Comparative Analysis of Change Point Detection: A Case Study for Long Time Series*

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Abstract— **Climate change is one of the threats of the last period, and its effects on water resources are notable. Determining its extent is necessary to manage water resources effectively, ensure the population's access to water, and reduce anthropogenic impacts on its quality. This study attempts to estimate the sensitivity of changepoint detection (CPD) methods to the modification of the time series length. The study is developed on a long monthly time series recorded at Sulina, in Romania. The study indicates the sensitivity of the Hubert segmentation procedure to outliers, CUSUM being more stable with respect to the Hubert method.**

Keywords—precipitation, change point, seasonality, series decomposition

I. Introduction

The Earth's hydrological cycle relies on precipitation to manage water supplies and nourish the natural world [1]. However, this balance is being reshaped by climate change, which has altered how often and how heavily it rains [2,3]. A primary driver of this change is rising heat; a warmer atmosphere traps more water vapor, leading to a surge in intense rainfall, especially in areas already susceptible to heavy weather [4,5].

Simultaneously, shifts in atmospheric circulation patterns, such as jet streams and monsoon systems, alter the timing, location, and precipitation type. Therefore, some regions are experiencing more intense and frequent flooding, while others face decreased rainfall, leading to drought conditions and water scarcity [6-8]. Moreover, climate models' projections indicate that these changes are likely to accelerate, with high latitudes expected to experience increased precipitation, while subtropical and some temperate regions may become progressively drier. These alterations have critical implications for freshwater availability, agricultural productivity, ecosystem stability, and disaster risk management [9-12].

Change Point Detection (CPD) is a technique used to identify points in a time series where the data's properties change significantly. These points, called changepoints, mark a modification in mean, variance, slope, frequency spectrum, underlying process generating the data, etc [13].

CPD is essential in many fields where finding shifts or anomalies over time is critical. For example, in finance [14], it can detect shifts in market trends; in manufacturing [15], it can spot equipment failures; in healthcare [16], it may identify sudden changes in patient vitals; in network security [17], it helps uncover intrusions.

There are various methods for CPD, such as CUSUM [18], machine learning methods [19], Bayesian techniques [20-22], etc. A review of various techniques for CPD is presented in [23]. Effective CPD improves decision-making, supports anomaly detection, and enhances the understanding of dynamic systems. They aim to detect either one or multiple CPs, based on different mathematical backgrounds.

This article examines the robustness of CPD methods applied to monthly precipitation series, comparing the results obtained for the series recorded during January 1965 – December 2019 (denoted by S) with those obtained for the series January 1965 – December 2005 (denoted by S1) at Sulina station, situated in the Nature Reserve Danube Delta in Romania [24].

The study addresses the following research question: How do different mathematical frameworks for CPD perform in identifying subtle yet ecologically critical shifts in precipitation regimes within the Danube Delta, and have these shifts accelerated in the 21st century compared to historical trends? By benchmarking multiple CPD methodologies against a unique dataset extending to 2019, this research seeks to identify the most reliable diagnostic tools for detecting the 'tipping points' that threaten the stability of the Delta's unique flora and fauna. Ultimately, this work provides a scalable methodological blueprint for monitoring climate-induced transitions in vulnerable ecosystems worldwide.

II. Data Series and Methodology

A. Data Series

The studied series is formed by the monthly precipitation recorded from 1965 to 2019 at a meteorological station in the Danube Delta, Romania. For simplicity, we call this series S (Fig. 1).

B. Methodology

The first stage was to determine the basic statistics, followed by the Shapiro-Wilk [25] and the Kruskal-Wallis normality test [26] to assess the differences between the statistical descriptors and statistical distributions of S and S1.

The second stage was outliers' detection. The Interquartile Range Method (IQR) [27] was utilized because it does not rely on the series' normality.

In the third stage, we performed the classical CPD tests - Pettitt [28], Buishand [29], Lee and Heghinian [30], which

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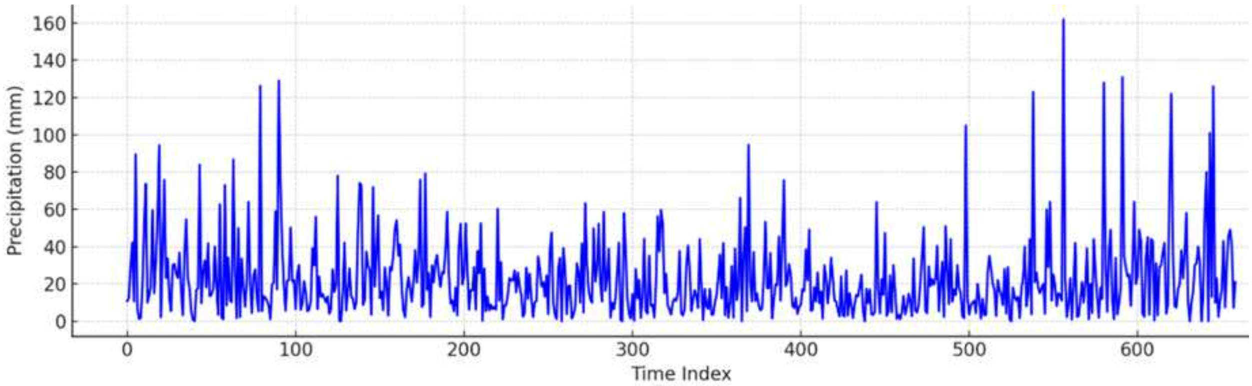

Figure 1. S series

find only the dominant change points (CP) and the segmentation procedure of Hubert [31], for multiple CPD. The results were compared with those obtained by CUSUM implemented in [32].

The Hubert test was also applied to the series cleaned using the Hampel filter [33], which involved:

- Calculate the median and the Median Absolute Deviation (MAD) within a sliding window (10, in this case).
- Identify any point that is more than k standard deviations (σ) from the median (where σ = 1.4826 MAD)
- Replace the detected outliers with the local median.

According to Taylor, "the CUSUM algorithm is iterative and utilizes cumulative sum charts and bootstrapping to detect the changes." Its stages are [32]:

a) Compute the average of the recorded values, (X_t), $t = 1, \ldots, n$, and denote it by $\bar{X}$.

b) Initiate the cumulative sum by $S_0 = 0$.

c) Compute

$$S_t = S_{t-1} + (X_t - \bar{X}), t = 1, \ldots, n. \quad (1)$$

d) Draw the chart of (S_t).

e) Determine the maximum and minimum of all S_t (S_{max} and S_{min}, respectively) and denote by

$$S_{diff} = S_{max} - S_{min}. \quad (2)$$

S_{diff} will serve to evaluate the change's amplitude.

f) Bootstrap the set of X_t.

g) Compute the CUSUM after bootstrapping.

h) Determine the maximum, minimum, and range for the values from h).

i) Compare the range from i) with S_{diff}.

Bootstrapping is generally performed 1000 times to determine if there are changepoints in the data series.

Denoting by N the number of samples in the bootstrap procedure for which the range is less than S_{diff}, the confidence level is (%): N×100/1000.

The moment, m, when the change point appears is determined using the following estimators:

1. CUSUM estimator: m is the index where the maximum of the absolute value of $(S_t), t = 1, \ldots, n$, is recorded.
2. Mean Squared Error, defined by:

$$\mathrm{MSE}(m) = \sum_{t=1}^{m}(X_t - \overline{X_1})^2 + \sum_{t=m+1}^{n}(X_t - \overline{X_2})^2 \quad (3)$$

where $\overline{X_1}$ and $\overline{X_2}$ are the means of the values before and after the CP. The CP moment m is when the MSE is the lowest.

This procedure's advantage is that it can be used to analyse the variation of any derived datasets, e.g., means, ranges, standard deviations, etc. After the CPD, the existence of the trend of each subseries was tested using the Mann-Kendall trend test [34] to determine the existence of a monotonic trend of each subseries. If the null hypothesis was rejected, the existence of the same mean of the neighbor segments was checked by the Kruskal-Wallis test.

III. Results and Discussion

A. Basic Statistics and Classical CP analysis

Fig. 2 presents a comparison of the basic statistics of the series S and S1. Whereas the minimum is zero for both series, the maximum is higher, with 43 mm for S compared to S1.

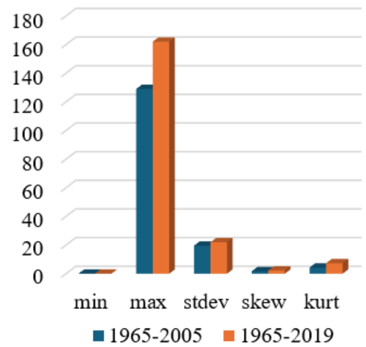

Figure 2. Basic statistics of S and S1

An increase of about 10% of the standard deviation (stdev), more than 20% of skewness, and about 70% of kurtosis is noticed for S with respect to S1.

Fig. 3 represents the histograms of S and S1 and the fitted theoretical Gaussian curves, indicating that no series is issued from a normal distribution.

The correlogram (Fig. 4) indicates no autocorrelation for lags between 1 and 10.

After performing the Kruskal-Wallis test, the null hypothesis that S and S1 come from the same underlying distribution could not be rejected at a significance level of 5% (p-value = 0.485). Normality can be reached by applying a Box-Cox transformation to each series. Therefore, all classical CPD could be applied to both series.

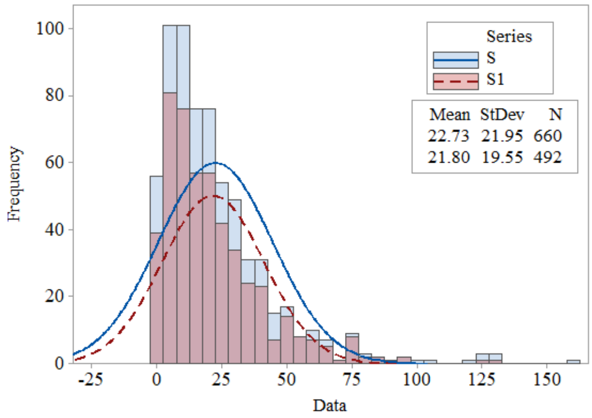

Figure 3. Histograms of S and S1

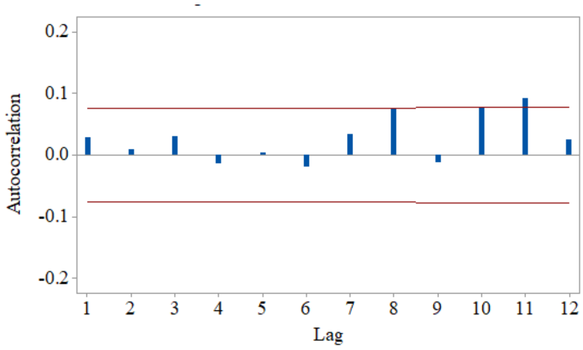

Figure 4. Correlogram of S series

Table I contains the comparative analysis of the results.

TABLE I. CHANGE POINTS DETECTED BY CLASSICAL METHODS

Tests	S1	S
Buishand	no	no
Pettitt	no, 212	no, 212
Lee&Heghinian	no, 212	no, 212
Hubert	91,93,492	91,93,557,558,581,582,592,593

*No means that the null hypothesis that there is a change point can be rejected

The first three tests – Buishand, Pettitt, and Lee & Heghinian – rejected the hypothesis that there is no change point, the last two indicating August 1982 (month no. 212) as a breakpoint.

For S1, the Hubert segmentation procedure found two CPs, but their proximity can suggest that they are aberrant values, given the change from a mean of 27.455 mm for the segment before August 1982 to 102.75 mm for two months and then a return to a segment with a mean of 21.341 mm.

In terms of standard deviation, the variation was from 25.162 mm to 38.538 mm, then to 16.896 mm. A similar behaviour appears in the case of S, for the months 557, 581, and 592.

Applying the same test on the filtered S series, the Hubert test provided the months 19,21, 64, 65, 316, 320, 584. It emphasizes again the instability of this test to the high values (even though they are not outliers in the sense of statistics).

B. Results of CUSUM analysis for S1

The CUSUM analysis for S1 indicates a CP in the mean in month 212, as shown in Fig. 5, in concordance with the first three tests presented.

Fig. 6 shows the plot of the standard deviations of S1. One may remark that there were two periods with different patterns in the standard deviation's evolution, with a higher variability before month 95.

The CUSUM chart of the S1 series standard deviations is presented in Fig. 7, confirming the existence of a CP (in the series standard deviation). When considering the coefficient of variation, no CP was detected for S1.

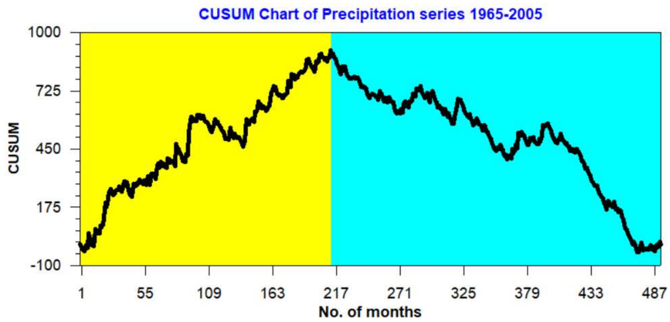

Figure 5. CUSUM chart for mean

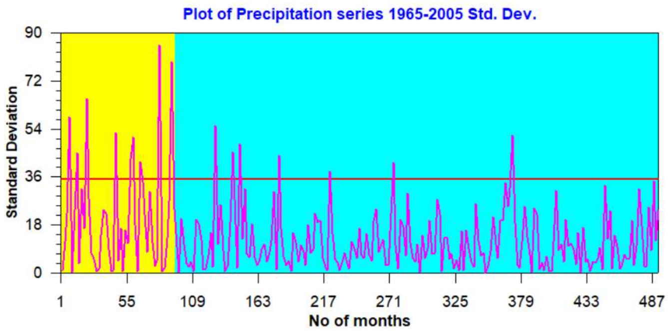

Figure 6. CUSUM chart for CP in the mean of S1

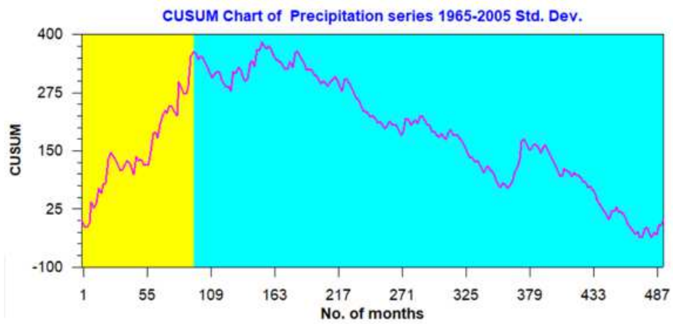

Figure 7. CUSUM chart of S1 standard deviations

C. Results of CUSUM analysis for S

The results of the CUSUM analysis for S are presented in Figs 8. and 9.

Fig. 8 shows four periods in the CUSUM chart of S, delimited by CPs in months 212, 421, and 537, the first two with a confidence level of 96%, and the last one with a confidence level of 99.5%.

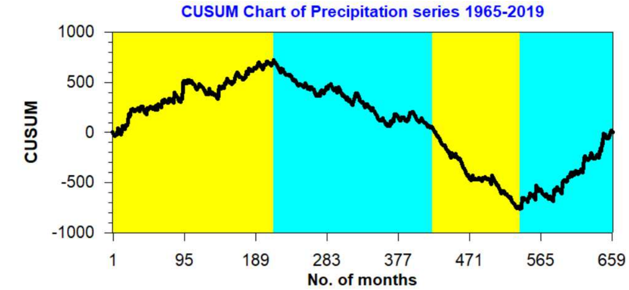

Figure 8. CUSUM chart for CP in the mean for S

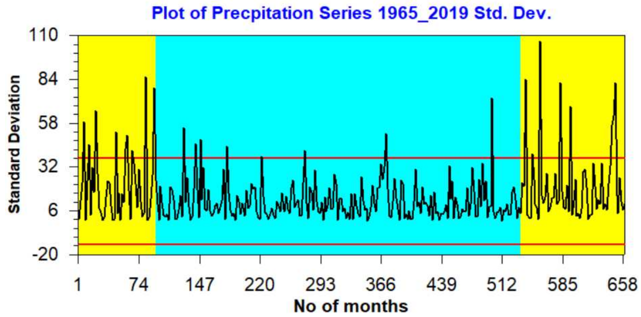

Figure 9. Plot of precipitation series S standard deviation

Two CPs in variance (Fig. 9) were detected in the months 94 and 534. The periods before the month 94 and after the month 534 present a higher variability compared to the period in the second segment (94-534). The confidence levels for the CPs are 98% and 99%, respectively.

D. Analysis of the trend of S1

The results of the Mann-Kendall (MK) test for the subseries of S1 before and after August 1982 (denoted S1.1 and S1.2) indicate no significant trend. Still, a negative trend is detected when the same test is performed on S1.

Given that S1.1 and S1.2 have different lengths, to test the null hypothesis that the means of S1.1 and S1.2 are equal against the hypothesis that they differ, the non-parametric Kruskal-Wallis test was performed for the pair (S1.1, S1.2). Since the value obtained was less than 5%, the null hypothesis was rejected, cross - validating the finding of the CUSUM test. The existence of a CP in the month 212 indicates that the average of S1.1 is higher than that of S1.2.

E. Analysis of the trend of S

Given the detected CPs in months 212, 421, and 537, we performed the MK for the subseries S2.1 (between the months 213 and 421), S2.2 (between the months 422 and 537), and S2.3 (after the month 538). The results from Table II indicate no significant trend for each subseries.

However, the Kruskal–Wallis test rejected the null hypothesis for both pairs (S2.1, S2.2) and (S2.2, S2.3), confirming the existence of a variation in the subseries averages.

The results from Table II indicate no significant trend for each subseries.

TABLE II. RESULTS OF THE MK TEST

Series	p-value	z
213-421	0.4647	0.7312
422-537	0.2111	1.2505
538-660	0.2429	0.2919

The high level of concordance with independent studies and the successful cross-validation against filtered data confirm that the identified trends are representative of the broader Dobrogea and Danube Delta region [35-39], effectively bridging the gap between local station observations and synoptic climatic shifts. Therefore, the detected CPs are robust indicators of regional climate evolution.

IV. CONCLUSIONS

The study indicates the existence of CPs in the precipitation series, the most significant being captured by the classical CPD methods. The series variation is not reflected in the subseries' increasing/decreasing trend, but in the variations in the average precipitation recorded in subperiods.

By applying the CUSUM method, we also detected CPs in the series standard deviations, which will be deeply investigated in future research. From a practical viewpoint, a CUSUM-detected shift in the mean requires managers to redefine the "safe yield" and long-term water allocation policies to align with a new baseline of total resource availability. Conversely, a shift in variance signals increased hydrologic volatility, necessitating higher reservoir buffer capacities and more robust flood-defense infrastructure to mitigate the risks of more frequent and intense extremes.

While the current study establishes the efficacy of CPD methods in identifying discrete shifts within the Danube Delta's precipitation series, these results open promising avenues for the time series research community. Future work should explore the integration of these detected change points into a Segmented Multifractal Detrended Fluctuation Analysis (SMF-DFA) framework.

This research offers three transformative perspectives:

- Refinement of Fractal and Multifractal Scaling: Standard MF-DFA often suffers from "crossover" artifacts when a single scaling exponent is applied across different physical regimes. By using our proposed CPD algorithm to define naturally occurring boundaries, researchers can apply Segmented MF-DFA to ensure that multifractal descriptors, such as the singularity spectrum width, accurately reflect the internal dynamics of homogeneous climate epochs rather than artifacts of non-stationarity [40,41].
- Decoupling Sources of Complexity: Future studies could utilize CPD-defined segments to investigate whether the origin of multifractality in precipitation shifts over time. This involves determining if the complexity is driven by long-range correlations (memory of the system) or by broad probability distributions (the presence of extreme events) [42].
- Early Warning Systems via Complexity Loss: A compelling hypothesis for future investigation is the relationship between complexity loss and regime shifts.

By monitoring the evolution of the multifractal spectrum between change points, it may be possible to identify a narrowing of the spectrum as a precursor to the tipping points detected by CPD. This would move the field toward a proactive diagnostic framework for ecosystem stability.

By merging the structural detection of CPD with the scaling insights of multifractal theory, we can develop a more nuanced understanding of how stochastic environmental variables evolve under the pressure of global warming.

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