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Are the Regional Precipitation and Temperature Series Correlated? Case Study from Dobrogea, Romania

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Abstract: In the context of climate change, this article tries to answer the question of whether a correlation exists between the precipitation and temperature series at a regional scale in Dobrogea, Romania. Six sets of time series are used for this aim, each of them containing ten series—precipitation and temperatures—recorded at the same period at the same hydro-meteorological stations. The existence of a monotonic trend was first assessed for each individual series. Then, the Regional time series (RTS) (one for a set of series) were built and the Mann–Kendall test was employed to test the existence of a monotonic trend for RTSs. In an affirmative case, Sen's method was employed to determine the slope of the linear trend. Finally, nonparametric trend tests were utilized to verify if there was a correlation between the six RTSs. This study resulted in the fact that the only RTS presenting an increasing trend was that of minimum temperatures, and there was a weak correlation between the RTS of minimum precipitations and maximum temperatures.

Keywords: MPPM; correlation; *Regional* series; precipitation; temperature

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1. Introduction

The 2021 UN's Intergovernmental Panel on Climate Change (IPCC) report [1] warned that the effects of climate change were already widespread, rapid, and in continuous augmentation, with human activity as the dominant cause for these changes, calling urgent and ambitious action in order to limit further damage to the planet.

Climate change is a global phenomenon that affects various aspects of the Earth's climate system [2]. Influencing other variables, precipitation and temperature are two of the most critical variables with complex patterns that depend on climate zones, topography, soil, lithology, vegetation, and land use [3–5]. Moreover, their connection makes the analysis and forecasting of climate change difficult, followed by the mitigation of its effects [6].

Researchers have found that global warming has led to a change in the precipitation pattern in many regions of the world [7–10]. Since the extreme precipitation and temperature events and their composed action may result in disasters affecting human lives and the economy, understanding the correlations between precipitation and temperature variations at a regional scale is an essential step in preventing the disasters' catastrophic effects [11–13]. In this context, studying the precipitation-temperature dependence is essential for understanding long-term climate evolution due to the fact that the variation in any factor can also influence other variables [14].

Starting from the remark that the relationship between extreme rainfall and temperature is still unclear, Utsumi et al. [15] studied this topic based on the data recorded in various geographical zones. Nicholls et al. [16] found a strong negative correlation between maximum temperature variations and those of the precipitations in New South Wales. At the same time, such an effect was not noticed in the rest of Australia. They hypothesized that the greenhouse effect might influence the temperature-precipitation dependence because no simultaneity in the diminishing temperature and precipitation augmentation was notified for the 20th century in most of the studied areas.

The correlation between seasonal temperatures and precipitations has also drawn the attention of researchers. Such a study was conducted for Italy by Ferrari et al. [17] and Europe by Lhotka and Kyselý [18] using the CORDEX models. Isaac and Stuart [19] showed that in the north of Canada and its eastern and western coasts, warm periods in the winter and cold summer are accompanied by increased rainfall. In the mountains, rainfall appears when temperatures decrease. In this context, Vrac et al. [20] raised the question of the climate models' reliability. Rajeevan et al. [21] found a positive correlation between precipitation and temperature in January and May and a negative one in July in India. Huang et al. [22] remarked on a negative correlation between both variables for the basin of Huanghe River during 1957–2006.

In an attempt to explain the interdependence between heat waves and other meteorological phenomena, Hafez [23] showed that the temperature increase was followed by evaporation rate augmentation, leading to changes in precipitation patterns. This may result in more intense rainfall in some regions or more severe droughts in others [24]. Additionally, changes in patterns can affect temperature through modifications in the surface energy balance. For example, increased cloud cover can reduce the amount of solar radiation absorbed by the Earth's surface, leading to lower temperatures [25].

The Most Probable Precipitation Method (MPPM) was introduced in [26] to model the spatial evolution of precipitation series on a regional scale. Since this method does not rely on the rainfall's characteristics, an algorithm was applied to model the regional distribution of dust aerosol in the UAE [27] and pollution in Europe [28]. Case studies proved the algorithm's performance compared to other classical methods [26,27,29]. It has the advantage of avoiding a high computation time, a deep knowledge of spatial statistics, and restrictions related to the set's characteristics. This article aligns with the actual research trend to clarify interdependences between temperature and precipitation. It is the continuation of the authors' works, analyzing the relationship between the Regional Series of Temperature—RTST—and the Regional Series of Precipitation—RTSP—built by a version of MPPM. Moreover, such a correlation has not been investigated for Dobrogea, Romania, to which this study refers.

2. Study Area and Data Series

Romania is situated between some zones of different influences: in the north—Scandinavian-Baltic; in the east—continental; in the west and center—oceanic; in the southwest—Mediterranean. These influences manifest through floods, landslides, and rapid snow melting. The Carpathians form an orographic barrier between the oceanic influence from the west and continental in the east [30].

The Dobrogea region (Figure 1), Romania, is delimited by the Danube River to the west, the Danube Delta to the north, and the Black Sea to the east. More than 80.75% of this territory has altitudes lower than 150 m, and the average height is 70 m. More than 80% of the soil is formed by cernisoils and loamy soils that favor water infiltration [31]. Ielenicz and Săndulache [32] indicated that its climate was excessively continental. During the period 1965–2010, the multiannual average temperature varied from 10.8 °C to 11.8 °C [33], with variations in the intervals [−1.2; 2] and [19; 22.5] °C in winter and summer, respectively. Lower precipitation was recorded in January, February, and October, while the most significant was at the end of spring and the beginning of summer or winter. Dobrogea is the part of Romania that is most affected by drought [34–39].

The data series subject to analysis contains six sets, each formed by ten series recorded at the same period and at the same hydro-meteorological stations. They do not present gaps and are reliable and verified, being provided by the National Administration of Meteorology, Romania.

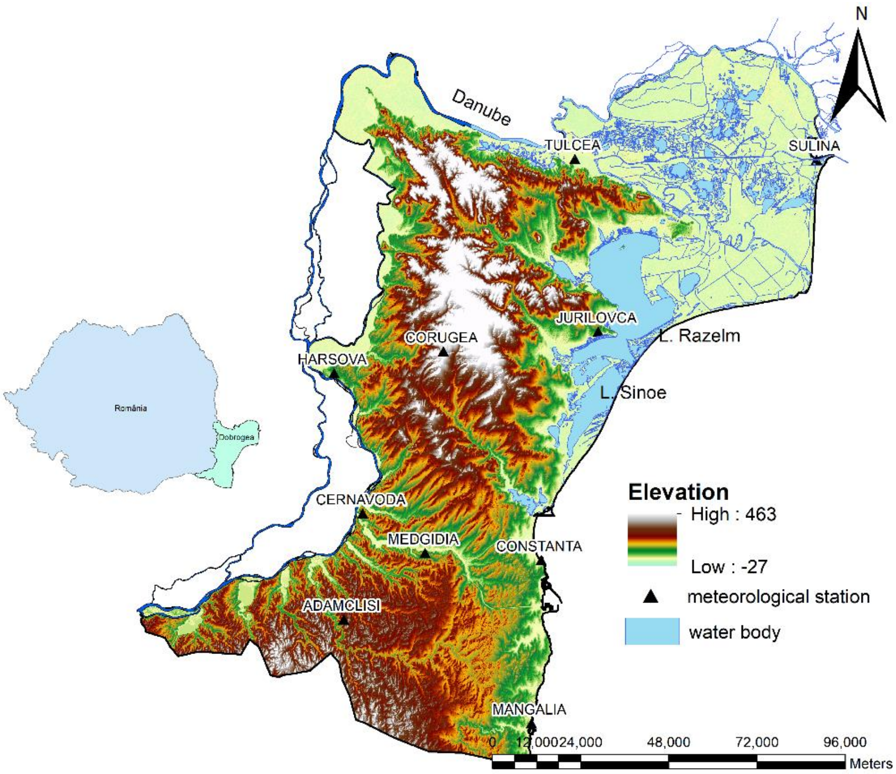

Figure 1. Location of Dobrogea in Romania [40].

The sets consist of the minimum, maximum, and total annual precipitation and minimum, maximum, and average annual temperature series recorded for 41 years at the main meteorological series (whose names are on the map from Figure 1) in Dobrogea. The maximum and total annual precipitation series (PrecMax and PrecTot) are represented in Figure 2.

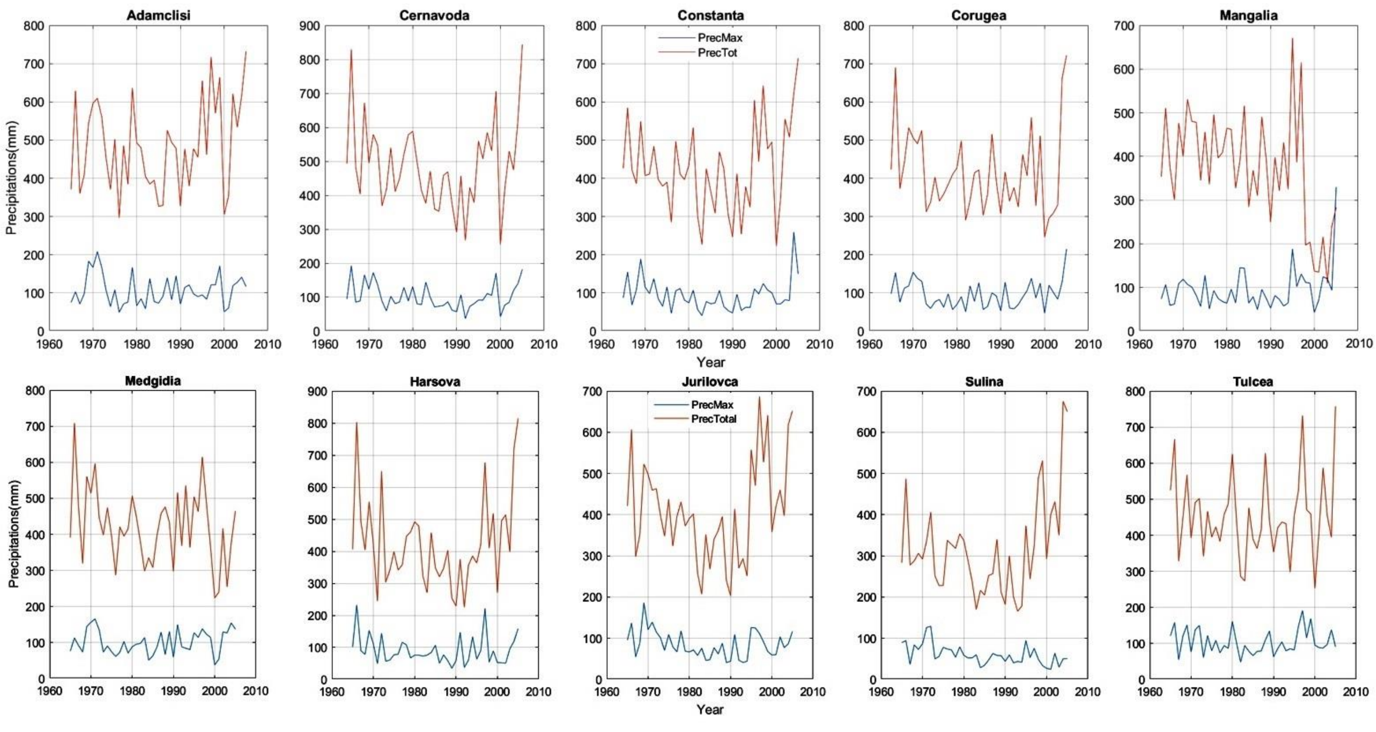

Figure 2. The total and maximum annual precipitation the meteorological stations.

The minimum, maximum, and average annual temperature series (TempMin, TempMax, TempAv) are shown in Figure 3. The minimum annual precipitation series is denoted in the following by PrecMin.

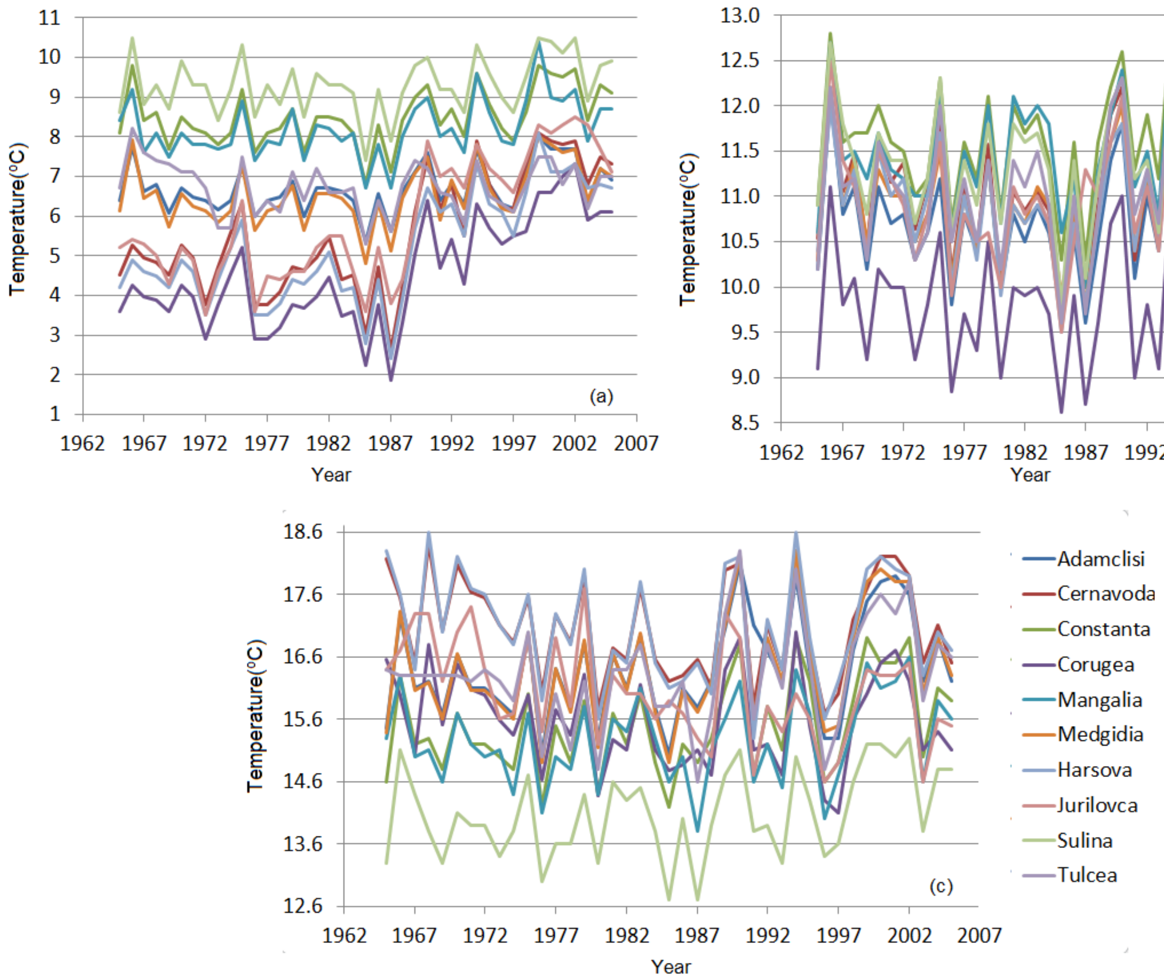

Figure 3. (**a**) TempMin (**b**) TempAv (**c**) TempMax series.

3. Methodology

The procedure steps are the following.

1. Determine the change points (breakpoints) of the data series. Remember that a change point (breakpoint) is a point where there is a change in the mean, variance, or both, or, alternatively, there is a change in the probability law followed by the time series. To test the null hypothesis where the time series has no breakpoint against the existence of a breakpoint, the Pettitt [41], Buishand [42], and Lee and Heghinian [43] tests were used. These were implemented in Khronostat [44]. The first test works for any series, while for the last two, series normality is required. The reader may see [41–44] for details on these procedures.
2. Test the null hypothesis that a series does not have a monotonic trend versus the existence of such a trend at a significance level of 5%, using the Mann–Kendall test [45,46] and Sen's slope [47].
3. Determine the RTS of the minimum, maximum, and total precipitation series, denoted by RTSPmin, RTSPmax, and RTSPtot, respectively.
4. Determine the RTS of the minimum, maximum, and average temperature series, denoted by RTSTmin, RTSTmax, and RTSTav, respectively.
5. Test hypothesis H_0 that RTS does not present a monotonic trend against H_1 and that such a trend exists for the RTSs of precipitations.

6. Test H_0 that RTS does not present a monotonic trend against H_1 and that such a trend exists for the RTSs of temperatures.
7. Test the hypothesis that there is a correlation between different RTSPs and RTSTs (for example RTSPmin—RTSTmin, RTSPmin—RTSTmax and so on) using the Spearman rho coefficient [48] and Kendall tau test [49].

These nonparametric tests were chosen because they do not rely on the series homoscedasticity or Gaussian distribution, and their sensitivity to outliers' existence is lower than that of parametric tests [50].

The chart flow of the study is presented in Figure 4.

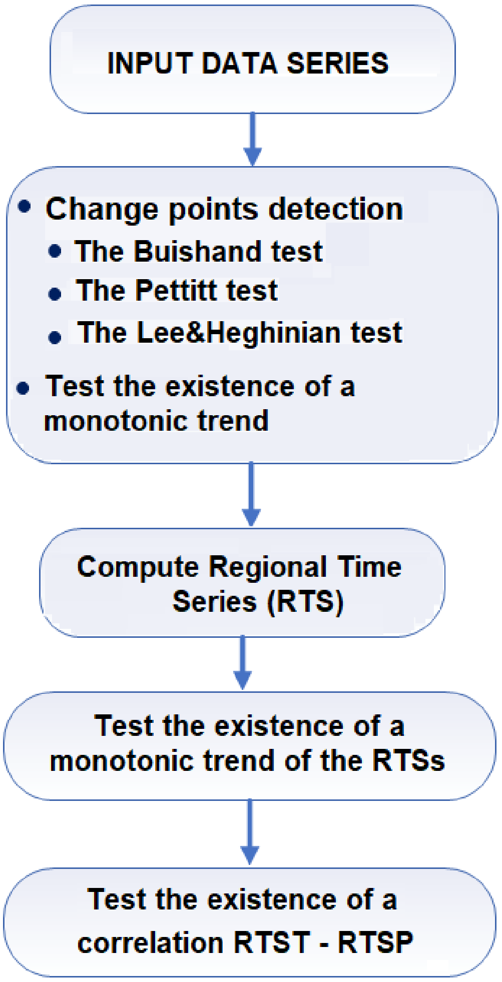

Figure 4. Chartflow of the study.

The method used to determine the regional series (at the third and fourth steps) was a version of the Most Probable Precipitation Method (MPPM) introduced by the authors [26,27]. To build an RTS, it can be supposed that the time series (precipitation, temperature, in this study) is recorded for T consecutive periods at m locations [26–29]. This is denoted by:

- (x_{tj}) $(t = \overline{1,T})$ the series collected at jth station $(j = \overline{1,m})$,
- $X = (x_{tj})$ $(t = \overline{1,T}, j = \overline{1,m})$ the matrix whose line t is formed by the values recorded at the moment t in all stations.

Then, the following procedure can be performed:

Select the number of clusters, k, to be used to run the k-means algorithm or hierarchical clustering to group the series recorded at different locations.

The optimum k must be found because its value impacts the *Regional series* fitting quality. Different methods have been proposed to solve this problem. Thirty are implemented in the R software in the package NbClust [51]. Some of the most known algorithms implemented are Friedmann [52], *gap* [53], Hartigan [54], Hubert [55], Scott [56], and Silhouette [57].

Given that the methods on which the algorithms rely are different, the output was, therefore, sometimes different. Therefore, the majority rule was usually employed to decide the optimum number of clusters, meaning that the 'best' k was the one that resulted in the highest number of methods.

From the clusters built in the previous step, we chose the one that contained the highest number of series. This was denoted by Cl_{max}. Then, a new matrix can be built, X_{Cl}, with the elements of the series (on the column) from Cl_{max}. If there are two or more clusters with the same number of elements, Cl_{max} is the cluster with the highest separation distance between the groups and the lowest inside them [58].

- RTS can then be built by computing the average values from each row of X_{Cl}. Thus, the RTS value at the moment t is the average of the tth row of X_{Cl} ($t = \overline{1, T}$).
- The modeling errors for each station can then be estimated by computing the difference between the recorded values and those of RTS.
- The fitting quality of RTS can then be evaluated by calculating the mean absolute error (MAE) and mean standard error (MSE) from the errors determined in the previous step.
- The RTS chart can be drawn.

Applications of this method or some version to different series are presented in [27,29]. Statistical analysis and modeling were performed with the R 4.3.2 software (https://www.r-project.org/).

4. Results and Discussion

The results of the break tests are presented in Tables 1 and 2 for all the series. The Buishand, Pettitt, and Lee and Heghinian tests provide different change points because they relied on different methodologies. All the tests were able to detect the existence of a single breakpoint (the most important one). The first and last tests worked in the hypothesis that the series was Gaussian. When the series is not Gaussian, Khronostat searched for a transformation to be applied for the series to reach the normality; if such a transformation could not be found, the tests could not be performed, as in the situation of the Jurilovca TempMin series. Some total precipitation series had breakpoints in the period 1994–1997, according to the Lee and Heghinian test.

Table 1. The break points of the precipitation series.

	PrecTot			PrecMin			PrecMax		
Series	**Buishand**	**Pettitt**	**Lee and Heghinian**	**Buishand**	**Pettitt**	**Lee and Heghinian**	**Buishand**	**Pettitt**	**Lee and Heghinian**
Adamclisi	-	-	1994	-	-	2004	-	-	1972
Cernavoda	-	-	2004	-	-	2004	-	-	1972
Constanta	-	1994	2001	-	-	1982	-	-	2003
Corugea	-	-	2003	-	-	2004	-	-	2004
Harsova	-	-	2003	-	-	2004	-	-	1966
Jurilovca	-	1994	1994	-	-	2004	reject	-	1973
Mangalia	-	1997	1997	-	-	2004	-	-	2004
Medgidia	-	-	1998	-	-	2004	-	-	2001
Sulina	reject	1994	1996	-	-	1966	-	-	1980
Tulcea	-	-	2004	-	-	1995	-	-	1995

Table 2. The break points of the temperature series.

	TempAv			TempMin			TempMax		
Series	**Buishand**	**Pettitt**	**Lee and Heghinian**	**Buishand**	**Pettitt**	**Lee and Heghinian**	**Buishand**	**Pettitt**	**Lee and Heghinian**
Adamclisi	rejected	1988	1988	reject	1988	1997	reject	-	1997
Cernavoda	-	-	1972	reject	1988	1988	-	-	1997
Constanta	-	-	2003	reject	1988	1998	reject	-	1997
Corugea	-	-	1972	reject	1988	1998	reject	-	1997
Harsova	-	-	1972	reject	1988	1988	-	-	1998
Jurilovca	rejected	1979	1979	not run	1988	not run	-	-	1998
Mangalia	-	-	2004	reject	1988	1993	reject	-	1997
Medgidia	-	-	2001	reject	1988	1987	reject	-	1997
Sulina	-	1970	1969	-	-	1998	-	-	1997
Tulcea	-	-	1995	-	-	1971	-	-	1988

Table 1 shows that the Buishand test rejected the null hypotheses only for the Sulina PrecTot and PrecMax series. The Pettitt test rejected it for all but Constanta, Jurilovca, Mangalia, and Sulina PrecTot (for which the breakpoints were 1997 or 1994). The Lee and Heghinian test found change points in 2003–2004 for most series. However, one should ignore these, given that there are only one or two records after the mentioned years, so the result cannot be validated.

The results of the same tests for the temperature series are presented in Table 2. The Buishand test rejected the null hypothesis mainly for the TempMin and TempMax series. Most of the change points found by the Pettitt and Lee and Heghinian test were in 1997–1998 for the TempMin and TempMax series. It can be remarked that no concordance existed between the change point moment in the precipitation and temperature series.

The results of the Mann–Kendall test at different significance levels are given in Table 3. Among the precipitation series, only Sulina PrecTot and PrecMax experienced decreasing trends (at a significance level of 0.001).

Table 3. Results of the Mann–Kendall test.

	Adamclisi	**Cernavoda**	**Constanta**	**Corugea**	**Harsova**	**Jurilovca**	**Mangalia**	**Medgidia**	**Sulina**	**Tulcea**
Tmin	+	***	*	***	***	***	*	*	+	
Tmax	*		*			**		*	*	
Tav			+	+			+			
PrecMin										
PrecMax									***	
PrecTot									***	

Note: The significance level of 0.1%, 1%, 5%, and 10% are represented in the table by ***, **, *, and +, respectively.

All but the Tulcea Tmin series presented trends at different confidence levels, the most significant (positive) corresponding to Corugea, Constanta, Harsova, and Jurilovca. At a significance level of 0.05, the hypothesis that the Jurilovca Tmax series had an increasing trend could not be rejected. These results did not indicate a significant relationship between the precipitation and temperature series when recorded in the same place.

To compute RTSs, first, the optimum number of clusters was determined to be $k = 2$. Then, the algorithm was run with $k = 2$ for each series set—PrecTot, PrecMax, PrecAv, TempTot, TempMax, and TempAv. The charts of the RTSs can be seen in Figure 5.

The modeling errors for each hydro-meteorological station were calculated by the difference between the recorded values at a specific location and the values of the Regional series. The RTS goodness of fit was evaluated using the mean absolute error (MAE) and mean standard error (MSE).

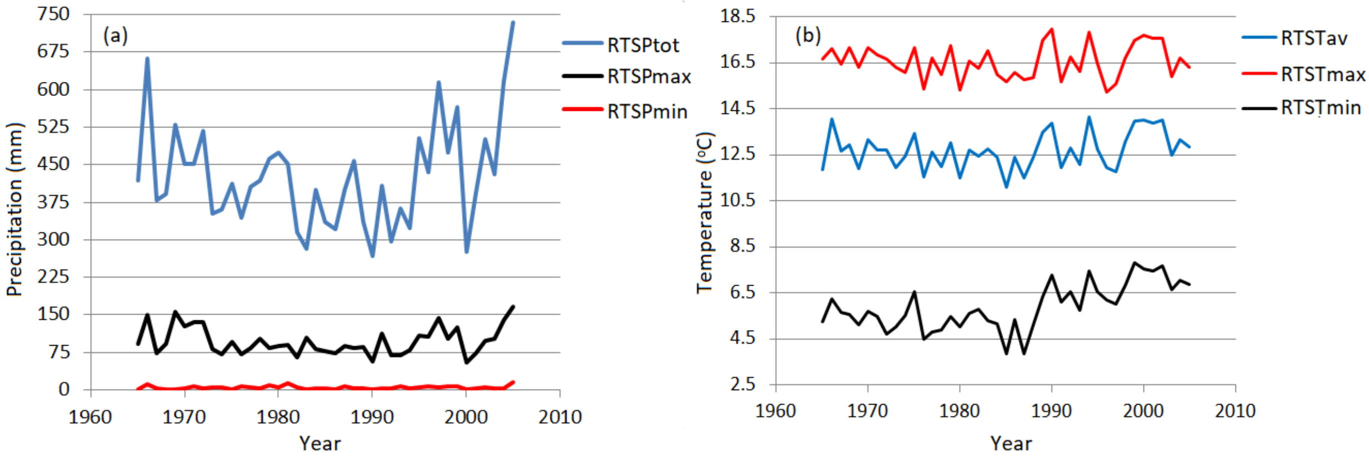

Figure 5. The RTS for (**a**) Precipitation and (**b**) Temperature series.

A comparison of the RTSP with IDW is provided in Table 4. The validation of the RTSTs was performed using the ROCADA database [19]. Additionally, a comparison with the IDW results for the temperature series is provided in Table 5. IDW was chosen for comparisons because as one of the most utilized spatial interpolation methods implemented in different GIS software, among which ArcGIS (and its freeware versions) was the most used and well-known [59–64]. Since the RTS model explored precipitation and temperature evolution in a zone, the average values of MAE and MSE are of interest (last rows in Tables 4 and 5).

Table 4. Comparison between the goodness of fit of the RTS and IDW for precipitation series.

	Min				**Max**				**Total**			
	MAE		**MSE**		**MAE**		**MSE**		**MAE**		**MSE**	
Site No.	**RTS**	**IDW**	**RTS**	**IDW**	**RTS**	**IDW**	**RTS**	**IDW**	**RTS**	**IDW**	**RTS**	**IDW**
Adamclisi	2.1	3.5	2.6	3.4	23.8	24.5	31.1	31.9	67.9	60.1	83.5	70.2
Cernavoda	2.3	2.2	3.7	3.3	14.0	18.5	19.1	23.3	64.3	53.8	76.8	71.0
Constanta	1.7	2.1	2.4	3.1	17.1	20.0	26.4	30.5	37.1	48.2	45.8	57.9
Corugea	1.5	1.7	2.2	2.4	14.6	16.7	19.3	22.4	42.2	49.2	55.4	62.4
Harsova	2.7	2	3.2	3.4	24.5	26.1	37.1	35.6	99.2	61.7	147.2	84.3
Jurilovca	2.2	2.4	2.8	3.1	17.7	19.9	21.1	24.8	64.3	69.9	86.1	88.1
Mangalia	2.0	2.6	3.4	3.6	24.7	26.9	32.6	42.2	53.2	56.9	72.7	72.6
Medgidia	1.8	2.2	2.8	3.1	19.3	18.9	23.8	22.4	48.0	47.2	55.6	57.1
Sulina	2.1	2.8	4.0	3.9	37.0	36.2	45.2	43.5	116.7	92.9	131.4	111.5
Tulcea	2.8	2.6	3.6	3.8	22.4	26.3	29.3	33.3	58.2	171.2	74.5	182.9
Average	2.6	3.4	3.1	3.3	21.5	23.3	28.5	31.0	65.1	71.1	82.9	85.81

The lower the MAE and MSE were, the better the model was. In the present case, all the MAEs from the proposed algorithm were lower than those from IDW. The same was true for the MSEs. Therefore, IDW performed the worst in all cases.

The MAEs and MSEs obtained after fitting the regional series are presented in Figure 6. It can be remarked that the MAE and MSE for each RTS did not significantly differ or have the same shapes. As expected, the highest MAE and MSE corresponded to PrecTot in the case of the precipitation series case and TempMin for the temperature series. Given the high range of values for the time series belonging to the sets of total annual precipitation and minimum temperatures (the brown curves in Figure 2 and the curves in Figure 3a), this result was expected.

Table 5. Comparison between the fitting results from this approach (RTS) [19] and IDW for temperature series.

	Min				Average				Max			
	MAE		MSE		MAE		MSE		MAE		MSE	
Site no.	**RTS**	**IDW**	**RTS**	**IDW**	**RTS**	**IDW**	**RTS**	**IDW**	**RTS**	**IDW**	**RTS**	**IDW**
Adamclisi	0.84	0.58	1.00	0.68	0.19	0.27	0.22	0.29	0.31	0.37	0.44	0.40
Cernavoda	0.50	1.00	0.58	1.25	0.13	0.16	0.16	0.20	0.53	0.95	0.60	1.04
Constanta	2.61	2.06	2.65	2.10	0.71	0.71	0.74	0.73	1.07	0.75	1.13	0.80
Corugea	1.34	1.62	1.40	1.66	1.10	1.18	1.11	1.19	0.98	0.91	1.03	0.95
Harsova	2.32	2.62	2.38	2.69	0.53	0.78	0.60	0.71	1.28	1.39	1.33	1.54
Jurilovca	0.69	0.91	0.83	1.10	0.08	0.18	0.10	0.33	0.32	0.55	0.42	0.67
Mangalia	0.70	1.31	0.81	1.35	0.11	0.83	0.12	0.87	0.55	0.85	0.63	0.91
Medgidia	0.56	0.35	0.64	0.41	0.17	0.12	0.27	0.14	0.63	0.29	0.76	0.39
Sulina	3.42	3.00	3.47	3.04	0.46	0.47	0.51	0.50	2.46	2.11	2.51	2.14
Tulcea	0.94	0.80	1.18	0.89	0.19	0.23	0.22	0.26	0.31	0.52	0.44	0.58
Average	1.39	1.42	1.49	1.52	0.37	0.49	0.41	0.52	0.84	0.87	0.93	0.94

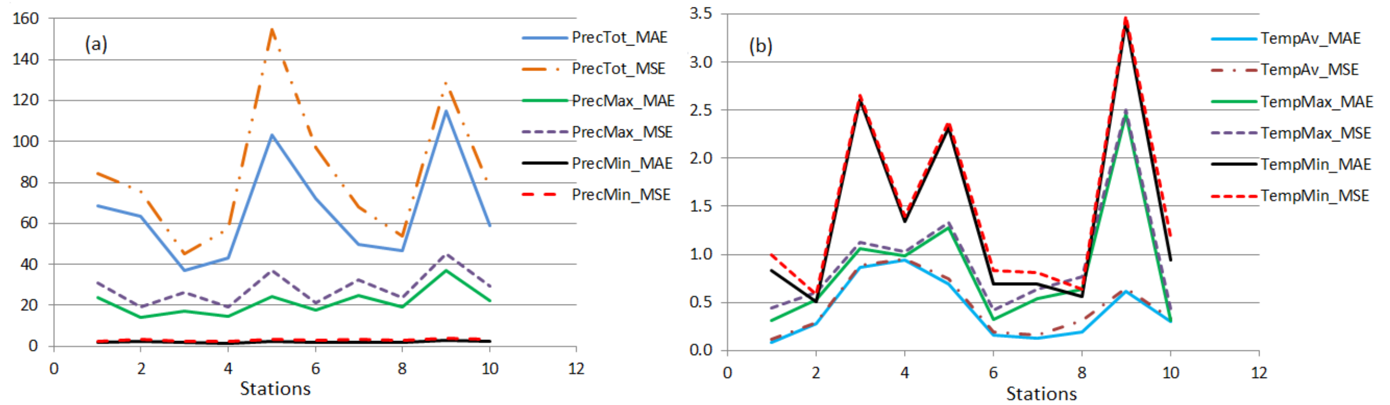

Figure 6. The average MAEs and MSEs at each station with respect to RTSs for (**a**) Precipitation, and (**b**) Temperature.

The Mann–Kendall test rejected the null hypothesis, at a significance level of 0.05, only for RTSTmin. Applying Sen's procedure to the mentioned series, a slope of the linear trend equal to 0.053 was found. The graphical representation of the RTSTmin (the black dots), the regression line (black), the limits of the confidence interval (dotted lines, blue and red), and the residual in the linear model is represented in Figure 7.

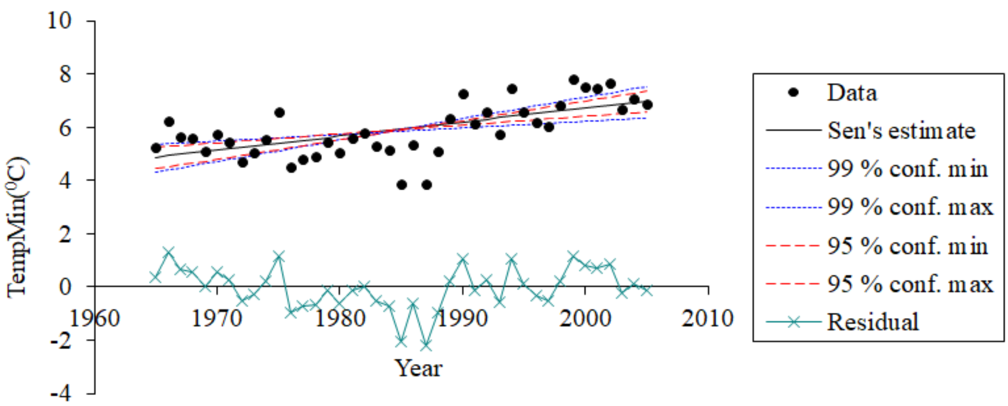

Figure 7. The result of the Mann–Kendall test and Sen's slope for RTSTmin.

The causes of the observed trend cannot be assessed by the statistical methods for testing the null hypothesis in the Mann–Kendall test. Moreover, when working with annual data, such an attempt is not realistic. The regional time series emphasizes the tendency in the entire region that covers different sub-zones with different climate influences (continental or oceanic), including variate relief and different altitudes. Therefore, RTS summarizes all these aspects. If the majority of the local series exhibits a monotonic trend in the same direction (positive or negative), the regional trend can be expected to be the same. If the tendencies at different stations are opposite, the regional trend is either absent or has the same sign (positive or negative) as the predominant individual series trends.

Table 6, which contains the *p*-values of the Spearman and Kendall tau tests, results in the hypothesis that there is a correlation between the RTSPs and RTSTs being rejected for all pairs but RTSPmin—RTSTmax.

Table 6. Comparison of the Spearman and Kendall tau tests.

Spearman	**RTSTav**	**RTSTmax**	**RTSTmin**
RTSPtot	0.7468	0.5341	0.5353
RTSPmax	0.7215	0.7793	0.6431
RTSPmin	0.4697	0.0537	0.7488
Kendall tau	**RTSTav**	**RTSTmax**	**RTSTmin**
RTSPtot	0.6613	0.4651	0.5293
RTSPmax	0.7109	0.6131	0.6531
RTSPmin	0.4252	0.0420	0.7531

For the mentioned pairs, the Kendall tau test did not reject the correlation hypothesis, whereas the Spearman test rejected it. Still, in the last test, the *p*-value was slightly higher than 0.05 (the standard significance level to which the tests are usually performed). Based on these findings, one can conclude that at a significance level of 0.06, none of these tests rejected the correlation hypothesis. Still, the correlation coefficient (ρ) was very low ($\rho = -0.3035$ − Spearmann, $\rho = -0.2217$ − Kendall test). Our results are concordant with those from different parts of the world [10–12].

In this study, complete and verified data series were utilized. Therefore, no supplementary bias was introduced. As a consequence, the evaluation of the model's quality was conducted by residual values. The lower the MAEs and MSEs, the better the model quality was. When the data series were not complete, a detailed discussion had to be conducted since errors would be introduced in building the regional series, affecting the correlation between the RTSP and RTST. The following situations should be treated:

(a) Only a set of initial data series had missing values (for example, only two missing values were found in the average temperature series recorded at Adamclisi),
(b) Both sets of data series had missing values that were not recorded in the same station or period (for example, there were missing values for the minimum temperature series at Adamclisi in 1970 and 1981 and missing values for the minimum precipitation series at Corugea in 1969, 1992, and 2003),
(c) Both sets of data series had missing values recorded at the same time at the same station (for example, there are missing values of the minimum temperature and precipitation series recorded at Constanta in 1971, 1983, and 1994).

Different interpolation methods for replacing the missing values had to be applied in each case; the entire study had to be performed, and the results were compared. These analyses deserve a separate study that permits drawing correct conclusions, which is beyond this article.

5. Conclusions

This article aimed to determine the regional precipitation and temperature series in Dobrogea, Romania, and answer whether precipitation and temperature are correlated. Even if this topic has been studied, this is the only approach using a built Regional series employing a new method introduced by the authors, MPPM, and not the individual series recorded at different locations. Most breakpoints for the minimum temperature series were found in 1988, and for the maximum, in 1997, whereas, for the precipitation series, the most frequent change point was 2004. Moreover, no common breakpoint was found for the temperature and precipitation series when recorded at specific points.

The Mann–Kendall test from each series emphasized the existence of significant monotonic trends at a 99% confidence level only for Sulina PrecMax and PrecTot, Jurilovca Tmin and Tmax, Cernavoda and Corugea Tmax. Additionally, no concordance between the existence of an increasing/decreasing trend of precipitations/temperature series was emphasized.

The correlation study emphasized only a slight negative correlation coefficient between the RTSPmin and RTSTmax. Further studies should be performed using more series to confirm the above findings. Moreover, the most recent data series (the last 16 years) should be used, which are, unfortunately, publically unavailable at this moment. Additionally, research should be developed on monthly data to emphasize the seasonal characteristics/correlation of such series, in which case the mechanism of interaction between the temperature and precipitation series should also be investigated.

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