FROM WET TO EXTREME WET SPELLS – CASE STUDY OF SHKODRA

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Abstract

Precipitation is a primary element of climate, and changes in its long-term pattern are crucial to changes in the climate itself. Periods of heavy precipitation exert a significant influence on the monthly precipitation totals, consequently impacting the water resources of a specific region. The high frequency of such periods of heavy precipitation is a critical factor in determining the fragility of the water balance in a given area, as well as the complexity of managing water reserves. In this study, we have examined the Maximum Consecutive Wet Days (CWDmax) on both monthly and annual time scales to determine whether a given month or season can be considered a wet or very wet period for a given year or decade. In the wet months or seasons resulting from the CWDmax analyses, the identification of very wet or extremely wet periods was undertaken by estimating the monthly maximum consecutive 5 to 10 days of precipitation (the RX5day and RX10day indices, respectively). Finally, the weight of the RX5day and RX10day indices on the total monthly, seasonal, and annual total precipitation was estimated. The estimation of these indices was based on daily precipitation data from Shkodra city over the period 1950–2022, with the objective of identifying signals of climate change impact on local precipitation changes.

***Key words*: *Rainy season; wet periods; precipitation trend; water resources; climate changes.*

Përmbledhje

Reshjet janë një element kryesor i klimës dhe ndryshimet në modelin afatgjatë të tyre, janë thelbësore për ndryshimet e vetë klimës. Periudhat me reshjeve të bollshme kanë një ndikim të rëndësishëm në shumat mujore të reshjeve, *rrjedhimisht kanë ndikim edhe në burimet ujore për një rajon specifik. Frekuenca e lartë e periudhave me reshje të tilla është një faktor kritik në përcaktimin e bilancit ujor në një zonë të caktuar, si dhe në kompleksitetin e menaxhimit të rezervave ujore. Në këtë studim, është analizuar Maksimumi i Ditëve të Njëpasnjëshme të Lagështa (DNJLmax) në bazë mujore dhe vjetore për të parë nëse një muaj ose stinë e caktuar mund të konsiderohet si një periudhë e lagësht ose shumë e lagësht, për një vit ose dekadë specifike. Nga analizat e DNJLmax, për muajt ose stinët që rezultojnë të lagështa, është kërkuar për periudha shumë të lagështa ose jashtëzakonisht të lagështa duke vlerësuar maksimumet mujore të reshjeve në periudha 5 deri në 10 ditore të njëpasnjëshme (përkatësisht indekset RX5d dhe RX10d shprehur në ditë). Në hapin final, është vlerësuar pesha e indekseve RX5d dhe RX10d në totalin e reshjeve mujore, stinore dhe vjetore. Këto indekse janë vlerësuar duke u bazuar në serinë e të dhënave të reshjeve ditore për qytetin e Shkodrës gjatë periudhës 1950 – 2022, me qëllim kapjen e sinjaleve të ndikimit të ndryshimeve klimatike në ndryshimet e reshjeve locale.*

Fjalë kyçe: *Stina e reshjeve, periudha të lagështa, trendi i reshjeve, burime ujore, ndryshimet klimatike.*

Introduction

A crucial statistical metric in analyzing the precipitation system is the number of consecutive wet days. It may be used as an indicator of hidden or complex phenomena related to climate change. According to recent works and studies, the redistribution of precipitation, including significant changes in precipitation trends and the shift of precipitation extremes, is directly related to climate change (Allan et al., 2008); (Wang et al., 2020); (Gao et al., 2017). In this regard, the study of CWD holds particular relevance for scientists and administrative authorities in various economic sectors within a nation.

In the context of specific regions associated with economic or industrial settlements, such as power plants, the significance of such analyses becomes particularly evident. Furthermore, such studies can serve to predict the effects of medium- or long-term health problems in the population. In this paper, we have studied the rainfall behavior in the city of Shkodra by analyzing the CDW for the period 1950-2022. This study builds upon earlier analyses of inflows to the Drin cascade dams (Prenga et al., 2014; Sula et al., 2019; Kushta et al., 2023), as well as other works on general climate processes (Porja, 2022; Porja et al., 2011). In (Sula et al., 2019), the issue of managing water inflows to HPP dams to ensure a better balance between production costs and lateral losses due to unavoidable outflows during intense rainfall is emphasized. A descriptive consideration of this process in the aforementioned reference revealed the existence of sequences of anxious dynamics on HPP water levels.

Consequently, forced water releases in accordance with safety protocols exhibit an unexpected and unpredictable escalation to flood levels, frequently impacting the Shkodra lowlands. In this context, a comprehensive analysis of the statistical characteristics of the climatic parameters is imperative and serves as a foundational starting point for the subsequent analysis of their data. In our recent study (Porja, 2008), we observed that the distribution of extreme behavior for certain climate parameters qualitatively aligns with the Gumble distribution. However, a more comprehensive and quantitative investigation has revealed that the corresponding distribution is non-stationary, thereby constraining the quantitative conclusions. Therefore, we have initiated our study by outlining the general statistical characteristics of the rainfall and the subsequent wet/dry days. Specifically, the distribution of CWD and related data, as well as the statistical similarities or dissimilarities between these indicators by monthly and other reference periods, are considered.

Methodology

The present study was initiated with a descriptive analysis of the raw rainfall data recorded at the Shkodra Meto station for the period 1950-2022. It is assumed that these data are measured correctly and in accordance with our research objectives, although no further information on the method and the hourly activity is maintained. The hourly data is particularly relevant for the present study, as the daily unit is too extensive for quantitative analysis. Despite this limitation, we have proceeded with their elaboration, and these features will be included in the final concluding remarks.

The subsequent phase of analysis involves the division of these series into monthly and seasonal categories. For each of these daughter series, the reported rainy days have been identified, and the indices of when a CWD set begins and ends have been determined. By subtracting these indices from the original data, we have obtained the series of rainy days sequences. Finally, the cumulative rainfall was read considering the raw series and the indices obtained so far. For each of these series, we identified the distribution that fits to the empirical histograms, and then the corresponding state and the legacy of a measurement therein are qualified based on these findings.

Furthermore, the identification of the distribution in this state is incorporated for enhanced identification of extreme events, which, logically, would be those events where the characteristic parameter, such as CWD, CDD, rainfall, etc., differs significantly from the mean. Despite the assumption that these distributions may be gamma-based or Gumble function (Porja, 2008), a search for additional candidate distributions was conducted through the quantitative estimation of goodness-of-fit descriptors. In this step of the analysis, the optimization procedure was carefully considered in order to better individualize the underlying distribution for the length of the days. This approach is expected to enhance the accuracy of future predictions. In regard to the primary objective of the study, which is centered on the identification of the dynamics and characteristics of the RX days, a descriptive analysis was initially conducted based on the direct estimation of the corresponding indices. Subsequently, we proceeded to an averaged estimation based on the distribution of events. It is noteworthy that the primary indicators, the mean $\bar{x} \equiv \int_{support} x\rho(x)dx$, and its deviation $\sigma(\overline{x}) \equiv \int_{support}(x-\bar{x})^2\rho(x)dx$, the corresponding distribution object, denoted by ρ(x), must be stationary. In practice, two approaches are commonly employed. The first involves inducing the system to a state of stationarity prior to measurement and the second approach involves allowing the time processes to run until the system reaches a stable state (Kushta et al, 2023). In instances where the stationarity of the state remains unproven through direct verification, the analysis is constrained to descriptive elements.

For this step, we have initiated the identification of the optimal histogram by assuming a stationary but unknown distribution. The initial candidates are evaluated by optimizing the bin size using the Scott rule. Subsequently, the non-stationary distribution is examined through the implementation of the Freedman-Djaconic optimization rule. The entities obtained through these procedures are then classified according to their goodness of fit. It was observed that the Scott rule was found to be inadequate, which serves as an indirect test of the non-stationarity of the underlying distribution. It is noteworthy that the gamma distribution Generalized Extreme Values, given by

$f(x) = \frac{1}{\Gamma(k)\alpha^k} x^{k-1} e^{-\frac{x}{\alpha}}$ or the Gumbel distribution given by $f(x) = \frac{1}{\beta}\exp(-\frac{x-\mu}{\beta} + \exp\left(-\frac{x-\mu}{\beta}\right))$ are commonly used for these applications but given the questionable nature of several assumptions regarding these distributions due to the nonlinearity of the underlying process, we have considered a wider range of candidates. The mathematical specifics of the sub-methods used in this study are addressed in the next paragraph. However, readers are directed to consult dedicated articles or papers for a more comprehensive overview. Nonetheless, a brief introduction to some specific elements of this analysis is provided, in particular the ad hoc stationarity analysis and the identification of the underlying periodic behavior. From a mathematical perspective, stationarity can be achieved by conducting a standard Levy analysis, which is essentially a parametric analysis and therefore not particularly practical. Alternatively, as posited by Umariov (2008), stationarity can be analyzed by q-Gaussian and the corollary of the corresponding q-central limit theorem (qCLT). The corresponding probability density function (PDF) is expressed in the form $\rho(x) = \frac{\sqrt{q-1}}{\sqrt{3-q}} * \frac{\Gamma\left(\frac{5-3*q}{2*(1-q)}\right)}{\Gamma\left(\frac{2-q}{1-q}\right)*b)} * \left(1 - \left(\frac{1-q}{(3-q)*b^2} * ((s-\mu)^2)\right)\right)^{\frac{1}{1-q}}$. In this case, if <5/3, the distribution is stationary; for 5/3 < q < 2, the distribution is non-stationary and has negative variance ($\sigma_q < 0$), and for 2 < q < 3, the variance is undefined while for the q > 3, the q-Gaussian is not a distribution object. In the following phase of the study, the quantitative estimation of non-stationarity for a distribution was done based on Tsallis' statistics.

The results of this phase were then compared with the overall behavior of the moths as a whole or for specific periods of the paned interval. The empirical mode decomposition (EMD), as introduced by Huang (1998) and discussed in other works, such as Flandrin (2003), was utilized. In this case, the non-stationary signal was decomposed into intrinsic mode functions (IMFs) by means of spline interpolation for the points $x(t) = \frac{\left(x_{\max,t}^{local} - x_{\min,t}^{local}\right)}{2}$ giving a discrete Fourier-like form $X(t) = \sum_{i=1}^{n} IMF_i + \varepsilon(t)$. In particular, the final IMF mode delineates the trend of the series. A comprehensive review of the empirical and descriptive analysis for RX and extreme events was conducted, with particular attention given to the range of wet days and the corresponding rainfall. These parameters were examined through an ad hoc qualification of prolonged wet days and abundant rain, based on statistical observations. Firstly, the precipitation data series for the Shkodra region and its derived series were examined.

Empirically, the period length of about 26,660 records is recognized as favorable for conclusive results. Each daughter series contains approximately 2,220 data points, which, while not substantial, is not negligible in the standard and representative sense. The empirical deviation of the arithmetic mean of precipitation per day has been observed to be higher than the mean itself, indicating heterogeneity and non-linearity for the data of daily precipitation by month. It is evident that the identification of the underlying distributions poses challenges in terms of statistical robustness. It is hypothesized that this challenge can be mitigated through the consideration of more specific data. However, the primary issue identified thus far, and consequently a salient feature, pertains to the non-trivial nature of utilizing the mean to identify relative extreme events, given the necessity of estimating means and theoretical deviations for more refined data. To enhance the reliability of the analysis of anomalous events, a distribution check for precipitation and the number of wet days was also conducted.

Identifying the statistical characteristics of the rainfall data

In order to proceed with the descriptive analysis, the initial step was to identify the distributions. Subsequently, an effort was made to achieve an acceptable fit of data-event frequency with functions recommended by the extant literature. The necessity for an optimal bin or discretion process was identified, and the subsequent step involved the certification of goodness of fit. It was observed at this stage that the optimization of the bin produced abnormal empty bins when using both PDF and CDF approaches, which poses a difficulty for the quantitative analysis of the distribution. However, following the elimination of the initial point corresponding to zero millimeters of rainfall per day, there was an enhancement in the fit. In this instance, the Weibull distribution was determined to be the optimal model based on negative likelihood criteria. The parameters of this distribution are shown in Table 1.

Table 1. Parameters of the best fitted distribution

Generalized Extreme Value distribution. k = 1.328 [1.279, 1.378] sigma = 4.13 [3.968, 4.30] mu = 2.608 [2.49, 2.73]	Log normal Distribution Mu = 1.543 [1.50, 1.58] Sigma = 1.84 [1.81, 1.87]	t Location-Scale Mu = 5.38 [5.13, 5.64] Sigma = 6.34 [6.07, 6.61] nu = 1.29 [1.22, 1.36]	A = 11.07 [10.72 11.43] B = 0.67 [0.66, 0.68]

The determination of the average can be based on the best-fit distribution, and in this case the CEVs have the best fit, but the absolute goodness of fit and the fit statistics indicate that the distribution and the corresponding state are highly perturbed and not relaxed as in the **Figure 1** and **Figure 2**.

The location parameter, corresponding to the long-term average, is significantly smaller than the arithmetic average for the raw data at 4.9982 mm/day and for the nonzero series at 14.5378 mm/day.

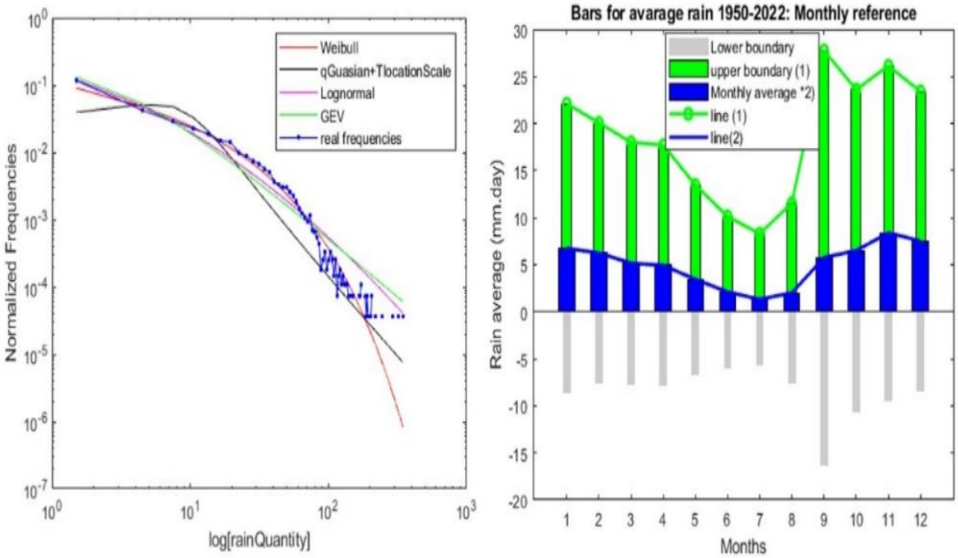

Figure 1. The upper panel shows the above monthly arithmetic means, while the lower panel shows the distribution of daily precipitation

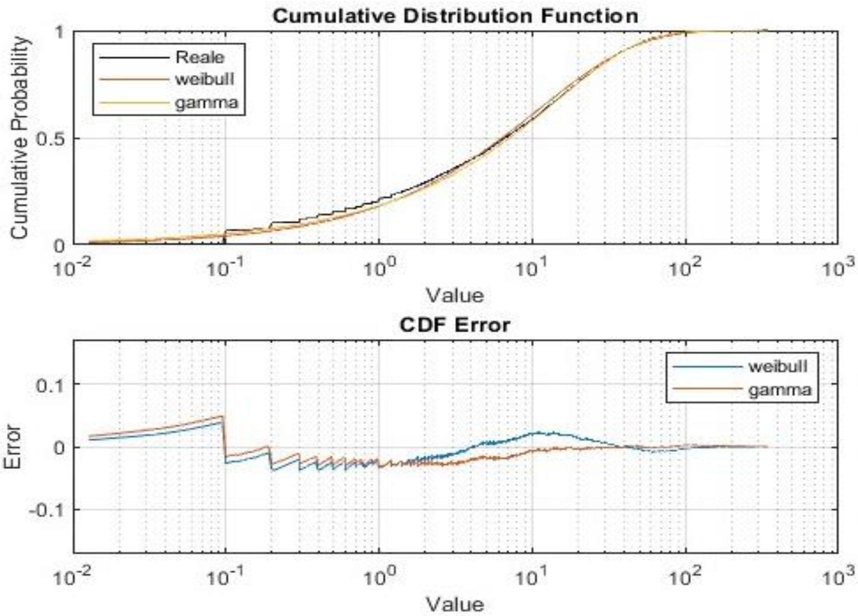

Figure 2. Representation of the alternatives using the CDF approach

Furthermore, a multifractal analysis based on the DFA techniques reveals that the daily precipitation series are highly heterogeneous. It is also evident that tLocationScalepdf, a constituent of the q-Gaussian family, is among the most suitable distributions (form17 PDF as per the MATLAB default setting). This finding suggests the potential for utilizing q-Gaussians in indirect measurement, given the employment of a Gaussian type subsequent to its identification as one of the most suitable PDFs.

Thus, by using the q-Gaussian function to directly analyze the stationarity, we obtained $q \sim 2.8$, so $d_{stationarity} = 1.8$, indicating a critical level of non-stationarity. We have associated these indicators of non-linearity and non-stationarity with intensive events that occur in the climate system. However, additional factors related to measurement, methodological reference, and the location of the station must be considered. It is crucial to acknowledge that, given the current data set, the precision with which we can measure precipitation levels, for instance, remains uncertain.

Consequently, the implementation of linear modeling approaches, such as ARIMA or NN models, necessitates a high degree of caution. Furthermore, it is imperative to diagnose series based on these models, such as CWD, for their linearity and characteristic properties prior to employing them to elaborate models.

Descriptive analysis of CWD and CDD characteristics

Here we considered the general statistical characteristics of the CWD/CDD distribution and its stationarity. We employed the fitting procedure previously outlined to analyze the data. Following the optimization of the bin and the verification of the distance from the stationary states using the q parameter from the q-Gaussian fit, it was determined that all of the distributions fitted to the histograms were non-stationary.

The analysis revealed that the optimal distributions were Weibull or General Extreme Value types. The goodness of fit of these distributions, as well as the distributions themselves, vary by month, as illustrated in **Table 2** and **Figure 3**. In the context of daughter series comprising grouped data from one or three months, there has been an enhancement in the goodness of fit. However, it is observed that the distributions remain stationary.

Table 2. Indicators of consecutive rainy days

Month	Empiric parameters			Reference Distribution Type	Fitting Goodness
	Mean	Deviance	Maximal		
January	16.6252	20.4201	218.8	Weibull	Fair
February	14.0164	17.9267	148	q-Gaussian	Fair
March	13.2956	17.7963	189	Gev	Good
April	12.1476	17.7261	202.3	Weibull	Good
May	9.7374	14.954	131.3	Weibull	Fair
June	8.3019	14.2326	132	Gev	Fair
Jully	7.981	15.5382	168.8	Weibull	Fair
August	10.882	19.9747	206.4	Weibull	Good
September	21.9947	37.1976	347.2	Weibull	Fair
October	18.4451	24.7178	195	Gev	Fair
November	17.4816	22.314	193.2	Gev	
December	16.9205	20.2597	148.7	Weibull	

It is noteworthy that the distribution fit is acceptable for the 3-month series, but we must emphasize that we have referred here to an optimization based on the FD formula. It is important to note that certain observed deficiencies in the fit could have been mitigated by incorporating the CFD; however, this approach would have obscured the impact of localized events. The CDF of the q-Gaussian, employed in this study for the purpose of controlling stationarity, remains intractable in closed form (analytically). Empirical evidence is also indicative and very informative regarding the objective of this study, and the distribution problem will be revisited in a future work.

The parameters of the distributions in **Table 2** are not included because the goodness of fit has not been qualified as a guarantee for quantitative references. Therefore, empirical values are considered in this presentation. It is noteworthy that the identification of the distributions was conducted using the aforementioned procedure; however, given their non-stationary nature, they are not further analyzed in this study. It is noteworthy that the GEV distribution exhibits an enhanced compatibility with the optimal histograms; however, the gamma distribution maintains its position within the comparable range of goodness of fit. A more thorough examination of these distributions will be reserved for a future publication.

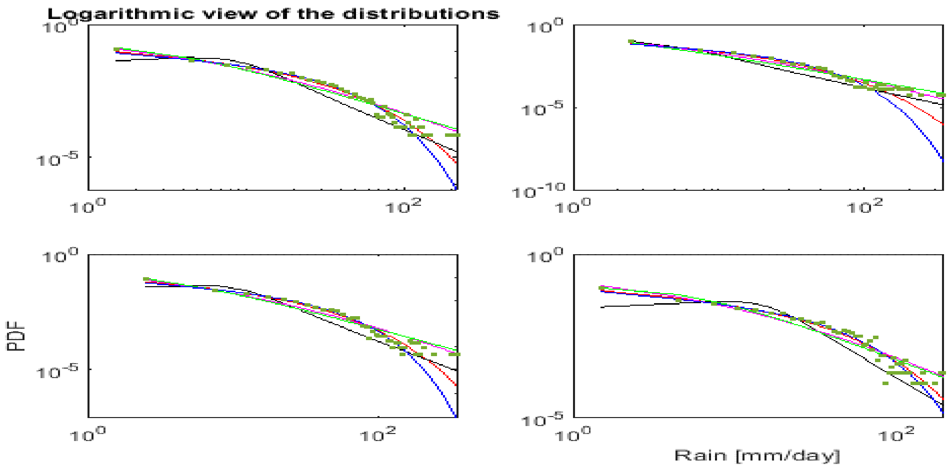

Figure 3. Five best-fit distributions of CWD based on grouped monthly reference, log-log representation: the Weibull in red, q-Gaussian in black, lognormal in magenta, GEV in green, gamma in blue, circles, real data.

Following the identification of the beginning and end of the CWD, the data series were partitioned into monthly bases. The distribution of events exhibits a Pareto-like shape, as illustrated in **Figure 4**. However, further investigation suggests that the gamma distribution provides a more accurate fit. By examining the fitted q-Gaussian properties, we observed that changes in the q-parameters indicate different regimes on the daughter data series.

Specifically, the behavior exhibited a clear power law trend for the periods January-March and September-December, while two other groups demonstrated a modified Pareto distribution. It is noteworthy that the level of precipitation is expected to vary between the grouped series as illustrated in **Figure 5**, however the differences in the shapes of the distributions indicate a change in the regime and are composed of several unexpected events.

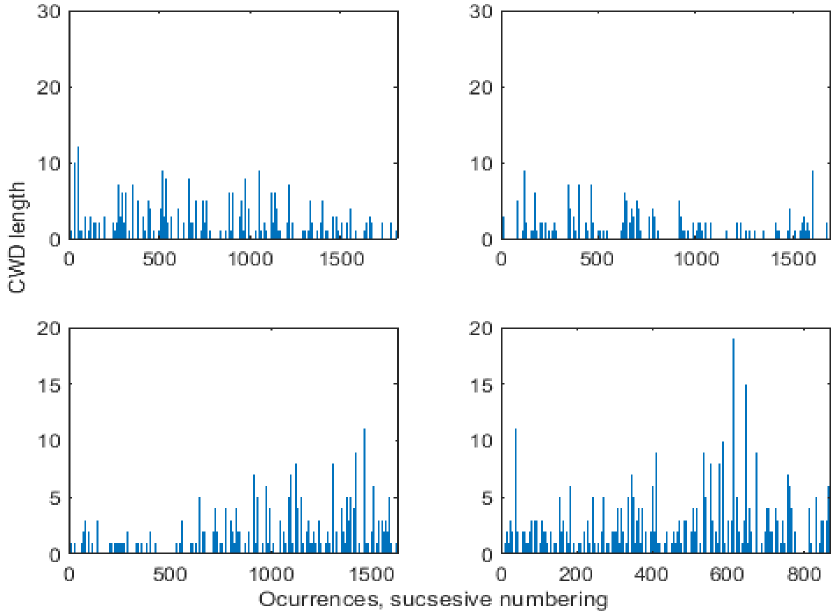

Figure 4. CWD refers to the 3-month precipitation of the data series

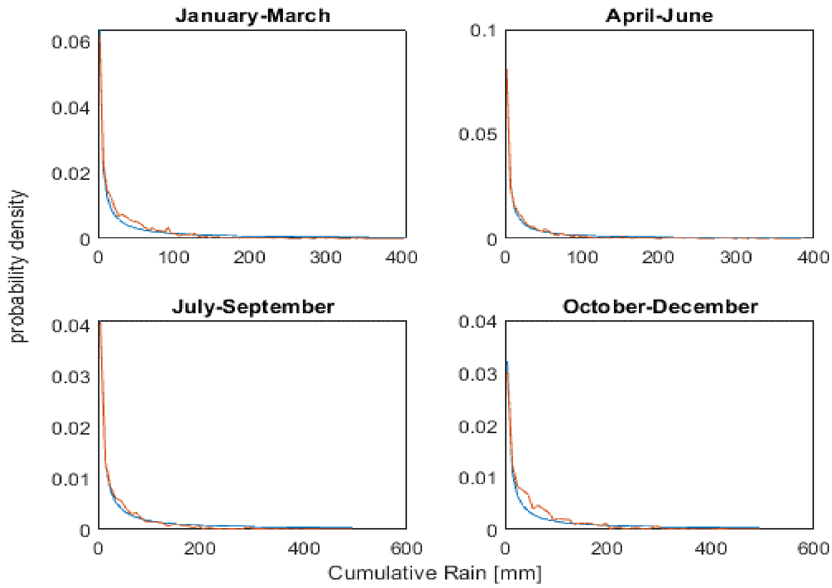

Figure 5. Distribution of cumulative rainfall

Concerning the average occurrences of CWD greater than 5, it is observed that there is an increasing trend for September-December, whereas for January-April, they occur almost symmetrically, as illustrated in **Table 3**.

Table 3. Arithmetic quantities for CWD series

	CDW more than 5 days			CDW more than 10 days		
Month	Occurrences	Mean	Deviance	Occurrences	Mean	Deviance
January	26	0.0906	0.2875	3	0.0105	0.1019
February	30	0.1068	0.3094	4	0.0142	0.1187

March	31	0.1033	0.3049	2	0.0067	0.0815
April	26	0.0841	0.2781	6	0.0194	0.1382
May	8	0.0231	0.1503	0	0	0
June	6	0.021	0.1436	0	0	0
July	0	0	0	0	0	0
August	0	0	0	0	0	0
September	3	0.0106	0.1026	0	0	0
October	18	0.0652	0.2474	5	0.0181	0.1336
November	33	0.1061	0.3085	6	0.0193	0.1378
December	38	0.1343	0.3416	8	0.0283	0.166

This behavior differs from that of the complete series and suggests the presence of a more stationary distribution for these grouped months. Conversely, the power-law nature of the distribution of cumulative precipitation is emphasized. The CWD>10 demonstrates a distinct pattern, as illustrated in **Figure 6**. It can be analyzed using a specific distribution; however, the 10-day bound is not fixed by the analytical characteristics of the current series. Instead, it is empirically borrowed from global references. An intriguing descriptive parameter is the precipitation that occurred during the CWD, as illustrated in **Figure 7** and **Figure 8**.

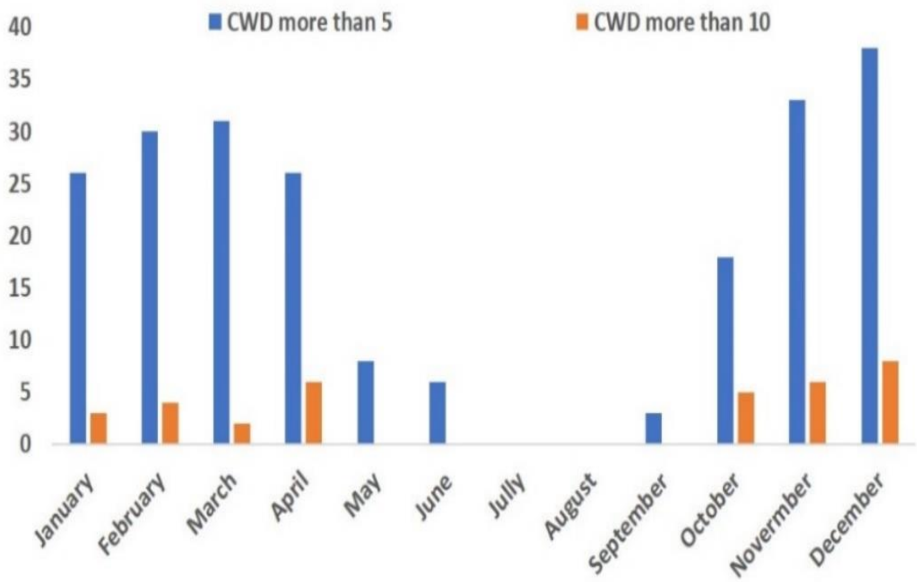

Figure 6. Average sequences of CWD above a critical value

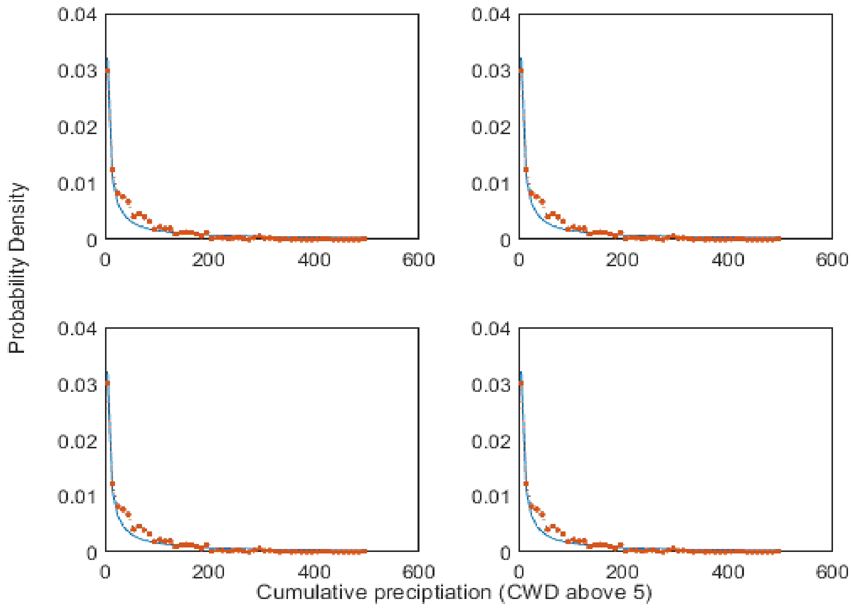

Figure 7. Cumulative rainfall during CWD over 10 days sequences

(Monthly references)

A very interesting behavior is observed for the general feature of consecutive dry and wet days. A pronounced difference is observed in the rate of occurrence of dry days and CWD, which is illustrated by the histograms in **Figure 8**. The duration of dry days appears to exceed that of wet days, suggesting a more persistent and prolonged occurrence of dry days. The prevalence of dry days is evident across diverse vent lengths, as depicted by histograms. The two vent distributions initially follow a generalized Pareto shape, but higher values are better described by a gamma distribution or even a Gumbel shape.

This ranking is based on Negative Likelihood criteria, but when Bayesian or AIC criteria are used, the goodness of fit changes. This outcome is attributable to the presence of numerous empty bins when the histogram is optimized by the Freedman-Djaconic rule, a method particularly suitable for cases involving non-stationarity and heterogeneity. In order to enhance the evidence of the distribution on partial histograms, we have also developed a step-by-step procedure based on an entropy approach. However, further evaluation in terms of statistical consistency is necessary, which extends beyond the scope of this descriptive analysis. Therefore, we will omit that evaluation for the time being. In the context of this ongoing analysis, we have also taken into consideration the remarks made by Gudko (2006), Sanjib et al. (2024), and Meon (2015). The former two authors' contributions pertain to the probability distribution on similar series, while the latter's work focuses on the recent analysis of the impact of climate change on flood behavior.

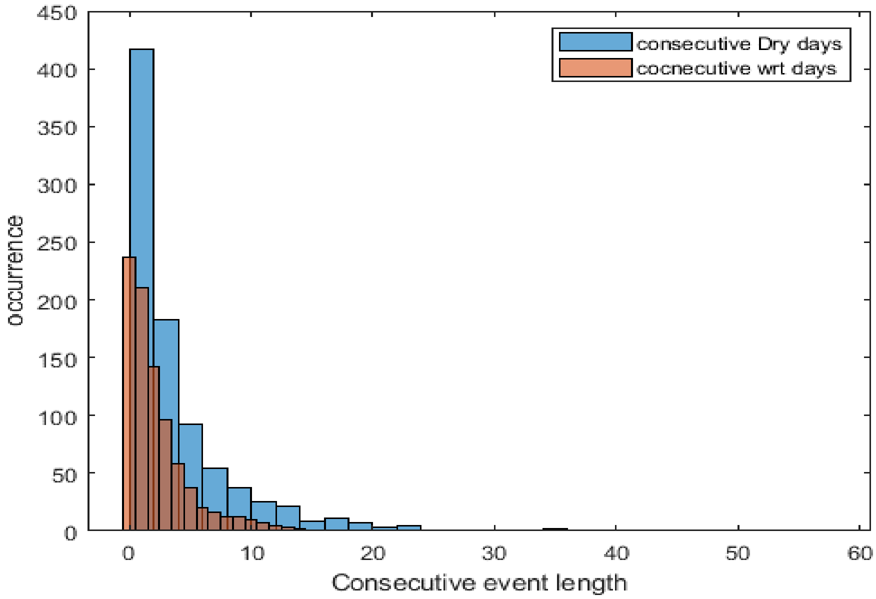

Figure 8. Histogram of dry and wet days

In the final step of this empirical and descriptive analysis, a preliminary discussion of the long-term behavior and the presence of seasonality on the time series is warranted. To this end, we propose the utilization of the empirical mode decomposition (EMD), a technique that has been demonstrated to be effective in the analysis of heterogeneous and non-linear time series (Flandrin, 2003; Huang, 1998).

The application of the EMD algorithm to decompose our series reveals substantial disparities between the final IMFs of CWD and CDD, suggesting that the pattern of dry and wet days manifests with a non-harmonized periodicity. A difference is also observed in the monthly or seasonal behavior of each series, in **Figure 9**. It is crucial to bear in mind that the final IMF signifies the long-term trend of the series. A discernible discrepancy in this trend is evident when comparing different seasons.

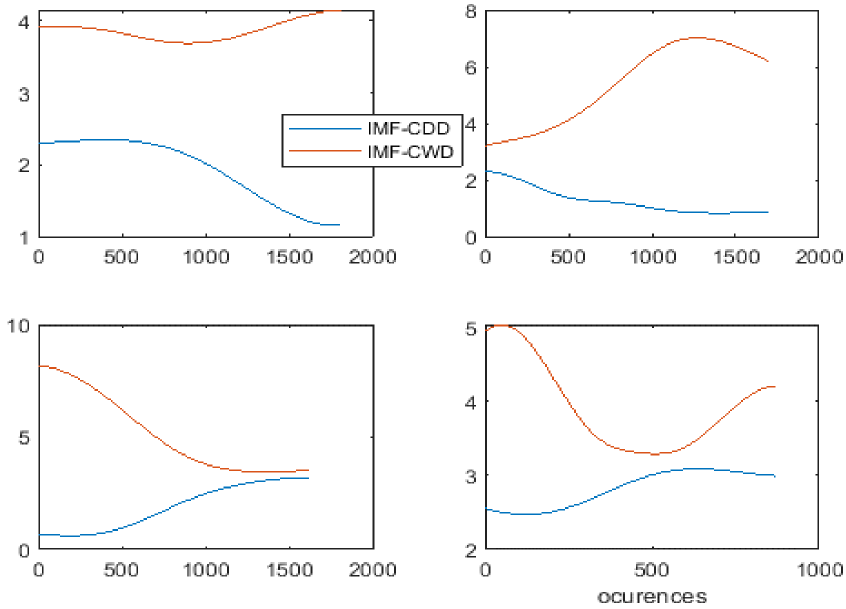

Figure 9. Trend by EMD decomposition of CWD and CDD series

Although the reference of the figure has hidden the real time because it refers to "events" on the x-axis, this difference is obvious. This difference is related to the highly dynamic and non-linear behavior of CDD and CWD. This finding deserves further study and data elaboration, but as an empirical feature observed so far, it is consistent with the argument that climate changes are noticeable in several outcomes and are more accentuated with time. The behavior of the CD and CW day's events also changes by months and seasons, as evidenced by the latest IMF trend.

It is worth noting that these findings and observations are based on a descriptive and empirical view of the system, within the scope of this presentation. In order to achieve a quantitative analysis and develop predictive capacities, further efforts are required in several areas. These include the collection of additional data and samples, the correction of time references of events through the imposition of minimal measurement intervals, and the enhancement of algorithms and evaluation techniques. The subsequent discussion of this system will concentrate on these areas. A comprehensive analysis could be achieved by considering the reception in a wider area, floods, and temperature records

Conclusions

A comprehensive analysis of daily rainfall data series, the Consecutive Wet Days (CWD) and Consecutive Dry Days (CDD) series for the city of Shkodra recorded during the period 1950-2022 has been conducted herein through empirical and descriptive analysis. The distributions that characterize the corresponding histograms for these series and their physical state are non-stationary, indicating intense dynamics on the one hand and forcing the analysis on the descriptive level on the other.

Consequently, the data sets of Consecutive Wet Days are associated with multiple processes driven by a Weibull or General Extreme Value distribution. In certain instances, the Gamma distribution emerges as a viable candidate. A significant difference is observed in the long-term behavior of each CWD and CDD series based on monthly and seasonal records, indicating that the effects of climate change are measurable and apparent in these parameters. Furthermore, disparities have been identified in the statistical indicators of these series, suggesting that Wet Days and Dry Days adhere to distinct regimes. These results are considered preliminary and will be followed by a more detailed and conclusive analysis in the near future.

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