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Innovative and successive average trend analysis of temperature and precipitation in Osijek, Croatia

Ali Danandeh Mehr[1] · Bahrudin Hrnjica[2] · Ognjen Bonacci[3] · Ali Torabi Haghighi[4]

Abstract

This paper examines monthly, seasonal, and annual trends in temperature and precipitation time series in Osijek during the period between 1900 and 2018. Two new methods, innovative trend analysis (ITA) and successive average methodology (SAM), together with the classic Mann–Kendall (M–K) and Sen's slope methods, have been applied to determine potential trends in the variables at different time scales. Moreover, time series decomposition using locally estimated scatterplot smoothing (STL) was conducted to determine trend, seasonality, and the relationship between the components of each variable. Regarding the air temperature, ITA showed a monotonic positive trend at relatively low ($T \leq 10$ °C) and high ($T \geq 13$ °C) temperature ranges in all seasons, excluding spring. A positive trend was also found in the medium temperature range in this season, which agrees with the results of M–K test. The highest Sen's slope was obtained in January, with the second highest in April. According to the results acquired for the observed precipitation time series, it was discovered that Osijek has experienced a decreasing trend in spring precipitation. However, there is no trend in annual precipitation at a 5% significance level. Differing from the M–K results, the ITA shows a decreasing trend in both spring and autumn seasons. Summer precipitation increases with a significant change in the high precipitating levels ($p \geq 100$ mm). Comparing successive pairs of partial trends in both historical temperature and precipitation, our results show that trends in peak and trough change-points are very close to each other, indicating a slight positive trend in temperature and a negative change in precipitation over the past century.

Keywords Innovative trend analysis · Successive average methodology · Mann–Kendall test · Temperature · Precipitation · Osijek

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1 Introduction

Trend analysis is an important part of environmental monitoring that allows for the study of the variation of environmental variables over time. Many researchers have explored temperature and precipitation trends at local and regional scales (Kadıoğlu 1997; Jones et al. 1999; Jain and Kumar 2012; Gocic and Trajkovic 2013; Addisu et al. 2015; Yao and Chen 2015; Tosunoğlu 2017; Nourani et al. 2018; Panda and Sahu 2019; Yacoub and Tayfur 2019; Güçlü 2020). Focusing on the Pannonian region, a large flat alluvial basin in Central Europe, also known as the Carpathian Basin, several studies have reported a rise in the temperature across the region (Bartholy and Pongrácz 2007; Koprivšek et al. 2012; Bonacci 2010, 2012; Melo et al. 2013; Zhu et al. 2019). Regarding climate change and more frequent extreme weather and climate disasters, especially droughts, fertile Pannonian lowland can be classed as an endangered area. It is necessary to make strategic

plans to mitigate the consequences of these changes on agriculture, which should be based on the analyses of long-lasting air temperature and precipitation time series. The Osijek station is one of the oldest meteorological stations in the Pannonian lowland, and the analysis of its climatological data can be of special regional importance. In a time of climate change (mostly global warming), this region should be prepared for an unknown, yet threatening future. According to the 6th National Communication of the Republic of Croatia under the UN Framework Convention on Climate Change, greater warming (between 1.5C and 2 °C) is projected in the eastern and central parts of the country in the winter. In the eastern part of Slavonia, where the Osijek station is located, a statistically significant increase (more than 12%) of precipitation is projected (Tadić et al. 2019a).

Different aspects of the time series of climatological parameters monitored at the Osijek meteorological station have already been investigated in other papers. For example, the historical series of annual precipitation in Osijek during the 1891–1990 period has been studied by Gajić-Čapka (1993). A noteworthy decreasing trend in annual precipitation was found in this continental lowland meteorological station. Kovačević et al. (2009) showed that weather changes during the period of 1996–2003 negatively affected maize yield in Eastern Croatia. The aridity index has been proven as a useful tool for characterizing the impacts of rainfall and temperature pattern on maize yield in southeast Europe. Using the method of rescaled adjusted partial sums (Garbrecht and Fernandez 1994), Bonacci (2010, 2012) revealed a statistically significant jump in the Western Balkans region, which started in the early 1980s. A recent study on historical air temperature at 67 meteorological stations (including Osijek station) showed that warming started during the period between 1987 and 1997 in the Western Balkans region (Bonacci 2010). At Osijek station, warming started in 1988. The difference between the mean annual temperature before and after the warming is about 0.83 °C (Bonacci 2010, 2012). Precipitation data from the period between 1961 and 2010 in Osijek was analyzed for spatial characteristics of trends in precipitation amounts and precipitation indices (Gajić-Čapka et al. 2015). The results revealed that the changes in annual and seasonal amounts are predominantly weak. A significant trend was only detected for autumn precipitation. Gajić-Čapka (2013) analyzed daily and multi-day (two and five day) precipitation at the Osijek meteorological station in the period of 1949–2009. They found that, over the year, the daily variability was high. The study demonstrated that there are no changes regarding the intensity and frequency of the 1-day, 2-day, and 5-day precipitation amounts during the historical period. Tadić et al. (2019a) applied principal component analysis to evaluate climate change impacts on the variation of precipitation and air temperature at the Osijek station. The study indicated that principal component analysis can be satisfactorily used for detecting trends in hydro-climatological variables.

Using measured precipitation and temperature data from 13 stations distributed across Croatia (the Osijek station included), Tadić et al. (2019b) explored the meteorological drought in the region. The results showed that a positive trend in the air temperature during the period of 1981–2018 strongly affected the occurrence and intensity of meteorological drought in the country. Despite several studies on temperature and precipitation trends in the Pannonian region, our review found that only a few studies explored temperature/precipitation trends in the region considering long-lasting (a century or more) observations. Likewise, most studies have been confined to classical trend analysis methods such as the Mann-Kenall (M–K) test, or linear regression analysis. To the best of our knowledge, the potential advantages of new methods, such as innovative trend analysis (ITA: Şen 2012; 2014) and successive average methodology (SAM: Şen 2019), have not yet been explored for the Pannonian region. Therefore, in this study, we aimed for trend analysis and partial trend identification in temperature and precipitation using these new methods. Moreover, the method of seasonal and trend decomposition using Loess (STL) was applied to explore the relationship between different components of the temperature/precipitation time series. The data collected at the Osijek meteorological station from the beginning of the twentieth century to the recent time (1900–2018) is used in the present study, thus providing us with crucial information about climate variation in the region.

2 Study area and data

The city of Osijek is in the northeastern part of the Croatian Pannonian lowlands near the Hungarian and Serbian border. It is also a river port along the Drava River, a rapidly growing urban area. The population has increased from 25,550 inhabitants in 1880 to 129,792 in 1999. After the war (1991–1995), according to the 2011 census, the total population of the city decreased to 108,048 inhabitants.

The Osijek station (Fig. 1), one of the oldest meteorological stations in Croatia, is operated by the Croatian state national network of meteorological stations, for which air temperature data is homogenized. Although its location was changed three times during the period between 1900 and 2018, there is no missing data. In the first period (1900–1943), its coordinates were 45° 33′ N and 18° 40′ E, while altitude was 91 m a.s.l. In the second period (1944–1991), its coordinates were 45° 12′ N and 18° 44′ E, and altitude was 91 m a.s.l. During these two time periods, the station was in the urban area of Osijek. The new location, which began its work in 1992 (Fig. 1 right), has

Fig. 1 Osijek meteorological station

the following coordinates: 45° 30′ 09″ N and 18° 33′ 41″ E with altitude 89 m a.s.l.

The broader Osijek area, located in the Pannonian lowlands, is a part of northeastern Croatia and experiences a temperate, and continental climate, which is considered to be Dfb according to the Köppen-Geiger climate classification. This indicates warm and moist summers and cold, often snowy, winters, with no significant precipitation difference between seasons (Cvitan and Patarčić 2018). Mean monthly, seasonal, and annual temperature, and total monthly, seasonal, and annual precipitation time series for the period 1900–2018 are shown in Figs. 2 and 3, respectively.

3 Methods

3.1 Mann–Kendall trend analysis

Most previous trend analyses of environmental data have been performed using a non-parametric Mann–Kendall trend test that makes no assumption about the underlying distribution of that data (e.g., Allen et al. 2015; Hori et al. 2017). This is a rank-based method which looks at the relative magnitudes of a given variable in its time series. The test is performed by calculating three different metrics: S statistic (Kendall, 1962), variance of S, and Z statistic, or test statistic.

$$S = \sum_{i=1}^{n} \sum_{j=i+1}^{n} sign(x_i - x_j) \tag{1}$$

$$\sigma^2 = Var(S) = \frac{1}{18} \left[n(n-1)(2n+5) - \sum_{i=n}^{n} t_i(i)(i-1)(2i+5) \right] \tag{2}$$

$$Z = \begin{cases} \frac{S-1}{\sigma} & for \ S > 0 \\ \frac{S-1}{\sigma} & for \ S < 0 \\ 0 & for \ S = 0 \end{cases} \tag{3}$$

where x_i and x_j are the data points (in this case, a temperature or precipitation value) at times i and j, respectively. $sign(x_i - x_j)$ equals $+1$ if x_i is greater than x_j and -1 if x_i is less than x_j.

The test statistics indicate whether the trend is increasing ($+$) or decreasing ($-$). The null hypothesis for M–K test is that there is no trend, and the alternative hypothesis is that there is an upward trend or downward trend. The trend is considered insignificant if Z is less than the significance levels (e.g., $\alpha = 5\%$), but significant if $Z \geq |\pm 1.96|$.
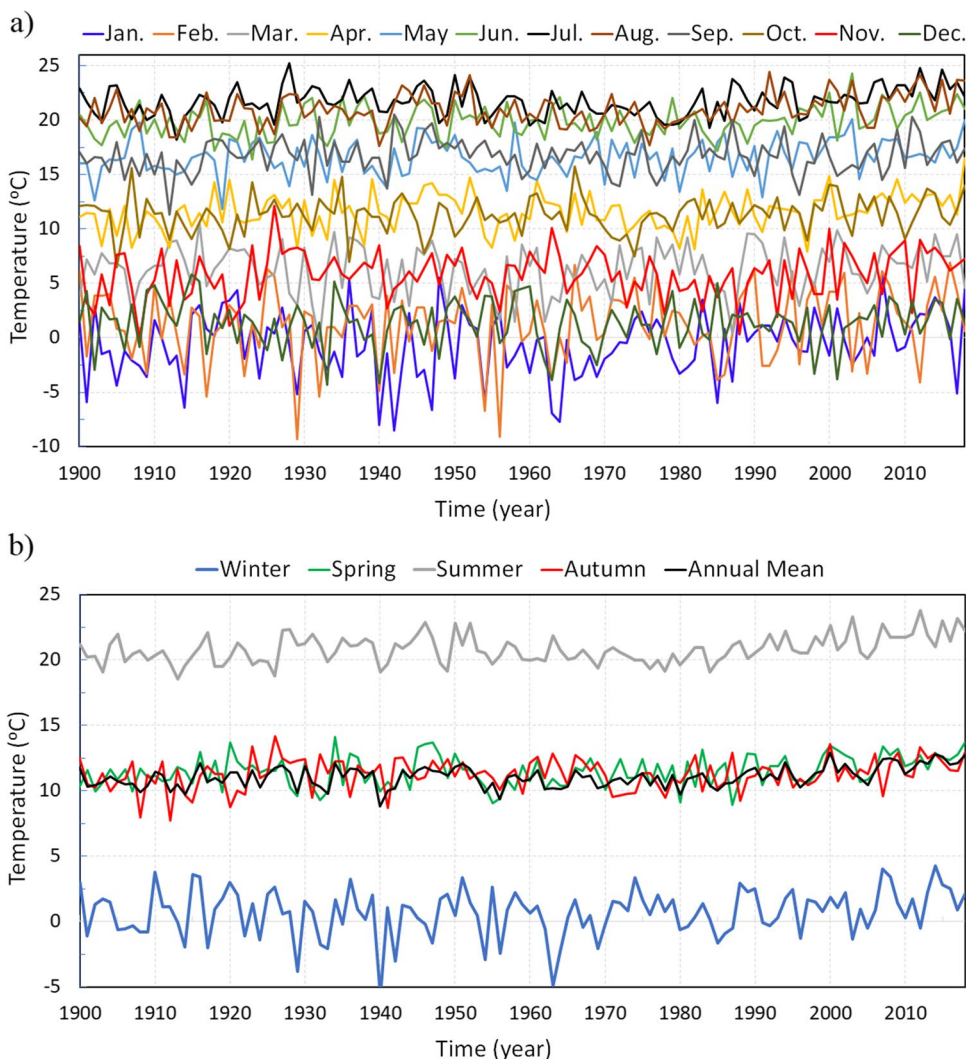
3.2 Sen's slop

Sen's slope (Sen 1968) is used to identify the magnitude of trend in a dataset. The method is non-parametric and is not sensitive to outliers. For a dataset with x_i and x_j as the sample data points, Sen's slope is calculated using Eq. (4).

$$Sen's \ slope = median \left\{ \frac{x_i - x_j}{j - i} : i < j \right\} \tag{4}$$

For a confidence level of 95%, we calculated lower and upper intervals (x_L and x_U) with respect to the number of pairs of time series elements (N) and standard deviation of M–K test (σ).

$$x_L = \frac{N - k}{2} \tag{5}$$

Fig. 2 Observed **a** monthly, and **b** seasonal and annual air temperature time series in Osijek (1900–2018)

By using Loess regressor, each observation is multiplied with the weight calculated in terms of distance (in time) between the time series value and the value to be smoothed. The weight value tends to be zero, while the distance tends to be infinite. For any point in time (t), the neighborhood weight value ($v_i(t)$) related to observation (t_i) can be calculated using tricube weight function (W):

$$x_U = \frac{N + k}{3} \tag{6}$$

$$Y_t = t_t + S_t + \epsilon_t. \tag{7}$$

where k is the product of critical Z statistics and standard deviation of M–K test.

3.3 Seasonal and Trend decomposition using Loess

The Seasonal and Trend decomposition using Loess (STL) is a popular method for decomposing time series (Sanchez-Vazquez, et. al. 2012; Hrnjica & Mehr 2020). The Loess is the method for determining the relationship between different components of a time series. It is a generalization of the moving average and the polynomial regression called LOcal rEgreSSion (LOESS). The STL method begins with the well-known time series component model by decomposing the time series (Y_t) into a trend (t_t), a seasonal (s_t), and noise (ϵ_t) or remainder components by using Loess regressor (Cleveland et al. 1990).
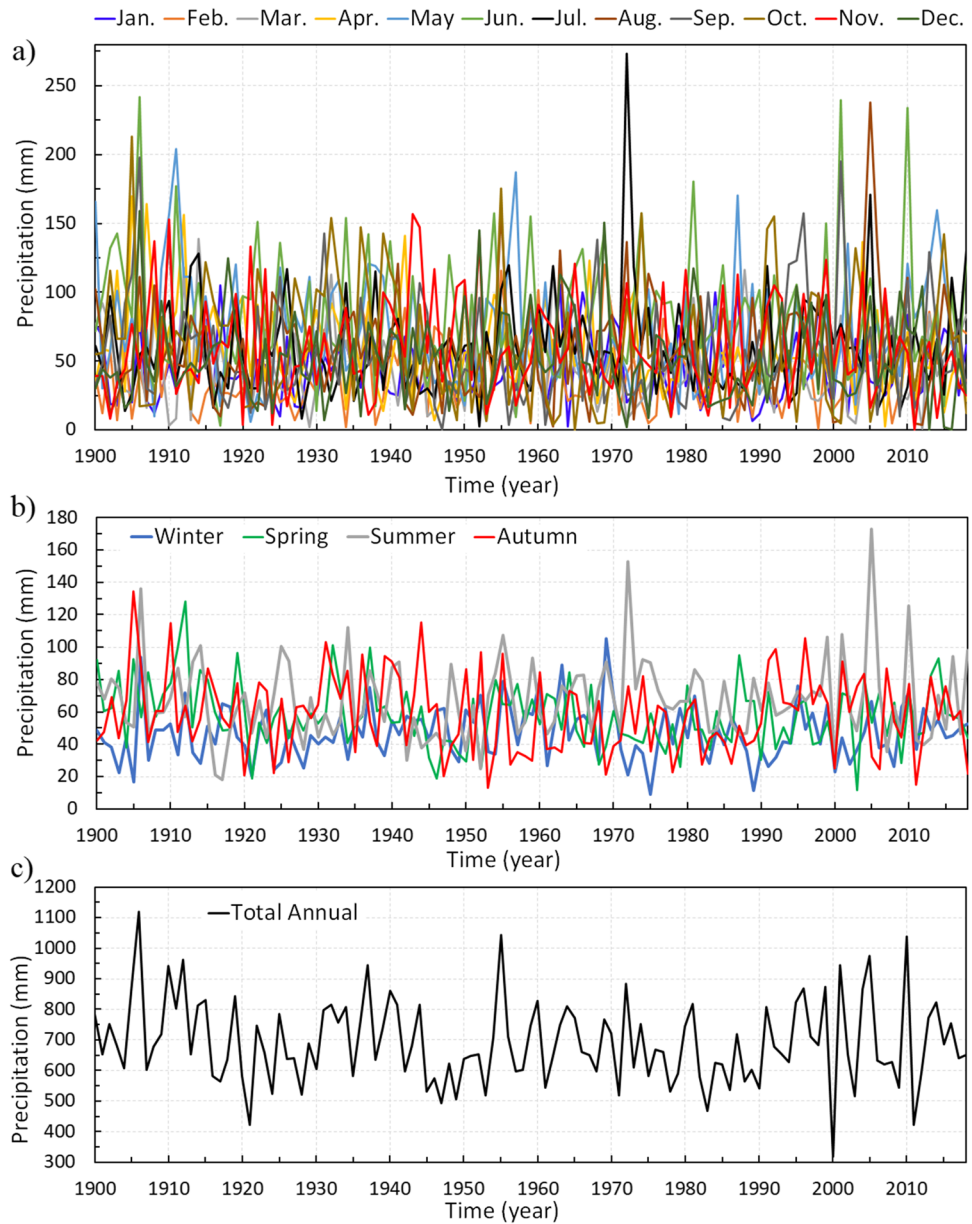
$$v_i(t) = W\left[1 - \left(\frac{|t_i - t|}{\lambda_k(t)}\right)\right], \tag{8}$$

where $\lambda_k(t) = |t_i - t_k|$ represents the distance between k^{th} farthest t_i and t. The parameters (k) determine the number of time series values included in the regression. The tricube weight function (W) is defined as:

Fig. 3 Observed **a** monthly, **b** seasonal, and **c** total annual precipitation in Osijek (1900–2018)

$$W(x) = \begin{cases} \left(1 - x^3\right)^3 & for\ 0 \leq x \leq 1 \\ 0 & for\ x \geq 1. \end{cases} \quad (9)$$

The STL method uses two loops, inner and outer, to decompose the given hydrometeorological time series. The inner loop is used to calculate trend and seasonal components using the Loess regressor. The outer loop is used to determine the robustness of weight which is used in the next inner loop to reduce the influence of transient and deviant behavior of trend and seasonal components. Once the trend and the seasonal components are determined in the inner loop, the outer loop calculates the corresponding remainder component. Compared to traditional time series decomposition, the STL has the following advantages

(Hyndman and Athanasopoulos 2018), which motivated us to include it in this study.

- In addition to monthly and quarterly, the STL supports any type of seasonality. This means that the decomposed seasonal component can consist of different cycles through time. This allows for the analysis of different values of positive and negative peak amplitude.
- It allows the season component to be changed over time, which is very useful for dynamics time series. However, it cannot handle the date variable automatically.
- STL is robust against outliers, so they do not affect the approximations of the trend and seasonal components.

- STL only supports additive decomposition (see Eq. 7), while multiplicative decomposition can be achieved by taking the logs of the data.

3.4 Innovative trend analysis

The innovative trend analysis (ITA) (Şen 2012, 2014) is a simple and effective method for trend detection by means of graphical distribution of historical data. In an ITA approach, the historical time series of observed data is split into two subseries of equal length, called serials. Then, the serials are sorted in ascending order and plotted against each other (Fig. 4). As illustrated in Fig. 4, the 45° diagonal line is passed through the scatter diagram that divides the plot into the trend-free zone along the 1:1-line, with an upper triangular area indicating the increasing trend zone, and a lower triangle area indicating the decreasing trend zone. The ITA approach has attracted many researchers in recent years (e.g., Dabanlı et al. 2016; Tosunoglu and Kisi 2017; Ay et al. 2018 among others).

3.5 Successive average methodology

Most trend analyzing methodologies in the literature discuss monotonic trends within a given hydrological time series. For long-term data, holistic monotonic analysis over the whole recording duration may lead to the loss of successive trends of different durations and slopes within the same time series. To manage the problem, Şen (2019) proposed a new partial trend methodology called successive arithmetic average methodology (SAM) in which peak and trough

change-points, initial and ending points of partial trend durations and slopes are identified.

The SAM starts with a search for the change-points among the potential and natural change-point occurrences in a long-term hydrological time series. Firstly, for the given time series with the length of n and the data points of x_1, $x_2, ..., x_n$, the vector of the successive arithmetic average is calculated according to the following formulation,

$$\overline{X}_i = \sum_{i=1}^{n} \left(\frac{1}{i} \sum_{j=1}^{i} x_j \right), \tag{10}$$

Then, the following statements are used to determine the position of local peak/trough change-points along the time axis.

$$
\begin{aligned}
&if \quad \overline{X}_{i-1} < \overline{X}_i > \overline{X}_{i+1} \quad then \; fix x_i \; as \, peak - change \, position \\
&if \quad \overline{X}_{i-1} > \overline{X}_i < \overline{X}_{i+1} \quad then \; fix x_i \; as \, trough - change \, position
\end{aligned} \tag{11}
$$

Finally, successive two change-points are connected by linear lines indicating partial duration trends. The corresponding slope (S_{ij}) is calculated using the following expression, in which Y_i and Y_j denote the corresponding positions (e.g., year for annual time series) of the two successive averages $\overline{X}_i$ and $\overline{X}_j$, respectively.

$$S_{ij} = \frac{\overline{X}_j - \overline{X}_i}{Y_j - Y_i} \tag{12}$$

4 Results and discussion

4.1 M–K test results

Table 1 presents the results of the M–K trend analysis for monthly observed temperature and precipitation. The M–K statistics Z value in each month was calculated and the associated significance level (p value) was obtained. As previously mentioned, the null hypothesis for this test is that there is no trend. If the p value of the test is less than the significant level of the test ($\alpha = 5\%$), the test rejects the null hypothesis. According to the table, the M–K test for the historical precipitation showed that the p values are greater than α in all months, excluding April, indicating that there is insufficient evidence to reject the null hypothesis. The corresponding Z statistic in April is -2.42, far from the critical $Z = \pm 1.96$, indicating a significant decreasing trend. Regarding the results for the air temperature, the M–K test does not show a significant increasing trend from April to June and August.

The results of the M–K test for observed temperature and precipitation at the seasonal and annual level were presented in Table 2. A significant increasing trend is obvious in mean
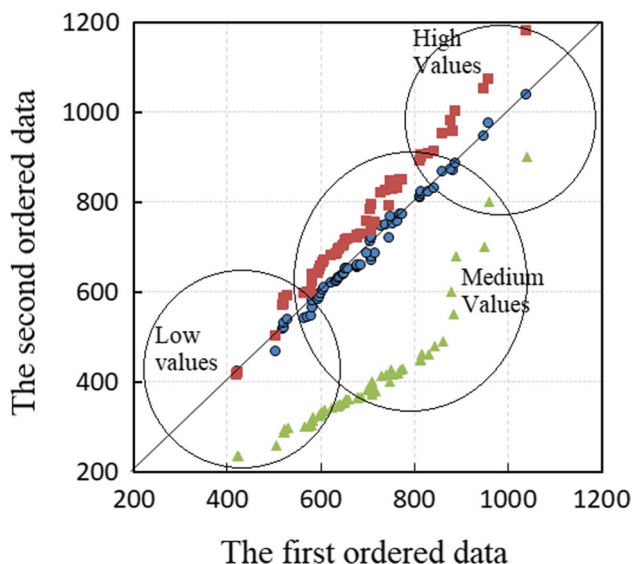

Fig. 4 ITA scatter plot illustrating increasing (squares), decreasing (triangles), and trendless time series (circles)

seasonal temperature in spring and summer seasons that creates a positive trend in annual temperature. By contrast, there is no trend in annual precipitation at a 5% significance level, even though spring precipitation decreases over time.

4.2 Sen's slope test results

The Sen's slope, along with the lower and upper limits of 95% confidence interval, was presented in Tables 3 and 4

for monthly and seasonal observations, respectively. The results showed a slightly positive trend for temperature in all months, seasons, and annual levels, excluding September and December. The highest slope is observed in January, followed by April. This is not in agreement with the results of the M–K test, which showed that the most significant trend appeared in August. Considering the Sen's slopes for precipitation series, it is obvious that Osijek experienced a decreasing trend in the period from March to June and

Table 1 Results of the Mann–Kendall trend for monthly temperature and precipitation (1900–2018)

Month	Temperature			Precipitation		
	Z	p value	Trend	Z	p value	Trend
Jan	1.64	0.10	No	0.420	0.674	No
Feb	1.30	0.20	No	1.128	0.259	No
Mar	0.87	0.38	No	−0.393	0.694	No
Apr	2.66	0.01	Yes	−2.421	0.015	Yes
May	2.31	0.02	Yes	−0.639	0.523	No
Jun	2.71	0.01	Yes	−0.094	0.925	No
Jul	1.96	0.05	No	0.583	0.560	No
Aug	2.90	0.00	Yes	0.606	0.544	No
Sep	0.31	0.75	No	−0.269	0.788	No
Oct	1.26	0.21	No	−1.314	0.189	No
Nov	1.32	0.19	No	−0.243	0.808	No
Dec	−0.21	0.84	No	−0.002	0.998	No

Table 2 Results of the Mann–Kendall trend test at seasonal and annual level

Season	Temperature			Precipitation		
	Z	p value	Trend	Z	p value	Trend
Winter	1.500	0.134	No	0.682	0.495	No
Spring	3.113	0.002	Yes	−2.159	0.031	Yes
Summer	3.345	0.001	Yes	0.455	0.649	No
Autumn	1.493	0.135	No	−0.859	0.390	No
Annual	3.59	0.00	Yes	−0.972	0.331	No

Table 3 Results of the Sen's slope test at the monthly level

Month	Temperature			Precipitation		
	Slope	Lower	Upper	Slope	Lower	Upper
Jan	0.014	−0.002	0.029	0.035	−0.102	0.159
Feb	0.010	−0.006	0.027	0.080	−0.063	0.228
Mar	0.005	−0.007	0.017	−0.030	−0.187	0.120
Apr	0.012	0.003	0.020	−0.200	−0.364	−0.036
May	0.010	0.001	0.019	−0.071	−0.269	0.126
Jun	0.010	0.003	0.019	−0.008	−0.236	0.210
Jul	0.007	0.000	0.014	0.043	−0.113	0.188
Aug	0.011	0.004	0.020	0.065	−0.124	0.256
Sep	0.000	−0.007	0.009	−0.021	−0.200	0.138
Oct	0.005	−0.003	0.013	−0.134	−0.357	0.068
Nov	0.008	−0.003	0.020	−0.017	−0.200	0.140
Dec	−0.001	−0.013	0.011	0.000	−0.161	0.158

Table 4 Results of the Sen's slope test at the seasonal and annual level

Season	Temperature			Precipitation		
	Slope	Lower	Upper	Slope	Lower	Upper
Winter	0.007	−0.002	0.016	0.032	−0.057	0.118
Spring	0.010	0.004	0.016	−0.122	−0.222	−0.012
Summer	0.010	0.004	0.015	0.025	−0.094	0.147
Autumn	0.005	−0.002	0.011	−0.056	−0.190	0.075
Annual	0.008	0.004	0.012	−0.330	−1.121	0.332

September to November. The highest decreasing trend is seen in April. According to Table 4, the summer temperature increased faster than in other seasons. Notably, annual precipitation demonstrated a decrease with a slope of 0.33.

4.3 STL results

The STL decomposition was performed on the observed historical temperature and precipitation data to detect any seasonal or trend changes. The decomposition was performed for both monthly and seasonal (winter, spring, summer, and autumn) levels. Generally, the obtained results show changes in trends and seasonality on monthly and seasonal levels that can be considered to be a sign of global climate change.

4.4 STL temperature decomposition results

The trend and seasonality analysis using STL was performed by using a *stlsplus* R package (Hafen 2016) which is based on the original *stl* R package with some advancements in plotting. Figure 5 shows the time series components of the

monthly temperature at Osijek in the period from 1900 to 2018. Figure 6 shows the time series decomposition of the quarterly (winter, spring, summer, and autumn) temperature values at Osijek in the period from 1900 to 2018. Monthly and quarterly based time series components show some changes over time in the seasonal and the trend components. The seasonal component shows some minor changes in magnitude. It can be stated that the lower magnitude change has greater values than the higher change. The changes are less than 1 °C, and mostly depend on the LOESS window for seasonal extraction.

Very important changes come from trend components. From both time series decompositions, it is seen that trend components have demonstrated some increasing trends in the past 19 years (2000–2018). It is the longest period with the trend above the average value. Figure 7 shows precisely the trend component with the average trend values. The increasing behavior of the trend for the past 19 years can clearly be observed.

Besides an increasing trend, the figure shows some anomalies (peaks and troughs) in the trend component in the past
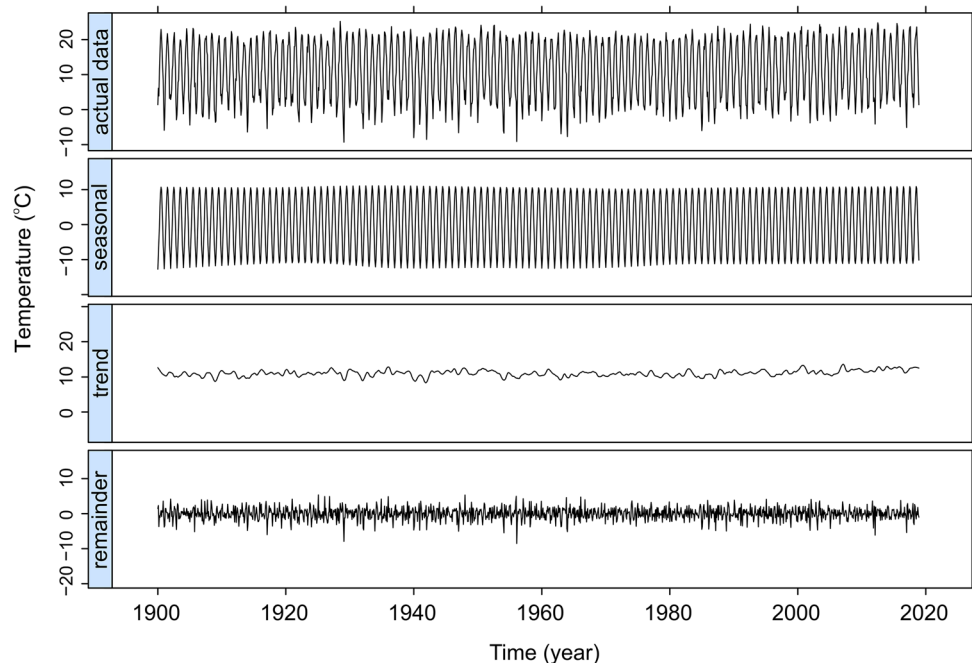

Fig. 5 STL time series components for monthly temperature in Osijek (1900–2018)

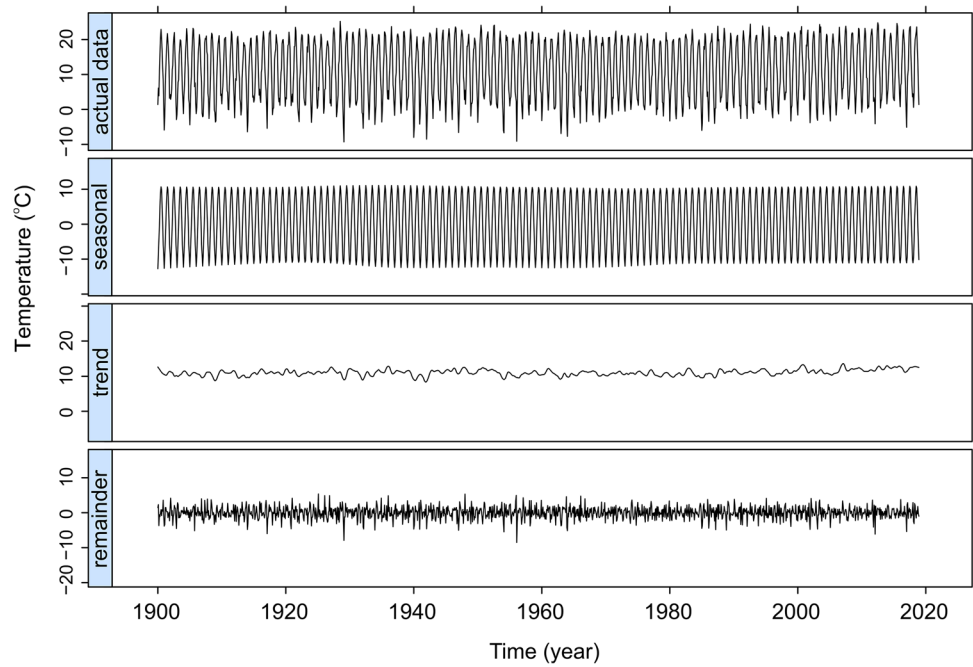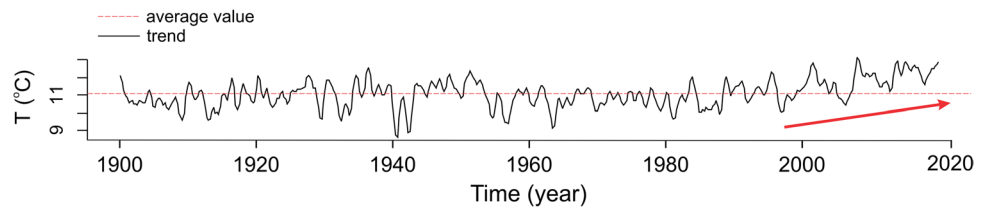**Fig. 6** STL time series components for quarterly temperature in Osijek (1900–2018)

Fig. 7 The trend component and average trend value

century. One can identify a decreasing trend during World War II. In addition, lower values of trend can be identified at the beginning of the twentieth century, as well as in the 1960s and 1970s. The troughs are reflected in the remainder component in greater quantities than in the seasonal component. This indicates that such anomalies are more likely due to noise in the data, rather than seasonal variations.

Figure 8 shows temperature changes in a specific period of the year during the observed period. The temperature changes in winter and autumn (Nov., Dec., Jan., Feb., and Mar.) are slightly higher than in spring and summer. This implies that winters and autumns are much different than summers and springs in terms of temperature, possibly indicating that climate change has affected winter and autumn more than spring and summer. In other words, seasonal variations of the temperature were not significantly changed during the period even though the temperature changes can be identified on a seasonal basis.

4.5 STL precipitation decomposition results

Figures 9 and 10 illustrate the results of STL analysis for the observed precipitation time series. From a decomposition point of view, one cannot detect any trend at any time period that indicates water balance in Osijek station. However, the seasonal component for the precipitation has changed over the time (see Figs. 9 and 10). The precipitation range in seasonal component is smaller than that of the remainder. Thus, the seasonal component has less influence on the time series than the remainder component. Comparing different components of precipitation, it can be concluded that the remainder (error components) is the most dominant component in the observed precipitation time series.

The seasonal component can be identified as a pattern of fluctuations (i.e., increase or decrease) that reoccur across periods of time, i.e., it is a periodic function with amplitude and period values. To analyze the seasonal component changes, the negative peak amplitude (NPA), positive peak amplitude (PPA), and the peak-to-peak amplitude (PTPA) were identified. The NPA and PPA represent the magnitude of a seasonal component on the positive and negative side of a cycle, respectively. Magnitude of the seasonal component of quarterly precipitation in Osijek is shown in Fig. 11. The first marked values (PPA, NPA) are at the beginning of the century. The point is also identified as the greatest amplitude in the observed period

Fig. 8 Variation in the seasonal component of the historical temperature time series at monthly (left panel) and quarterly (right panel) levels
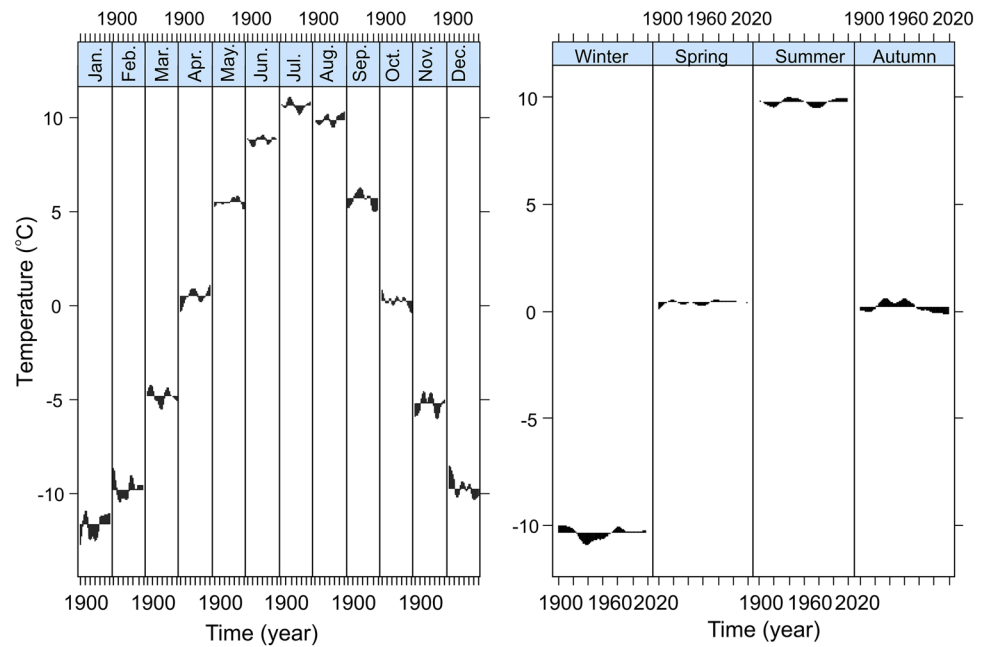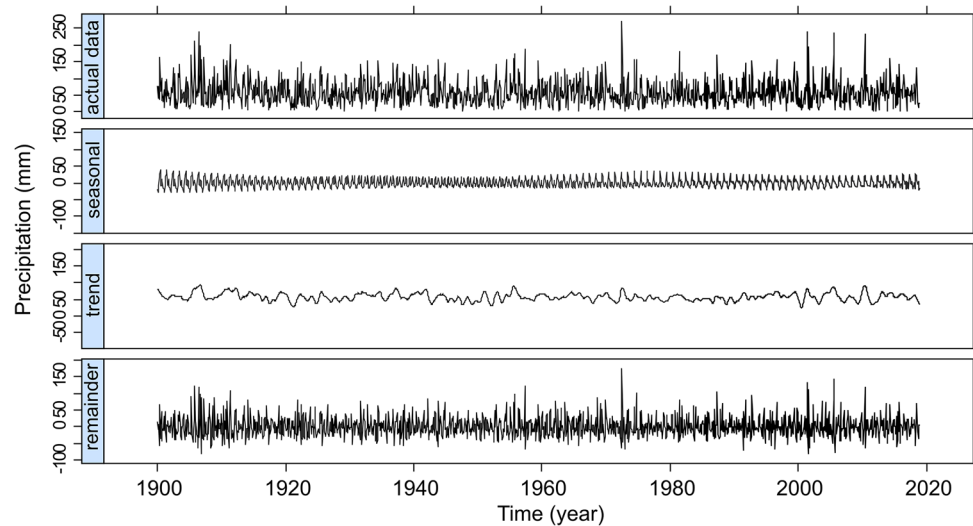

Fig. 9 STL time series components for monthly precipitation in Osijek (1900–2018)

(PTPA = 35 mm). Since then, a decreasing trend for both PPA and NPA amplitudes is seen until the second critical point, having a minimum PTPA of 10 mm. This indicates that the influence of the seasonal changes on total precipitation is decreasing. Moving forward, an increasing behavior for the PTPA was identified, until it reaches the 26 mm of PTPA, which is marked at the beginning of the 1970s. Since then, there is no uniform trend in the seasonal component. However, in the last 20 years, one can see a decreasing trend in the NPA. In fact, current NPA is four times lower than 120 years ago, while the PPA is more or less constant. This indicates that the seasonal changes of the precipitation have less influence in the summer than 120 years ago.

The seasonal component period starts in 1900, when the PTPA is 35 mm, so that the NPA is –23 mm, and PPA is 12 mm. Since then, the trend has constantly decreased until the middle of the twentieth century, where it reaches the minimum PTPA of 9 mm with NPA = –3 and PPA = 6 mm. From 1950 to 1970, the PTPA increases to 26 mm with NPA = –6 mm and PPA = 20 mm. Since this point, the seasonal component is decreasing, with the minimum value in 2018 reaching PTPA = 18 mm with NPA = –6 mm and PPA = 12 mm. However, the changes in the seasonal component of the precipitation have less influence on the whole time series than the corresponding remainder values. This also indicates that STL decomposition of the precipitation time series is remainder

dominant. The complex behavior of the seasonal component is clearly seen in Fig. 12, where precipitation variations for each month or season in a year are shown. The variation changes can be detected in any month or season of the year to a certain degree.

4.6 ITA results

Figures 13 and 14 illustrate the results of the ITA for the historical temperature and precipitation time series, respectively. Besides the general insight, the ITA represents the trend (positive or negative) in the "low," "medium," and "high" values of each variable. In Figs. 13 and 14, the

Fig. 10 STL time series components for quarterly precipitation in Osijek (1900–2018)
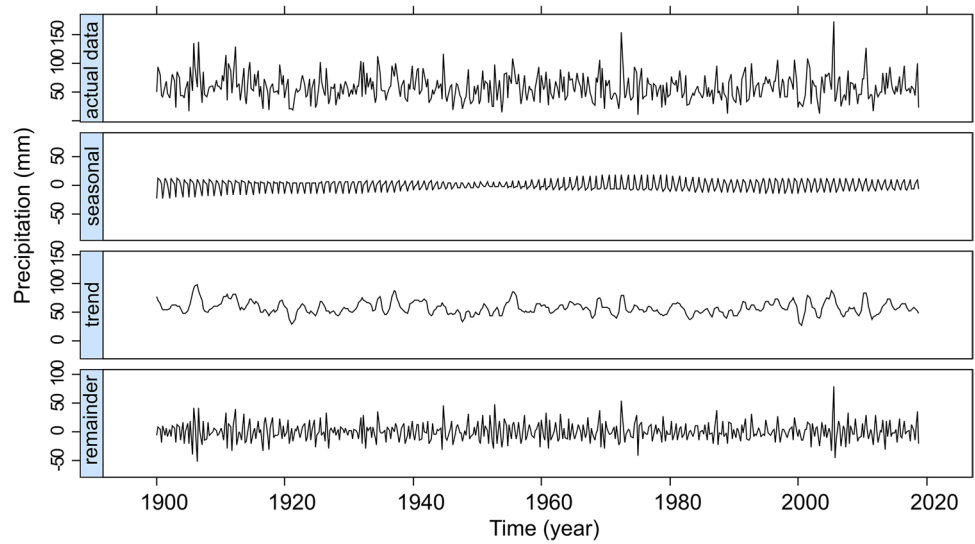
Fig. 11 Magnitude of the seasonal component of quarterly precipitation in Osijek (1900–2018) at different time periods
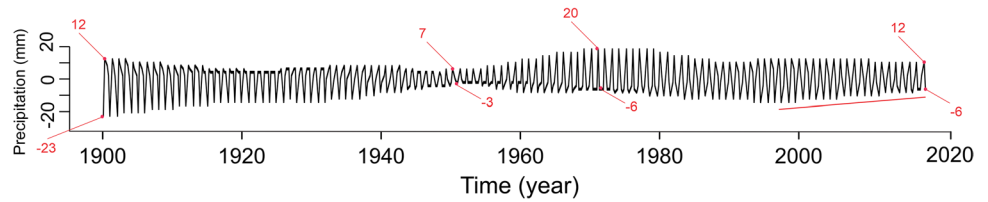
Fig. 12 Monthly (left) and quarterly (right) seasonal component changes for precipitation in Osijek (1900–2018)
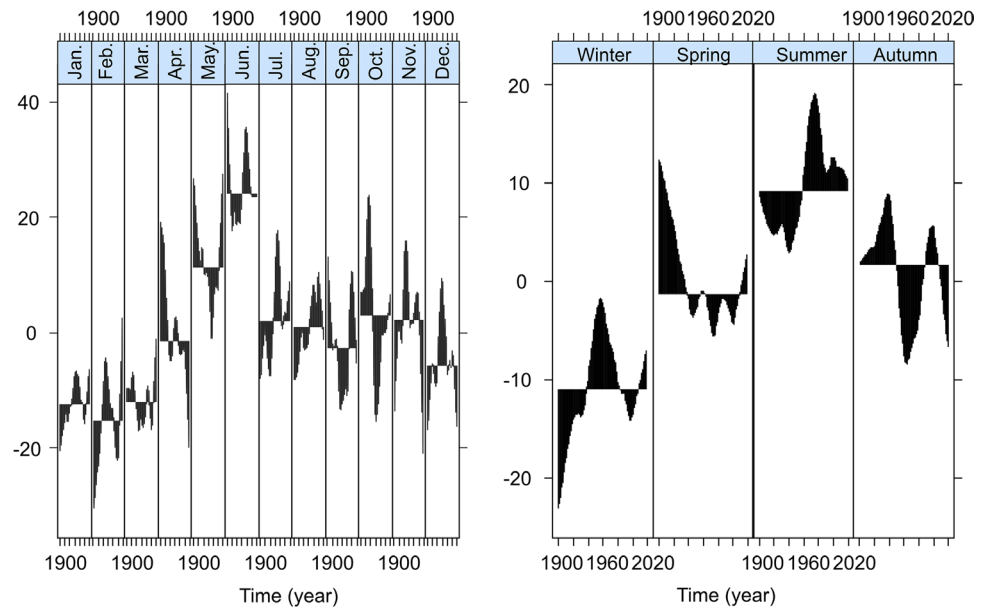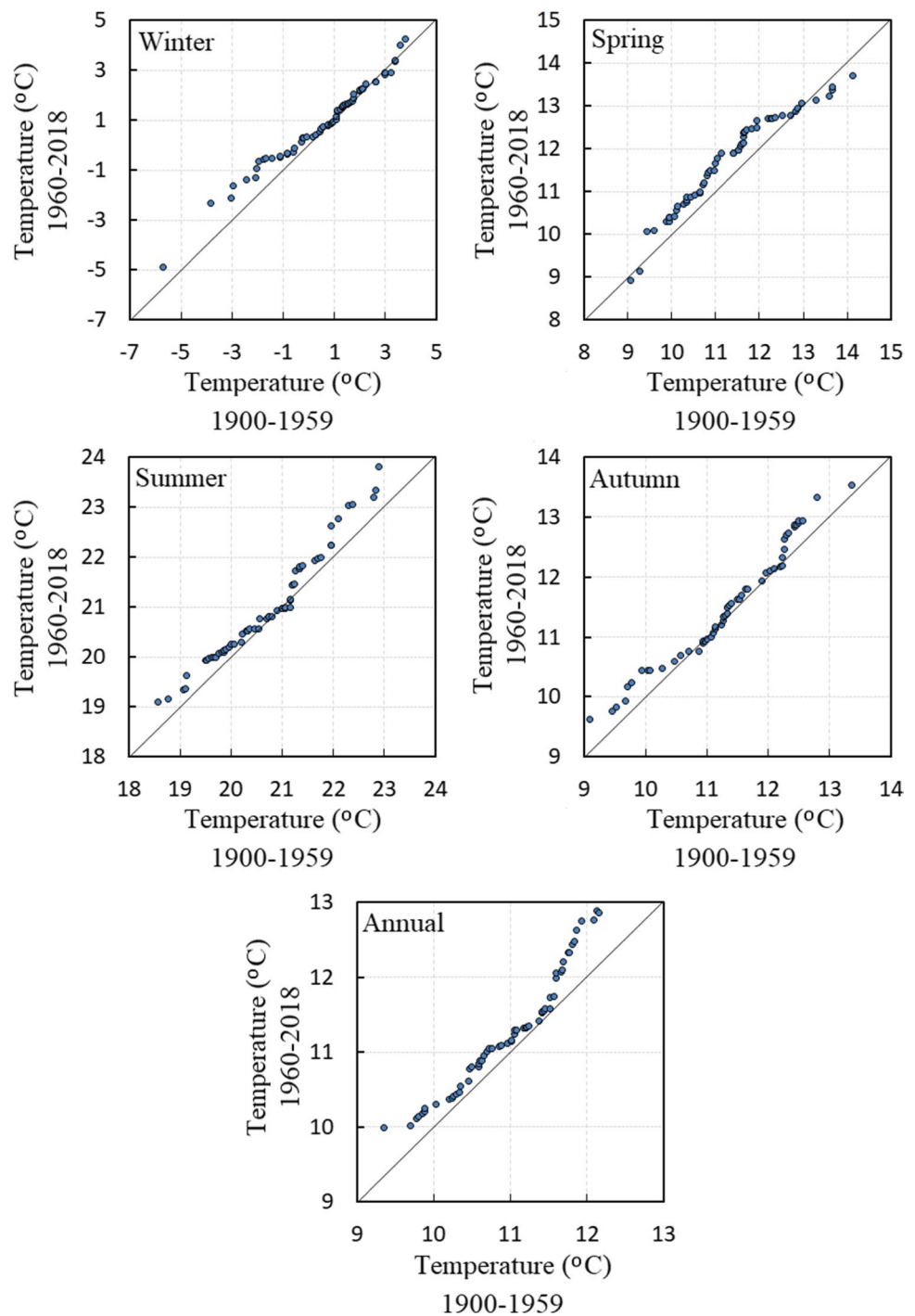
Fig. 13 Seasonal and annual trends in temperature during the period 1900–2018


entire time series of each variable at seasonal and annual levels was split temporally into two halves (1900–1959 and 1960–2018), with each half sorted in ascending order, and subsequently plotted against each other. Şen's temperature plots show a monotonic positive trend at relatively low and high temperatures in all seasons, excluding spring, where the decreasing trend in low (T ≤ 10 °C) and high (T ≥ 13 °C) temperature is observed. By contrast, a positive trend is shown at medium temperature in this season. From an

annual perspective, the figure clearly shows that the low, medium, and high temperatures in Osijek have increased over the period between 1960 and 2018, compared to the period between 1900 and 1959. The increasing rate in the high and low temperatures is higher than that of a medium temperature.

Figure 14 shows the seasonal and annual trends of precipitation in the Osijek station. The figure demonstrates that there is no significant change in winter medium

**Fig. 14** Seasonal and annual trends in precipitation during the period 1900–2018
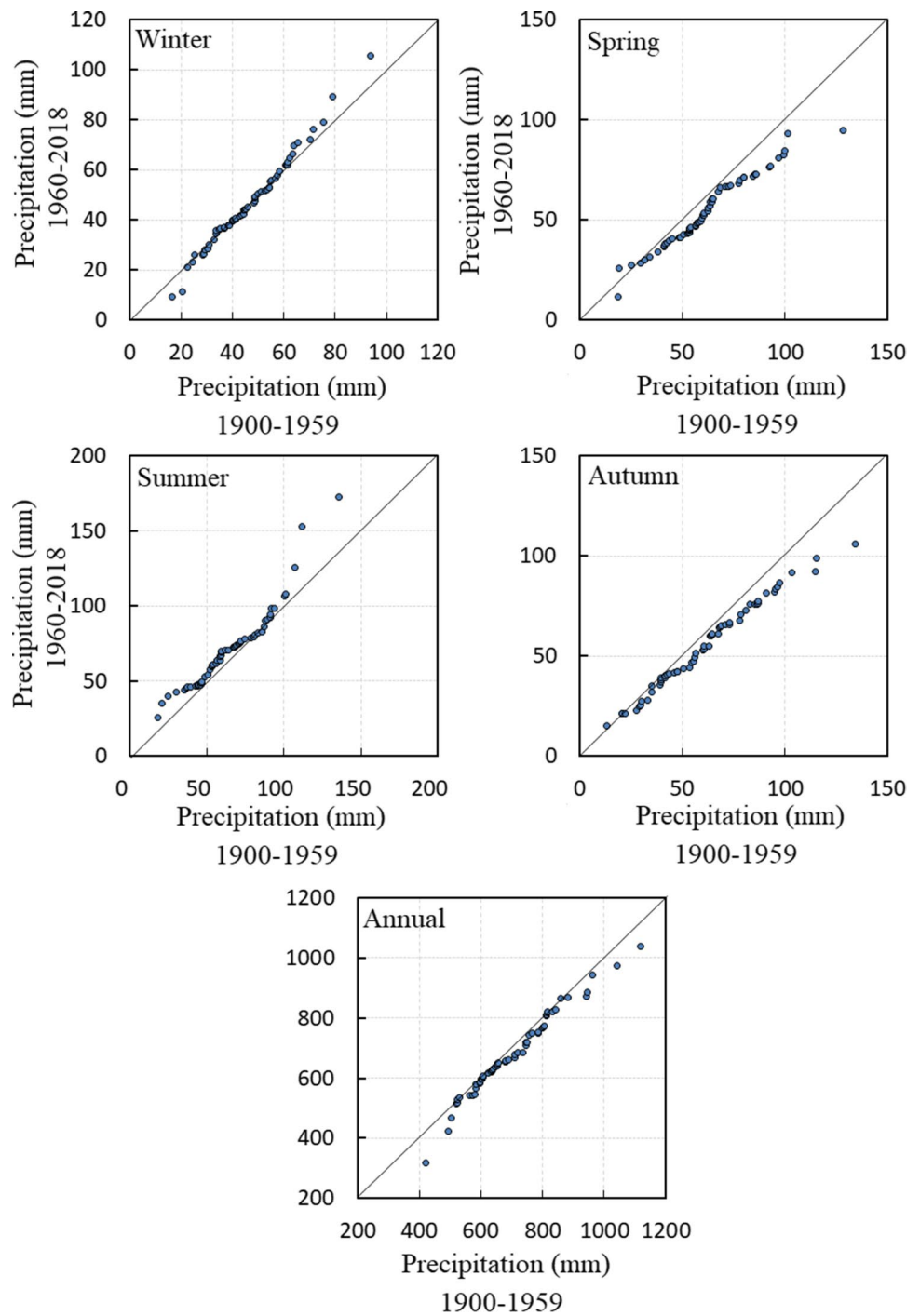
precipitation (30 mm $\leq p \leq$ 60 mm) during the past century. A similar pattern is also seen for annual medium precipitation (600 mm $\leq p \leq$ 800 mm). The different monotonic trend is seen in other seasons. While the figure implies a decreasing trend in the spring and autumn seasons, summer precipitation increases with a significant change in the high precipitating amounts ($p \geq$ 100 mm).

4.7 SAM results

Figure 15 illustrates the change points and partial trends of the mean annual temperature and total annual precipitation time series. On the top panels, the graphs demonstrate the SAM series together with change points, whereas the bottom panels of the graphs show the corresponding values at

Fig. 15 SAM and trend graphs for **a** mean annual temperature and **b** total annual precipitation in Osijek (1900–2018)
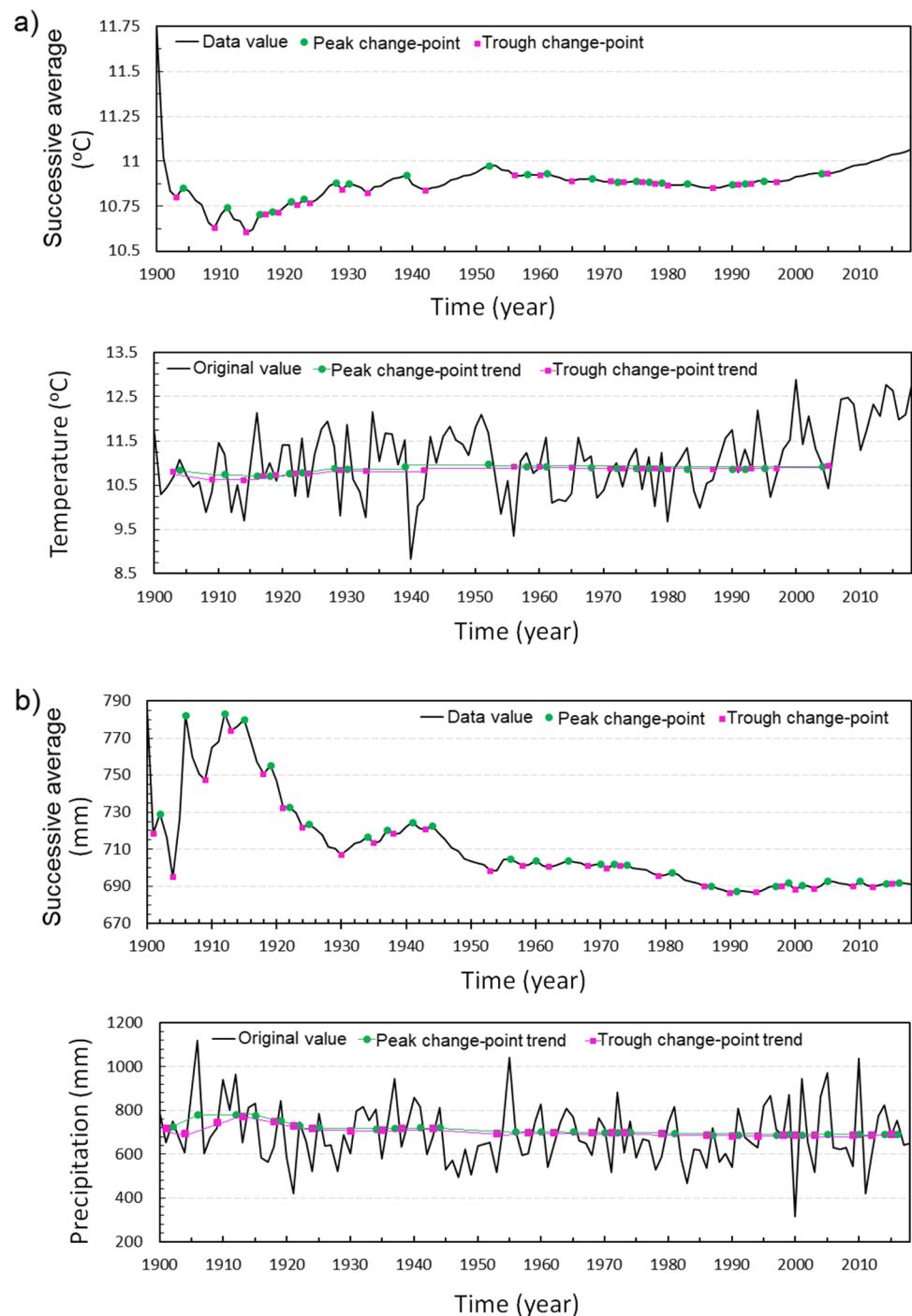
the change points and the trends of irregular durations in the original observations. The number of peak and trough change points at temperature and precipitation series is 23 and 27, respectively.

The figure shows that peak and trough change points follow each other alternately. It is obvious that in both cases (temperature and precipitation), the time duration between two change points is unequal, implying the existence of a natural partial trend within itself. Again, comparing successive pairs of the partial trends in both cases shows that trends in peak and trough change points are very close to each other. However, a significant difference in their slope appears at the beginning of the records (~1915) which might be due to the bias effect of the initial warm-up portion as described by Şen (2019). Since 1920, partial trends are very close to each other on the slope, with slight positive values in temperature and negative ones in precipitation. Therefore, the partial trends can be viewed as a single trend.

5 Summary and conclusion

This paper explores the trends in long-term (118 years) temperature and precipitation records in Osijek, located in the Pannonian lowlands, Croatia. Osijek meteorological station represents one of the crucial regional control points for climatological changes and variabilities in this broad and very important agricultural region. To perform trend analysis, four different methods were applied: the conventional M–K and Sen's slope test and the new ITA and SAM approaches. While the conventional methods were applied at monthly, seasonal, and annual levels, ITA was applied at seasonal and annual scales and the use of the SAM approach was confined to annual observations as suggested by Şen (2019). In addition, seasonal and annual records were decomposed using STL techniques to identify relationships between the trend and seasonality components of the observed time series. Each of these methods provided several insights into the temperature and precipitation pattern in the study region.

The results presented in this paper show statistically significant increasing trends for air temperature during the hot and dry part of the year, from April to August (during spring and summer). A statistically decreasing trend for precipitation is only found in April. It should be noted that decreasing trend (statistically insignificant but relatively high, $p = 0,031$) exists during the spring. Precipitation falling in this month and season is of crucial importance for tillage. Pandžić et al. (2020) noted that a significant correlation was discovered between drought damage in agriculture in Croatia and drought indices for the Zagreb-Grič Observatory for the period 2000–2012, and that the maize grain yield was most affected at times of severe droughts in August. The major conclusion is that trends in air temperature and precipitation indicate a danger to regional agricultural production, which must prepare for an uncertain future.

The other conclusions are summarized below:

- Summer temperature increases faster than in other seasons in the region. The highest Sen slope was observed in January, with the second highest in April. This is not in agreement with the results of the M–K test that showed that the most significant trend appears in August.
- There is a significant decrease in annual precipitation with a slope of 0.33. Osijek experienced a decreasing trend mainly in the period from March to June and September to November. The highest decreasing trend was seen in April.
- From an annual perspective, ITA showed that all observed low, medium, and high temperatures have increased in the second half of the past century. The increasing rates in high and low temperatures are greater than that of a medium temperature.

- Based on the SAM results, there is a natural partial trend with unequal duration within the annual temperature and precipitation time series. Trends in peak and valley change points are close to each other, indicating a slight positive trend for temperature and negative trend for precipitation.
- Based on STL decomposition, there is an increasing trend in the temperature over the last few decades. However, an increasing or decreasing trend was not detected in the precipitation series, perhaps due to the complex nature of this meteorological parameter. The method indicated certain amounts of change in the seasonal component.

This study was limited to the use of precipitation and temperature series directly. The effects of change in climatologic characteristics in Osijek could be analyzed using mixed or ancillary indices, such as a standard precipitation index, precipitation concentration index, or seasonality index in future studies.

Declarations

Ethics approval Not applicable.

Consent to participate Not applicable.

Consent for publication Not applicable.

Competing interests The authors declare no competing interests.

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