in Southern Asia, with a population of more than 13 million people and a predicted population of more than 20 million by 2025 [5]. Dhaka is experiencing severe environmental deterioration because of climate change, and its impacts on the environment are having a significant effect on biodiversity.

According to researchers, examining the effects of climate change on Dhaka, the city will be impacted in two keyways: flooding and drainage congestion, as well as heat stress [5]. Climate change has led many Bangladeshis' residing in rural areas to migrate to cities, resulting in a rapid increase in Dhaka's slum population. Because Dhaka's height fluctuates between 2 and 13 meters above sea level, there are concerns that even a minor rise in sea level by the turn of the era might drown large swaths of the city. Furthermore, Dhaka's rapid urbanization and urban areas with high densities have already made it more vulnerable to human-caused environmental disasters. Because of the population of the city, the negative effects of climate change are like those experienced by a substantial number of individuals, particularly the urban poor who live in flood-prone and water-logged areas. The difficulties caused by flooding are exacerbated by substandard housing and overcrowding. Floods in densely populated, poorly maintained areas can lead to other risks, which have a substantial influence on the health of city dwellers. Floodwaters in slums can combine with untreated sewage, causing diseases like diarrhea, typhoid, and scabies to spread. During floods, water supplies become contaminated as pipes in slum areas are likely to be broken or leak.

Experts agree that communities can take steps to mitigate the adverse effects of natural disasters by improving planning, putting in appropriate infrastructure, and building disaster preparedness, in addition to taking active steps to reduce the probability of global climate change itself. Therefore, methods for detecting climate change need to be utilized. Model simulations that are compatible with observed trends or other changes in the climate system can be evaluated using detection and attribution studies. Climate policy and adaptation decisions can be influenced by the findings of detection and attribution studies.

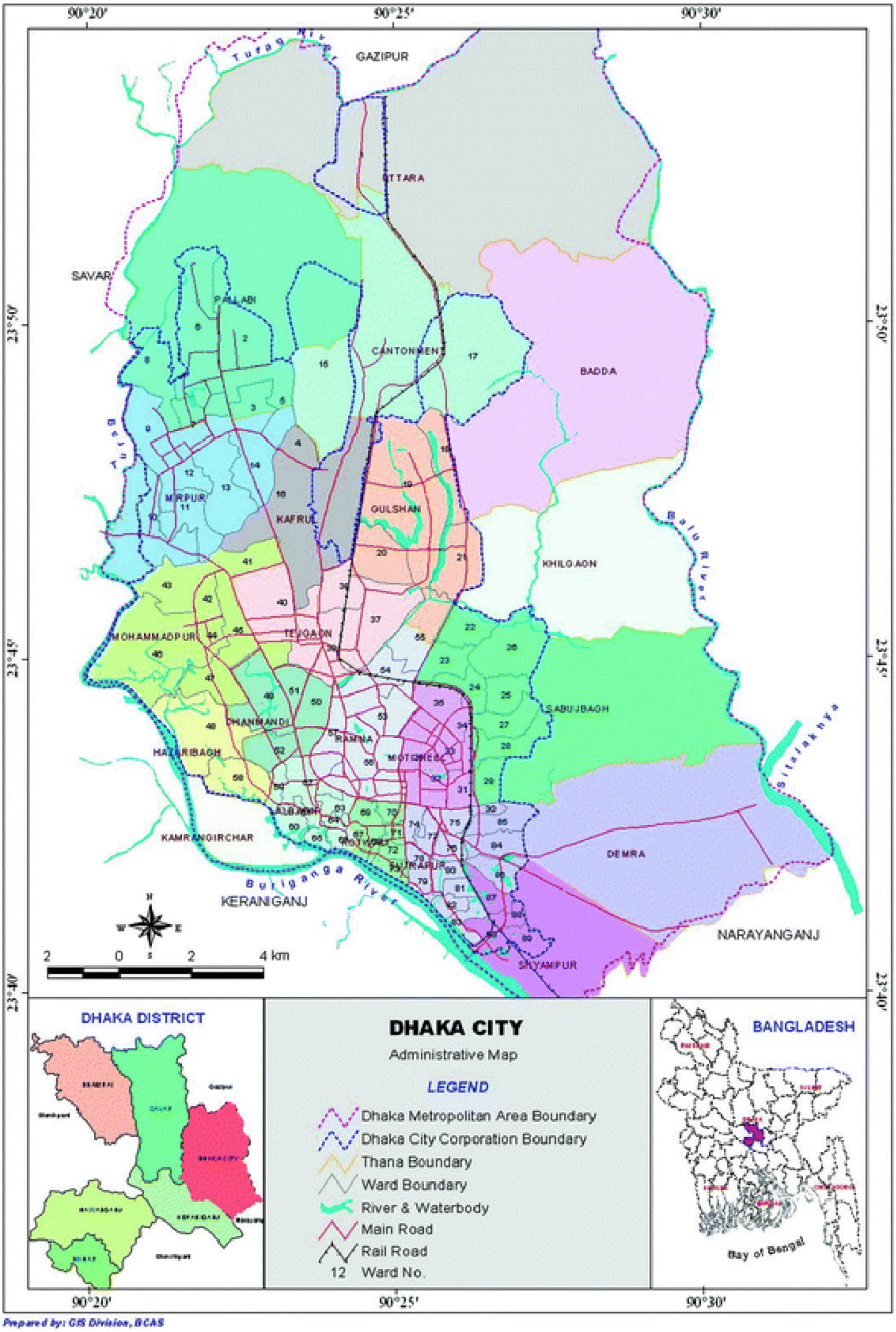


Figure 1.1: Climate Change Implications for Dhaka City
[6]

1.3 Statistical Approaches

Change point approaches have recently become popular for detecting prior sudden transitions in climatic time series data. A change point is a point in time when the underlying distribution's or the model's parameters used to define the time series rapidly change i.e., mean, variance, trend. Climate tipping points are abrupt, often irreversible events that have far-reaching effects on the Earth's system [7, 8]. Change-point detection techniques have been utilized in the Earth sciences to identify changes in temperature and precipitation [9], to detect regime shifts [10], changes in aerosol and cloud data [11], and historical changes in carbon uptake on land [12]. Change-point detection has also been widely used for the detection of artificial shifts. In the statistical literature, techniques for detecting movements in the mean and variance have gotten a lot of attention [13, 14]. Statistical analysis has proven to be a valuable technique for detecting previous climate patterns and variations. Change point analysis is one of the statistical methodologies that researchers have used to detect change points in a data stream, and it has been demonstrated to have the ability to detect sudden climate change candidates [15].

1.3.1 Moving Average

The moving average is a straightforward technical analysis technique. A moving average (also known as a rolling average or running average) is a statistical calculation that analyzes data points by calculating the averages of distinct subsets of the entire data set. It's also known as a rolling mean or a moving mean. The effects of random, short-term changes over a specific time frame or window are minimized by calculating the moving average.

1.3.1.1 Types of Moving Averages

The two primary types of moving averages are as follows:

- **Simple Moving Average (SMA):** A simple moving average (SMA) is the most basic type of moving average. It is computed by taking the arithmetic mean of a set of variables. In other words, the SMA is a simple technical indicator that is calculated by adding up all of the recent data points in a series and dividing the total by the number of time periods or window size. For example, A set of numbers or prices in the case of financial instruments is summed together and then divided by the number of prices in the list.

- **Exponential Moving Average (EMA):** The exponential moving average (EMA) is a kind of moving average that provides more weight to recent values in order to be more responsive to incoming data points. To calculate an EMA, start by calculating the SMA for a certain time period or window. The multiplier for weighting the EMA must then be calculated (referred to as the "smoothing factor"). This usually refers to the formula:

$$2/(selected\ time\ period\ or\ window + 1) \tag{1.1}$$

  So, for a 20-day moving average, according to equation (1.1), the multiplier would be [2/ (20+1)] = 0.0952.
  The current EMA is calculated by calculating the period from the first EMA to the most recent time period in the last step. As a result, the EMA provides recent values a higher weighting than the SMA, which gives all values equal weighting.

1.3.2 Moving Variance

Variance is a statistical term that describes how different something is from the average or mean. It's determined by squaring the differences between each number in the data set and the mean, then dividing the sum of the squares by the number of values in the data set. A variance is a measurement of how far a set of data (numbers) deviates from its mean (average) value, according to Layman. The term "variance" refers to determining the expected variation from the actual value. The square of standard deviation equals the value of variance; variance is represented as s^2, or Var (X). Variance can be calculated simply by following the steps given below:

1. Find the average of the data set. Calculate the average of a set of data points.
2. Now square each value after subtracting the mean.
3. Calculate the variance by taking the average of these squared values.

In the sliding window method, A moving variance is a statistical calculation that analyzes data points by a window of specified length moves over the data sample by sample, and the block computes the variance over the data in the window. For every sample the window moves over, the block computes the variance over the data in the window.

1.3.3 Window Shifting Method

The window shifting method is a window of specified length, moves over the data, sample by sample, and the statistic is computed over the data in the window. This algorithm is exactly as it sounds; a window is formed over some part of data, and this window can slide across the data to tracks different portions of it. The sliding window or window shifting algorithm's fundamental idea is to reduce time complexity by reducing multiple for loops into a single for loop. The Sliding Window Algorithm is most commonly employed for problems involving linear data structures such as arrays, lists, and strings. This algorithm is used to perform required operations on a given big buffer or array with a defined window size.

for example,

A	B	C	D	E

Suppose, we have a window of size k = 2. If we shift this window by k then we will get the following subarrays -
Here, each time we are considering two elements.

- First time we consider first two elements.
- Then we shift our window by one element every time from left to right.
- Finally, we get the output of the previous windows element and replaces the window with the next element (outside of the window).

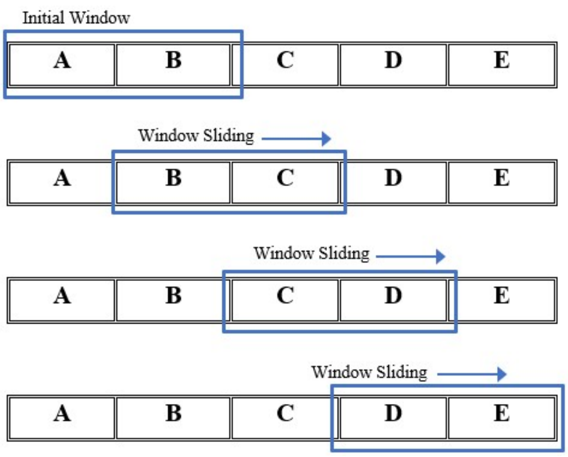


Figure 1.2: Window Sliding Technique

1.4 Model Design

In the figure, we show the model design of our model

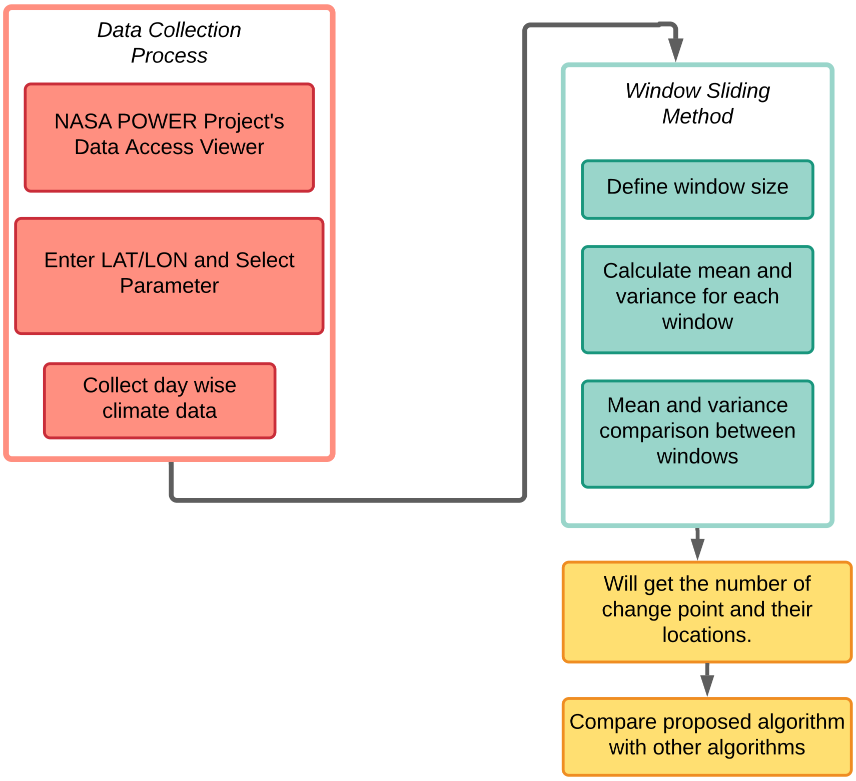


Figure 1.3: Proposed framework for climate change detection

1.5 The Significance of the Study

In this study, we will propose a change point detection algorithm used for climate change research and we will discuss the procedure of the detection system and present in more detail the informational approach, in which we employ statistical approaches to monitor climate change. The usefulness and adaptability of this approach will be demonstrated here. Our method, which represents a shift in the variance, as well as the mean and variance, gives uncertainty estimates in the number and location of change points via a fast probabilistic solution to the multiple change-point problems. On our data set, we apply the sliding window approach. The statistic is generated over the data in the window, which moves over the data sample by sample. The statistic calculated over the current sample's window and the previous samples is the output for each input sample.

Our contribution is summarized below:

- We obtained our data from the NASA Langley Research Center (LaRC) POWER Project funded through the NASA Earth Science/Applied Science Program. The POWER Project which is Provides solar and meteorological data sets from NASA research for support of renewable energy, building energy efficiency and agricultural needs.

- Our study area is Dhaka, Bangladesh (23.8103° N, 90.4125° E). We collect everyday meteorological data such as maximum temp, minimum temp, precipitation, relative humidity and wind speed from 31st December 2005 to 31st December 2020.

- A detection model which can detect most accurate change point number and their position from our dataset is implemented in 'Python'.

- We apply techniques like moving average and moving variance over a sliding frame of time series data to track climate change.

- We compare the current output with previous output, if current output and previous output will be increased or decreased at a time then climate change occur otherwise no change occurred.

1.6 Organization of this book

The following is the structure of our book. We begin in chapter I, which introduces the reason and result of climate change in Dhaka and also describes the need for a statistical approach in detecting climate change. In chapter II, we will be summarizing some ideas on existing work related to our research idea. The problem statement and proposed work are introduced in Chapter III. Chapter IV will be about methodology. Result analysis and evaluation of the proposed algorithm will be described in chapter V. Effects and Issues with the system will be described in chapter VI and the paper concludes with a discussion about future work in chapter VII.

1.7 Conclusion

Bangladesh is one of the countries, especially Dhaka city that will be most affected by global climate change in the coming decades. Bangladesh's remarkable accomplishments in creating jobs and reducing poverty over the last two decades may be threatened by these changes. To reduce the bad impact of climate change everyone needs to be aware. Until researchers create error free climate predicting mechanism, Climate policy and adaptation decisions can be influenced by the

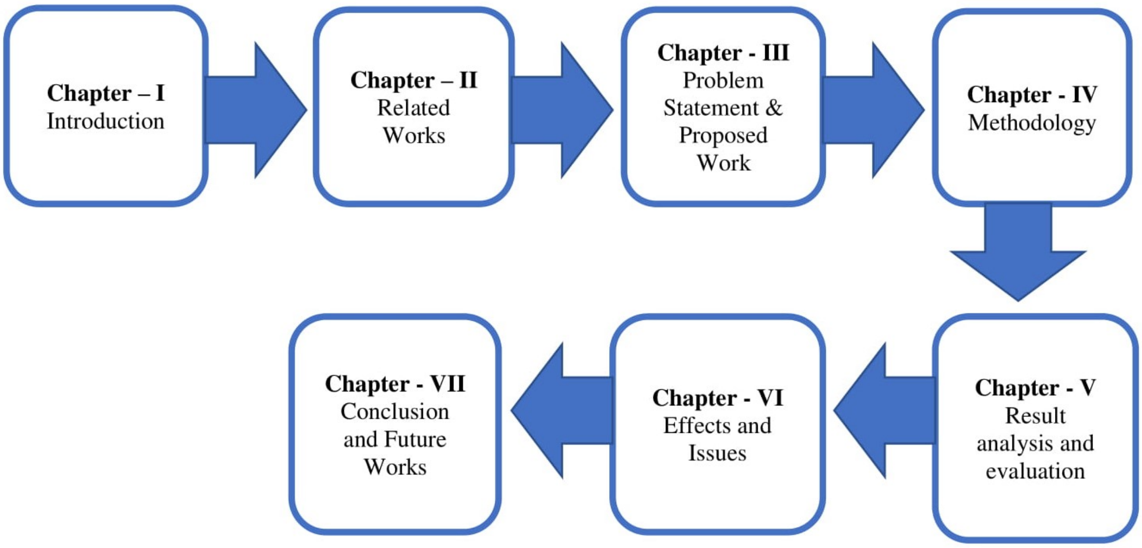


Figure 1.4: Flow chart of this book

findings of detection and attribution studies. To track climate change, a novel climate change detection algorithm which contains statistical techniques like moving average and moving variance over a sliding frame of time series data is proposed to monitor the change.

2
Related Works

2.1 Introduction

For decades, researchers in the statistics and machine learning fields have been interested in detecting sudden changes in time-series data, a technique known as changepoint detection. Some pioneering research revealed strong change point detection performance by comparing the probability distributions of time-series samples over past and current intervals, which has been researched for centuries. There are many ways to find the change point of climate series data and one of them is statistical approaches. Many researchers work in this field, and they can detect the change point and predict climatical changes.

2.2 State of the Art

In the past few years, detection changepoint from time-series data or climate data has reached to a higher level using statistical and machining learning methods. CPD has been researched in the fields of data mining, statistics, and computer science over several decades. This problem encompasses a wide range of real-world issues. Medical condition monitoring, Climate change detection, Speech recognition, Image analysis, Human activity analysis are some of the examples where researches for change point being held. In the next few section, we have described most of the previous research on detecting the change point from time-series data.

2.2.1 Changes point detection in time series dataset

Change points mean abrupt variations in time-series data. Detection change points in the time series dataset there have been faced some challenges like online detection, offline detection, scalability, and so on. For change point detection, a variety of machine learning algorithms have been developed, improved, and adapted [16]. Measures of performance are required in order to compare alternative CPD algorithms and determine the expected result performance. Many performance criteria have been developed to evaluate change point detection algorithms in terms of the decisions they make [17].

2.2.2 Relative density-ratio estimation for change-point detection in time-series data

Researchers in the statistics and data mining fields for decades have been interested in detecting abrupt changes in time-series data, known as change point detection. Change point detection methods can be divided into two categories based on the detection delay: Real-time detection and Retrospective detection. Real-time change point detection is targeted towards applications like robot control that require immediate responses. On the other hand, whereas retrospective change-point detection requires longer reaction times, it produces more reliable and accurate results. Climate change detection, genetic time-series analysis, signal segmentation, and intrusion detection in computer networks are just a few examples of applications that benefit from retrospective change point detection. In This paper [18], described detecting change points through density-ratio estimators like KLIEP, uLSIF, RuLSIF. This KLIEP-based KL-divergence estimator was used to detect change points and demonstrated to be promising in experiments [19]. The uLSIF solution can be estimated analytically, it has the best non-parametric convergence rate, numerical stability, and robustness, and it is more robust than KLIEP.

2.2.3 Climate change detection using a spatial cumulative sum technique

The purpose of this research [20] is to offer a scalable data processing framework with a novel change detection method for monitoring seasonal climatic changes. This study makes use of day-by-day weather data from Global Weather Data for SWAT Inc. The seasonal average of climate parameters such as maximum temperature, minimum temperature, precipitation, wind, relative humidity, and solar is calculated using the MapReduce method, which stores a huge volume of climate data in a distributed way on Hadoop Distributed File System (HDFS). This work proposes a spatial autocorrelation-based climate change detection system to track seasonal climatic variations. The suggested climatic change detection algorithm is compared to existing methods such as pruned exact linear time, binary segmentation, and segment neighborhood. The experimental findings show that the suggested climate change detection technique is effective.

2.2.4 Climate change detection and attribution by statistical methods

Most current statistical methods for detection and attribution (D&A) rely on linear regression models, in which observations are regressed onto expected response patterns to various external forcings. It's difficult to account for climate modeling uncertainty in regression-based approaches. The researchers developed a new statistical methodology for detection and attribution that addresses these issues. This article [1] presents a new statistical framework based on additive decomposition for dealing with climate modeling uncertainty in D&A, as well as the statistical inference methods required for D&A within this new statistical framework. The maximum likelihood approach is used to estimate each forced response.

2.2.5 Change Detection and Trend Assessment in Climatological Parameters Using Statistical Analysis

Jaiswal et al. [21] due to the importance of climatic variability on water availability, irrigation demand, agricultural production, and other aspects of life, a study of change detection and trend on monthly, seasonal, and yearly historical series of several climatic variables was conducted. Various non-parametric statistical tests were used to find change points followed by trend analysis in this study. Pettitt's test, von Neumann ratio test, Buishand's range test, and standard normal homogeneity (SNH) test on Monthly, seasonal, and annual long-term records of lowest temperature, maximum temperature, relative humidity, wind speed, sunlight hour, and pan evaporation of Raipur, India was used for change detection, while non-parametric tests including linear regression, Mann-Kendall, and Spearman rho tests were used for trend analysis. The yearly series of lowest temperature, wind speed, and sunlight hour revealed substantial change points, but evaporation suggested a questionable case and maximum temperature verified homogeneity at a 95% confidence level. The lowest and maximum temperature demonstrated a strong rising tendency in the summer and winter months, according to statistical trend analysis of meteorological variables. Because of the strong falling trend in wind speed and the falling trend in the sunshine hour series, the influence of this rising trend may not be noticeable on pan evaporation.

2.2.6 The informational approach is used to detect change points in environmental time series.

The Schwarz Information Criterion (SIC) is used to detect change-points in the time series of surface water quality data in this study. In this paper [22] discovered change-points in the mean and variance of the eight-time series observed in the Ave River hydrological basin's monitoring site. Whereas one change-point was observed in seven water monitoring sites, two statistically significant change-points were identified in the RAV site series using the binary segmentation approach. Since some time, series do not meet the assumptions of normality and uncorrelated, a simulation study is conducted to assess the methodology's efficacy when used to non-normal data and/or when a temporal correlation is present. The study's [22] main conclusion is that when there is positive autocorrelation, even if it is weak, the approach tends to find erroneous change-points, and the true significance is more than what is considered when establishing the crucial point.

2.2.7 A trend study of temperature and rainfall to predict climate change in Bangladesh's northern region

Climate change studies throughout the country have received much interest from researchers and policymakers in recent years. Climate models are used in many global climates change research around the country to evaluate future forecasts and uncertainties. Bhuyan et al. [23] focuses on the climatic features of Bangladesh's northwestern region and compares them to data from the Bangladesh Meteorological Department (BMD). Using MPI-ESM-LR (CMIP5) model data, the 5th Phase Coupled Model Inter-comparison Project (CMIP5) detected the trend of future mean temperature during the period 2040 to 2100, as well as the maximum temperature and rainfall during the period 1981 to 2008. As per MPI-ESM-LR (CMIP5) model data, the northwestern region's predicted typical temperature will rise by 1.62°C between the time period of 2040 and 2100.

2.3 Conclusion

Through the background research, we can jump to a conclusion that there are so many algorithms to detect the change point and statistical approach is much convenient to find the change point location. A change-point analysis is preferred to control charting for evaluating historical data, especially when such data sets are big. A change-point analysis has the advantage of controlling the change-wise error rate. Consequently, any change detection is more likely to genuine.

3
Problem Statement and Proposed Work

3.1 Introduction

In this section, we will describe why change point detection is crucial in the climate dataset and can be proved as an efficient addition to the detect change points from the climate dataset, as a result, we can predict climate change easily. Through the problem statement, we will discuss why this research is important. In the next section, we have proposed an algorithm for detecting change points from the climate dataset, and we also describe the goal of this study through the research objectives.

3.2 Problem Statement

Global climate change has already had an impact on the ecosystem. Glaciers have diminished, river and lake ice has broken down early, plant and animal ranges have altered, and trees are quickly damaged [24]. Dhaka city of Bangladesh is the most vulnerable one of the cities in the world, which will also have a negative impact on climate change. Due to its physiographic location, socioeconomic infrastructure, and reliance on natural resources, Bangladesh is one of the most susceptible countries to climate change. Because of climate change, Bangladesh often has to pay high prices during natural calamities or disasters. The majority of its people affected by these disasters [25]. As a result, detecting climate change is crucial in order to avoid this negative effect.

3.3 Proposed Work

Now a day's change point detection is a common phenomenon in the statistic and machine learning world and there are lots of processes to detect the change point in any time-series data or any synthetic data. Therefore, in this paper, we proposed a technique to find the change point from time-series data in the easiest way. We had briefly review previous works related to this field. Then we had been developed a sample data set to identify the change point properly. We had also compared our result to another change point detection algorithm to get a better result. As we had used statistical approaches like mean and variance calculation so it had been easier to detect change points.

Here, we had proposed a change point detection algorithm on climate time series data to predict climate changes, which will help to reduce the harmful effects of climate change on the environment by identifying climate change. We had compared our proposed climate change detection algorithm with another statistical method such as Pruned Exact Linear Time (PELT) method. The experimental results prove the efficiency of the proposed climate change detection algorithm.

In this study, changepoint analysis was chosen as an analytic tool to solve a climate-related problem. Specifically, 15 years of temperature, precipitation, relative humidity, and wind speed information contained in a climate dataset for Dhaka, Bangladesh.

The research study is to discover any interesting trends and potential abrupt shifts in the climate dataset.
The objective of our study are -

1. To develop a statistical method for detect change points in climate data to predict climate change.
2. To compare the proposed statistical method with previous statistical methods.

3.4 Conclusion

In this research, we had tried to detect change points in climate data series through statistical approaches to find out climate change. Although, we can also see that there are some limitations in our method. These problems can be overcome by choosing the appropriate threshold value. If we can choose the correct threshold values for our data set, then we can find the actual change point location, like other change point detection algorithm.

4
Methodology

4.1 Introduction

In this section we will fully describe our methodology as well as different algorithms for our model. Also we will try to include proper structure of the model. First, We had to gather meteorological data. Secondly, we had developed a system that will find out change points in the meteorological dataset using the statistical method. We also explain how to data collection, data preprocessing, and dataset development process. In this chapter, we had described many other statistical and machine learning methods to detect change points in climatologcal data to predict climate changes.

4.2 Steps throughout the development of the system

In this section, we had discussed how to develop our method in this study. At first, we collect daily meteorological data then we process our dataset for future analysis. Then, we apply our method to the dataset, as a result, we get output which detects change point in climate data. We implemented our method through the python programming language. Now, we will show our method developing process with proper details of the algorithm.

4.2.1 Dataset Development

This research study is to detect change points in climate data to identify the climate changes and describe another method to detect change points in climate data. We had chosen our reserach area as Dhaka, Bangladesh. So, we need meteorological data of Dhaka city for our study.
We had to collect meteorological data of Dhaka city from the Data Access viewer of NASA's POWER Project. We had provided there latitude and longitude of Dhaka city, selected the time range, and selected our needed parameters. Finally, we get our needed dataset for this study. That dataset contains climate parameters such as maximum temperature, minimum temperature, precipitation, wind, and relative humidity. In figure 4.1 shown, flow chart of our dataset development process.

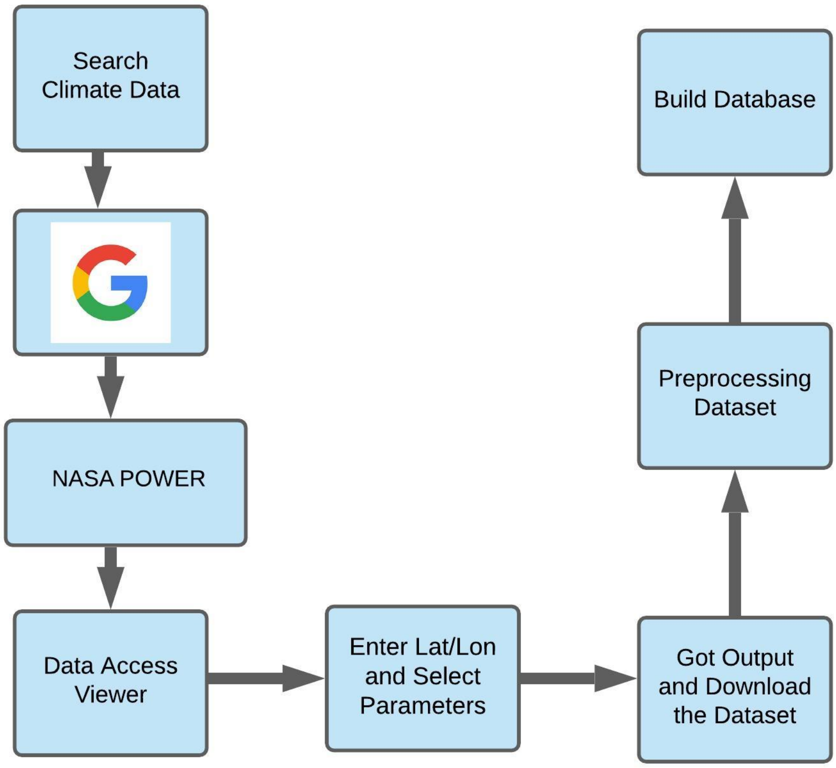


Figure 4.1: Flow chart of Dataset Development

4.2.1.1 Data Collection Method

The term "data" refers to a collection of facts, figures, objects, symbols, and events obtained from many sources. Data collection in statistics is the process of obtaining data for the research in order to solve a research topic. It helps in the evaluating of the problem's outcome. To develop assumptions about future probabilities and possibilities, most organizations prefer data collection methods.

The data collection method is divided into two categories based on the type of data is obtained:

1. **Primary Data Collection methods:** Primary data is gathered through first-hand experience and has never been utilized before. The data acquired through primary data gathering methods is very accurate and specific to the research's purpose.

   There are two types of primary data collection techniques:

   (a) **Quantitative methods:** In these approaches, demand is forecast based on historical data. Long-term forecasts are commonly made using these basic data collection methods (2). It is based on mathematical analyses that employ a variety of formats, including closed-ended questions, correlation and regression approaches, and mean, median, and mode metrics.

   (b) **Qualitative methods** There are no mathematical computations involved. This technique is strongly connected with non-quantifiable elements. The efficacy of qualitative research is primarily reliant on the talents and abilities of the researchers, and the results may not be seen as credible because they are mostly based on the researcher's own judgements and interpretations [26]. This information can be gathered in a variety of ways. They are- Observation Method, Interview Method, Questionnaire Method, Schedules.

2. **Secondary Data Collection methods:** Data that has been used previously is known as secondary data. Data can be obtained from both internal and external sources to the organization by the researcher. It indicates that the data has already been collected and is being analyzed. Magazines, newspapers, books, and journals are examples of secondary data. It could be either published or unpublished information.

   (a) Internal sources of secondary data:

      - Organization's health and safety records
      - Mission and vision statements
      - Financial Statements
      - Magazines

- Sales Report
- CRM Software
- Executive summaries

(b) External sources of secondary data:

- Government reports
- Press releases
- Business journals
- Libraries
- Internet

The objective of our research study is to detect change points in the climate dataset to predict climate changes. So, we need daily meteorological data, that's why we collect the dataset for our research study from the Data Access Viewer of the POWER project which is Provides solar and meteorological data sets from NASA research for support of renewable energy, building energy efficiency, and agricultural needs. The Data Access Viewer is a responsive web mapping application providing data subsetting, charting, and visualization tools in an easy-to-use interface.
At this step, we choose the data collection method that makes up the core of our data gathering strategy. We use Secondary Data Collection methods to collect our data. Quantitative and qualitative techniques can both be used in secondary data collection procedures. Our dataset is a quantitative dataset. Secondary data is more easily accessible and thus less time-consuming and costly than primary data.

4.2.1.2 Preprocessing of Dataset

After collecting meteorological data from the internet through API, which is organized by NASA's POWER Project, now we have gathered and structured the raw data in a proper way for future analysis.

4.2.2 Python Packages for Change Point Detection

The objective of change point detection is to locate changes in a signal's underlying model. This topic has sparked a lot of interest in the fields of statistics and signal processing [27, 28, 29]. 'Changepoint' is an excellent package in the R programming language to detect change point. This package allows users to perform change point analysis on a time series using a variety of search methods. However, there are a few other Python libraries that provide change point detection.

	Date	LAT	LON	Elevation(meters)	MaxTemperature (C)	MinTemperature (C)	Precipitation (mm)	RelativeHumidity (%)	WindSpeed (m/s)
0	31-12-05	23.810310	90.412510	8.810000	24.210000	10.880000	0.000000	75.380000	4.280000
1	01-01-06	23.810310	90.412510	8.810000	24.170000	10.690000	0.000000	75.000000	3.930000
2	02-01-06	23.810310	90.412510	8.810000	24.410000	11.430000	0.000000	72.410000	3.210000
3	03-01-06	23.810310	90.412510	8.810000	23.680000	12.470000	0.000000	74.000000	3.390000
4	04-01-06	23.810310	90.412510	8.810000	23.710000	11.220000	0.000000	75.800000	4.600000
5	05-01-06	23.810310	90.412510	8.810000	23.200000	11.340000	0.000000	72.520000	4.510000
6	06-01-06	23.810310	90.412510	8.810000	23.420000	10.230000	0.000000	76.190000	4.270000
7	07-01-06	23.810310	90.412510	8.810000	22.880000	12.170000	0.000000	76.030000	4.170000
8	08-01-06	23.810310	90.412510	8.810000	22.970000	11.690000	0.000000	71.560000	5.040000
9	09-01-06	23.810310	90.412510	8.810000	23.350000	9.450000	0.000000	70.810000	5.290000
10	10-01-06	23.810310	90.412510	8.810000	22.820000	8.690000	0.000000	76.110000	5.150000

Figure 4.2: Weather station data

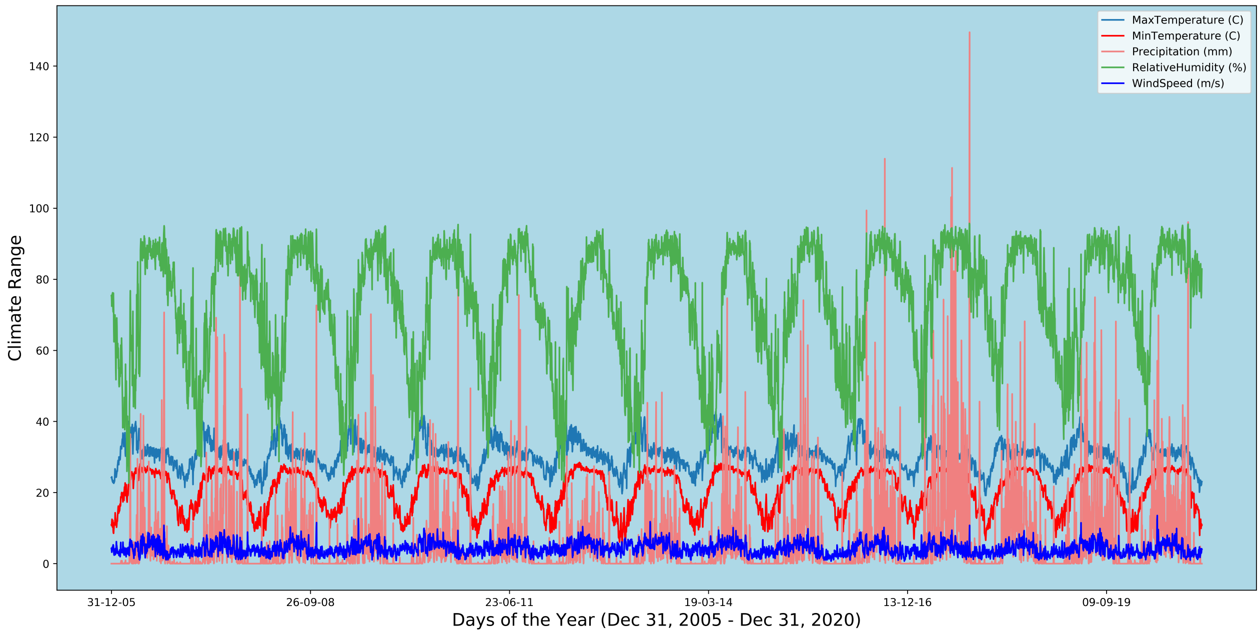


Figure 4.3: Weather station data

The ruptures package: Ruptures is a Python package for detecting offline change points. Methods for analyzing and segmenting non-stationary signals are included in this package. This package focuses on ease of use by providing a well-documented and consistent interface.The ruptures library is built entirely in Python and is compatible with Mac OS X, Linux, and Windows [30]. Figure 4.15 illustrates a basic flowchart.

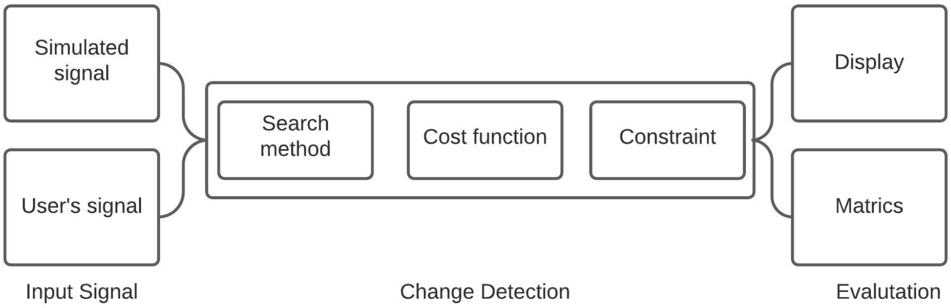


Figure 4.4: Schematic view of the ruptures package

4.2.3 Algorithm Background

Change point detection methods are divided into two main branches: Online Change Point Detection and Offline Change Point Detection. In the below, we give a brief description about that:

4.2.3.1 Offline Change Point Detection

Offline change point detection methods that retrospectively detect changes when all samples are received [31]. Change point detection approaches are "offline" when they don't use live streaming data, and require the complete time series for statistical analysis. Because offline approaches analyze the whole time series, they are generally more accurate. A few characteristics of offline change point detection are as follows [32]:

- All data is received and processed at the same time
- All changes are of interest, not just the most recent change in the sequence

4.2.3.2 Online Change Point Detection

Online change point detection methods, that aim to detect changes as soon as they occur in a real-time setting [31]. In contrast with offline change point detection, online change point detection is used on live-streaming time series, usually to for the purpose of constant monitoring or immediate anomaly detection [32]. Online CPD processes individual data points as they become available, with the intent of detecting state changes as soon as they occur [16]. There are a few characteristics of online change point detection:

- Fast "on-the-fly" processing, in order to quickly assess shifts in the time series trend

- Assessment of only the most recent change in the time series, not previous changes

Bayisan Online Changepoint Detection:

We care about when the generating parameters change if we see our data as observations from a climate timeseries. A changepoint is an abrupt change in these parameters, and changepoint detection is the modeling and inference of these events.

The Bayesian online change point detection process proposed by Adam and MacKay [33] is essentially a filtering process on an infinite state hidden Markov model, in which the observed time series can be divided into a set of connected segments, each segment being generated by a hidden model called "the observation model." The beginning time index of a new segment is specified as a "change point." The length of a segment is specified as "duration," and duration is calculated using a model called "the duration model." They look at the case where model parameters are independent before and after the changepoint, and they come up with an online approach for precise inference of the most recent changepoint. Then, using a simple message-passing algorithm, they compute the probability distribution of the length of the current "run," or time since the last change point.

We had applied the BOCD algorithm over our collected dataset and applying this algorithm, we could be able to detect changepoint and their location in our dataset. This change point means that in that location occurs climate changes. In the below, we had given the output of the implementation of BOCD in the form of plots:

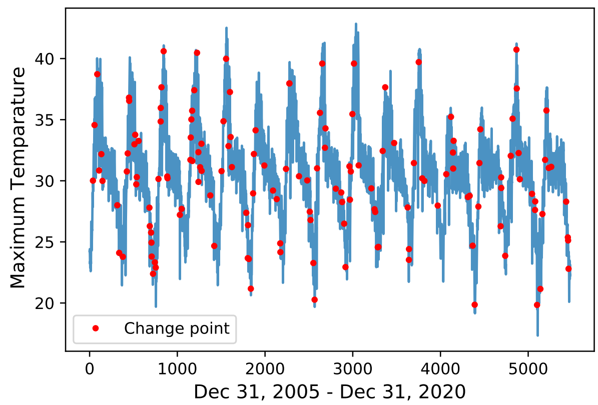


Figure 4.5: Python implementation of BOCD for maximum temperature

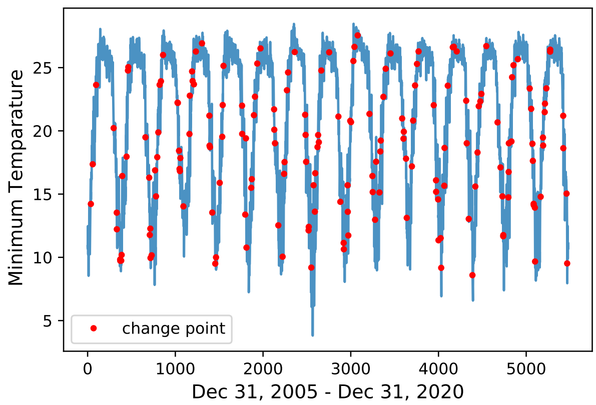


Figure 4.6: Python implementation of BOCD for minimum temperature

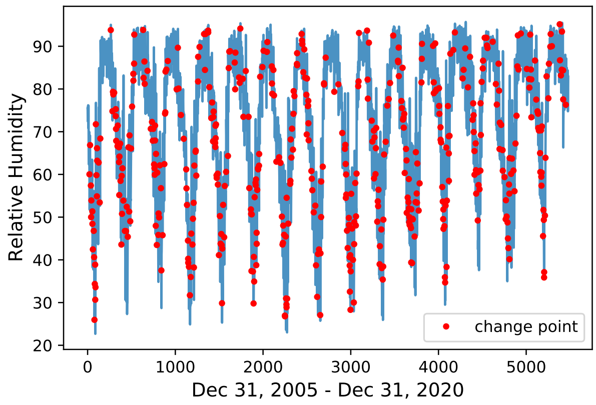


Figure 4.7: Python implementation of BOCD for relative humidity

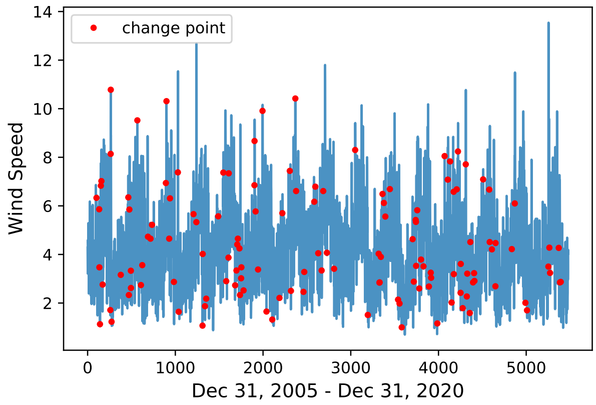


Figure 4.8: Python implementation of BOCD for wind speed

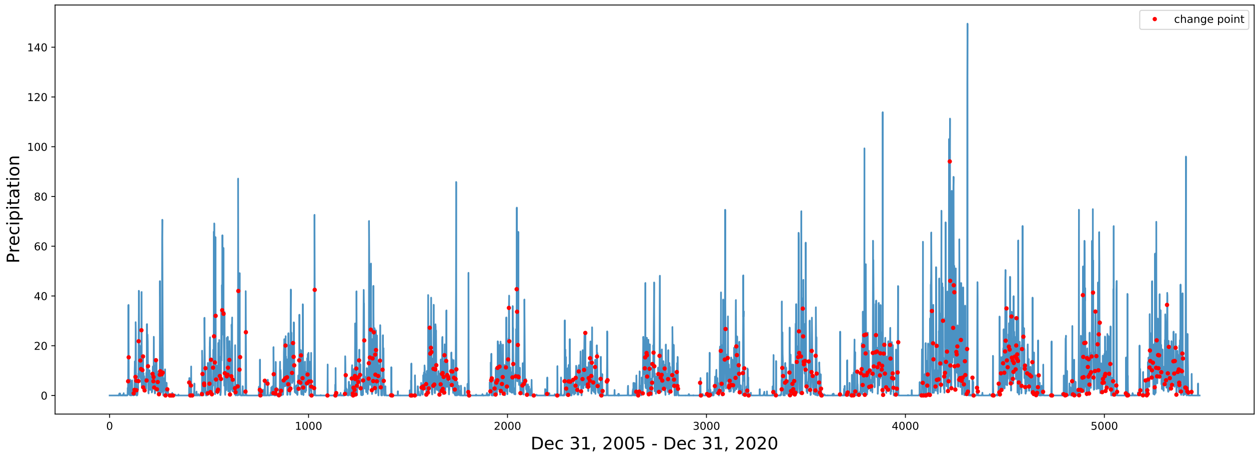


Figure 4.9: Python implementation of BOCD for precipitation

4.2.4 Search Method Background

This section provides a brief background on some of the search methods available in the ruptures package, including Pelt, binary segmentation, and dynamic programming.

4.2.4.1 PELT search method

The PELT algorithm is a popular method for finding change points through cost minimization. To identify numerous change points, the PELT method is performed to the entire data set first, then partition repeatedly and separately until no more change points are found. The PELT algorithm's major premise is that the number of change points rises linearly with the size of the dataset, implying that the change points are distributed across the data and not confined into a single area [34].

The PELT method is an exact method, and generally produces quick and consistent results. It detects change points through the minimization of costs. The algorithm has a computational cost of *O(n)*, where *n* is the number of data points [35].

This method based on the algorithm of optimal partitioning [36], but involves a pruning step within the dynamic program. Jackson, et al. [36] proposed a search method that aims to minimize:

$$\sum_{i=1}^{m+1} [C(y_{\tau_{i-1}+1}, ..., y_{\tau_i}) + \beta] \tag{4.1}$$

Where C is a cost function for the segment i^{th} and β is a penalty to guard against over fitting.
The PELT method modifies the optimal partitioning method of [36] by pruning. It combines optimal partitioning and pruning to achieve exact and efficient computational cost which is linear in *n*. The optimal segmentation is F(n) where,

$$F(n) = \min_{\tau} \{ \sum_{i=1}^{m+1} [C(y_{\tau_{i-1}+1}, ..., y_{\tau_i}) + \beta] \} \tag{4.2}$$

When we reach *F(n)* the optimal segmentation for the entire data has been identified and the number and location of changepoints have been recorded [35].

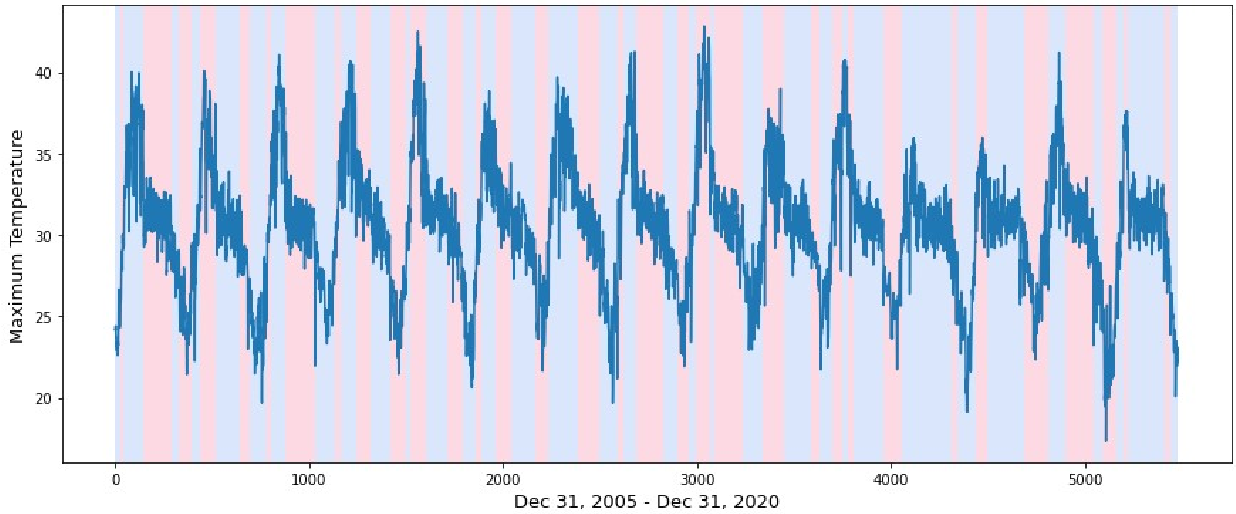


Figure 4.10: Python implementation of PELT for maximum temperature

4.2.4.2 Binary segmentation search method

The binary segmentation algorithm is likely the most well-known search strategy in the literature on changepoints. Scott and Knott (1974) [37] and Sen and Srivastava (1979) [38] are two early uses of the binary segmentation search technique (1975). Any single changepoint approach can be extended to multiple changepoints with this algorithm.

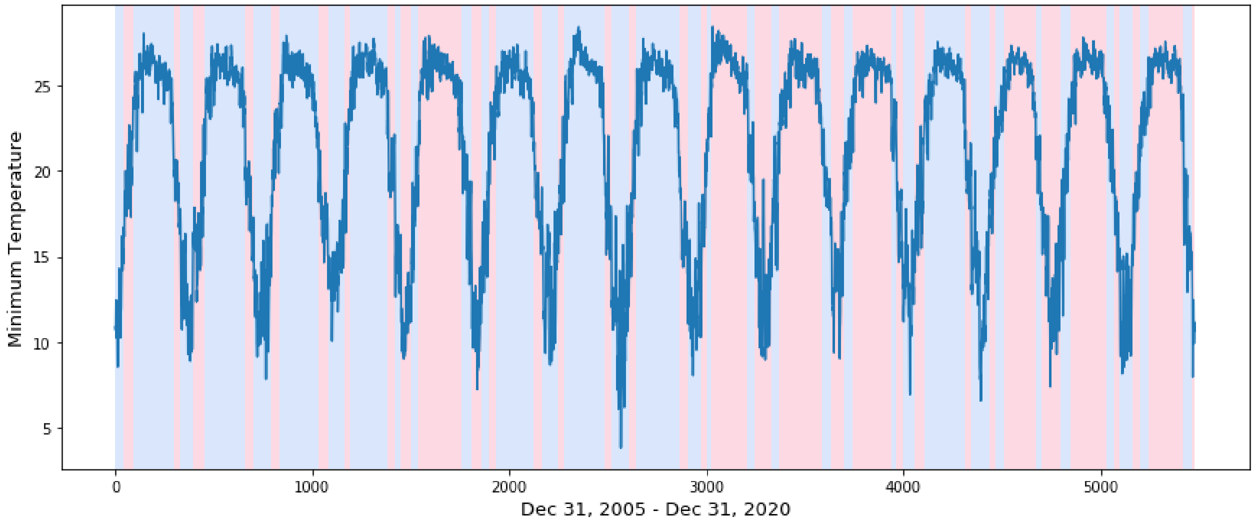


Figure 4.11: Python implementation of PELT for minimum temperature

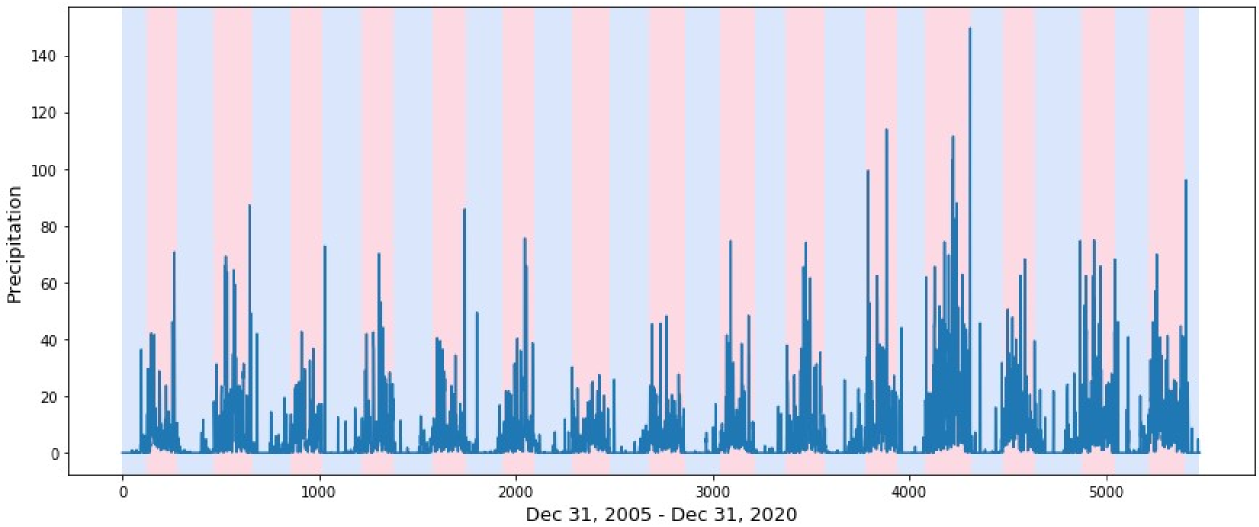


Figure 4.12: Python implementation of PELT for precipitation

This algorithm begins by applying the single changepoint technique on the entire sequence, that is, it determines whether there is a split of the sequence such that the cost function across the two sub sequences plus the penalty term is less than the cost function on the entire sequence.

The data is separated into two sections, one before and one after the identified changepoint. Then, for each new section, use the detection method. If either or both tests are true, split the segments at the newly found changepoint(s) into new segments, applying the detection algorithm to each one. This technique is continued until there are no more changepoints to be found. The Binary Segmentation Algorithm is a time-saving algorithm. Binary segmentation is a quick algorithm with a computational cost of $O(n)$, where n is the length of the data.

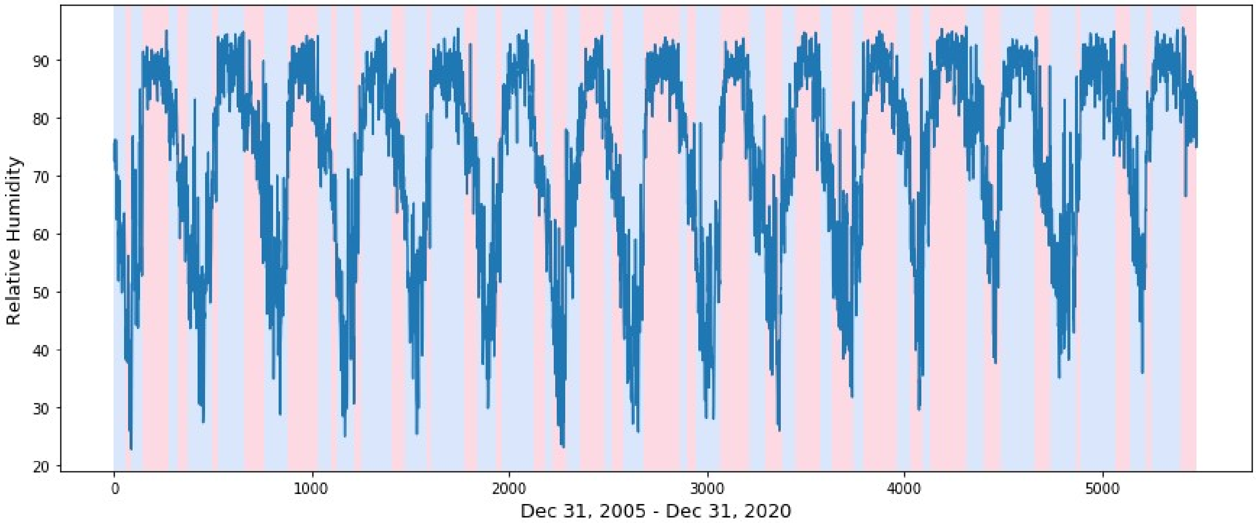


Figure 4.13: Python implementation of PELT for relative humidity

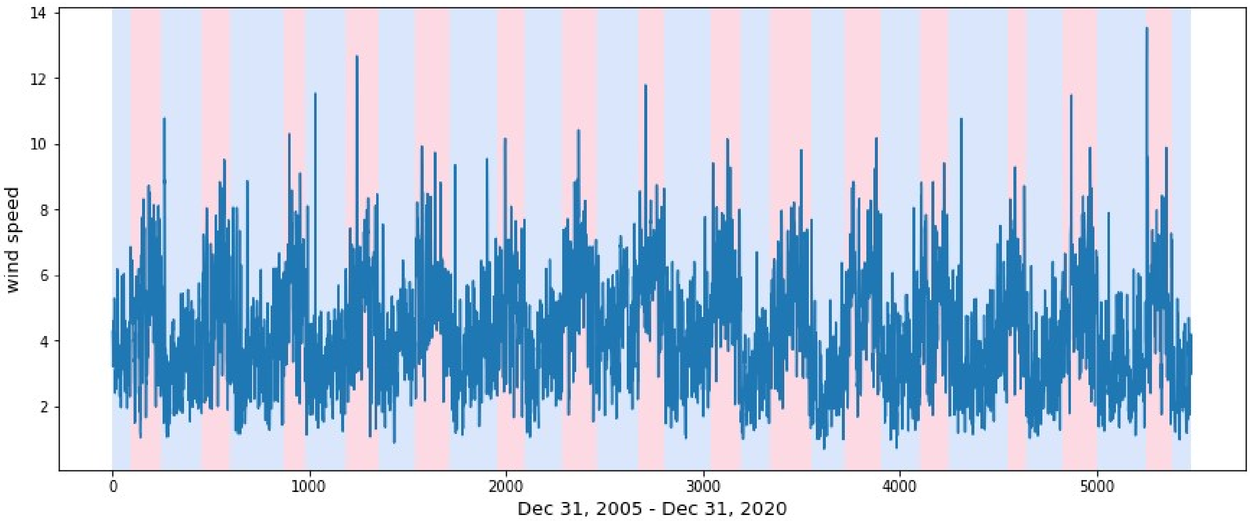


Figure 4.14: Python implementation of PELT for wind speed

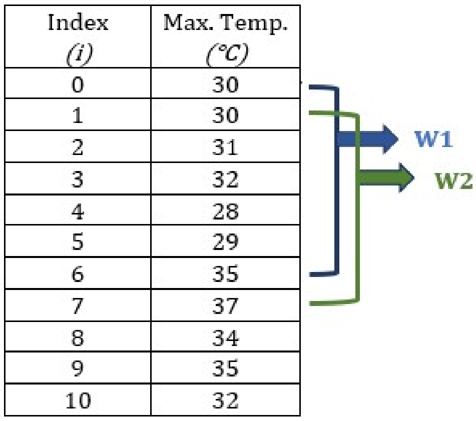
4.2.5 Proposed Algorithm

Window Shifting Method: The sliding window or window shifting technique is a technique for locating subarrays in an array that meet certain criteria. We execute this by keeping a window of a subset of items and resizing and moving that window within the bigger list until we discover a solution. The impulse response of the sliding window approach is finite. The sliding window method is used to study a statistic over a finite period of data. This approach is used to conduct operations on a large buffer or array with a specified window size.

Sliding Window Technique is one of the most important methods for change point detection in time series that is employed in many efficient methods. SWA is a time series analysis tool that can be used for a variety of purposes [39]. Sliding

Window Technique is widely used in medical, weather, and financial time series applications because it operates through a time series sequence and recognizes change points whenever the time series value changes. SWA is a temporal approximation of the time series data's real value [40]. The work proposes to predict weather change in days. The change point in SWA is detected whenever the value of the time series points changes. A sliding window moves through the time series sequences until a change point is encountered. window size W plays an important role in the segmented. The window size is the width of the time series points. In SWA, the width is fixed as two points in one window [41].

Now, we implementing the sliding window method using a sample dataset -



Index (*i*)	Max. Temp. (℃)
0	30
1	30
2	31
3	32
4	28
5	29
6	35
7	37
8	34
9	35
10	32

Figure 4.15: Window shifting techique in sample dataset

Here, Window size, W = 7
At first,we calculate the mean and variance for window W_1 then we slide this window by a unit index. Therefore, now it discards *index 0* from the window and adds *index 7* to the window. Hence, we will get our new window W_2, then we calculate mean and variance for window W_2. Thus, we calculate the mean and variance for each window.

- Average calculation for each window

$$Mean, \bar{t} = \frac{1}{W} \sum_{i=0}^{W} t_i \tag{4.3}$$

  Where W is window size, i is index number, and t is max. temp.

- Variance calculation for each window

$$Variance, {S_t}^2 = \frac{1}{W-1} \sum_{i=0}^{W} (t_i - \bar{t})^2 \tag{4.4}$$

Where W is window size, i is index number, t is max. temp, and $\bar{t}$ is the mean value of max. temp. of the corresponding window.

In the table 4.1, we show the result after calculating each window mean and variance.

Windows (W)	Mean Temp. ($\bar{t}$) (°C)	Variance Temp. (${S_t}^2$) (°C)
W_1	30.714286	5.2380952
W_2	31.714286	10.571429
W_3	32.285714	10.571429
W_4	32.857143	11.142857
W_5	32.857143	11.142857

Table 4.1: Mean and Variance calculation for each window

The window is automatically trimmed at the ends if there aren't enough components to fill it. When the window is trimmed, only the components that fill the window are averaged and the variance is taken over only the elements that fill the window.
Our proposed algorithm's concept in this study is that we had compared between as well two window's mean and variance. If two window's mean and variance increased and decreased at a time, then climate change occurs, otherwise, no climate change occurs.

For example,

Suppose, the mean value of $W_1 = m_{curr}$
the variance of $W_1 = v_{curr}$
the mean value of $W_2 = m_{new}$
the variance of $W_2 = v_{curr}$

Now, we compare the mean and variance of W_2 with mean and variance of W_1
if $\{m_{curr} > m_{new}\ and\ v_{curr} > v_{curr}\}$ or $\{m_{curr} < m_{new}$ and $v_{curr} < v_{curr}\}$ then change point found so climate change occur otherwise, change point not found so climate change doesn't occur. After that, we could detect the accurate number of change point and their location from the dataset by implementing them in 'Python'.

4.3 Conclusion

As different algorithms will have different accuracy in their own rules. It is possible to utilize an algorithm to its highest accuracy by changing the dataset in a way that only the preferred algorithm will work good enough for making the decision. There are some algorithms where the performance grows higher with increasing data, for many other algorithms, it might not work in the same way. As we are using climate dataset of a particular time period which was not used before in any other research, and we apply several algorithms to determine which one will be good fit for the current dataset.

5
Result and Analysis

5.1 Introduction

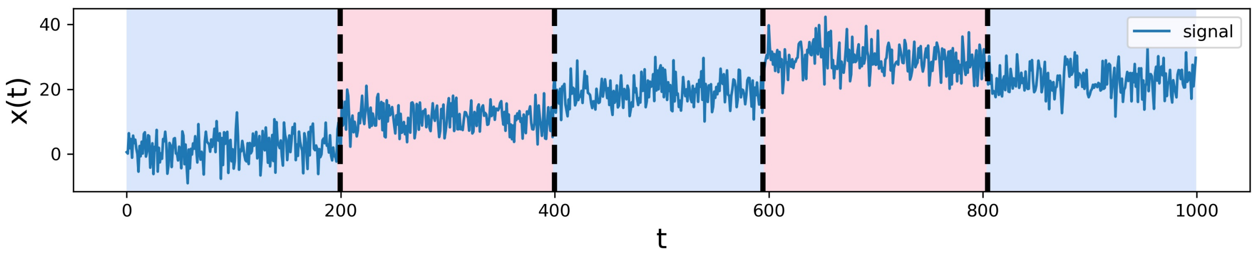


Figure 5.1: Detecting change-point in a generated signal

In the figure 5.1 shown, a time series with four change-points at moments $t_1 = 200$, $t_2 = 400$, $t_3 = 600$, and $t_4 = 800$. Observations among these points have different probability distributions: $P_1(x(t))$ for $0 < t < t_1$, $P_2(x(t))$ for $t_1 < t < t_2$, $P_3(x(t))$ for $t_3 < t < t_4$, and $P_4(x(t))$ for $t_4 < t < 1000$.

5.2 Analysis of Proposed Algorithm

5.3 Comparison with Another Algorithm

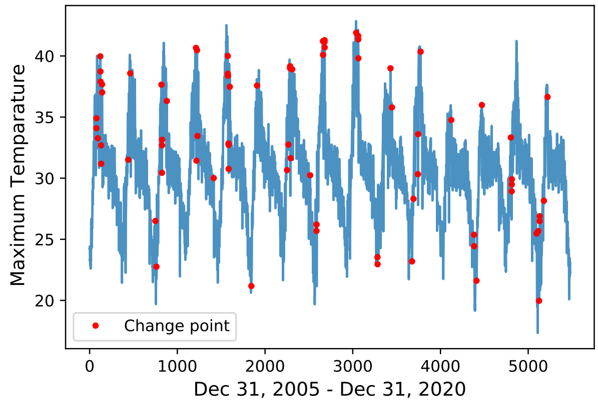


Figure 5.2: Python implementation of window sliding for maximum temperature

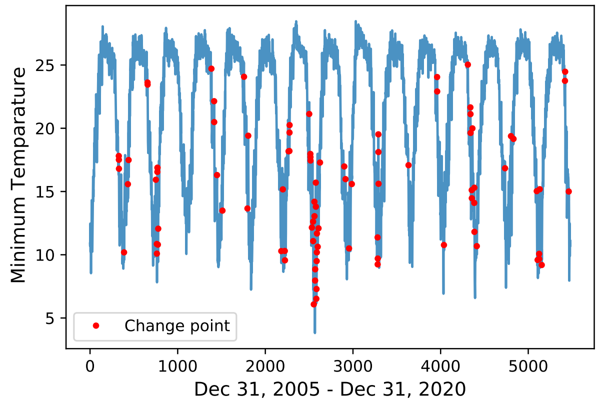


Figure 5.3: Python implementation of window sliding for minimum temperature

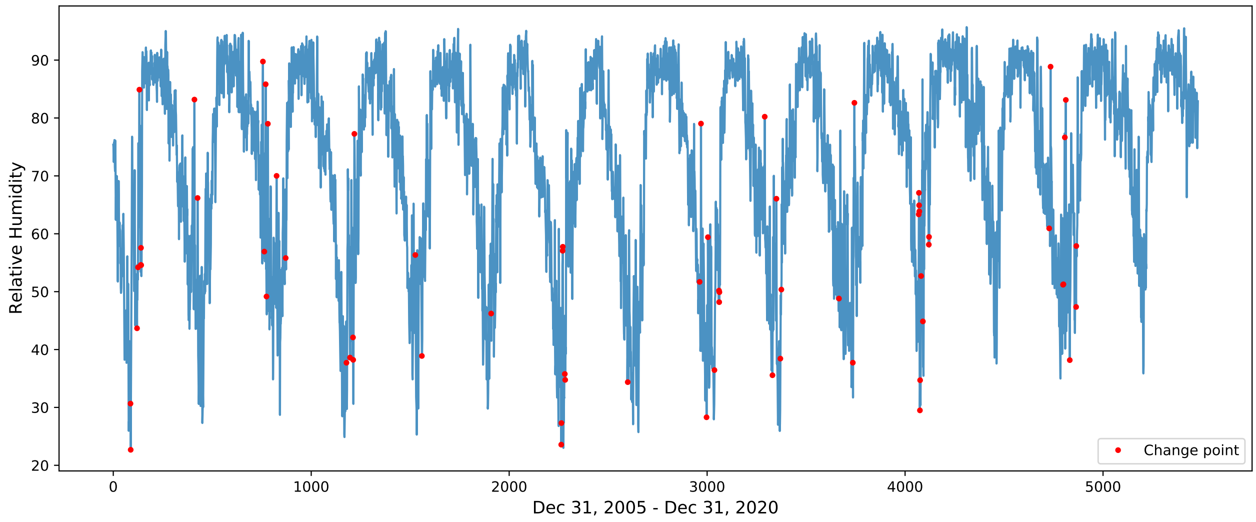


Figure 5.4: Python implementation of window sliding method for relative humidity

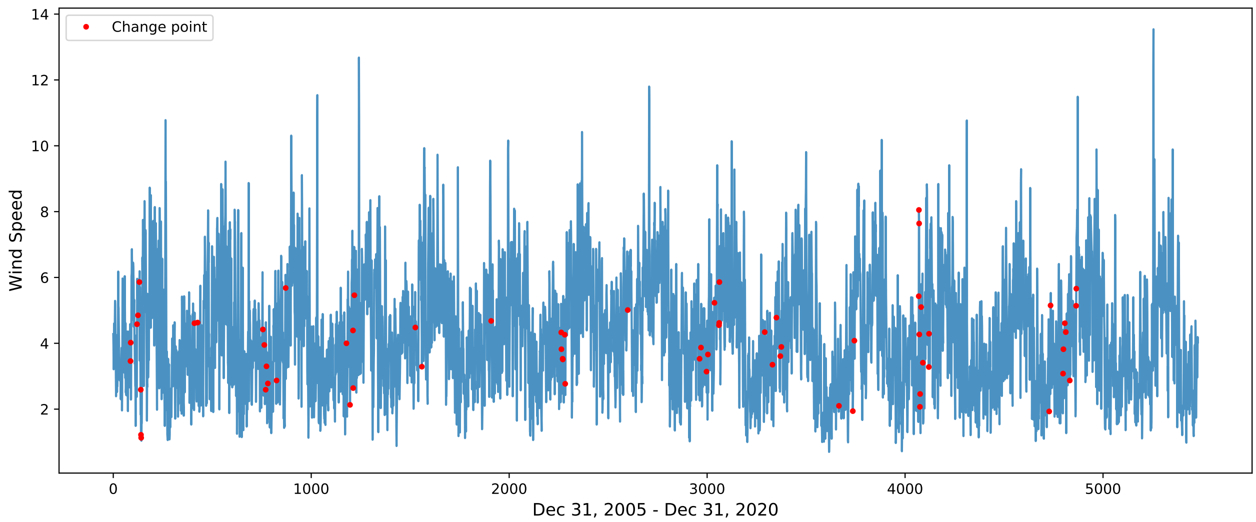


Figure 5.5: Python implementation of of window sliding for wind speed

Methods	Number of Change point
Window Sliding	
Pelt	
BOCD	

Table 5.1: Number of change point in CPD methods

5.4 Comparative analysis of the performance of different algorithms

Methods	Computations	Memory
Binseg	$O(T^3)$	$O(T^2)$
Pelt	$O(T^3)$	$O(T^2)$
Window	$O(W^2T)$	$O(W^2)$
RuLSIF	$O(KWT)$	$O(KW)$
ONNC	$O(T)$	$O(l)$
ONNR	$O(T)$	$O(l)$

Table 5.2: Computational complexity and memory usage of the change-point detection algorithms.

where T is the total number of observations in the time series; W is the window width; K is the number of kernels; l is the lag size. They also need $O(l)$ memory to store the last l values of $d(t)$ score, where l is the lag size between the mini-batches. This makes the ONNC and ONNR algorithms scalable and suitable for change-point detection in large time series.

5.5 Evaluating Models

5.5.1 Classification Accuracy

5.6 Conclusion

6
Effects and Issues

6.1 Introduction

Within the next few sections, we had argued some of the issues that can occur while developing our algorithm for finding the change point in the climate dataset. Many social effect, economical effect may rise against the system. It's true that removing every issue from a developing system in the first place is impossible. But most issues can be minimized if we discover what will be the possible solution to the technological and social drawback. So future research can be led to a new destination.

6.2 Social Issue & Economic Effects

Climate change affects all countries, but low-income developing countries are more vulnerable — first, because they have less capacity to cope, and second, because they rely primarily on agriculture and fishing [42]. We believe that our research region, Dhaka, is the most affected of all the cities under this situation.

Bangladesh, a low-lying alluvial plain, is one of the most vulnerable least developed countries, according to the IPCC. Bangladesh, according to the UN's Mortality Risk Index, is the most susceptible country due to floods and cyclones. Bangladesh's densely populated coastal region along the Bay of Bengal is a vulnerability front line where people are constantly exposed to sea level rise, flooding, erosion, tropical cyclones, storm surge, saltwater intrusion, and fluctuating rainfall patterns [43].

- **Tropical Cyclones and Storm surges:**
- **Temperature Rise:** Because human-induced warming is superimposed on a naturally varying climate, the temperature rise has not been, and will not be, uniform or smooth across the country or over time.
- **Flooding:** Bangladesh has suffered considerable losses due to major inland monsoon floods that occur every three to five years, resulting in agricultural losses, destruction of roads and other infrastructure, interruption of industry and commerce, and injuries and human deaths. Over two-thirds of Bangladesh was flooded in 1998, resulting in damages and losses of over $2 billion, or 4.8 percent of GDP.
- **Agriculture and Food Security:**

6.3 Conclusion

Some ethical and social issue can never be avoided. Also, some technological issue might create a bigger trouble in odd situations. More or less, research over a new idea will generate negative impact in some scenario but that doesn't mean that an experiment is useless. Appropriate investment and proper development can open a new era for people in the future.

7
Conclusion and Future Work

7.1 Introduction

This paper describes a statistical method which is called the "Window Shifting Method" to detect change points in the climate dataset. In this paper, we implemented some search methods like PELT, BinSeg, DP and showed their outcome for our dataset, and we also implement some machine learning algorithm like the bayesian approach, Online Neural Network to detect change point from our given climate dataset.

7.2 Conclusion

Bangladesh is one of the most vulnerable countries to climate change due to its physiographic location, socioeconomic infrastructure, and reliance on natural resources. Bangladesh frequently pays significant prices during natural catastrophes or tragedies as a result of climate change. The vast majority of its citizens have been impacted by these tragedies. Experts agree that, in addition to taking active actions to lower the chance of global climate change, localities can take steps to limit the negative consequences of natural disasters by improving planning, putting in appropriate infrastructure, and developing disaster preparedness. As a result, it is necessary to employ strategies for detecting climate change.

In This paper describes an easy process of detecting the change point and locating that point for climate time series data. In this paper we use day wise data set of Dhaka area, and we apply sliding window algorithm to detect the change point of maximum temperature, minimum temperature, precipitation, wind speed, relative humidity. We also compare our result to PELT algorithm to find the accuracy of our method. The experimental results prove the efficiency of the proposed climate change detection algorithm. Finally, we can say that if we can fix an ideal value of threshold to calculate the value of mean and variance then we will find better result to detect the change point.

7.3 Future Work

In the future we will develop our algorithm by fixing threshold value. We will work to get an ideal threshold value. We will also develop an algorithm to detect the threshold value. We will use our climate data set to predict the climate change issue. We plan to use climate change values to anticipate seasonal diseases in the future.

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Appendices

A
Supporting Information

B
Supporting Information