

Article

Urban Water Security and Hydro-Climatic Trends: The Case of Krakow (Poland)

Mariola Kędra

Cracow University of Technology, Faculty of Environmental Engineering and Energy,
Department of Geoenvironment and Water Management, Warszawska 24, 31-155 Krakow, Poland;
mariola.kedra@pk.edu.pl; Tel.: +48-012-628-2813

Abstract

In 2018, over half of the world's population lived in urban areas, and this figure is expected to continue to increase over the next 25 years. Water security in growing urban areas is becoming increasingly important. Current global warming can pose additional challenges for sustainable water resource management. In this study, the city of Krakow (Poland) and its water supply system were considered. The MK and Spearman tests were used to detect trends in the studied data and the residuals from the Ensemble Empirical Mode Decomposition (EEMD) method. The analyses indicate that for 1971–2020, significant increasing trends ($p < 0.05$) in annual air temperature ($0.36\text{--}0.46\text{ }^{\circ}\text{C/decade}$) were accompanied by significant trends in annual precipitation, with differences in direction and intensity (approx. -8 and 30 mm/decade). Similarly, significant trends in annual river flow for the two main sources of drinking water for Krakow (the Raba and Rudawa rivers) differed in both direction and intensity ($0.51\text{ m}\cdot\text{s}^{-1}$ and $-0.05\text{ m}\cdot\text{s}^{-1}$, respectively). The study also examined trends for individual months of the year, which largely explained the observed annual trends. Furthermore, the results of cross-correlation and autocorrelation analyses suggest that the identified decreasing trend in the Rudawa flow may be partly related to the significantly reduced underground recharge in the Rudawa catchment. The information obtained in this work can be used for more realistic and sustainable water resource management and urban-water-security planning.

Keywords: water security; urban area; hydro-climatic trends; river flow; precipitation; statistical test; ensemble empirical mode decomposition; water resources; sustainable management

Academic Editor: Giuseppe Barbaro

Received: 18 March 2026

Revised: 20 June 2026

Accepted: 26 June 2026

Published: 29 June 2026

Copyright: © 2026 by the author.

Licensee MDPI, Basel, Switzerland.

This article is an open access article distributed under the terms and conditions of the [Creative Commons Attribution \(CC BY\)](https://creativecommons.org/licenses/by/4.0/) license.

1. Introduction

The 2018 Revision of World Urbanization Prospects, published by the Population Division of the United Nations Department of Economic and Social Affairs, indicates that currently, 4.2 billion, or 55%, of the world's population lives in urban areas, and this figure is expected to increase to 6.7 billion, or 68%, by 2050 [1]. In 2018, the urban population exceeded 80% in Northern America, Latin America, and the Caribbean, while in Europe and Oceania, it amounted to 74% and 68%, respectively [1]. As water is an essential resource for humans, water security in growing urban areas is becoming increasingly important. The term “water security”, in more frequent use since 2000 [2], has been widely defined by United Nations University [3] as “the capacity of a population to safeguard sustainable access to adequate quantities of acceptable quality water for sustaining

livelihoods, human well-being, and socio-economic development, for ensuring protection against water-borne pollution and water-related disasters, and for preserving ecosystems". Water security can be considered at various levels of social organization, including the global, national, municipal and household levels. Urban water security differs from water security at other levels in a number of elements that are specifically valid at this level [2]. In particular, urban areas, with their high population density, are generally incapable of meeting their water supply from within the urban area itself, and the typical solution is to supply water from outside the area, sometimes from far away [2].

Achieving water security requires a holistic approach and a long-term perspective [3]. From an extended perspective, one of the most frequently discussed and challenging issues is current global warming. Global warming results in changing precipitation levels and in the hydrological cycle, especially regarding the extremes (e.g., [4–6]). Higher surface temperatures cause greater evaporation and consequently, drying of the surface, thus increasing the intensity and duration of drought [5]. According to the Clausius–Clapeyron equation [7,8], the water-holding capacity of air increases by about 7% for every 1 °C temperature increase. This leads to increased water vapor in the atmosphere as the climate warms [5]; increased atmospheric moisture contributes to more intense precipitation events, resulting in increased runoff and risk of flooding [9]. In urban areas, an increased risk of heavy flooding can be expected due to global warming, as impervious surfaces limit rainwater drainage (e.g., [10–13]). A recent study of 1056 extreme weather events (droughts and pluvials—periods with relatively large amounts of precipitation) during 2002–2021 confirms that the total intensity of these events was strongly correlated with global mean temperature; this suggests that continued warming of the globe will cause more frequent, more severe, and longer and/or larger droughts and pluvials [14]. Additionally, mean precipitation is expected to change over most land areas in response to global warming [15]. Moreover, the modeling results show that about half of the uncertainty in precipitation trends is driven by internal climate variability over the majority of land masses [16]. It is also clear that ongoing changes in hydro-climatic conditions are not uniform over larger areas; instead, local and regional differences are expected [5], due to complex interactions in the climate system and differences in response to climate forcing [17]. For the European land area, for example, for the recent decade (2015–2024), the average annual temperature was 2.19–2.26 °C above the pre-industrial level, but it was only 1.51–1.60 °C above this level globally, while the year 2024 was the warmest year in Europe since the instrumental record-keeping began [18]. Clearly, Europe is warming faster than the global average [18–20]. In the context of urban water security, the regional/local warming level can be crucial; this implies the need to monitor potential changes in hydro-climatic conditions for individual cities and their surroundings, including river catchments from which water is supplied to these cities.

This study focuses on water security in urban areas in the context of changing climatic conditions that can significantly affect water resources. The study area is situated in Poland, Central Europe. Poland, with a population of approx. 38 million, ranks at a distant 24th place in the European Union (EU-27) in terms of the amount of available freshwater resources per capita (1583 m³) per year [21]. In the years 2000–2019, the mean annual total gross abstraction from surface freshwaters in Poland amounted to 8753.4 million m³, or 15.8%, mainly used for cooling in electricity production (74.6%), but also for agriculture (12.1%), public water supply (7.4%), and for manufacturing industry (3.9%) [22]. It is clear that the smaller water resources become, the greater the challenge of managing them appropriately and sustainably to meet the current and future needs of society and the environment.

In this study, trend analysis was applied to both the original data and the residual signal obtained after separating the oscillatory components from the data using Ensemble EMD (EEMD) [23], which is an improvement of the EMD method [24]. This approach has

been used in a number of studies, including the study of air temperature [25,26] and sea surface temperature trends [27,28], the analysis of variability and trends of the monthly flow of the Parana River (South America) [29] and runoff variations in the Jing River of the Yellow River [30], the analysis of daily flow variations in the Seine and Wimerieux Rivers in France [31], and the study of daily water level fluctuations in a mountain reservoir [32].

In the context of urban water security, the city of Krakow and its water supply system were taken into consideration. It is interesting and socioeconomically important to evaluate how mean precipitation has changed in response to atmospheric warming in the urban surroundings over the last 50 years (1971–2020) and to assess how this translates into changes in the resulting river flow used for urban water supply. The specific objectives of this study are to determine: (1) the strength of the warming trend in annual and monthly air temperature in Krakow for the years 1971–2020, (2) the direction and intensity of the simultaneous annual and monthly precipitation trends, (3) the direction and intensity of the trends in the resulting river flow, (4) whether the river flow trends are consistent with the identified precipitation trends, and (5) whether the direction of trends extracted using the EEMD method is consistent with the direction of trends in the original data. The information thus obtained can be used in more realistic and sustainable water resource management and future planning for urban water security in the study area.

2. Materials and Methods

2.1. Study Area and Data Description

Krakow is the second largest city in Poland in terms of population (803,282) and the fourth in terms of area (327 km²) as of 1 January 2023 [33]. The city is located in southern Poland, Małopolska region, between the 49°58′–50°07′ N and 19°47′–20°13′ E coordinates. It stretches latitudinally along the Vistula valley (Figure 1). The highest peak of the city is Sowiniec Hill (358 m a.s.l.). The river network in Krakow consists of the Vistula and its tributaries, including the Wilga (right bank) and the Sanka, Rudawa, Prądnik, and Dłubnia (left bank). In Krakow, the water supply network, including connections, is 2396 km long. It is largely built in a ring system (water pipes form closed circuits), which translates into high reliability of the system in terms of water delivery to consumers [34,35]. The Krakow water supply system is based on four water treatment plants (WTPs), and water is taken from the Sanka, Rudawa and Dłubnia rivers; the borehole in Mistrzejowice; and from the Dobczyce Reservoir on the Raba River (Table 1) [35–37]. Table 1 shows that the main source of the water supply for Krakow is the Raba River, followed by the Rudawa River.

Table 1. Characteristics of the Krakow water supply system as of the end of 2024 [35].

Water Treatment Plant (WTP)	Water Intake	Maximum Capacity (m ³ /day)	Current Production (m ³ /day)	No. of Customers Supplied (Approx.)
Raba	Dobczyce Reservoir on the Raba River	186,000	110,000	350,000
Rudawa	Rudawa River	55,000	22,000–28,000	200,000
Bielany	Sanka River	50,000	12,000–15,000	70,000–150,000
Dłubnia	Dłubnia River and deep wells in Mistrzejowice	32,000	20,000	200,000

Due to data availability, research on Krakow's water security was focused on the Raba and Rudawa rivers—the right-bank and left-bank tributary of the Vistula, respectively (Figure 2). Table 2 presents the characteristics of natural conditions in the studied river catchments.

From its source in the Gorce Mountains (780 m a.s.l.) to its mouth (180 m a.s.l.), the Raba River is 132 km long, with an average slope of 4.5‰; the catchment is medium-sized, with a total area of 1537 km² [38]. A large part of the basin is typical for mountainous and submontane

catchments. The Dobczyce Reservoir (DR), with a holding capacity of 125 million m³, was built in 1986 on the Raba River. The dam is 30.5 m high and is located at river kilometer 60.1 [39].

Table 2. Physiographic characteristics of the studied river catchments [38].

Catchment/Streamflow Station	Catchment Area (km ²)	River Length (km)	Mean Elevation (m a.s.l.)	Mean Catchment Slope (‰)	Aspect
Raba/Stróža	644	32.4	778	30	N
Rudawa/Balice	290	24.8	331	11	SE

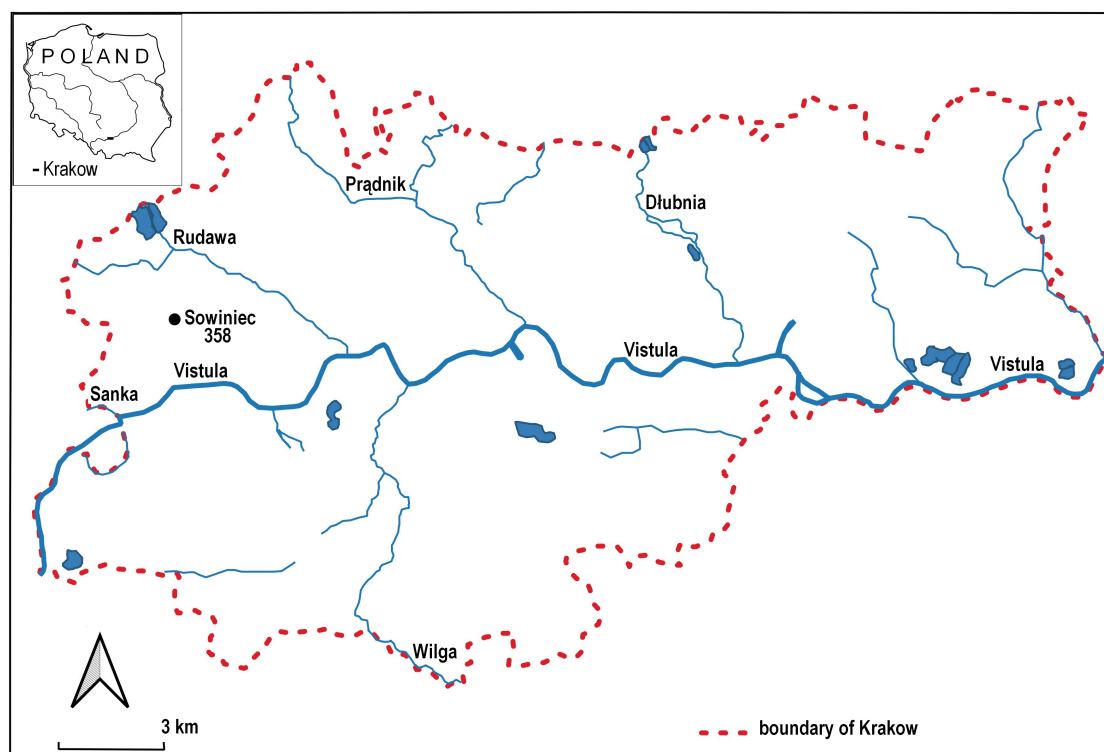


Figure 1. River network within the administrative boundary of Krakow.

The Rudawa catchment is located on the border of the Silesian–Krakow Monocline and the Carpathian Foredeep. The Rudawa River is 35 km long, with a catchment area of 318 km² and an average slope of 5.6‰. The water gauge in Balice is located 10 km from the river mouth.

Data for the study come from in situ measurements recorded by the Polish Institute of Meteorology and Water Management—the National Research Institute [40]. Monthly air temperature and river flow data were averaged over a 12-month annual period to obtain annual mean values. Monthly precipitation data were summed over a 12-month annual period to obtain annual precipitation totals. The annual values of mean air temperature in Krakow–Balice (T), total precipitation in Stróža (P1) and Krakow–Balice (P2), and mean river flow in Stróža on the Raba River (Q1) and in Balice on the Rudawa River (Q2) were taken into account. Multi-year monthly series from individual months of the year were also examined.

The data cover a 50-year period (1971–2020); the analysis concerns calendar years for T, P1, and P2 and hydrological years (from November 1970 to October 2019) for Q1 and Q2. For each data series examined (monthly or yearly), the number of observations is 50, unless a different length is specified, as noted in the Discussion section. Table 3 shows the

details for meteorological stations used in the study. Basic statistics for the data are shown in Table 4.

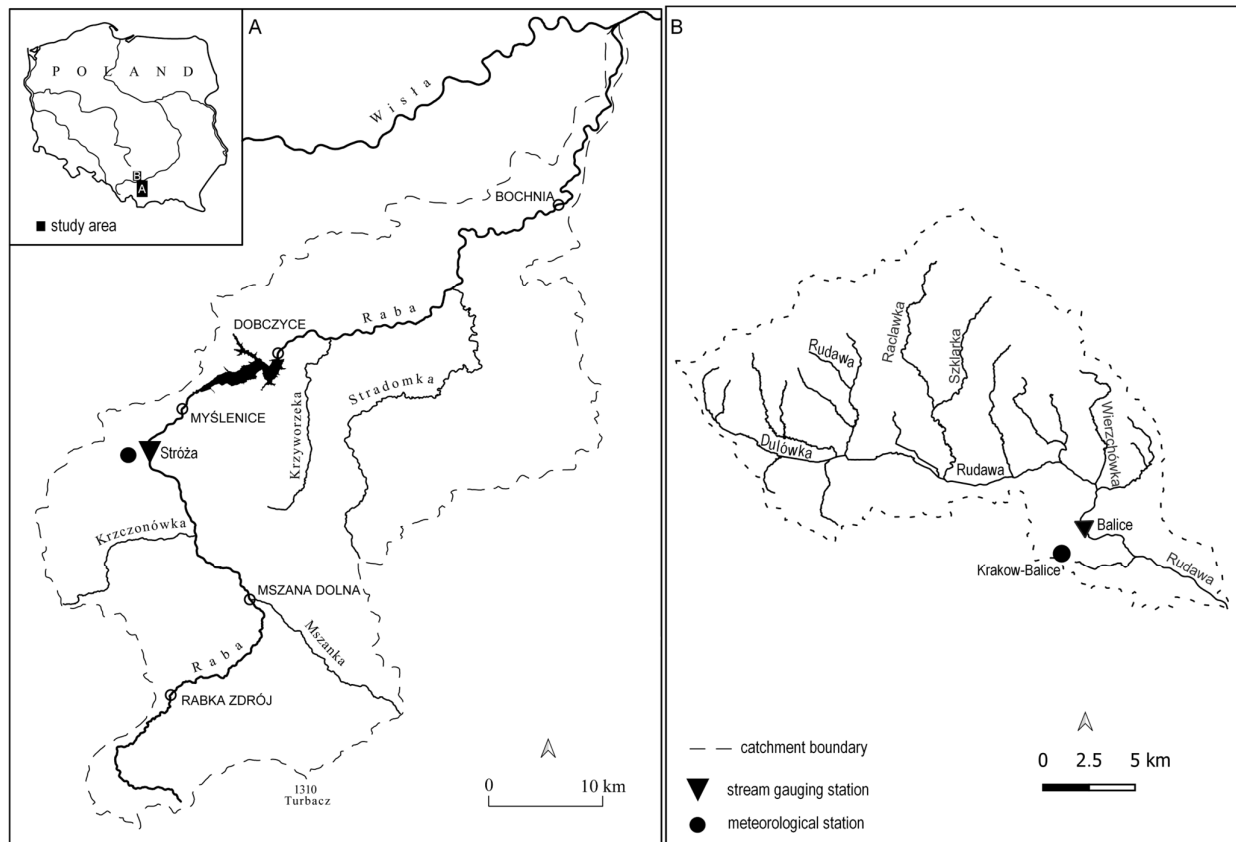


Figure 2. Study area: (A) the Raba River catchment and (B) the Rudawa River catchment.

Table 3. Details for weather/precipitation stations used in the study.

Meteorological Station	Latitude (N)	Longitude (E)	Elevation (m a.s.l.)	River Catchment
Stróża	49°47'47"	19°55'03"	307	Raba
Kraków–Balice	50°04'49"	19°48'07"	237	Rudawa

Table 4. Basic statistics for annual and monthly data for 1971–2020.

Code	Statistic	Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
T (°C)	Min	6.65	−10.5	−8.0	−2.1	5.2	9.7	13.9	15.4	14.6	10.5	5.7	−1.2	−6.0
	Mean	8.61	−2.0	−0.5	3.5	8.8	13.8	16.9	18.7	18.3	13.8	8.9	3.6	−0.3
	Max	10.79	3.6	5.0	7.1	13.8	17.1	22.2	21.6	21.9	16.3	12.4	6.9	4.2
	Std	0.99	3.2	3.2	2.3	1.7	1.5	1.5	1.6	1.5	1.5	1.6	2.0	2.3
P1 (mm)	Min	595.0	11.3	2.2	4.2	0.6	29.8	23.3	19.4	22.7	18.9	12.9	0.5	0.0
	Mean	909.0	48.2	44.7	52.3	67.9	106.1	112.8	119.6	104.2	87.3	63.5	54.3	48.2
	Max	1525	118	129	123	159	440	215	290.8	270.4	254	205	109	97.8
	Std	169.3	25.8	26.1	26.4	34.9	64.0	54.0	57.7	57.0	51.7	41.0	24.0	24.1
P2 (mm)	Min	468.9	7.2	1.0	1.6	4.4	23.3	4.2	14.2	12.2	14.2	7.7	0.2	0.0
	Mean	667.4	36.8	30.7	35.8	47.1	77.3	85.3	88.9	76.3	63.0	49.3	41.0	34.7
	Max	1021	101	110	80.0	128	302	197	285	186	180	160	90.4	87.7
	Std	111.1	18.8	20.3	20.5	26.8	43.7	43.4	50.2	38.0	35.0	33.8	18.0	19.0
Q1	Min	6.4	1.9	2.6	3.6	3.1	3.3	2.3	2.2	1.3	1.8	1.5	1.5	1.8

(m ³ s ^{−1})	Mean	10.1	8.2	9.4	14.8	14.1	11.7	11.5	12.1	9.2	8.6	7.0	6.6	8.4
	Max	17.8	23.4	27.2	34.3	27.3	52.1	32.8	45.1	26.7	53.0	21.3	18.8	22.6
	Std	2.2	4.5	5.5	7.4	6.8	9.7	7.9	9.7	6.8	10.1	5.9	4.1	4.9
Q2 (m ³ s ^{−1})	Min	1.8	0.9	1.2	1.2	1.2	1.3	1.1	0.9	0.8	0.9	1.0	1.1	1.1
	Mean	2.2	2.3	2.4	2.7	2.4	2.3	2.2	2.2	2.0	2.0	1.9	2.0	2.1
	Max	4.0	4.8	5.7	6.1	4.9	8.0	7.4	8.0	4.6	7.3	4.3	3.9	4.2
	Std	0.6	1.0	0.9	1.0	0.8	1.0	1.1	1.2	0.9	1.1	0.8	0.7	0.7

2.2. Methods

Each time series has been carefully checked to ensure that there are no processing errors or erroneous values. The Empirical Mode Decomposition (EMD) method [24], with improvements [41], and its extension, Ensemble EMD (EEMD) [23], were used to extract physically meaningful information from the data. The MATLAB 7.1+ code for EMD is available in [42]. The EMD method is completely data-driven, facilitating the analysis of non-linear and non-stationary processes. The EMD algorithm decomposes a signal into its underlying oscillatory components, called Intrinsic Mode Functions (IMFs), and a residual. The residual of the signal is the portion of the original signal not decomposed by the EMD algorithm. The original signal can thus be reconstructed by summing all IMFs and the residual [24]. In EMD, Hermite interpolation (piecewise cubic Hermite interpolating polynomial) was used to minimize the boundary effect of the method. In EEMD, white noise is added to the original signal before its decomposition using EMD. The final result of EEMD is the ensemble mean of corresponding IMFs obtained from a number of ensemble members, N [23]. In this study, $N = 1000$ was assumed. The quality of decomposition obtained from EEMD and the mathematical independence of the determined IMFs were assessed using the overall index of orthogonality (IO) [24]. For the original signal $x(t)$ ($t = 1, 2, \dots, T$) and its decomposed components $C_i(t)$ ($i = 1, 2, \dots, n$), the IO can be defined as [24,43]

$$IO = \sum_{t=1}^T \left(\sum_{i=1}^n \sum_{j=1, j \neq i}^n \frac{C_i(t)C_j(t)}{x^2(t)} \right), \quad (1)$$

where $C_n(t)$ is the residual. If the IMF components are orthogonal with each other, the IO should be 0 [24]. In order to assess the stability of the determined final residual (the ensemble mean, RES), a 95% confidence interval (CI) for RES was calculated based on $N = 1000$ ensemble members. In addition, at each time point, the normalized confidence interval width, defined as the ratio of the confidence interval width to the total range of RES changes ($\max(\text{RES}) - \min(\text{RES})$), was determined and then averaged to obtain the normalized mean confidence interval width (W).

To assess the strength of potential monotonic trends in the studied time series and residuals obtained from EEMD, a linear trend analysis was performed. Since a number of data sets (e.g., annual P and Q in Stróža and monthly data) failed the parametric Shapiro–Wilk [44] test for normality of distribution at the standard significance level of 0.05, the non-parametric two-sided Mann–Kendall (MK) test was applied for trend detection, as it does not require the assumption of normality [45,46]. The MK test also took ties into account. Because the presence of serial correlation in a time series changes the dispersion of the distribution of the test statistic S in the MK test [47], to meet the requirement of serial-independence, the variance correction approach proposed by Hamed and Rao [48] was also used. The magnitude of trends (a) was quantified using Theil–Sen’s (TS) slope [49,50]; as a very robust estimator of slope, it computes a weighted median slope of all the slopes calculated between each pair of points in a time series.

Moreover, the non-parametric Spearman test was also used to detect a monotonic trend. This test is based on the Spearman rank correlation coefficient (r_s); the null hypothesis is that the time series does not exhibit a trend [51]. In order to meet the requirement of serial-independence in the Spearman test [52], the variance correction proposed by Hamed and Rao [48]

was used. The extent and significance of correlations and partial correlations between the studied variables (T, P, Q) were quantified using the Spearman rank correlation coefficient. The same significance level of $\alpha = 0.05$ was adopted in each test.

3. Results

3.1. Air Temperature

Figure 3 shows the original signal (annual air temperature series (T) in Krakow–Balice for 1971–2020, top panel) and the results of the EEMD method, that is, three intrinsic mode functions (IMFs) or modes of variability, as well as the residual component, RES (bottom panel). The mean oscillation periods of IMF1, IMF2, and IMF3 are 2.9 yr, 6.8 yr, and 9.5 yr, respectively (Table S1). Furthermore, in the bottom panel of Figure 3, the 95% confidence interval (CI) for RES is also shown; its relative width is very small ($W = 0.9\%$, Table S4).

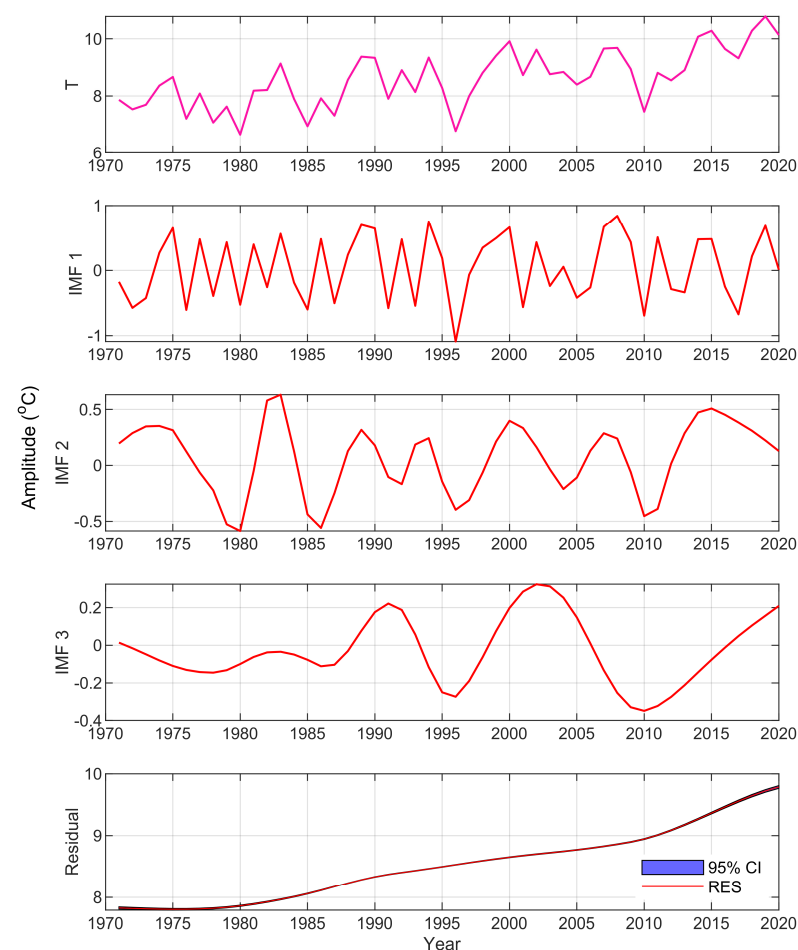


Figure 3. Annual air temperature series (T) in Krakow–Balice for 1971–2020 (**top** panel); intrinsic mode functions (IMF1–IMF3) and the residual (RES, **bottom** panel) extracted by EEMD. The **bottom** panel also shows the 95% Confidence Interval (CI) for RES based on 1000 realizations.

Figure 4 shows the annual T with the EEMD residual, as well as the linear trend for T and RES and its details. The increasing trends are significant ($p < 0.05$). It can be seen that the residual largely follows the trend line for T, while the trend intensity for T ($0.46\text{ }^{\circ}\text{C}$ per decade) is about 28% higher than for the EEMD residual ($0.36\text{ }^{\circ}\text{C}$ per decade).

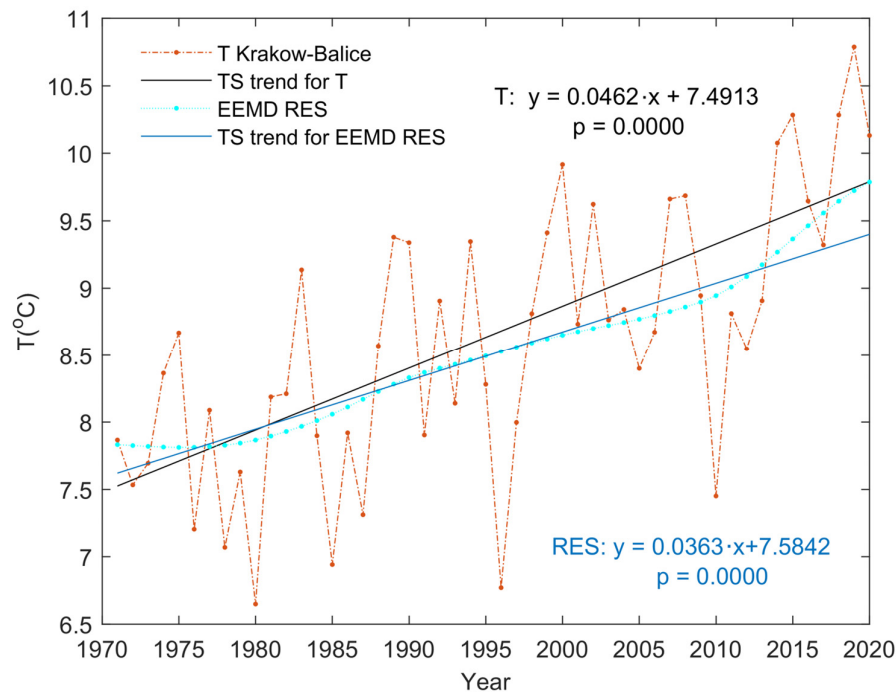


Figure 4. Annual air temperature series (T) in Krakow–Balice for 1971–2020 and the residual (RES) from EEMD. The linear trend with TS slope fitted to T and RES is also shown, with its details.

The summary results of the assessment of the existence and magnitude of the air temperature trends are presented in Table 5. The results of the Spearman test for the data indicate significant upward trends in T in the annual series and for 7 months (from April to November, except May), while for the EEMD residuals, this is also observed in January and March. The MK test results are consistent with the Spearman test results. TS slope estimates associated with the MK test are presented in the last column of Table 5 and, for comparison purposes, in Figure 5a. Trends in T were the strongest in April, June, July and August (0.54–0.68 °C per decade), strong trends were found in September and November (0.43–0.54 °C per decade), and a weaker trend in October (0.30–0.47 °C per decade).

Table 5. Results of the assessment of the air temperature trends in Krakow–Balice (T) for 1971–2020. Significant values ($p < 0.05$) are in bold.

		Spearman Test		MK Test		TS Slope
		rs	p-Val	Z	p-Val	(°C/Year)
Year	Data	0.6901	0.00	5.1613	0.00	0.0462
	RES	0.9946	0.00	4.2186	0.00	0.0363
Jan	Data	0.1381	0.33	0.7362	0.46	0.0225
	RES	1.0000	0.03	3.3915	0.00	0.0076
Feb	Data	0.2067	0.15	1.3888	0.16	0.0442
	RES	0.6619	0.10	1.5316	0.13	0.0394
Mar	Data	0.1556	0.28	1.0374	0.30	0.0233
	RES	0.9535	0.04	2.9467	0.00	0.0395
Apr	Data	0.6117	0.00	4.2244	0.00	0.0584
	RES	0.9993	0.01	3.5374	0.00	0.0361
May	Data	0.2248	0.12	1.4556	0.15	0.0216
	RES	0.7321	0.08	2.3634	0.02	0.0320
Jun	Data	0.6684	0.00	5.0278	0.00	0.0678

	RES	1.0000	0.01	4.2631	0.00	0.0588
Jul	Data	0.5983	0.00	4.0741	0.00	0.0613
	RES	0.9617	0.02	3.7744	0.00	0.0484
Aug	Data	0.6570	0.00	4.7199	0.00	0.0647
	RES	0.9873	0.01	3.9578	0.00	0.0541
Sep	Data	0.4008	0.01	2.8527	0.00	0.0485
	RES	0.9504	0.01	3.4523	0.00	0.0431
Oct	Data	0.3700	0.01	2.7691	0.01	0.0467
	RES	0.8638	0.03	4.3574	0.01	0.0303
Nov	Data	0.4818	0.00	3.0533	0.00	0.0543
	RES	0.9952	0.03	3.3511	0.00	0.0438
Dec	Data	0.1972	0.17	1.3301	0.18	0.0293
	RES	-0.0446	0.92	-0.3254	0.74	-0.0168

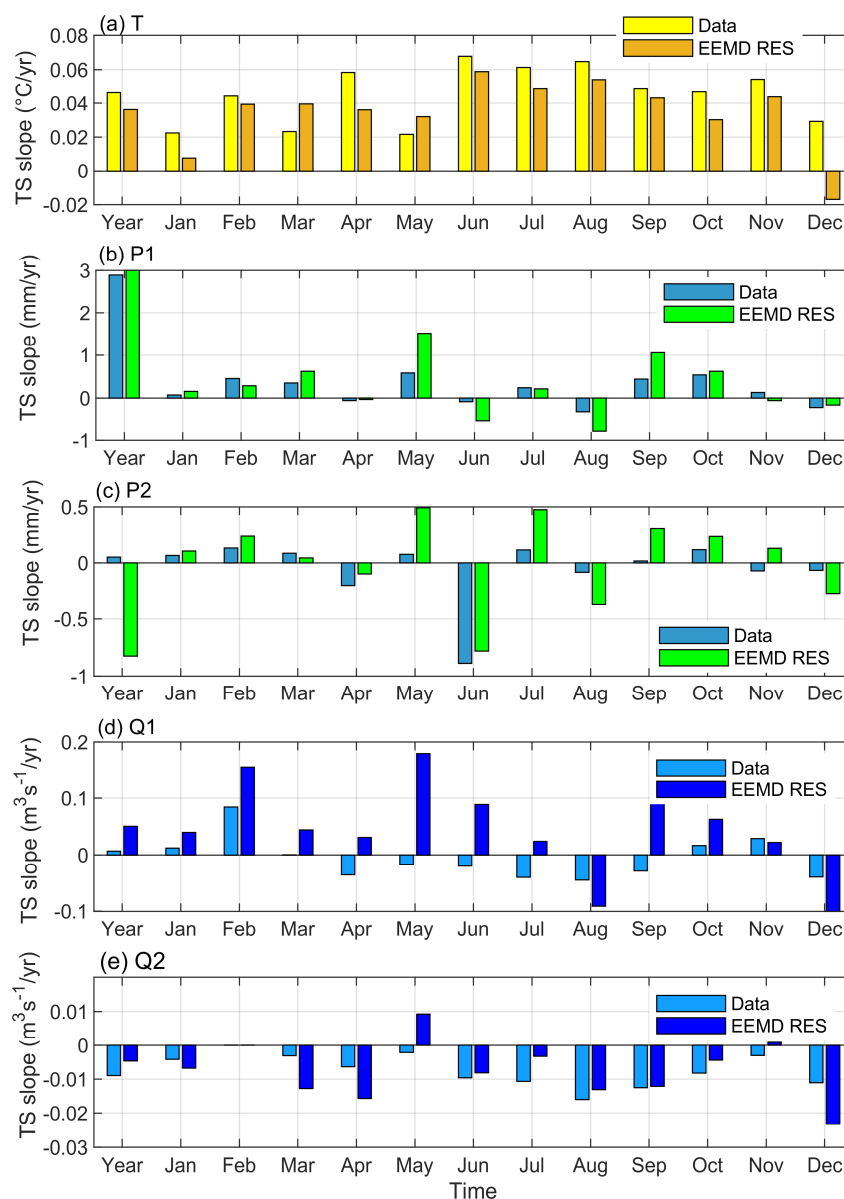


Figure 5. Comparison of the TS slope estimation results for 1971–2020 for: (a) T; (b) P1; (c) P2; (d) Q1; (e) Q2.

3.2. Precipitation

Figure S1 presents the original signal (annual precipitation series P1 for 1971–2020, top panel) and the results of the EEMD method, that is, four IMFs and the residual (RES, bottom panel). The mean oscillation periods of IMF 1–4 are 2.8 yr, 5.7 yr, 11.3 yr, and 50.0 yr, respectively (Table S2). The 95% confidence interval (CI) for RES is also shown in the bottom panel of Figure S1; and $W = 3.6\%$ (Table S4) means that the CI is narrow.

Figure 6a shows the annual, P1 along with the residual from EEMD, as well as the linear trend with the TS slope for P1 and RES and its details. The increasing trend for P1, with an intensity of 28.9 mm per decade, is not significant ($p = 0.0977$), while the trend for RES is significant ($p = 0.0003$). It can be observed that the residual closely follows the trend line for P1, and the trend intensity for P1 (28.9 mm per decade) is about 4% lower than that of the EEMD residual (30.0 mm per decade).

Figure S2 presents the original signal (annual precipitation series P2 for 1971–2020, top panel) and the results of the EEMD method, that is, four IMFs and the residual (bottom panel). The mean oscillation periods of IMF 1–4 are 2.8 yr, 8.4 yr, 11.0 yr, and 35.0 yr, respectively (Table S2). Also in the bottom panel of Figure S2, the 95% confidence interval (CI) for RES is also shown; and $W = 4.2\%$ (Table S4) means that the CI is narrow.

Figure 6b shows the annual P2 and EEMD residual, as well as the linear trend with slope TS for P2 and RES and its details. It can be seen that the residual largely follows the trend line for P2. The trend for P2 of 0.5 mm per decade is statistically insignificant ($p = 0.9200$), while the decreasing trend for RES (−8.2 mm per decade) is statistically significant ($p = 0.0001$).

A summary of the results of the assessment of the existence and magnitude of the precipitation trends is presented in Table 6. The results of the Spearman and MK tests for the P1 data indicate a significant upward trend only for February, while for the EEMD residuals of P1, significant upward trends were identified in the annual series and for 5 months: February, May, July, September and October, and significant downward trends for 4 months: June, August, November and December. TS slope estimates for P1 associated with the MK test are presented in Table 6 and for comparison purposes, in Figure 5b. Upward trends in P1 were the strongest in May (15.2 mm per decade), strong trends were found in September and October (6.2–10.6 mm per decade), and weaker trends were observed in February (2.8–4.5 mm per decade) and July (2.1 mm per decade). Downward trends in P1 for November and December are weak (0.6–1.6 mm per decade) and stronger for June and August (5.3–7.6 mm per decade).

Table 6. Results of the assessment of precipitation trends for 1971–2020. Significant values ($p < 0.05$) are in bold.

		P1					P2				
		Spearman Test		MK Test		TS Slope	Spearman Test		MK Test		TS Slope
		rs	p-Val	Z	p-Val	(mm/Year)	rs	p-Val	Z	p-Val	(mm/Year)
Year	Data	0.2657	0.06	1.6562	0.10	2.8905	0.0181	0.90	0.1004	0.92	0.0500
	RES	0.9988	0.02	3.6326	0.00	2.9977	−1.0000	0.01	−4.0328	0.00	−0.8233
Jan	Data	0.0400	0.78	0.2509	0.80	0.0733	0.0406	0.78	0.3179	0.75	0.0667
	RES	0.5883	0.21	1.5049	0.13	0.1568	0.6157	0.17	3.7655	0.11	0.1051
Feb	Data	0.2905	0.04	2.2418	0.03	0.4500	0.1054	0.46	0.7529	0.45	0.1304
	RES	1.0000	0.03	3.4814	0.00	0.2848	0.9541	0.04	2.9587	0.00	0.2358
Mar	Data	0.2620	0.07	1.7316	0.08	0.3500	0.0637	0.66	0.4768	0.63	0.0857
	RES	0.9018	0.12	1.8412	0.07	0.6221	0.1380	0.77	0.4429	0.66	0.0429
Apr	Data	−0.0378	0.79	−0.1924	0.85	−0.0577	−0.0740	0.60	−0.5688	0.57	−0.2000
	RES	−0.1234	0.79	−0.2275	0.82	−0.0317	−0.2791	0.55	−0.5039	0.61	−0.0988
May	Data	0.2572	0.07	1.6814	0.09	0.5840	0.0562	0.69	0.2844	0.78	0.0750
	RES	1.0000	0.03	3.3858	0.00	1.5151	1.0000	0.03	3.4550	0.00	0.4937

Jun	Data	−0.0156	0.91	−0.1840	0.85	−0.0868	−0.3075	0.03	−2.0746	0.04	−0.8875
	RES	−0.9574	0.04	−2.9807	0.00	−0.5253	−1.0000	0.03	−3.3697	0.00	−0.7796
Jul	Data	0.0679	0.63	0.5187	0.60	0.2375	0.0725	0.61	0.2091	0.83	0.1143
	RES	1.0000	0.03	3.4001	0.00	0.2105	0.6315	0.16	1.7396	0.08	0.4744
Aug	Data	−0.1360	0.34	−0.9955	0.32	−0.3154	−0.0271	0.85	−0.1840	0.85	−0.0826
	RES	−0.9917	0.03	−3.2479	0.00	−0.7648	−0.6808	0.14	−1.8008	0.07	−0.3654
Sep	Data	0.1448	0.31	1.0874	0.28	0.4429	0.0323	0.82	0.0753	0.94	0.0159
	RES	1.0000	0.03	3.3748	0.00	1.0561	1.0000	0.03	3.4565	0.00	0.3030
Oct	Data	0.2302	0.11	1.5391	0.12	0.5344	0.0748	0.60	0.5019	0.62	0.1167
	RES	0.9856	0.03	3.1837	0.00	0.6189	0.5154	0.27	1.2997	0.19	0.2343
Nov	Data	0.0424	0.77	0.3346	0.74	0.1316	−0.0345	0.81	−0.3513	0.73	−0.0718
	RES	−0.8731	0.04	−2.7800	0.01	−0.0600	0.8945	0.04	2.6815	0.01	0.1287
Dec	Data	−0.1201	0.40	−0.9787	0.33	−0.2214	−0.0656	0.65	−0.4852	0.63	−0.0667
	RES	−1.0000	0.02	−3.6625	0.00	−0.1637	−0.8112	0.08	−2.1929	0.03	−0.2706

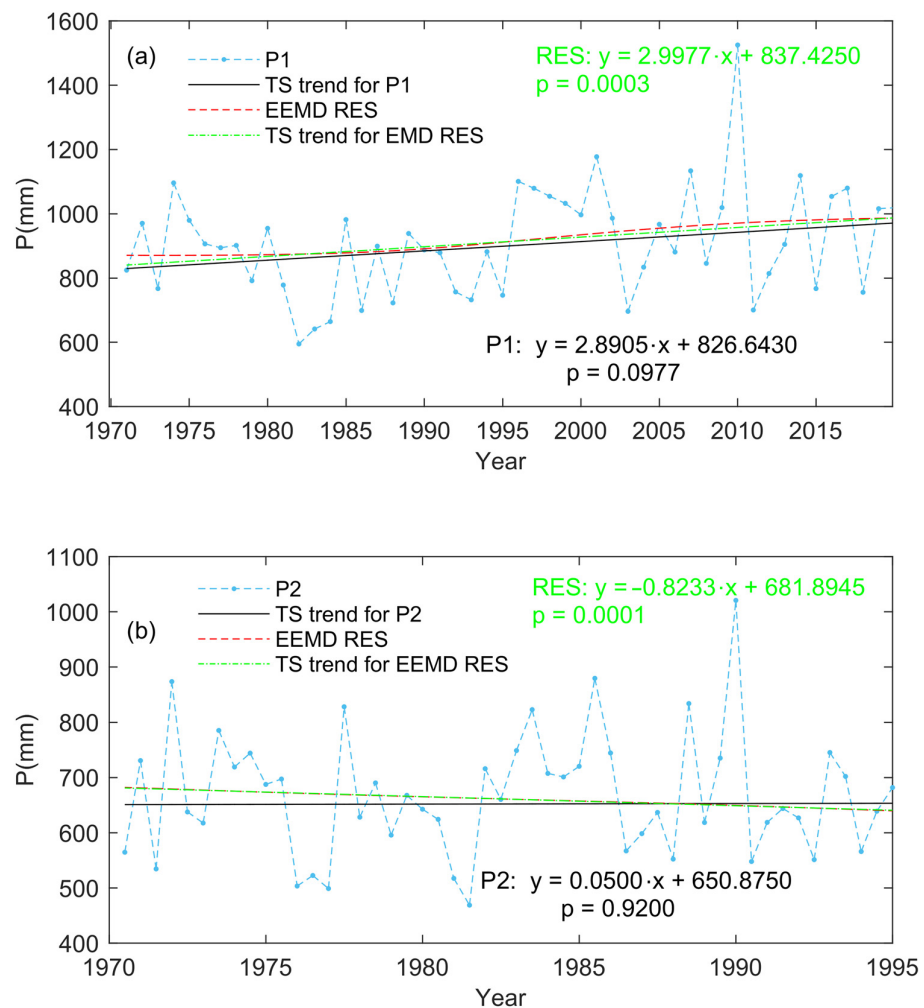


Figure 6. Annual total precipitation series in (a) Stróža (P1); (b) Krakow–Balice (P2) for 1971–2020, along with the residual from EEMD. The linear trend with TS slope fitted to T and RES is also shown, with its details.

The results of the Spearman and MK tests for the P2 data indicate a significant downward trend only for June, while for the EEMD residuals of P2, significant downward trends were identified in the annual series and for June, with significant upward trends

for 4 months: February, May, September and November. Furthermore, for December, a downward trend in the EEMD residual of P2 was identified using only the MK test. TS slope estimates for P2 related to the MK test are shown in Table 6 and for comparison purposes, in Figure 5c. Upward trends in P2 were stronger for May (4.9 mm per decade) and weaker for February (2.4 mm per decade), September (3.0 mm per decade) and November (1.3 mm per decade). Downward trends in P2 were stronger for June (7.8–8.9 mm per decade) and weaker for December (2.7 mm per decade).

3.3. River Flow

Figure S3 depicts the original signal (annual river flow series Q1 for 1971–2020, top panel) and the results of the EEMD method, that is, four IMFs and the residual (RES, bottom panel). The mean oscillation periods of IMF 1–4 are 3.2 yr, 5.9 yr, 11.1 yr, and 24.7 yr, respectively (Table S3). The 95% confidence interval (CI) for RES is also shown in the bottom panel of Figure S3; and $W = 2.2\%$ (Table S4) means that the CI is narrow.

Figure 7a shows the annual Q1, along with the residual from EEMD, as well as the linear trend with the TS slope for Q1 and RES and its details. The increasing trend for Q1 of $0.07 \text{ m}^3\text{s}^{-1}$ per decade is insignificant ($p = 0.7633$), while the trend for RES of $0.51 \text{ m}^3\text{s}^{-1}$ per decade is significant ($p = 0.0002$). It can also be noticed that the EEMD residual departs from the trend line for Q1, and the trend intensity for Q1 is over 7 times lower than the trend intensity for the residual, with the trends being consistent in direction.

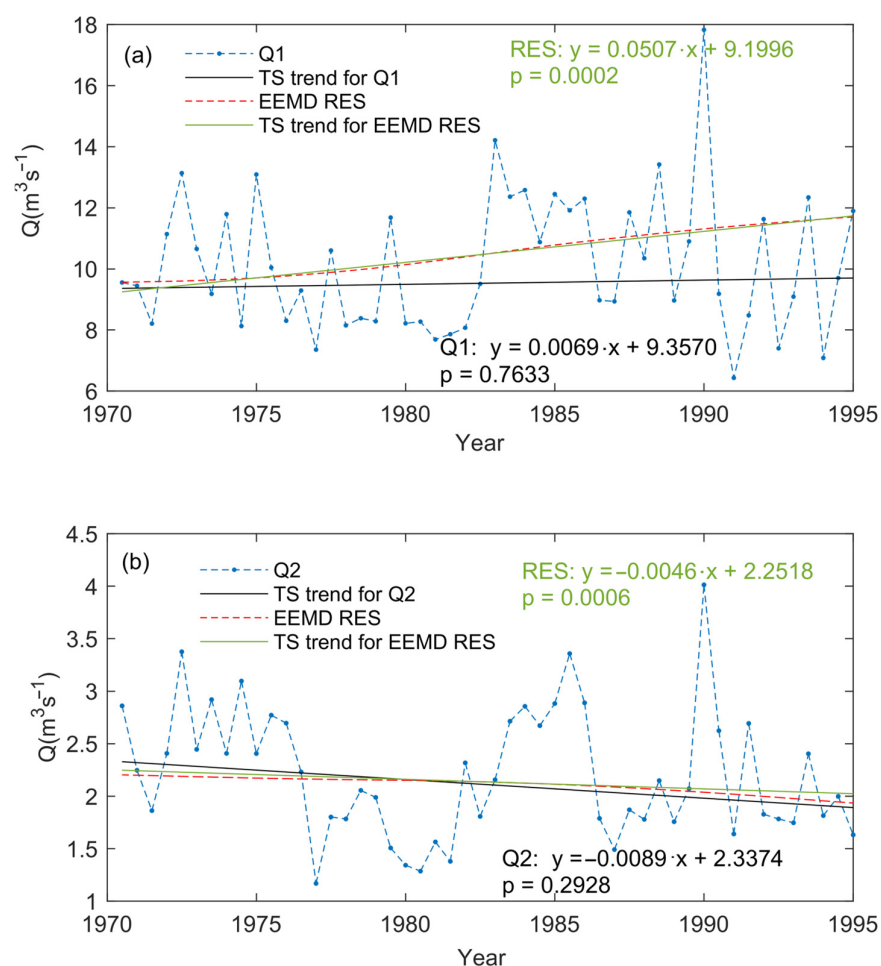


Figure 7. Annual river flow series for (a) Q1; (b) Q2 for 1971–2020 and the EEMD residual. The linear trend with TS slope fitted to T and RES is also shown, with its details.

Figure S4 presents the original signal (annual river flow series Q2 for 1971–2020, top panel) and the results of the EEMD method, that is, four IMFs and the residual (bottom panel). The mean oscillation periods of IMF 1–4 are 3.0 yr, 7.7 yr, 30.0 yr, and 35.0 yr, respectively (Table S3). The 95% confidence interval (CI) for RES is also shown in the bottom panel of Figure S4; and $W = 4.6\%$ (Table S4) means that the CI is narrow.

Figure 7b shows the annual Q2 and EEMD residual, as well as the linear trend with slope TS for Q2 and RES and its details. It can be seen that the EEMD residual closely follows the trend line for Q2. The decreasing trend for Q2 of $0.09 \text{ m}^3\text{s}^{-1}$ per decade is insignificant ($p = 0.2928$), while the decreasing trend for RES of $0.05 \text{ m}^3\text{s}^{-1}$ per decade is statistically significant ($p = 0.0006$). The trend intensity for Q2 is almost twice as high as that for the EEMD residual, with the trends being consistent in direction.

Table 7 presents the summary results regarding the assessment of the existence and magnitude of trends in the studied river flow. The results of the Spearman and MK tests for the Q1 data indicate no significant trends, while for the EEMD residuals of Q1, significant upward trends were identified for the annual series and for 4 months: February, May, September and October, and significant downward trends for 2 months: August and December. Furthermore, for July, an upward trend in the EEMD residual of Q1 was identified using only the MK test. TS slope estimates for Q1 associated with the MK test are presented in Table 7 and for comparison purposes, in Figure 5d. Upward trends in Q1 were the strongest in May ($1.79 \text{ m}^3\text{s}^{-1}$ per decade), strong trends were found in February ($1.56 \text{ m}^3\text{s}^{-1}$ per decade), and weaker trends in September and October (1.06 and $0.63 \text{ m}^3\text{s}^{-1}$ per decade, respectively) and July ($0.24 \text{ m}^3\text{s}^{-1}$ per decade). Downward trends in Q1 were strong for August and December (0.91 and $1.01 \text{ m}^3\text{s}^{-1}$ per decade, respectively).

Table 7. Results of the assessment of river flow trends for 1971–2020. Significant values ($p < 0.05$) are in bold.

		Q1					Q2				
		Spearman Test		MK Test		TS Slope	Spearman Test		MK Test		TS Slope
		rs	p-Val	Z	p-Val	($\text{m}^3\text{s}^{-1}/\text{Year}$)	rs	p-Val	Z	p-Val	($\text{m}^3\text{s}^{-1}/\text{Year}$)
Year	Data	0.0630	0.66	0.3011	0.76	0.0069	−0.2459	0.28	−1.0521	0.30	−0.0089
	RES	1.0000	0.02	3.7172	0.00	0.0507	−1.0000	0.03	−3.3717	0.00	−0.0046
Jan	Data	0.0417	0.77	0.4015	0.69	0.0126	−0.1034	0.47	−0.5187	0.60	−0.0041
	RES	0.5883	0.21	1.5043	0.13	0.0397	−1.0000	0.02	−3.5147	0.00	−0.0067
Feb	Data	0.2676	0.06	1.7901	0.07	0.0843	0.0010	0.99	−0.0167	0.99	0.0000
	RES	0.9765	0.03	3.2123	0.00	0.1555	−0.0612	0.89	0.0000	1.00	0.0000
Mar	Data	0.0060	0.97	0.0084	0.99	0.0009	−0.0336	0.81	−0.3430	0.73	−0.0031
	RES	0.2452	0.59	0.9309	0.35	0.0440	−1.0000	0.03	−3.4549	0.00	−0.0127
Apr	Data	−0.0523	0.71	−0.4015	0.69	−0.0353	−0.1200	0.40	−0.7781	0.44	−0.0063
	RES	0.1510	0.73	0.4042	0.69	0.0308	−0.9935	0.03	−3.2770	0.00	−0.0157
May	Data	−0.0205	0.89	−0.3011	0.76	−0.0163	−0.0397	0.78	−0.2845	0.78	−0.0021
	RES	1.0000	0.03	3.3858	0.00	0.1793	0.9543	0.02	3.3869	0.00	0.0093
Jun	Data	−0.0830	0.56	−0.4852	0.63	−0.0197	−0.1927	0.18	−1.1798	0.24	−0.0096
	RES	0.4639	0.29	1.4454	0.15	0.0885	−0.7148	0.12	−1.7857	0.07	−0.0081
Jul	Data	−0.1042	0.47	−0.6692	0.50	−0.0400	−0.2405	0.20	−1.2033	0.23	−0.0106
	RES	0.8875	0.06	2.5901	0.01	0.0244	−0.3445	0.46	−0.6805	0.50	−0.0032
Aug	Data	−0.1405	0.33	−0.8365	0.40	−0.0449	−0.3201	0.03	−2.2756	0.02	−0.0160
	RES	−0.7763	0.07	−2.3172	0.02	−0.0912	−1.0000	0.02	−3.6956	0.00	−0.0131
Sep	Data	−0.1279	0.37	−0.8867	0.38	−0.0288	−0.3017	0.09	−1.6797	0.09	−0.0125
	RES	1.0000	0.03	3.3918	0.00	0.1064	−1.0000	0.03	−3.4484	0.00	−0.0121
Oct	Data	0.0565	0.69	0.5521	0.58	0.0168	−0.1837	0.41	−0.7844	0.43	−0.0082
	RES	0.9259	0.04	2.7993	0.01	0.0627	−0.5889	0.20	−1.5449	0.12	−0.0044

Nov	Data	0.0773	0.59	0.6190	0.54	0.0291	−0.0987	0.49	−0.5773	0.56	−0.0030
	RES	0.5029	0.28	1.1229	0.26	0.0220	−0.1269	0.78	0.0844	0.93	0.0009
Dec	Data	−0.1437	0.31	−1.0205	0.31	−0.0392	−0.2502	0.08	−1.7318	0.08	−0.0110
	RES	−1.0000	0.03	−3.3888	0.00	−0.1005	−1.0000	0.03	−3.4567	0.00	−0.0234

The results of the Spearman and MK tests for the Q2 data indicate no significant trends, while for the EEMD residuals of Q2, significant downward trends were identified for the annual series and for 5 months: January, March, August, September and December, with a significant upward trend only for May. TS slope estimates for Q2 related to the MK test are shown in Table 7 and for comparison purposes, in Figure 5e. An upward trend in Q2 was relatively strong for May ($0.09 \text{ m}^3\text{s}^{-1}$ per decade). A downward trend in Q2 was the strongest for December ($0.23 \text{ m}^3\text{s}^{-1}$ per decade); strong downward trends were identified for March, August and September ($0.12\text{--}0.13 \text{ m}^3\text{s}^{-1}$ per decade); and weaker trends for January ($0.07 \text{ m}^3\text{s}^{-1}$ per decade).

3.4. Correlation Analysis

Figure 8 shows the range of correlations between annual series of precipitation and river flow in the studied catchments, along with the value of the Spearman cross-correlation coefficient (r_s).

Annual P1 and Q1 are strongly positively correlated (Figure 8a), while for annual P2 and Q2 (Figure 8b), the correlation is moderate but also positive and statistically significant.

Tables 8 and 9 present the results of testing the Spearman cross-correlation coefficient between precipitation, river flow, and air temperature for individual months of the year for the studied catchments. Table 8 shows that P1 and Q1 are strongly positively correlated in June, July and October; moderately correlated in February, March, May, August and November; and weakly correlated in January, April and December. After excluding the effect of T, the correlations between P1 and Q1 remain essentially similar. T and Q1 are moderately positively correlated in January and February and weakly negatively correlated in May, July, August, and September. After excluding the effect of P1, the correlations between T and Q1 are only significant for January and February, remaining at the same level. T and P1 are weakly positively correlated in February and weakly negatively correlated in August and September.

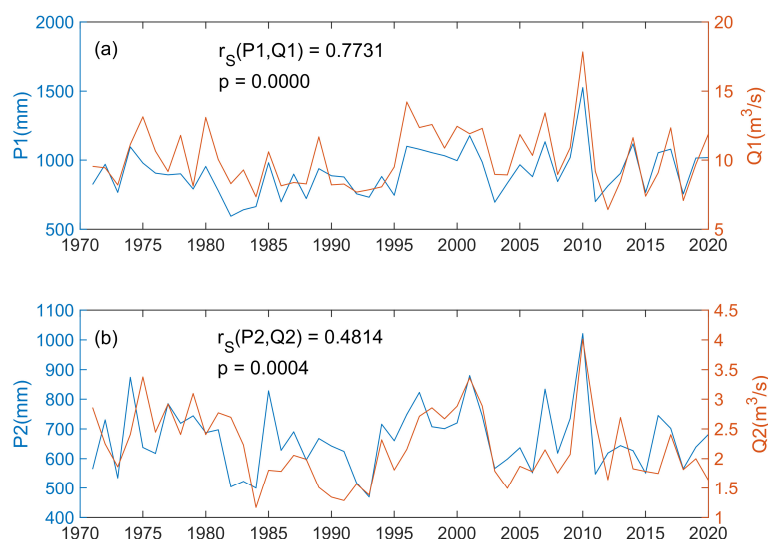


Figure 8. Annual series of precipitation and river flow for (a) P1 and Q1; (b) P2 and Q2 for the years 1971–2020 and Spearman cross-correlation coefficient r_s between the corresponding P and Q.

Table 8. Results of cross-correlation tests between P1, Q1 and T for 1971–2020. Significant ($p < 0.05$) values are in bold.

	rs (P1, Q1)	rs (P1, Q1) Controlling T	rs (T, Q1)	rs (T, Q1) Controlling P1	rs (T, P1)
Year	0.7731	0.7836	−0.0357	−0.2044	0.1204
Jan	0.3687	0.3458	0.4379	0.4200	0.1391
Feb	0.5008	0.3922	0.6543	0.5950	0.3389
Mar	0.4841	0.4829	−0.0811	−0.0714	−0.0385
Apr	0.3842	0.3782	−0.1392	−0.1190	−0.0771
May	0.6332	0.6092	−0.3230	−0.2445	−0.2186
Jun	0.7750	0.7715	−0.2601	−0.2351	−0.1460
Jul	0.7015	0.6804	−0.2991	−0.1932	−0.2357
Aug	0.6556	0.6213	−0.2797	−0.0867	−0.3324
Sep	0.5939	0.5232	−0.3920	−0.2246	−0.3784
Oct	0.7381	0.7299	−0.1679	0.0501	−0.2716
Nov	0.6699	0.6710	0.0528	0.0736	−0.0854
Dec	0.3803	0.3786	0.0956	0.0872	0.0396

Table 9. Results of cross-correlation tests between P2, Q2 and T for 1971–2020. Significant ($p < 0.05$) values are in bold.

	rs (P2, Q2)	rs (P2, Q2) Controlling T	rs (T, Q2)	rs (T, Q2) Controlling P2	rs (T, P2)
Year	0.4814	0.4729	−0.1947	−0.1665	−0.1030
Jan	0.4487	0.4375	0.1849	0.1493	0.1168
Feb	0.2925	0.1637	0.3491	0.2558	0.4442
Mar	0.5237	0.5372	−0.1167	−0.1817	0.0718
Apr	0.2592	0.2443	−0.1358	−0.1026	−0.1457
May	0.2462	0.2560	0.0921	0.1170	−0.0848
Jun	0.5809	0.6077	−0.0183	0.2200	−0.3232
Jul	0.2942	0.2653	−0.1974	−0.1480	−0.2000
Aug	0.3327	0.2889	−0.2700	−0.2110	−0.2295
Sep	0.4375	0.3064	−0.4399	−0.3103	−0.4296
Oct	0.3653	0.3152	−0.2322	−0.1292	−0.3243
Nov	0.5179	0.5107	0.1038	0.0273	0.1558
Dec	0.1712	0.1784	−0.0371	−0.0631	0.1429

Table 9 shows that P2 and Q2 are moderately positively correlated in January, March, June, September, and November and weakly positively correlated in February, July, August, and October. After excluding the effect of T, the correlations between P2 and Q2 in February and July are no longer statistically significant and remain similar in the following months. T and Q2 are weakly positively correlated in February and weakly negatively correlated in September. After excluding the effect of P2, the correlations between T and Q2 are significant only for September, remaining essentially the same. T and P2 are moderately positively correlated in February and negatively correlated in September (moderately) and in June and October (weakly).

No lag effect was found between the examined P and Q values on an annual and monthly basis.

3.5. Uncertainty Analysis

The obtained values of the two uncertainty measures for the EEMD method for each examined time series are presented in Table S4 and for comparison purposes, in Figure 9 (an overall index of orthogonality, IO) and Figure 10 (normalized mean confidence interval width, W, for the residual). The critical lines at the ± 0.10 level in each panel of Figure 9 show the

adopted thresholds between which the IO values indicate that the orthogonality of the IMFs is generally preserved, and the energy balance of the EMD decomposition is acceptable [24,25]. A negative value below the threshold of -0.10 , seen for Q2 in September, can be interpreted as an overcompensation error related to the presence of a sharp peak (in 2010) for the 50-year river flow series. This means that the decomposition process at the location of the sharp peak lost stability (IMF components began to overlap in the antiphase).

Figure 10 shows that for each time series, the obtained W values are below the 10% threshold of the total range of residual changes, which confirms the high numerical precision of the determined residual.

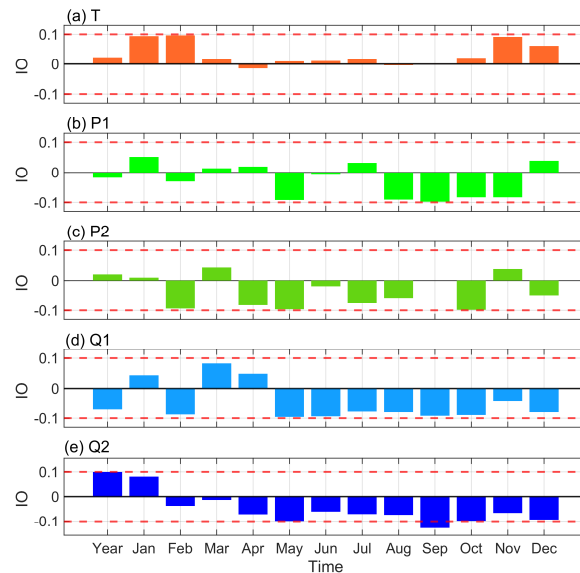


Figure 9. An overall index of orthogonality (IO) determined for the analyzed time series using the EEMD method for: (a) T; (b) P1; (c) P2; (d) Q1; (e) Q2. The red dashed lines ($IO = \pm 0.10$) indicate the adopted critical decomposition acceptability thresholds for EEMD. Values outside this range suggest EEMD decomposition errors.

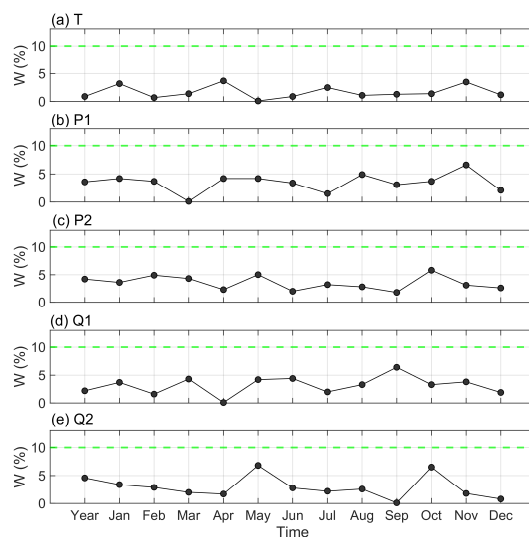


Figure 10. The W index, which defines the average relative width of the 95% confidence interval of the EEMD residual for: (a) T; (b) P1; (c) P2; (d) Q1; (e) Q2. The green dashed line marks the adopted threshold (10% of the max–min range of residual changes), below which the confidence interval is classified as narrow.

4. Discussion

Assessing hydro-climatic trends in the context of urban water security and implementing sustainable water resource management strategies are crucial worldwide, especially in urban areas affected by overexploitation of natural resources (e.g., [53–56]) and exposed to various natural hazards (e.g., flash floods, heat waves). This paper attempts to address the issue of urban water security in the context of changing climatic conditions (i.e., atmospheric warming, with increasingly frequent extreme weather phenomena, especially heavy rainfall, heat waves, and prolonged drought) [57].

While global, regional, and local mean air temperature trends over the past few decades have often been identified as statistically significant (e.g., [58–68]), the accompanying mean precipitation trends are frequently insignificant at the standard 0.05 significance level (e.g., [5,64,68–76]). Precipitation is an intermittent phenomenon, with a remarkable variability in time and space (e.g., [77,78]). The intermittent nature of precipitation is one of the main sources of uncertainty in hydrologic forecasting and remains difficult to model at many time scales [79]. Given the nature of the phenomenon and the difficulties in its modeling, this study investigated the long-term (50-year) variability of annual and monthly precipitation, as well as annual and monthly river flow and air temperature, using relatively new decomposition methods (EMD and EEMD). Because the EMD method is adaptive and entirely data-driven [23,24], the signal decomposition results obtained using EMD are independent of the chosen research model (e.g., wavelet model) or the model assumptions (e.g., Morlet or Haar wavelet). On the other hand, data are often subject to some random noise. Therefore, using EEMD can at least partially remove this noise from the data during signal decomposition. Using the EEMD method allow us to separate the underlying oscillatory components (IMFs) from the residual signal, interpreted in [24] as the overall adaptive trend, and investigate long-term trends in the residual. This approach allows for comparison of the direction and intensity of trends in the original data and those obtained from the decomposition method used. It turns out that most trends identified using the EEMD method are significant ($p < 0.05$) and consistent with the direction of trends in the original data, but they differ in intensity. Interestingly, in Stróža, the upward trend in annual precipitation P1 is more intense (approx. 3.3% of the average per decade) and is accompanied by an upward trend in the Raba River flow Q2 (approx. 5.0% of the average per decade), while in Krakow–Balice, the downward trend in precipitation P2 is less intense (approx. 1.2% of the average per decade) and is accompanied by a downward trend in the Rudawa River flow Q2 (approx. 2.3% of the average per decade).

The obtained results regarding annual air temperature and precipitation trends are largely consistent with the results of similar studies conducted in the study area. For example, for the years 1951–2015, Kubiak-Wójcicka [64] identified a significant ($p < 0.05$) increasing trend in annual mean air temperature in Krakow–Balice, with an intensity of 0.24 °C per decade, accompanied by an insignificant increasing trend in total annual precipitation of 3.63 mm per decade, while in Krakow, for the years 1951–2013, no change in precipitation was observed by Szwed [70]. The analysis of area-averaged values of annual air temperature for 1951–2020 (70 years) shows that in Europe, the air temperature has been increasing linearly since 1985, with an intensity of 0.55 °C per decade [65]. In this context, the increase in annual air temperature in Krakow–Balice by 0.36–0.46 °C per decade between 1971 and 2020 identified in this study seems realistic.

In regards to the trends in annual river flow in the study area, significant trends observed for the flow of the Raba and Rudawa rivers differ in both direction and intensity. The reason for these differences may be lower precipitation for P2 (see Table 4), the observed downward (upward) trend in P2 (P1) and the difference in retention capacity of the Rudawa catchment compared to that of the Raba catchment. The catchments differ in regards to physiographic conditions and land use; the upper part of the Raba catchment,

located upstream of the Dobczyce Reservoir, is a mountainous catchment with predominant forests (50%), agricultural areas occupying 45% of the catchment area, and built-up areas comprising 5% [72], while the Rudawa catchment is an upland catchment, with agricultural lands constituting 74% of the catchment area, forests—21%, and meadows—5% [80]. To better understand the identified trends in river flow in the context of natural conditions of the studied catchments, the lag-1 autocorrelation coefficient (r_1) was calculated for the mean monthly river flow sequence of Q1 and Q2 (Table 10).

Table 10. Lag-1 autocorrelation coefficient (r_1) and underground recharge coefficient (RC in %) for Q1 and Q2 over the 50-year period (1971–2020) and in two 25-year subperiods.

	1971–2020		1971–1995		1996–2020	
	r_1	RC	r_1	RC	r_1	RC
Q1	0.25	30.4	0.28	34.2	0.22	27.3
Q2	0.59	67.9	0.70	72.3	0.50	53.0

As shown in Table 10, the r_1 for Q1 and Q2 over the 50-year period (1971–2020, 600 values) is 0.25 and 0.59, respectively; for the period of 1971–1995 (300 values), it is 0.28 and 0.70, respectively; and for the period of 1996–2020 (300 values), it is 0.22 and 0.50, respectively. It can therefore be seen that the r_1 for Q2 is more than twice as high as that for Q1 in each of the examined periods, and its values indicate moderate and statistically significant autocorrelation. The calculated value of r_1 for Q1 (0.28) for the 25-year period (1971–1995) is close to the value of r_1 for Q1 (0.27) reported in [81] for the 20-year period (1971–1990). It is also clear that in the second 25-year period (1996–2020), the r_1 values are lower than in the first 25-year period (1971–1995) for both the Raba and Rudawa rivers. According to the empirical formula given for Polish rivers in the work of Bartnik and Jokiel [81]:

$$r_1 = 0.009 \cdot RC - 0.026, \quad (2)$$

the underground recharge coefficient (RC in %), i.e., the share of underground runoff in the total runoff, is approx. 30% for Q1 and 68% for Q2 in the period of 1971–2020 and decreased in the second 25-year period (1996–2020) compared to the results for the first 25-year period (1971–1995), from approx. 34% and 72% to 27% and 53%, respectively (Table 10). This may suggest that the identified decreasing trend in annual Q2 is related to reduced underground recharge, which, as indicated by r_1 , has a significant impact on the Q2 flow rate. Also, the work in [82] confirms that within the Małopolska Upland (including, among others, the Rudawa River catchment), rivers are supplied, to a large extent with groundwater, even more than 60%, which is the result of deeply incised valleys in carbonate rocks with high water-bearing capacity.

To examine in detail the dynamics of r_1 changes for the mean monthly flow sequence of Q1 and Q2, r_1 was calculated in a 25-year time window (300 values), with a shift of one year (12 values). Twenty-six values/windows were obtained, the first time window covering the years 1971–1995, and the last one covering the years 1996–2020. Figure 11 presents the obtained results, together with the assessment of the linear trend based on ordinary least squares (OLS) regression. For Q1 (Figure 11a), the trend in r_1 is statistically insignificant ($p = 0.8800$), while for Q2 (Figure 11b), the decreasing trend (-0.0054) is statistically significant ($p = 0.0000$). The decreasing trend in r_1 for Q2 translates into a corresponding decreasing trend in RC, with the slope of -0.5408 , consistent with the linear relationship between r_1 and RC shown in Equation (2). This means that from 1971–1995 to 1996–2020, the RC for Q2 gradually decreased by about 0.5% per year, indicating a gradual decrease in the share of underground recharge in total runoff Q2. The reason for this decrease requires further investigation. On the other hand, the $r_s(P2, Q2)$ values calculated for two 25-year periods (1971–1995 and 1996–2020) are 0.3797 and 0.6015, respectively,

confirming the increase in correlation between P2 and Q2 in the second period compared to that in the first period and thus, the reduction in the influence of underground recharge on the total runoff Q2. Given the positive and statistically significant correlation between annual P2 and Q2 (Table 9) and the downward trend in annual P2, the downward trend in annual Q2 seems reasonable. The above analysis suggests that the identified downward trend in Q2 is partly due to the gradually decreasing underground recharge, as demonstrated by the downward trend in RC for Q2.

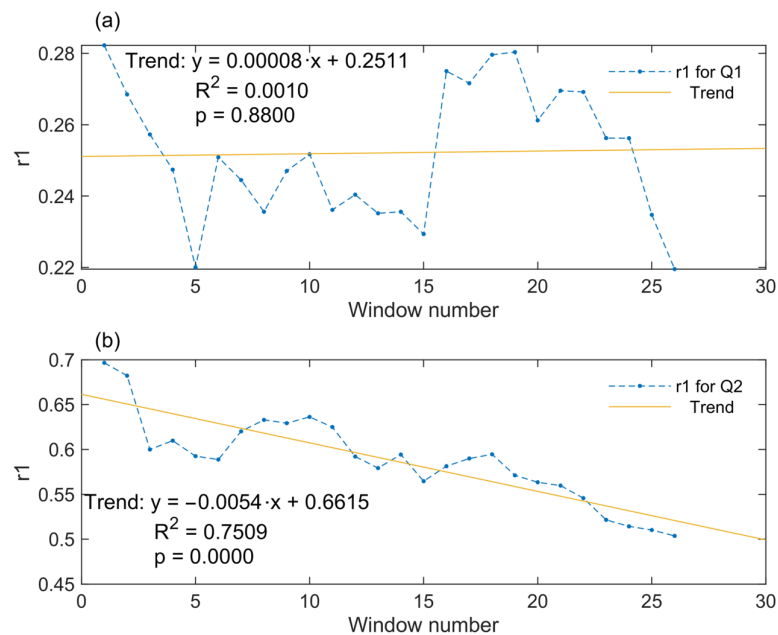


Figure 11. Lag-1 autocorrelation (r_1) calculated in a 25-year time window (300 values), with a shift of one year (12 values), over the years 1971–2020 for (a) the mean monthly series of Q1; (b) the mean monthly series of Q2. The linear trend (OLS regression) fitted to r_1 is also shown, with its details.

Taking into account the broader context of the Upper Vistula River Basin, Mostowik et al. [61] showed that for the period 1986–2015, annual runoff for Bieszczady rivers (Eastern Carpathians) does not exhibit significant trends. Also, the results of a multi-temporal analysis of annual river flow in the Upper Vistula Basin indicate substantial differences in trends for the years 1951–2015 [83].

In the context of water security in urban areas, ensuring adequate water quantity and quality is essential. However, it is also possible to significantly reduce the consumption of potable water from the municipal water works by collecting rainwater when its utilization does not require drinking water; in the case of Beira, Mozambique, up to a 40% reduction was achieved using this method [84]. On the other hand, the expansion of impervious surfaces in urban areas leads to increased nutrient loads discharged via surface runoff into receiving water bodies [85], and changing climatic conditions may further exacerbate the situation. In the case of the city of Lublin (eastern Poland), a study [85] conducted using a modeling tool shows that projected increases in temperature and precipitation could increase nutrient loads by up to 30%. In the case of a medium-sized city (Toruń, central Poland), a study [86] addresses the problem of natural hazards (droughts and floods) related to climate change and their impact on water security in terms of quantity. In the analyzed period (1971–2020), a slight increase in annual precipitation and a significant increase in the number of days without precipitation was accompanied by a significant increase in the average annual air temperature [86]. Meteorological hazards related to drought (days without precipitation) clearly outweighed the occurrence of days with

heavy precipitation [86]. The analysis of water table fluctuations observed at the Jedwabno infiltration intake showed a high sensitivity of the aquifer to atmospheric conditions, while in the case of the surface water intake, the greatest impact corresponded to events related to low flows of the Drwęca River [86].

With respect to the quality of tap water in Krakow, the values of individual parameters measured in water supplied to Krakow residents are several to a dozen times lower than the permissible concentrations, which indicates its very high quality and complete health safety [87]. In regards to the amount of water taken into the Krakow supply system, in the early 1960s, it became clear that the existing water treatment plants in Krakow would soon be unable to meet the city's growing needs, and the Vistula's severe pollution precluded its use for water supply purposes; the technically and economically most advantageous option was to draw water from the Raba River reservoir in Dobczyce [88]. For this purpose, a nearly 40 m high intake tower was built near Brzączowice, with six diagonal pumps, four with a capacity of 4000 m³/h and two with a capacity of 3000 m³/h, and water can be drawn from three different depths, depending on the best water quality [88]. The construction of the Dobczyce Reservoir resulted in, among other things, a change in the flow dynamics [89] and water temperature distribution [90] of the Raba River below the reservoir, while ensuring basic drinking water resources for Krakow. As shown in Table 1, the current production of the water intake from the Dobczyce Reservoir in relation to the maximum capacity is 59%, while for the water intake from the Rudawa River, it is 45% of the maximum capacity; it seems, therefore, that there is a possibility of increasing the production of water taken from the Dobczyce Reservoir, and taking into account the detected increasing trends in the flow of the Raba River, such a possibility should also exist in the future.

In summary, this study shows that for the Raba River, which is the main water source for Krakow, a statistically significant long-term trend of increasing annual flow is observed, accompanied by a significant trend of increasing annual precipitation, which seems to be important and useful information for water management. On the other hand, for the Rudawa River, which is the second largest water source for Krakow in terms of maximum capacity and current production, an identified significant downward trend in annual flow is observed, accompanied by a significant downward trend in annual precipitation, which should be taken into consideration for future water management and planning.

5. Conclusions

Based on the EEMD method, the conducted analysis indicates that for the years 1971–2020:

- A statistically significant ($p < 0.05$) linear trend in mean annual air temperature in Krakow–Balice is approx. 0.36 °C/decade;
- A statistically significant ($p < 0.05$) linear trend in annual precipitation totals is approx. 30.0 mm/decade in Stróża and approx. −8.2 mm/decade in Krakow–Balice;
- A statistically significant ($p < 0.05$) linear trend in mean annual flow for the Raba River in Stróża is increasing, amounting to 0.51 m³/s per decade, while for the Rudawa River in Balice, it decreases and amounts to −0.05 m³/s per decade;
- In Stróża the significant upward trend in precipitation is more intense (approx. 3.3% of the average/decade) and is accompanied by a significant upward trend in the Raba River flow (approx. 5.0% of the average/decade), while in Krakow–Balice, the significant downward trend in precipitation is less intense (approx. 1.2% of the average/decade) and is accompanied by a significant downward trend in the Rudawa River flow (approx. 2.3% of the average/decade);
- For May, significant increasing trends in precipitation are accompanied by significant increasing trends in the examined river flow.

The trends identified by the EEMD method are largely consistent with the trends in the original data, but differ in intensity. However, while the former are mostly statistically significant at $\alpha = 0.05$, the latter are statistically significant only for air temperature in Krakow–Balice.

The results of cross-correlation and autocorrelation analysis suggest that the identified decreasing trend in the Rudawa flow may also be related to the significantly reduced underground recharge in the Rudawa catchment. Therefore, in the changing climate, the situation should continue to be monitored to prepare for potential future changes in the flow rates of the studied rivers.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/su18136591/s1>, Figure S1: EEMD results for annual P1; Table S1: Results of EEMD method for T, with mean oscillation period (OP in years) and amplitude (AM in °C) of each IMF; Figure S2: EEMD results for annual P2; Table S2: Results of EEMD method for P, with mean oscillation period (OP in years) and amplitude (AM in mm) of each IMF; Figure S3: EEMD results for annual Q1; Table S3: Results of EEMD method for Q, with mean oscillation period (OP in years) and amplitude (AM in m³/s) of each IMF; Figure S4: EEMD results for annual Q2; Table S4: Results of the EEMD method: Orthogonality Index and relative width of CI.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data that support the findings of this study were retrieved from the publicly available website <https://danepubliczne.imgw.pl/> (accessed on 1 July 2025) of the Polish Institute of Meteorology and Water Management—the National Research Institute.

Conflicts of Interest: The author declares no conflicts of interest.

References

1. United Nations, Department of Economic and Social Affairs, Population Division. *World Urbanization Prospects: The 2018 Revision*; (ST/ESA/SER.A/420); United Nations: New York, NY, USA, 2019; pp. 9–10. Available online: <https://population.un.org/wup/assets/WUP2018-Report.pdf> (accessed on 1 December 2025).
2. Hoekstra, A.Y.; Buurman, J.; Van Ginkel, K.C. Urban water security: A review. *Environ. Res. Lett.* **2018**, *13*, 053002.
3. United Nations University, Institute for Water, Environment and Health. *Water Security & the Global Water Agenda: A UN-Water Analytical Brief*; United Nations University, Institute for Water, Environment and Health: Hamilton, ON, Canada, 2013. Available online: https://www.unwater.org/sites/default/files/app/uploads/2017/05/analytical_brief_oct2013_web.pdf (accessed on 1 December 2025).
4. Allan, R.P.; Soden, B.J. Atmospheric warming and the amplification of precipitation extremes. *Science* **2008**, *321*, 1481–1484.
5. Trenberth, K.E. Changes in precipitation with climate change. *Clim. Res.* **2011**, *47*, 123–138.
6. Fischer, E.M.; Knutti, R. Observed heavy precipitation increase confirms theory and early models. *Nat. Clim. Change* **2016**, *6*, 986–991.
7. Clapeyron, E. Mémoire sur la puissance motrice de la chaleur. *J. l'École Polytech.* **1834**, *23*, 153–191.
8. Clausius, R. Über die bewegende Kraft der Wärme und die Gesetze, welche sich daraus für die Wärmelehre selbst ableiten lassen. *Ann. Phys.* **1850**, *155*, 368–397.
9. K.E. Trenberth, Conceptual framework for changes of extremes of the hydrological cycle with climate change. *Clim. Change* **1999**, *42*, 327–339.
10. Huong, H.T.L.; Pathirana, A. Urbanization and climate change impacts on future urban flooding in Can Tho city, Vietnam. *Hydrol. Earth Syst. Sci.* **2013**, *17*, 379–394.
11. Papalexiou, S.M.; Montanari, A. Global and regional increase of precipitation extremes under global warming. *Water Resour. Res.* **2019**, *55*, 4901–4914.

12. Zhou, Q.; Leng, G.; Su, J.; Ren, Y.; Zhou, Q.; Leng, G.; Su, J.; Ren, Y. Comparison of urbanization and climate change impacts on urban flood volumes: Importance of urban planning and drainage adaptation. *Sci. Total Environ.* **2019**, *658*, 24–33.
13. Xu, H.; Ma, C.; Xu, K.; Lian, J.; Long, Y. Staged optimization of urban drainage systems considering climate change and hydrological model uncertainty. *J. Hydrol.* **2020**, *587*, 124959.
14. Rodell, M.; Li, B. Changing intensity of hydroclimatic extreme events revealed by GRACE and GRACE-FO. *Nat. Water* **2023**, *1*, 241–248.
15. Zappa, G.; Bevacqua, E.; Shepherd, T.G. Communicating potentially large but non-robust changes in multi-model projections of future climate. *Int. J. Climatol.* **2021**, *41*, 3657–3669.
16. Bevacqua, E.; Zappa, G.; Lehner, F.; Zscheischler, J. Precipitation trends determine future occurrences of compound hot–dry events. *Nat. Clim. Change* **2022**, *12*, 350–355.
17. van Heerwaarden, C.C.; de Arellado, J.V.G.; Teuling, A.J. Land-atmosphere coupling explains the link between pan evaporation and actual evapotranspiration trends in a changing climate. *Geophys. Res. Lett.* **2010**, *37*, L21401.
18. European Environment Agency. Global and European Temperatures. 2025. Available online: <https://www.eea.europa.eu/ims/global-and-european-temperatures> (accessed on 16 July 2025).
19. Luterbacher, J.; Werner, J.P.; Smerdon, J.E.; Fernández-Donado, L.; González-Rouco, F.J.; Barriopedro, D.; Ljungqvist, F.C.; Büntgen, U.; Zorita, E.; Wagner, S. European summer temperatures since Roman times. *Environ. Res. Lett.* **2016**, *11*, 024001.
20. van der Schrier, G.; van den Besselaar, E.J.M.; Klein Tank, A.M.G.; Verver, G. Monitoring European average temperature based on E-OBS gridded data set. *J. Geophys. Res. Atmos.* **2013**, *118*, 5120–5135.
21. Eurostat Data. Available online: <https://ec.europa.eu/eurostat/data/database> (accessed on 1 December 2025).
22. Kędra, M. Cooling water for electricity production in Poland: Assessment and new perspectives. *Energies* **2023**, *16*, 2822.
23. Wu, Z.; Huang, N.E. Ensemble empirical mode decomposition: A noise assisted data analysis method. *Adv. Adapt. Data Anal.* **2009**, *1*, 1–41.
24. Huang, N.E.; Shen, Z.; Long, S.R.; Wu, M.C.; Shih, H.H.; Zheng, Q.; Yen, N.-C.; Tung, C.C.; Liu, H.H. The empirical mode decomposition and the Hilbert spectrum for nonlinear and non-stationary time series analysis. *Proc. R. Soc. London Ser. A Math. Phys. Eng. Sci.* **1998**, *454*, 903–995.
25. Wu, Z.; Huang, N.E.; Long, S.R.; Peng, C.-K. On the trend, detrending, and variability of nonlinear and nonstationary time series. *Proc. Natl. Acad. Sci. USA* **2007**, *104*, 14889–14894.
26. Ma, H.; Qiu, X.; Luo, J.-p.; Gu, P.-q.; Liu, Y.-l. Analysis of temperature time series based on Hilbert-Huang Transform. *J. Hydrodyn.* **2015**, *27*, 587–592.
27. Huang, W.C.; Lee, J.C. Projection of sea surface temperature based on empirical mode decomposition and its application in typhoon number forecast. *J. Mar. Sci. Technol.* **2023**, *31*, 7.
28. Chang, C.-W.; Lee, J.-C.; Huang, W.-C. Hydrological data projection using Empirical Mode Decomposition: Applications in a changing climate. *Water* **2024**, *16*, 2669. <https://doi.org/10.3390/w16182669>.
29. Antico, A.; Schlotthauer, G.; Torres, M.E. Analysis of hydroclimatic variability and trends using a novel empirical mode decomposition: Application to the Paraná River Basin. *J. Geophys. Res. Atmos.* **2014**, *119*, 1218–1233. <https://doi.org/10.1002/2013JD020420>.
30. Zhang, H.B.; Huang, W.C.; Xi, Q.Y.; Wang, B.; Lan, T. Assessment on long-term fluctuations of runoff and its climate driving factors. *J. Mar. Sci. Technol.* **2016**, *24*, 329–337.
31. Huang, Y.; Schmitt, F.G.; Lu, Z.; Liu, Y. Analysis of daily river flow fluctuations using empirical mode decomposition and arbitrary order Hilbert spectral analysis. *J. Hydrol.* **2009**, *373*, 103–111. <https://doi.org/10.1016/j.jhydrol.2009.04.015>.
32. Kędra, M.; Wójcicka, Ł.; Zydroń, T.; Kijowska-Strugała, M.; Cebulski, J. The influence of water level hydrodynamics on potential changes in the morphology of a mountain reservoir shore zone. *CATENA* **2023**, *231*, 107363.
33. Statistics Poland. *Area and Population in the Territorial Profile in 2023*; Statistics Poland: Warsaw, Poland. 2023. Available online: <https://stat.gov.pl/obszary-tematyczne/ludnosc/ludnosc/powierzchnia-i-ludnosc-w-przekroju-terytorialnym-w-2023-roku,7,20.html> (accessed on 1 July 2025).
34. Krakow Waterworks Company. Infrastructure. Waterworks Facility. Available online: <https://wodociagi.krakow.pl/pl/o-firmie/infrastruktura/zaklad-sieci-wodociagowej> (accessed on 1 December 2025).
35. Krakow Waterworks Company. Infrastructure. Available online: <https://wodociagi.krakow.pl/pl/o-firmie/infrastruktura> (accessed on 1 December 2025).
36. Cichoń, T.; Królikowska, J. Protection of water resources for sustainable development. *Desal. Water Treat.* **2018**, *128*, 442–449.

37. Krakow Waterworks Company. Water Quality. Where Do I Get My Water? Available online: <https://wodociagi.krakow.pl/jakosc-wody/skad-mam-wode.html> (accessed on 1 December 2025).
38. Chelmicki, W. Location, classification and characteristics of the basin. In *The Upper Vistula Basin, Part I*; Dynowska, I., Maciejewski, M., Eds.; PWN: Warszawa-Kraków, Poland, 1991; pp. 15–29. (In Polish)
39. Hennig, J.; Hennig, I.; Roszkowski, A. Retention reservoirs. In *The Upper Vistula Basin, Part II*; Dynowska, I., Maciejewski, M., Eds.; PWN: Warszawa-Kraków, Poland, 1991; pp. 121–143. (In Polish)
40. Polish Institute of Meteorology and Water Management—The National Research Institute (IMWM–NRI). Database. Available online: <https://danepubliczne.imgw.pl/> (accessed on 1 July 2025).
41. Wang, G.; Chen, X.-Y.; Qiao, F.-L.; Wu, Z.; Huang, N.E. On Intrinsic Mode Function. *Adv. Adapt. Data Anal.* **2010**, *2*, 277–293.
42. Patrick Flandrin. Available online: <http://perso.ens-lyon.fr/patrick.flandrin/emd.html> (accessed on 4 March 2026).
43. Zhang, D.; Cai, C.C.; Chen, S.; Ling, L. An improved generic algorithm for optimizing ensemble empirical mode decomposition method. *Syst. Sci. Control. Eng.* **2019**, *2*, 53–63.
44. Shapiro, S.S.; Wilk, M.B. An analysis of variance test for normality. *Biometrika* **1965**, *52*, 591–611.
45. Mann, H.B. Nonparametric tests against trend. *Econometrica* **1945**, *13*, 245–259.
46. Kendall, M.G. *Rank Correlation Methods*, 4th ed.; Charles Griffin: London, UK, 1975.
47. Yue, S.; Pilon, P.; Phinney, B.; Cavadias, G. The influence of autocorrelation on the ability to detect trend in hydrological series. *Hydrol. Process.* **2002**, *16*, 1807–1829.
48. Hamed, K.H.; Rao, A.R. A modified Mann-Kendall trend test for autocorrelated data. *J. Hydrol.* **1998**, *204*, 219–246.
49. Theil, H. A rank-invariant method of linear and polynomial regression analysis I, II, III. *Proc. R. Neth. Acad. Arts Sci.* **1950**, *53*, 386–392, 521–525, 1397–1412.
50. Sen, P.K. Estimates of the regression coefficient based on Kendall’s tau. *J. Am. Stat. Assoc.* **1968**, *63*, 1379–1389.
51. Khaliq, M.N.; Quarda, T.B.M.J.; Gachon, P.; Sushama, L.; St-Hilaire, A. Identification of hydrological trends in the presence of serial and cross correlations: A review of selected methods and their application to annual flow regimes of Canadian rivers. *J. Hydrol.* **2009**, *368*, 117–130.
52. Wang, W.; Chen, Y.; Becker, S.; Liu, B. Linear trend detection in serially dependent hydrometeorological data based on a variance correction Spearman rho method. *Water* **2015**, *7*, 7045–7065. <https://doi.org/10.3390/w7126673>.
53. Faulkner, S. Urbanization impacts on the structure and function of forested wetlands. *Urban Ecosyst.* **2004**, *7*, 89–106.
54. Ouyang, X.; Tang, L.; Wei, X.; Li, Y. Spatial interaction between urbanization and ecosystem services in Chinese urban agglomerations. *Land Use Policy* **2021**, *109*, 105587.
55. Lyu, R.F.; Zhang, J.M.; Xu, M.Q.; Li, J.J. Impacts of urbanization on ecosystem services and their temporal relations: A case study in Northern Ningxia, China. *Land Use Policy* **2018**, *77*, 163–173.
56. Kowalczak, P.; Kundzewicz, Z.W. Water-related conflicts in urban areas in Poland. *Hydrol. Sci. J.* **2011**, *56*, 588–596.
57. Intergovernmental Panel on Climate Change (IPCC). *Climate Change 2021: The Physical Science Basis. Working Group I Contribution to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*; Cambridge University Press: Cambridge, UK, 2021. Available online: https://www.ipcc.ch/report/ar6/wg1/downloads/report/IPCC_AR6_WGI_SummaryVolume.pdf (accessed on 1 July 2025).
58. Degirmendžić, J.; Kożuchowski, K.; Żmudzka, E. Changes of air temperature and precipitation in Poland in the period 1951–2000 and their relationship to atmospheric circulation. *Int. J. Climatol.* **2004**, *24*, 291–310.
59. Rahmstorf, S.; Foster, G.; Cahill, N. Global temperature evolution: Recent trends and some pitfalls. *Environ. Res. Lett.* **2017**, *12*, 054001.
60. Kędra, M.; Szczepanek, R. Land cover transitions and changing climate conditions in the Polish Carpathians: Assessment and management implications. *Land Degrad. Dev.* **2019**, *30*, 1040–1051.
61. Mostowik, K.; Siwek, J.; Kisiel, M.; Kowalik, K.; Krzysik, M.; Plenzler, J.; Rzonca, B. Runoff trends in a changing climate in the Eastern Carpathians (Bieszczady Mountains, Poland). *CATENA* **2019**, *182*, 104174.
62. Kędra, M. Sensitivity of mountain catchments to global warming: A case study of the San Basin, Poland. *Water Environ. J.* **2020**, *34*, 648–660.
63. Krauskopf, T.; Huth, R. Temperature trends in Europe: Comparison of different data sources. *Theor. Appl. Climatol.* **2020**, *139*, 1305–1316.
64. Kubiak-Wójcicka, K. Variability of Air Temperature, Precipitation and Outflows in the Vistula Basin (Poland). *Resources* **2020**, *9*, 103.
65. Twardosz, R.; Walanus, A.; Guzik, I. Warming in Europe: Recent trends in annual and seasonal temperatures. *Pure Appl. Geophys.* **2021**, *178*, 4021–4032.
66. Wang, Y.-R.; Hessen, D.O.; Samset, B.H.; Stordal, F. Evaluating global and regional land warming trends in the past decades with both MODIS and ERA5-Land land surface temperature data. *Remote Sens. Environ.* **2022**, *280*, 113181.

67. Tariq, M.; Aruffo, E.; Chiacchiaretta, P.; Di Carlo, P. Hydro-climatic trends in central Italy: A case study from the Aterno-Pescara River Watershed. *Sustainability* **2025**, *17*, 493. <https://doi.org/10.3390/su17020493>.
68. Rajwa-Kuligiewicz, A.; Bojarczuk, A. Evaluating the impact of climatic changes on streamflow in headwater mountain catchments with varying human pressure. An example from the Tatra Mountains (Western Carpathians). *J. Hydrology Reg. Stud.* **2024**, *53*, 101755.
69. Niedźwiedź, T.; Twardosz, R.; Walanus, A. Long-term variability of precipitation series in east central Europe in relation to circulation patterns. *Theor. Appl. Climatol.* **2009**, *98*, 337–350.
70. Szwed, M. Variability of precipitation in Poland under climate change. *Theor. Appl. Clim.* **2019**, *135*, 1003–1015.
71. Donat, M.G.; Lowry, A.L.; Alexander, L.V.; O’Gorman, P.A.; Maher, N. More extreme precipitation in the world’s dry and wet regions. *Nature Clim. Change* **2016**, *6*, 508–513.
72. Kędra, M. Altered precipitation characteristics in two Polish Carpathian basins, with implications for water resources. *Clim. Res.* **2017**, *72*, 251–265.
73. Wypych, A.; Ustrnul, Z.; Schmatz, D.R. Long-term variability of air temperature and precipitation conditions in the Polish Carpathians. *J. Mt. Sci.* **2018**, *15*, 237–253.
74. Nazeri Tahroudi, M. Comprehensive global assessment of precipitation trend and pattern variability considering their distribution dynamics. *Sci. Rep.* **2025**, *15*, 22458.
75. Battisti, R.; Dapper, F.P.; da Silva, A.C.S.; Mesquita, M.; da Silva, M.V.; Andrade, R.R.; Lopes, A.G.C. Assessing precipitation trends between 1960 and 2021 using multiple trend indexes in the GOIÁS State and Federal District, Brazil. *Int. J. Climatol.* **2025**, *45*, e8750.
76. Mo, L.; Zhang, Z.; Yao, J.; Ma, Z.; Cong, X.; Yu, X. Analysis of hydrological changes in the Fuhe River Basin in the context of climate change. *Sustainability* **2024**, *16*, 7418. <https://doi.org/10.3390/su16177418>.
77. Trenberth, K.E.; Asrar, G.R. Challenges and opportunities in water cycle research: WCRP contributions. *Surv. Geophys.* **2014**, *3*, 515–532.
78. Schleiss, M.; Smith, J.A. Two simple metrics for quantifying rainfall intermittency: The burstiness and memory of interamount times. *J. Hydrometeorol.* **2016**, *17*, 421–436.
79. Rigby, J.R.; Porporato, A. Precipitation, dynamical intermittency, and sporadic randomness. *Adv. Water Resour.* **2010**, *33*, 923–932.
80. Duda, R.; Paszkiewicz, M. The assessment of groundwater recharge by infiltration method in selected catchments. *Biul. Państwowego Inst. Geol.* **2009**, *436*, 103–108. Available online: <https://bibliotekanauki.pl/articles/2063185> (accessed on 16 March 2026).
81. Bartnik, A.; Jokiel, P. Some remarks on autocorrelation in time series of average monthly flows of Polish rivers. (Kilka uwag o autokorelacji w szeregach czasowych średnich miesięcznych przepływów rzek Polski). *Wiadomości. IMGW* **1998**, *21*, 3–22. (In Polish)
82. Dynowska, I. Water balance. In *The Upper Vistula Basin, Part I*; Dynowska, I., Maciejewski, M., Eds.; PWN: Warszawa-Kraków, Poland, 1991; pp. 223–227. (In Polish)
83. Górnik, M. Changing trends of river flows in the Upper Vistula Basin (East-Central Europe). *Acta Geophys.* **2020**, *68*, 495–504.
84. Santos, M.M.; Ferreira, A.V.; Lanzinha, J.C.G. The possibilities of capturing rainwater and reducing the impact of floods: A proposal for the city of Beira, Mozambique. *Sustainability* **2023**, *15*, 2276. <https://doi.org/10.3390/su15032276>.
85. Szalińska, E.; Jarosińska, E.; Orlińska-Woźniak, P.; Jakusik, E.; Warzecha, W.; Ogar, W.; Wilk, P. Total nitrogen and phosphorus loads in surface runoff from urban land use (city of Lublin) under climate change. *Environ. Sci. Pollut. Res.* **2024**, *31*, 48135–48153. <https://doi.org/10.1007/s11356-024-34365-9>.
86. Kubiak-Wójcicka, K.; Jamorska, I.; Górski, L. The identification of risks for drinking water intakes in urbanized area: The case study of Toruń (Central Poland). *Water* **2021**, *13*, 3378.
87. Krakow Waterworks Company. Water Quality. Available online: <https://wodociagi.krakow.pl/pl/jakosc-wody> (accessed on 1 March 2026).
88. Krakow Waterworks Company. Water Treatment Plant Raba. Available online: <https://wodociagi.krakow.pl/pl/ofirmie/infrastruktura/zaklad-uzdatniania-wody-raba> (accessed on 1 March 2026).
89. Kędra, M. Dam-induced changes in river flow dynamics revealed by RQA. *Eur. Phys. J. Spec. Top.* **2023**, *232*, 209–215. <https://doi.org/10.1140/epjs/s11734-022-00689-1>.
90. Kędra, M. Long-term trends in river water temperature: A case study of the Raba River (Polish Carpathians). *E3S Web Conf.* **2017**, *19*, 02016. <https://doi.org/10.1051/e3sconf/20171902016>.

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.