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**ATMOSPHERE PHYSICS**

# ABOUT THE VARIATIONS OF PRECIPITATION AND TEMPERATURE EVOLUTION IN THE ROMANIAN BLACK SEA LITTORAL

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*Abstract*. The article reports the results of the analyses of the annual precipitation and mean annual temperatures evolution at Constanta meteorological station for the period 1961–2009. The break points have been detected and the existence of the trends of extreme climate indices was studied. An increasing trend of the annual mean temperature especially after 1998 and a relative stationary trend of the precipitation were detected. Also, we address the self-organized criticality of data and the multifractal properties of the daily precipitation and temperature series.

*Key words*: precipitation, temperature, break tests, long range dependence property, fractality, climatic indices.

## 1. INTRODUCTION

After the study of the period between 1816 and 2000, IPPC 2001 [33] emphasized that over the 20$^{th}$ century the global average surface temperature increased of about 0.6$^{o}$C and the precipitation augmented between 0.5 and 1% per decade over most mid-and high latitudes of the Northern Hemisphere continents. IPPC 2007 Report [34] confirmed the conclusion of the climate change. The biggest part of Europe is affected by the increment of average precipitation per wet day [9, 18] excepting the Mediterranean area, where a negative trend in precipitation was observed from 1950 [22]. Significant increase of precipitation quantity has been registered in Eastern North America and South America, Northern Europe and Northern and central Asia. The climate warming could have serious impact on the precipitation occurrence, frequency and intensity [13, 17]. Studies concerning the climate evolution in Romania indicate a diminution of annual precipitation, excepting some regions situated in the North-Eastern and South-Eastern parts of the territory. In November 2009, the report of Romanian National Meteorological Administration remarked a decrease of the annual precipitation trend for the period 1901–2008, even if an augmentation of 6.7% with respect to the multi-annual average was noticed for 2001–2008. Therefore we analysed the temperature and precipitation evolution at Constanta, to detect the changes in their evolution trend, in the context of the global warming.

## 2. DATA AND METHODS

The study data is mainly formed by the annual precipitation and the annual mean temperature series collected at Constanta meteorological station, situated on the Black Sea Littoral, in Dobrudja, in the period 1961–2009. This is one of the oldest stations from Romania, founded in July 1885, situated at 12.80 m altitude and 120 m distance from the beach. Subsequently, to derive the trend of climate indices extremes and to study the self organized criticality of the data series, the daily precipitation and mean daily temperatures were also used.

The steps of our study were:

1. Test of data normality, by the Shapiro – Wilk test [26].

2. Detection of the series' break points, by the Hubert's segmentation procedure [12].

Remember that a break (change) point is one where a change occurs in the data generating process. The null hypothesis is: $H_0$: *The series is has no break points* and its alternative is: $H_1$: *The series has at least a break point.*

3. Performing the Kendall tau test [17], to test the null hypothesis ($H_0$) that *the series is random vs.* the alternative ($H_1$) that *the series has an increasing* (or decreasing) trend. If $H_0$ is rejected, Sen' slope estimate is used to compute the slope of the linear increasing (decreasing) trend [25].

4. The outliers' detection and testing the data homogeneity.

Since the annual series are normally distributed, the outliers' detection was done using the boxplot [5]. A homogeneous climate time series is defined as one where variations are caused only by variations in climate [1]. Data homogeneity is assessed using the RHtestV2 software, based on two-phase regression model with a linear trend for the entire base series [29].

5. Detecting the trend of climate indices extremes, using the RClimDex 1.0 software. Kendall's tau test was performed together with the Sen' slope estimate, to compute the slopes of the indices linear trends because this method doesn't assume a distribution for the residuals and is robust to the effect of the series outliers.

Denoting by TG, TN and TX respectively the mean, minimum and maximum temperature, the indices are defined by [30]:

- SU25 [days] – Annual count when TX (daily maximum) > 25ºC;
- FD0 [days] – Frost days - Annual count when TN (daily minimum) < 0ºC;
- GSL [days] – Growing season length - count between first span of at least 6 days with TG > 5ºC and first span after July 1 of 6 days with TG < 5ºC;

- TXx [ºC] – Max$T_{max}$ – Monthly maximum value of daily maximum temperature;
- TXn [ºC] – Min $T_{max}$ – Monthly minimum value of daily maximum temperature;
- TNx [ºC] – Max$T_{min}$ – Monthly maximum value of daily minimum temperature;
- TNn [ºC] – Min$T_{min}$ – Monthly minimum value of daily minimum temperature;
- TX10p [days] – Cool days – Percentage of days when TX < 10th percentile;
- TX90p [days] – Warm days – Percentage of days when TX > 90th percentile;
- TN10p [days] – Cool nights – Percentage of days when TN < 10th percentile;
- WSDI [days] – Warm spell duration indicator – Annual count of days with at least 6 consecutive days when TX > $90^{th}$ percentile;
- CSDI [days] – Cold spell duration indicator – Annual count of days with at least 6 consecutive days when TN < $10^{th}$ percentile;
- DTR [ºC] – Diurnal temperature range – Monthly mean difference between TX and TN;
- Rx1day [mm] – Maximum 1 day precipitation amount – Monthly maximum 1 day precipitation;
- Rx5day [mm] – Maximum 5 days precipitation amount – Monthly maximum consecutive 5 day precipitation;
- SDII [mm/day] – Simple day intensity index – Annual precipitation divided by the number of the wet days;
- R10mm [days] – Number of heavy precipitation days – Annual count of days with the precipitation quantity ≥10 mm;
- R20mm [days] – Number of very heavy precipitation days – Annual count of days with the precipitation quantity ≥ 20 mm;
- R25mm [days] – Annual count of days with the precipitation quantity ≥ 25 mm;
- CDD [days] – Consecutive dry days – Maximum number of consecutive days with the daily precipitation amount less than 1 mm;
- CWD [days] – Consecutive wet days – Maximum number of consecutive days with the daily precipitation amount greater or equal to 1 mm;
- R95p [days] – Very wet days – Annual count of days with rainfall greater or equal to $95^{th}$ percentile;
- R99p [days] – Extremely wet days – Annual count of days with rainfall greater or equal to $99^{th}$ percentile;

- PRCPTOT [mm] – Annual total wet-day precipitation total – the annual total precipitation in wet days.

For comparison, locally weighted regression was also used to calculate the indices trend [6]. This method performs a regression around a point of interest using only data in a span, in the stages:

- Compute the regression weights for each data point in the span. The weights are given by: $w_i(x_0) = \left[1 - \left|(x_0 - x_i)/h(x_0)\right|^3\right]^3$, where $x_0$ is the predictor value associated with the response value to be smoothed, $x_i$ are nearest neighbours of $x_0$ as defined by the span, $h(x_0)$, the distance along the abscissa from $x_0$ to the most distant predictor value within the span,
- Perform a weighted linear least squares regression,
- Compute the smoothed value by the weighted regression at the predictor value of interest.

6. To investigate the dynamics property of rainfall and temperature series, we look for the self-organized criticality (SOC) property. This concept, introduced by Bak *et al*. [2] refers to the tendency of many systems driven by an energy input at a slow and constant rate to enter states characterized by scale - free behaviour [31]. It is a necessary condition for SOC that a system is able to produce both a temporal power law relationship (generally 1/f behaviour) and a spatial power law [15]. SOC of rainfall has been studied [24, 31], but this type of analysis wasn't done for atmospheric temperatures.

It is known that the memory of a process can be described using the empirical autocorrelation function (ACF). For the long range dependent (LRD) data, the ACF decays very slowly to zero; for short-range dependence it decays quikly to zero. The strength of the dependence is quantified by the Hurst exponent (*H*): if $0 < H <$ 0.5 the series is long range anti-correlated, if $0.5 < H < 1$, it is long range correlated, $H = 0.5$ corresponds to a Brownian noise, and $H = 1$ indicates $1/f$ noise, typical of systems in a SOC state. Aggregate variance, R/S, Periodogram, Absolute moments, Variance of residuals, Whittle estimators were used to calculate the Hurst coefficient [4, 14, 16, 21, 28]. To decouple the short-range from long-range correlations in a series to study the effects of long-range dependence, the internal schuffling has also been done. If the original signal has long-memory, then the ACF of the internally-shuffled series will still show power-law behaviour [16].

7. For the precipitation series the multifractality has also been analysed.

A multifractal object is defined as an object which is invariant by translation although the dilation factor needed to be able to distinguish the detail from the whole object depends on the detail being observed [7, 19, 27]. The multifractal property is characterized by the multifractal exponent spectrum $\tau(q)$ or the $f(\alpha)$ - spectrum defined in the following [3].

For a two-dimensional field $p(x, y)$ discretised on a grid, after defining a measure $\varepsilon(x, y) = p(x, y) / \int p(x, y)\mathrm{d}x\mathrm{d}y$, and its integral $\mu_i(\lambda)$, the partition function is calculated: $Z_q(\lambda) = \sum_i \mu_i(\lambda)^q$, where $q > 0$ is the order of the moment and the sum runs over the boxes. If the random fields has scaling properties, then $Z_q(\lambda) \sim \lambda^{\tau(q)}$ for $\lambda \to 0$. *The multifractal exponent spectrum* $\tau(q)$ is then defined by fitting $\log Z_q(\lambda)$ *vs.* $\log \lambda$, by the least squared method.

*The generalized fractal dimension* is [8]: $D(q) = \tau(q)/(q-1)$.

The $f(\alpha)$*-spectrum* [8], that is related to $\tau(q)$ *via* Legendre transform:

$$f(\alpha(q)) = q\alpha(q) - \tau(q), \; \alpha(q) = \frac{\mathrm{d}\tau(q)}{\mathrm{d}q},$$

where $\alpha$ *is the Hölder exponent* [10].

The field is *multifractal* if $D(q)$ decreases with $q$. The field is *monofractal* if $D(q)$ is constant. The chart of $f(\alpha)$ is a single-humped function for a multifractal and it reduces to a point for a monofractal.

## 3. RESULTS

In Fig. 1a we present the evolution of annual precipitation series together with its multi-annual mean precipitation. It reveals the succession of the humid and dry year over the study period. Starting to 1995 the annual precipitation was higher than the mean multi-annual precipitation (excepting 2000, 2001 and 2003 which are the driest years). The same behaviour has been registered by the mean annual temperatures (but 2003) (Fig. 1b).

In the following we shall denote respectively by ConP and ConT the annual series of precipitations and mean temperatures. The hypothesis that these series are normally distributed couldn't be rejected at the significance level of 0.05. The break test gave respectively 1995 as change point for ConP and 1998 for ConT.

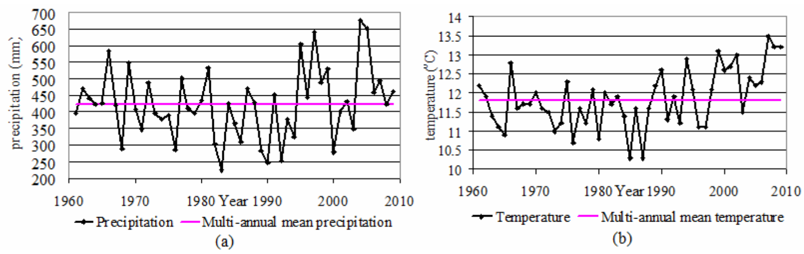


Fig. 1 – Constanta – annual precipitation series and mean annual temperature series (1961–2010).

The results of the Kendall test, with Sen's slope estimate, are presented in Fig. 2, where the dots represent the data values. Since the p-value corresponding to the test for ConP is greater than 0.05, we reject the hypothesis that there is an increasing trend of precipitation series. For ConT, the hypothesis of the existence of an increasing linear trend (with the slope 0.0243) was accepted at the confidence level of 0.01.

The boxplots analysis emphasized the existence of one outlier of ConP (674.6 mm of precipitation registered in 2004) and of no outliers of ConT.

Table 1 contains the extreme indices, the slope, the standard deviation of the slope of the linear trend of the indices evolution and the p-values. If a *p*-value is less than 0.05 and the standard deviation of the slope is less than the absolute value of slope estimate, the hypothesis that the trend is statistical significant is accepted at 0.95 level of confidence; this is the case of SU25, GSL, TXx, TX90p, WSDI, DTR, Rx5day, SDII. Figure 3 presents the charts of the indices' evolution.

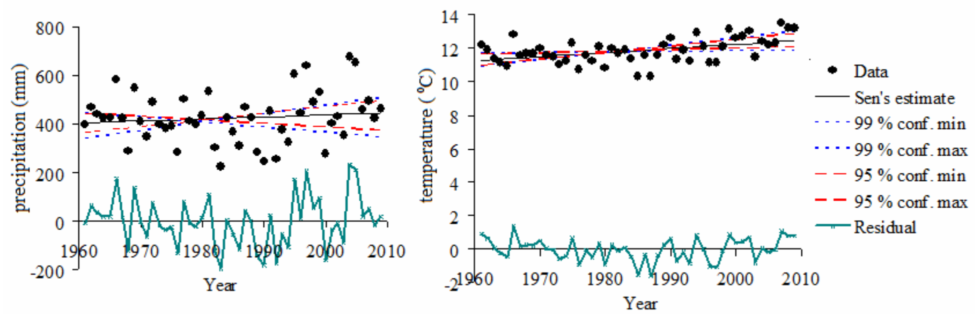


Fig. 2 – Results of Sen's slope estimate for ConP and ConT.

*Table 1*

Extreme climatic indices

| Indices | Slope | Std. of slope | p -value |
|---|---|---|---|
| SU25 | 0.719 | 0.13 | 0 |
| FD0 | -0.049 | 0.079 | 0.538 |
| GSL | 0.931 | 0.324 | 0.006 |
| TXx | 0.045 | 0.021 | 0.038 |
| TXn | 0 | 0.003 | 0.997 |
| TNx | 0 | 0 | 0.09 |
| TNn | 0.032 | 0.026 | 0.218 |
| TX10p | -0.099 | 0.034 | 0.005 |
| TX90p | 0.236 | 0.041 | 0 |
| TN10p | -0.002 | 0.021 | 0.911 |
| WSDI | 0.401 | 0.104 | 0 |
| CSDI | 0.025 | 0.05 | 0.614 |
| DTR | 0.029 | 0.006 | 0 |
| Rx1day | 0.443 | 0.271 | 0.109 |
| Rx5day | 0.681 | 0.288 | 0.022 |
| SDII | 0.031 | 0.012 | 0.012 |
| R10mm | 0.048 | 0.037 | 0.198 |
| R20mm | 0.025 | 0.02 | 0.22 |
| R25mm | 0.022 | 0.015 | 0.145 |
| CDD | -0.058 | 0.094 | 0.543 |
| CWD | -0.008 | 0.012 | 0.5 |
| R95p | 1.312 | 0.666 | 0.055 |
| R99p | 0.689 | 0.447 | 0.13 |
| PRCPTOT | 1.56 | 1.031 | 0.137 |

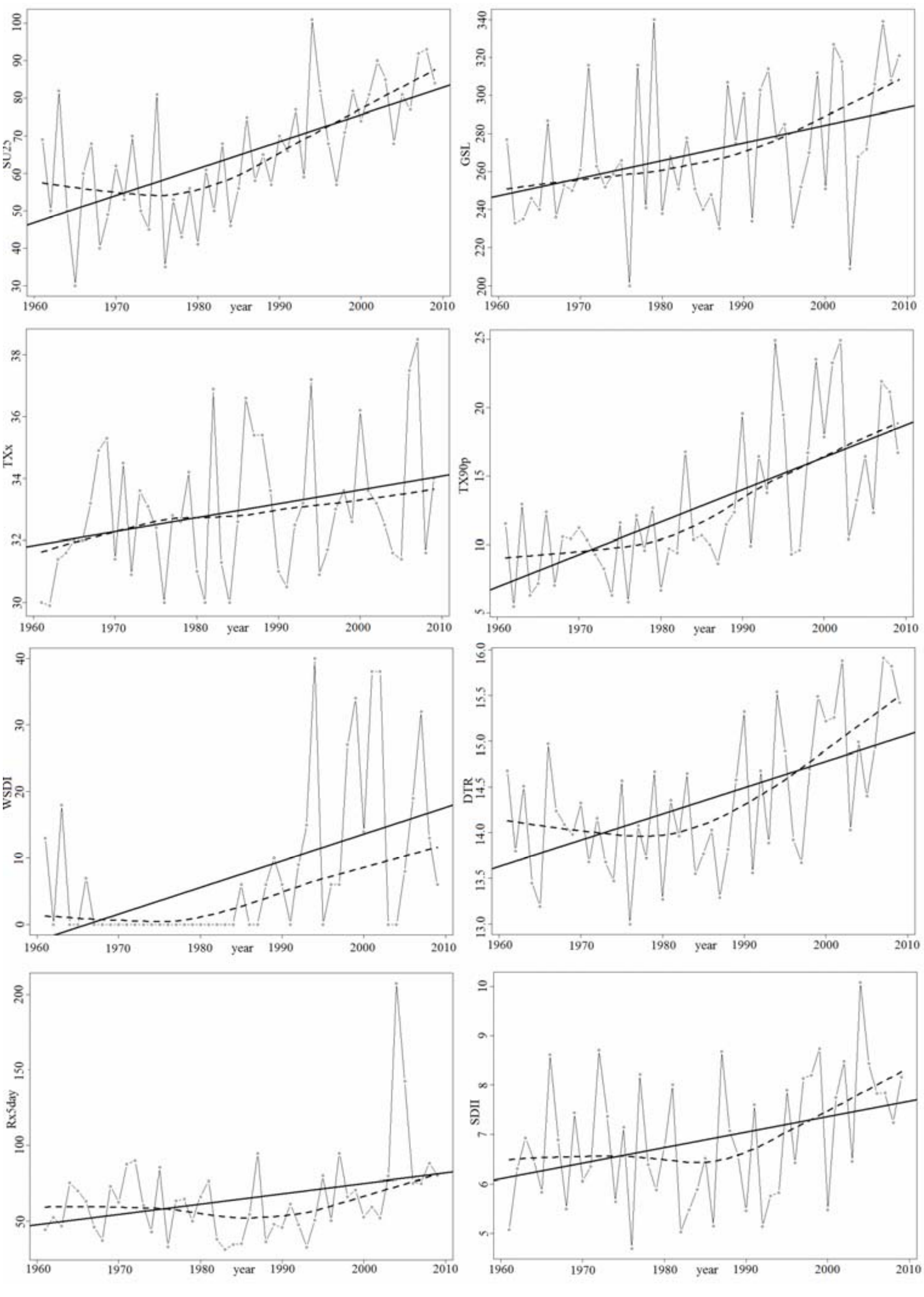


Fig. 3 – Charts of extreme climatic indices trend.

SU25 had the highest slope, indicating an accentuate increase of maximum temperatures over $25^0$. Its evolution is analogous to that of TX90p that shows the augmentation of number of days with very high temperature, especially after 1998. Figure 4 depicts the evolution of maximum temperature in the mentioned period.

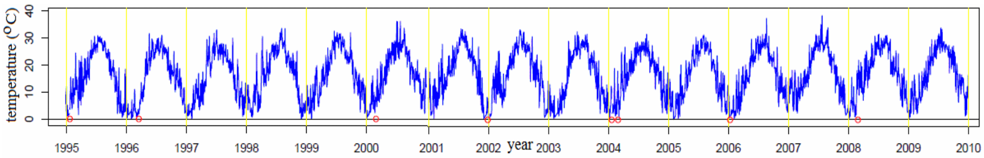


Fig. 4 – Charts of maximum temperature in the period 1995–2010.

The increasing trend of TXx indicates also the increase of the superior limit of minimum temperatures, in concordance with the evolution of DTR.

Between the indices with significant linear increasing trend only two refer to the precipitation evolution: Rx5day and SDII. They prove that the periods with heavy precipitation became longer and the precipitation repartition is unequal in time. This assertion sustained by the histogram of precipitation (Fig. 5) that has a heavy tail to the right.

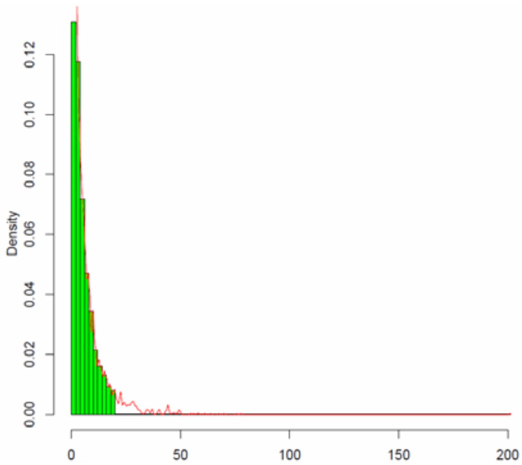


Fig. 5 – Histogram of precipitation.

Analysing the trends obtained by the locally weighted methods, we remark that TX10p (Fig. 6) registered a decreasing trend, so the percentage of cool days is smaller, especially after 1998. This remark is in concordance with the chart of evolution of minimum temperature (Fig. 7).

The analysis of ACFs of daily data emphasized the different behaviour of the two series (Fig. 8).

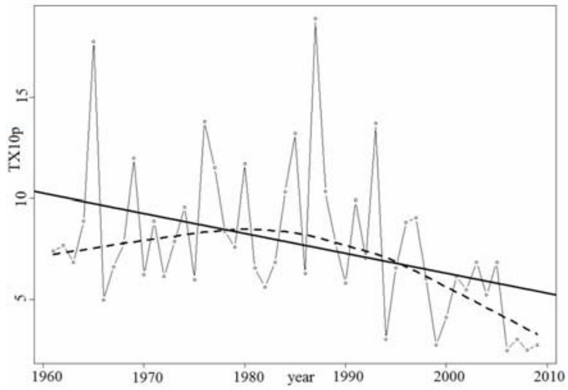


Fig. 6 – Evolution of TX10p.

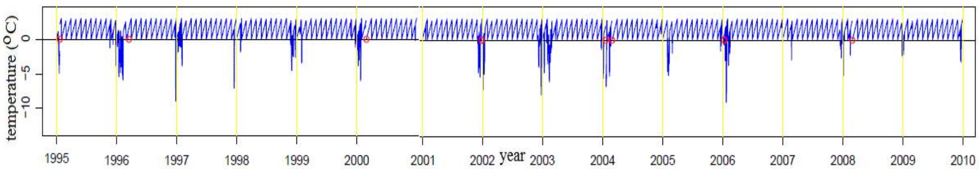


Fig. 7 – Charts of minimum temperature in the period 1995–2010.

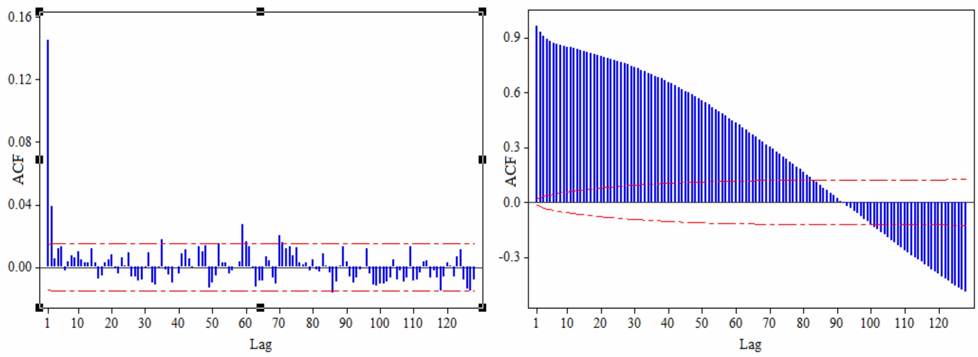


Fig. 8 – Charts of ACF of daily precipitation and temperatures.

The values of the Hurst coefficient for daily precipitation series (together with the corresponding correlation coefficient or confidence intervals at 95%) are presented in Table 2. Since the correlation coefficient in the periodogram methods is small, we shall not consider the value of *H* calculated by this method. All methods, but Absolute moments indicate that both data series has LRD.

The values of *H*, calculated after internal shuffling are given in Table 3. They don't differ significantly for the first series, so the precipitations behave similarly on long and short term.

*Table 2*

Values of the Hurst coefficient for initial daily series

| Daily precipitation series | | |
|---|---|---|
| | Hurst coefficient | Correlation coefficient (%)/ 95% C.I. |
| Aggregated Variance | 0.527 | 97.37% |
| R/S | 0.585 | 99.88% |
| Periodogram | 0.541 | 6.16% |
| Absolute moments | 0.472 | 94.13% |
| Variance of residuals | 0.721 | 96.49% |
| Whittle | 0.585 | 95% C.I: [0.575; 0.595] |
| Daily temperature series | | |
| | Hurst coefficient | Correlation coefficient (%)/ 95% C.I. |
| Aggregated Variance | 0.596 | 91% |
| R/S | 0.527 | 95.23% |
| Periodogram | 0.823 | 44.49% |
| Absolute moments | 0.481 | 93.18% |
| Variance of residuals | 0.836 | 93.29% |
| Whittle | 0.999 | 95% C.I: [0.993; 1.006] |

*Table 3*

Values of the Hurst coefficient after the internal shuffling of daily series

| Daily precipitation series | | |
|---|---|---|
| | Hurst coefficient | Correlation coefficient (%)/ 95% C.I. |
| Aggregated Variance | 0.536 | 96.22% |
| R/S | 0.568 | 99.87% |
| Periodogram | 0.532 | 4.81% |
| Absolute moments | 0.480 | 93.46% |
| Variance of residuals | 0.672 | 98.67% |
| Whittle | 0.505 | 95% C.I: [0.496; 0.515] |
| Daily temperature series | | |
| | Hurst coefficient | Correlation coefficient (%)/ 95% C.I. |
| Aggregated Variance | 0.659 | 98.60% |
| R/S | 0.590 | 99.30% |
| Periodogram | 0.523 | 3.66% |
| Absolute moments | 0.549 | 89.47% |
| Variance of residuals | 0.640 | 99.32% |
| Whittle | 0.516 | 95% C.I: [0.506; 0.526] |

The results given after shuffling by Aggregated variance, R/S and Absolute moments methods are slightly different for the second series, but the Variance of residuals and the Whittle estimators methods provide lower values. The big difference between the estimated values of *H* by the Whittle method appeared in the case of temperature series is due to the periodicity of the initial one (removed by the shuffle property).

To decide if the initial series have long memory, the ACF of shuffled series were built (Fig. 9). Since they don't show a power low behaviour, we can say that the memory property is present on short periods, not on long term. So, the series don't present the SOC property.

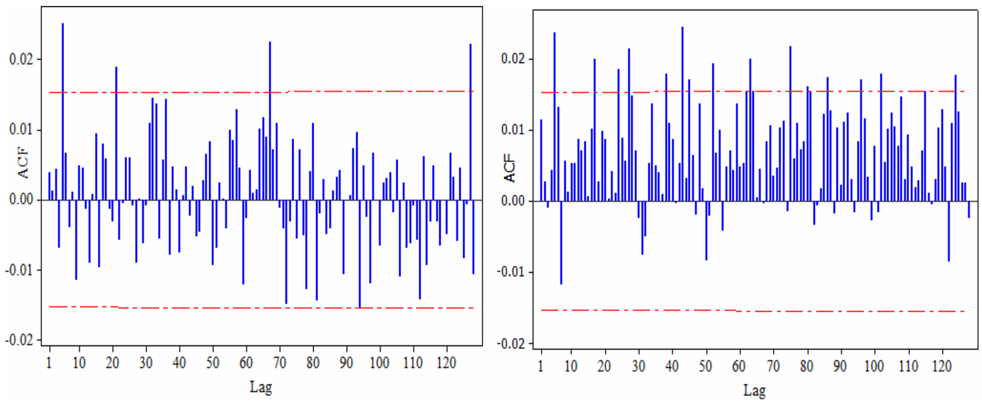


Fig. 9 – ACF of shuffled daily precipitation and temperatures series.

The results of multifractal analysis for ConP are presented in Fig.10, where the multifractal exponent spectrum and the $f(\alpha)$-spectrum are plotted. Since $\tau(q)$ is decreasing function of $q$, it results that ConP has a multifractal character, confirmed by the form of $f(\alpha)$-spectrum.

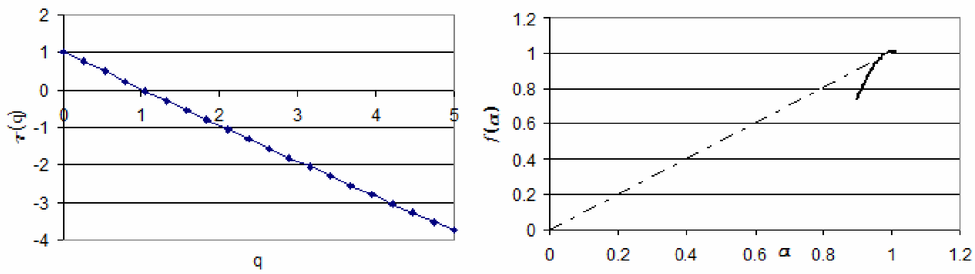


Fig. 10 – Multifractal spectra $\tau(q)$ and $f(\alpha)$ – spectrum.

## 4. CONCLUSIONS

The study proves that a climate change occurred in the Black Sea region, the last period. It is characterized by:

- the increasing of the mean multiannual temperature from $11.6^0$C (before 1998) to $12.7^0$C (after 1998); moreover, the mean multiannual temperature of the years 2007–2009 was of $13.3^0$C. This modification is emphasized by the increasing trend of some extreme climate indices – SU25, GSL, TX90p, TXx, WSDI, DTR – and the decreasing trend of the percentages of cool days;
- changes in precipitation regime, for which the mean multiannual precipitation increased from 395 mm (before 1995) to 488.7 mm (after 1995), with unequal repartition of the wet days, emphasized by the augmentation of Rx5day.

The analysis of daily series leads to the rejection of the hypothesis of SOC of data. The existence of the multifractal character of ConP emphasizes the existence of a pattern of the process that generates the series.

Our research confirms the conclusions of IPCC2007 report and those from the literature that the climate warming could have drastic effects on precipitation occurrence and repartition [23, 32].

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