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Research Article

# A Dual-Method Evaluation of Long-Term Precipitation Changes in Türkiye's Eastern Black Sea Basin

Ahmet Iyad Ceyhunlu[1*]

[1] Sakarya University of Applied Sciences, Faculty of Technology, Department of Civil Engineering, Sakarya, Türkiye. ror.org/01shwhq58

*Corresponding author:
ahmetceyhunlu@subu.edu.tr

**Abstract:** In this study, the long-term and seasonal precipitation dynamics of the Eastern Black Sea Basin were investigated using monthly total precipitation data from six meteorological stations for the period 1994–2024. Two contemporary trend analysis techniques—the Multi-Risk Level Identification (MRLI) method and the Trend Polygon Star Concept Method (TPSCM)—were applied to provide a comprehensive evaluation of precipitation behavior. The MRLI approach identified increasing, decreasing, or stable trends across a range of risk percentiles by determining critical precipitation thresholds from best-fitting theoretical distributions validated through the Kolmogorov–Smirnov (K-S) test. The results revealed substantial spatial variability: while Giresun exhibited consistently increasing trends at all risk levels, Artvin and Trabzon showed mixed behavior with both upward and downward tendencies depending on the percentile. In addition, a basin-wide evaluation indicated that approximately 65% of the overall trends were increasing, whereas 35% displayed decreasing tendencies, highlighting a general intensification of precipitation conditions in the region. The remaining stations showed diverse responses across low-, medium-, and high-risk classes. The TPSCM method offered further insights into intra-annual variability by categorizing month-to-month precipitation transitions into four directional regions representing shifts between early and late sub-periods. The spatial distribution of these regions varied considerably among provinces, indicating notable temporal changes in seasonal rainfall structures. Overall, the combined application of MRLI and TPSCM enabled a detailed assessment of both long-term and seasonal precipitation characteristics, providing a robust basis for advanced hydrological planning and climate adaptation strategies in the Eastern Black Sea Basin.

***Keywords:*** *MRLI, TPSCM, Eastern black sea basin, Trend analysis, Precipitation*

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## I. INTRODUCTION

The Eastern Black Sea Basin is one of the most hydrologically dynamic regions of Türkiye, characterized by steep topography, strong orographic uplift, and pronounced temporal variability in hydrometeorological processes (Kartal et al., 2024). As climate change intensifies worldwide, precipitation regimes in mountainous coastal regions have become increasingly sensitive to shifts in atmospheric circulation patterns, moisture transport pathways, and the frequency and magnitude of extreme weather events. Understanding how these evolving climatic drivers influence long-term precipitation behavior is essential for sustainable water resources management, flood mitigation, agricultural planning, and ecosystem conservation. In responsive and high-rainfall catchments such as those of the Eastern Black Sea Basin, even modest changes in precipitation characteristics can substantially alter hydrological responses, underscoring the need for robust and comprehensive trend assessments (Güçlü, 2018; Ceribasi, 2019; Şen, 2021; Şan et al., 2021).

Traditional trend analysis methods are commonly used to detect temporal changes in hydroclimatic variables; however, these approaches often rely on limited risk classifications and may not adequately capture changes across different segments of the distribution. Recent developments in trend analysis have introduced more nuanced methodologies capable of evaluating trends at multiple risk levels and examining temporal transitions with greater detail. Two of these innovative approaches are the (MRLI) method and the (TPSCM). The MRLI technique provides a flexible framework for detecting increasing, decreasing, or stable trends at any desired percentile, thereby offering a more refined characterization of precipitation behavior under varying hydrological risks. In parallel, the (TPSCM) analyzes transitions between consecutive months within a two-dimensional space, allowing seasonal structure, intra-annual variability, and potential shifts in the precipitation cycle to be detected visually and analytically (Güçlü et al., 2018; Achite et al., 2021; Ahmed et al., 2022; Şen, 2024).

Despite the importance of the Eastern Black Sea Basin and the growing need for advanced diagnostic tools, studies employing these two modern methods remain limited in the regional hydrology literature. Therefore, the present study aims to analyze long-term precipitation records from the Eastern Black Sea Basin using both the MRLI method and the Trend Polygon Star Concept Method. By integrating these complementary approaches, the study seeks to (i) determine



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trend behavior across multiple hydrological risk levels, (ii) reveal potential changes in seasonal precipitation dynamics, and (iii) contribute to a deeper understanding of climate-related hydrological variability in one of Türkiye's most rainfall-sensitive basins. The findings are expected to provide valuable insights for regional water management strategies and climate adaptation planning (Şen, 2017a; Şen, 2017b; Ceyhunlu & Cuma, 2025; Akçay et al., 2022).

## II. MATERIAL AND METHOD

In this section, the materials, instruments, and devices used should be presented clearly and in detail. Experimental setups, preparation steps, and analysis methods should be described in a way that ensures the reproduce reproducibility of the study. The specifications of the devices, equipment, or software used should be stated whenever possible. Standard solutions can be briefly summarized if appropriate sources are cited; however, new components that have been modified or adapted should be described in detail. Furthermore, sustainable analyses and data evaluation approaches should be described, including the benefits of the results and the presentation of the results.

### *A. Study Area*

The study area covers the Eastern Black Sea Basin, located along the northeastern coastline of Türkiye. This region extends approximately between 40.5°–41.5°N latitude and 36.0°–42.0°E longitude, encompassing the provinces of Ordu, Giresun, Trabzon, Rize, Artvin, and Gümüşhane. The basin is characterized by steep mountainous terrain rising sharply from the coastline, producing intense orographic precipitation throughout the year. The climate of the region is classified as humid and temperate, with abundant rainfall, mild summers, and cool, wet winters (Hırca et al., 2022). Due to its rugged topography and high annual precipitation, the Eastern Black Sea Basin hosts one of the most dynamic hydrological systems in Türkiye, making it highly sensitive to climate variability and extreme hydrometeorological events. Economically, the region relies primarily on agriculture—most notably tea and hazelnut production—as well as forestry, fisheries, and growing tourism activities. The geographical location and physiographic features of the basin are shown in Figure 1.

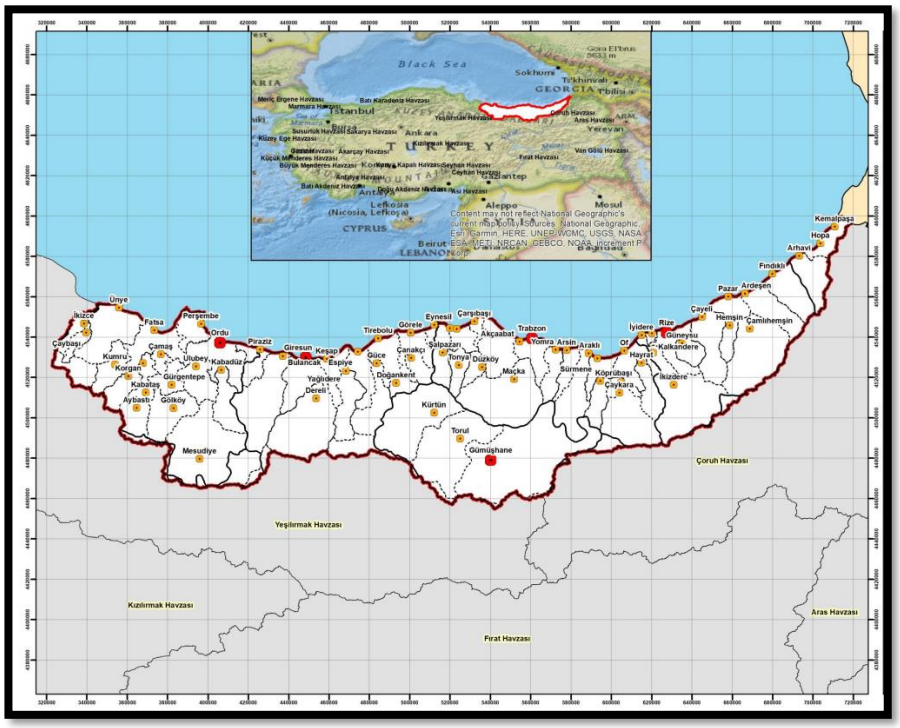



Figure 1. Eastern Black Sea Basin's Location.

This study is based on monthly total precipitation data for the period 1994–2024. The precipitation time series used in this study were obtained from the Turkish State Meteorological Service (MGM), which provides operational measurement datasets processed through standard quality-control procedures. While undetected minor inhomogeneities cannot be entirely excluded, the percentile-based structure of the MRLI approach minimizes their potential influence by assessing trends across the full distribution rather than relying on single aggregated indicators. Table 1 provides detailed information on the meteorological observation stations, including their key characteristics and geographic locations from which the precipitation records were sourced.

Table 1. Statistical properties of the observation stations.

| Station No | Station Name | Coordinates | | Altitude | Data Years |
|---|---|---|---|---|---|
| 17045 | Artvin | 41°10'30.6"N | 41°49'07.2"E | 597 | 1994-2024 |
| 17034 | Giresun | 40°55'21.6"N | 38°23'16.2"E | 84 | 1994-2024 |
| 17088 | Gümüşhane | 40°27'36.9"N | 39°27'55.5"E | 1210 | 1994-2024 |
| 17033 | Ordu | 40°59'01.8"N | 37°53'09.0"E | 10 | 1994-2024 |
| 17040 | Rize | 41°02'24.0"N | 40°30'04.8"E | 4 | 1994-2024 |
| 17038 | Trabzon | 40°59'56.9"N | 39°46'45.3"E | 37 | 1994-2024 |

As presented in Table 1, meteorological stations with continuous monthly precipitation records for the period 1994–2024 were selected to represent the Eastern Black Sea Basin in this study. Understanding long-term changes in precipitation is particularly important in regions where climate variability strongly influences hydrological responses. Rising global temperatures, altered evaporation rates, and shifting atmospheric circulation patterns have intensified hydroclimatic extremes, causing some areas to become increasingly prone to drought while others face heightened risks of short-duration, high-intensity rainfall and subsequent flash floods (Ceribasi et al., 2021a). Given the steep topography and high annual rainfall of the Eastern Black Sea Basin, identifying robust precipitation trends is crucial for developing flood mitigation strategies and supporting basin-scale water management efforts.

*B. Multi-Risk Level Identification (MRLI) Method*

The Multi-Risk Level Identification (MRLI) method represents a recent advancement in hydrometeorological trend analysis, providing a flexible and distribution-based framework for detecting trends across a wide spectrum of risk levels (Şen, 2024). Rooted in the seesaw trend methodology, MRLI evaluates directional changes by comparing cumulative distribution functions (CDFs) between different time periods, thereby overcoming the limitations of traditional approaches that typically rely on central-tendency indicators or classify risk into only a few categories (e.g., low, medium, high). In contrast, MRLI enables trend assessment at any desired percentile of the distribution. Risk classes such as 99%, 98%, 96%, 90%, 80%, 65%, 50%, 40%, 30%, 20%, and 10% may be employed—and adjusted as needed—to capture both moderate and extreme behaviors within the dataset. In this study, MRLI percentiles were selected to ensure representation of extreme, moderate, and low precipitation conditions across the full distribution. High thresholds (e.g., 99%, 98%, 96%) characterize the upper-tail behavior associated with extreme precipitation, mid-range percentiles (e.g., 80%, 65%, 50%) capture typical hydrometeorological variability, and lower percentiles (e.g., 30%, 20%, 10%) reflect dry conditions or low-intensity rainfall. These thresholds are consistent with the conceptual principles of the MRLI framework and with previous applications of percentile-based trend analysis in hydrology, allowing a balanced and comparable assessment across all stations. Şen (2024) rigorously formalized the theoretical foundations of this method, demonstrating its ability to reveal nonlinear, hidden, and risk-dependent trends in precipitation and streamflow time series. Numerous hydrometeorological applications have further highlighted the strength of CDF-based, percentile-specific trend analysis in detecting subtle distributional changes that conventional non-parametric tests may overlook. By integrating MRLI into the present study, a more robust, risk-sensitive, and spatially explicit evaluation of precipitation trends across the region is achieved (Ceribasi et al., 2026).

A key advantage of the MRLI method is its ability to evaluate the trend characteristics associated with every value within the dataset. As a result, MRLI provides critical insights into whether a variable exhibits increasing, decreasing, or stable behavior at different risk levels, making it a valuable tool for future-oriented planning in fields such as water resources, agriculture, energy production, irrigation management, drought assessment, and flood analysis. In this study, Normal, Log-Normal, Weibull, Gamma, and Generalized Extreme Value (GEV) theoretical probability distributions were tested for each station, and the best-fitting distribution was identified based on the (K–S) goodness-of-fit evaluation. The method is based on the use of theoretical cumulative distribution functions (CDFs).

The application of the MRLI method to any hydrometeorological dataset involves the following steps:

1. The dataset is divided into two equal parts. For instance, a 50-year record is split into two 25-year segments.
2. Values in the first half of the dataset are sorted in ascending order.
3. Theoretical CDF and corresponding Z values are computed for the sorted dataset.
4. An F(x) curve is constructed using the theoretical CDF and Z values (Figure 2)

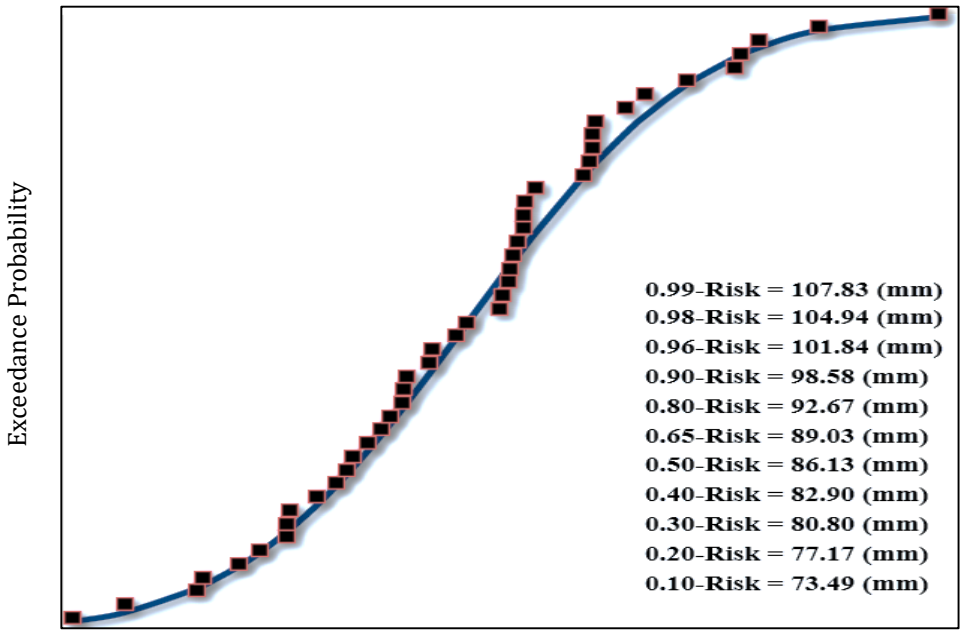



Figure 2. A hypothetical CDF F(x) Curve.

5. Absolute differences between the theoretical CDF and the F(x)-derived values are calculated.
6. The maximum absolute difference is identified and compared to the critical value in the (K-S) table.
7. In the (K-S) test, if the maximum absolute difference between the empirical and theoretical cumulative distribution functions exceeds the critical value, the null hypothesis is rejected, indicating that the dataset does not follow the tested distribution. Conversely, if the test statistic is lower than the critical value, the null hypothesis cannot be rejected.
8. Hydrometeorological values corresponding to predefined risk percentiles (e.g., 99%, 98%, 96%, etc.) are extracted from the F(x) curve (Figure 3)
9. These steps are repeated for the first half, second half, and entire dataset.
10. Risk values are tabulated: early-period values are placed in the RE column, late-period values in the RL column, and whole-record values in the RW column.
11. A final column (S) is added to represent the risk slope, indicating whether the trend at a given risk level is increasing, decreasing, or stable. The slope is computed as:

$$S = \frac{R_L - R_E}{n/2} \quad (1)$$

where S denotes the risk slope, RL the late-period risk value, and RE the early-period risk value.

12. Linear plots of S values are then generated to illustrate the trend direction for each risk class, completing the analysis.

$$T_i = R_{W_i} - S_j\left(\frac{n}{2} - i + 1\right) \qquad i = 1,2,\dots,\frac{n}{2} \quad (2)$$

$$T_{\frac{n}{2}+i} = R_{W_j} - S_j\left(\frac{n}{2} + i\right) \qquad i = 1,2,\dots,\frac{n}{2} \quad (3)$$

Where; RW=Whole Record Risk Level

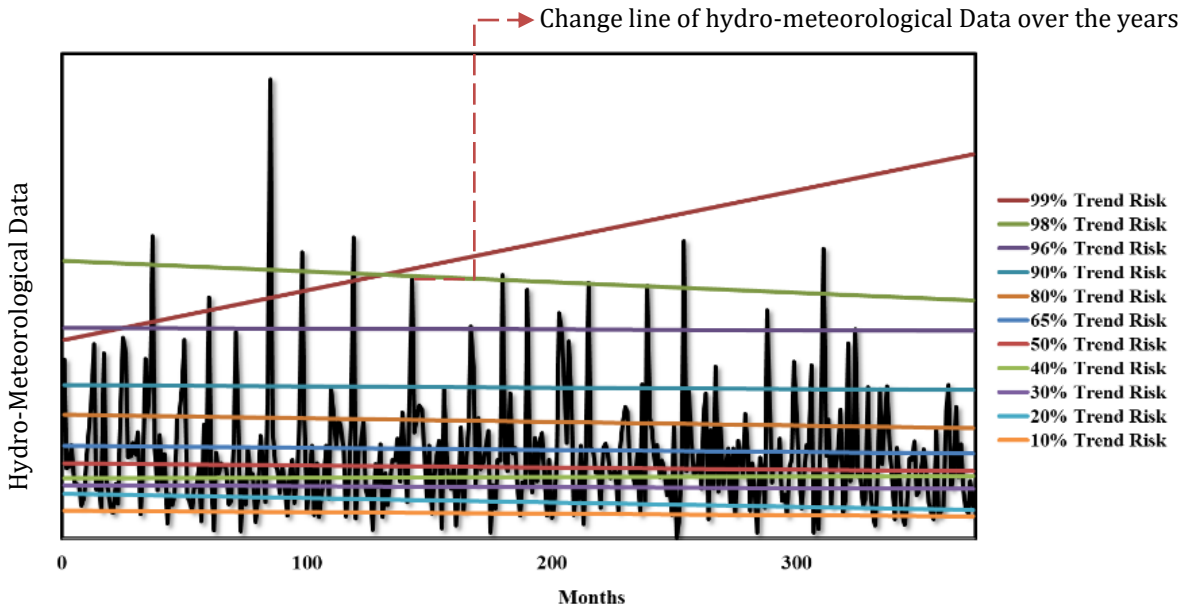



Figure 3. Hypothetical Graph Showing Linear Lines of Risk Classes.

*C. Assessment of Theoretical Distribution Fit Using the (K-S) Test*

The (K–S) test was employed to evaluate the goodness-of-fit between the empirical precipitation data and the selected theoretical probability distributions. The test is based on the maximum absolute difference between the empirical cumulative distribution function (ECDF) of the observed data and the theoretical cumulative distribution function (CDF) of the fitted distribution. For a given sample of size n, the ECDF is computed by sorting the observations in ascending order and assigning cumulative probabilities of i/n to the i-th ordered value. The K–S statistic (D) is then defined as the largest vertical distance between the ECDF and the theoretical CDF across all data points. A smaller D value and a higher associated p-value indicate a better fit between the observed data and the assumed distribution. The K–S test, originally developed by Kolmogorov, (1933) and later extended by Smirnov (1948), remains one of the most widely used non-parametric tools for assessing the agreement between empirical and theoretical distributions.

To illustrate the implementation of the K–S test, consider a simple example with a small synthetic time series consisting of five monthly precipitation values: 20, 35, 40, 50, and 60 mm. First, the values are sorted in ascending order and the empirical cumulative probabilities are assigned as 1/5, 2/5, 3/5, 4/5, and 5/5 for each ordered value, respectively. Next, assuming that the data follow a Normal distribution, the theoretical CDF values are calculated at each of these observed data points using the estimated mean and standard deviation of the sample. The K–S statistic (D) is obtained by taking the maximum absolute difference between the empirical probabilities and the corresponding theoretical CDF values. If the resulting D value is smaller than the critical value (or if the p-value is greater than the chosen significance level), the null hypothesis that the data follow the assumed distribution cannot be rejected. In this study, the same procedure was systematically applied to each station and for all candidate distributions, and the distribution with the smallest D and highest p-value was selected as the best fit.

*D. Trend Polygon Star Concept Method (TPSCM)*

The Trend Polygon Star Concept Method, originally proposed by Sen (2021), is a spatially oriented trend analysis technique designed to evaluate month-to-month variations in hydrological variables such as precipitation. The method conceptualizes the transition between any two consecutive months as a vector in a two-dimensional coordinate system (Ceribasi et al., 2021b). This system is divided into four quadrants, and the quadrant in which each vector falls provides diagnostic information about the direction and nature of the trend. A hypothetical example of the method applied to monthly data is presented in Figure 4.

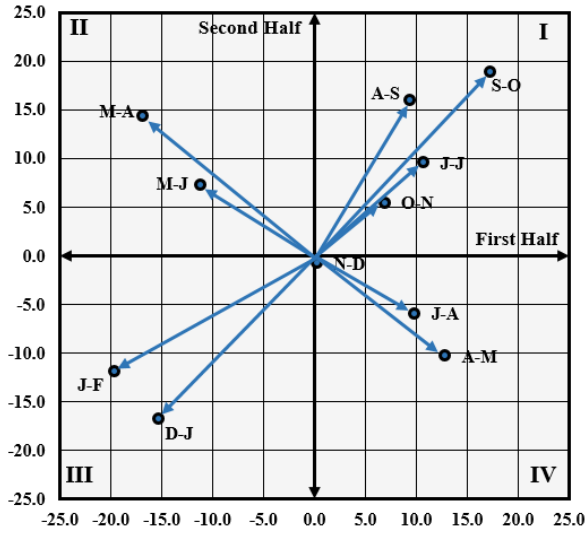



Figure 4. Hypothetical application of the (TPSCM)to monthly data.

As illustrated in Figure 4, all vectors originate from the coordinate system's origin, and each vector represents the magnitude and direction of the transition between two successive months. Longer vectors correspond to more pronounced changes between months. The horizontal and vertical components of each vector reflect differences between the first and second halves of the dataset (Ceribasi et al., 2021b). Interpretation of the hypothetical results shown in the figure yields the following observations:

- Month labels are represented by their initials (e.g., J for January, A for April, D for December).
- Each vector labeled with two letters denotes the transition from one month to the next (e.g., A–M indicates the transition from April to May).
- In TPSCM, each month is represented by its standard initial, and the polygon is constructed in a fixed chronological sequence from January to December. Because the months follow a continuous order, repeated initials (e.g., M or J) do not cause ambiguity; their meaning is fully determined by their position within the 12-month cycle.
- Vectors corresponding to the transitions J–J, S–O, A–S, and O–N fall within Quadrant I, indicating increasing trends in both halves of the dataset for these month pairs.
- Vectors associated with J–F and D–J transitions lie in Quadrant III, suggesting decreasing trends in both the early and late subsections of the dataset.
- Transitions M–A and M–J are located in Quadrant II, where the first half of the record exhibits a decreasing trend while the second half shows an increasing trend.
- Transitions A–M, J–A, and N–D appear in Quadrant IV, representing the opposite case: the first portion of the dataset displays an increasing trend, whereas the second half demonstrates a decreasing trend.

Quadrants II and IV, where the direction of the trend reverses between the two subsections of the dataset, may indicate notable alterations in the seasonal cycle over the study period (Köyceğiz & Büyükyıldız, 2019; Acar et al., 2022).

## III. RESULTS AND DISCUSSIONS

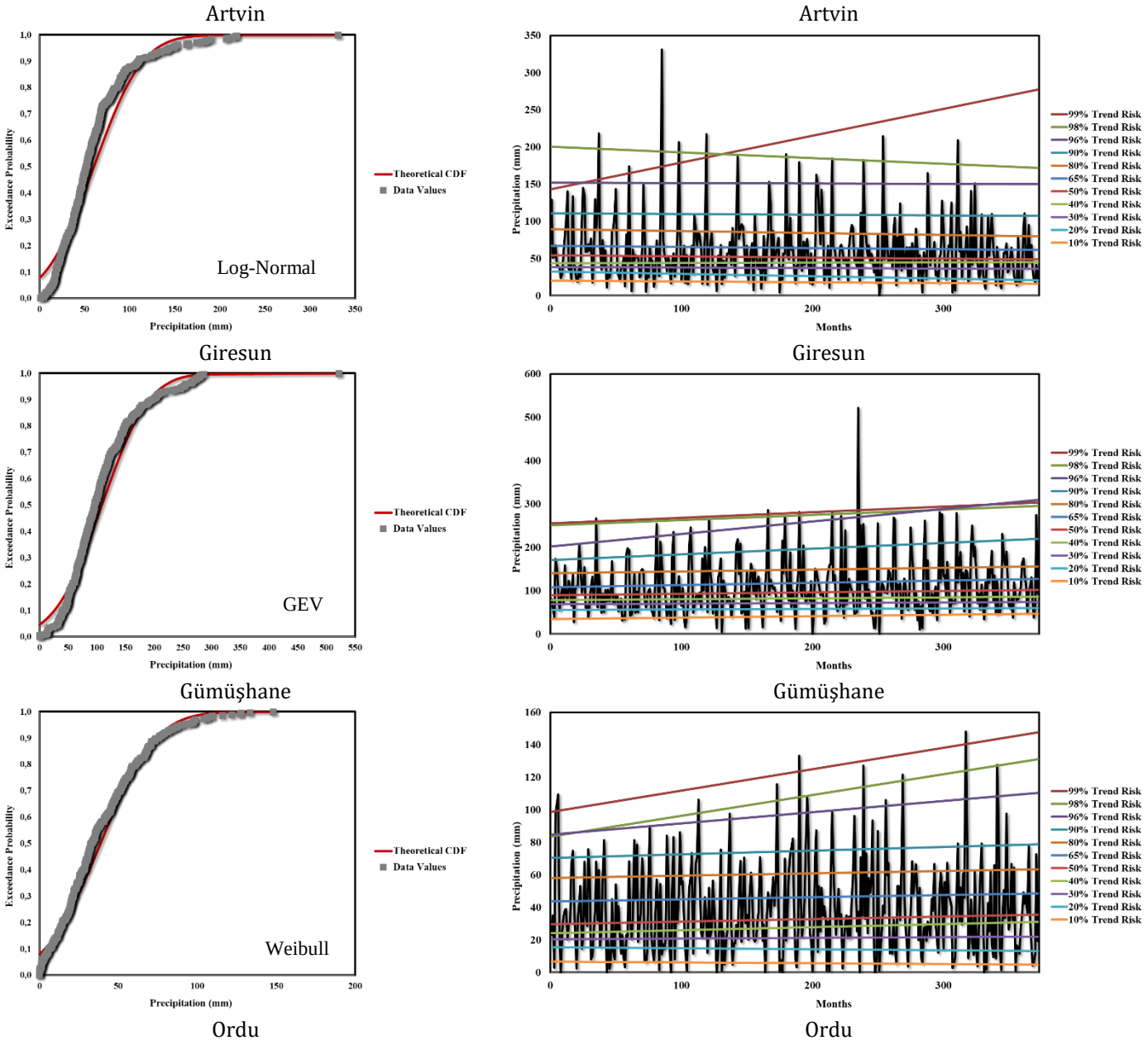
In this study, monthly total precipitation data from six observation stations within the Eastern Black Sea Basin were analyzed, covering the period from 1994 to 2024. The trends in precipitation were examined using two advanced methods: the (MRLI) method and the Trend Polygon Star Concept method. In the MRLI analysis, risk levels were determined across multiple percentiles, allowing for a detailed assessment of increasing, decreasing, or stable precipitation trends over the study period. Meanwhile, the (TPSCM) provided insight into intra-annual variability by evaluating transitions between consecutive months and highlighting potential shifts in seasonal precipitation patterns. The results obtained from both methods are presented in the following figures, providing a comprehensive understanding of temporal and seasonal trends in precipitation across the Eastern Black Sea Basin.

In Table 2, the total precipitation data for the Eastern Black Sea Basin for the period 1994–2024 were subjected to a CDF analysis, and the most suitable probability distribution function was determined based on goodness-of-fit results from the (K-S) test.

Table 2. Selecting the most suitable theoretical distribution (according to the k-s test).

| Station No | Tested Distributions | Best-fit Distribution | K–S Statistic | p-value | Interpretation |
|---|---|---|---|---|---|
| 17045 | Normal, Lognormal, Weibull, Gamma, GEV | Lognormal | 0.07 | 0.10 | Strong fit |
| 17034 | Normal, Lognormal, Weibull, Gamma, GEV | GEV | 0.026 | 0.95 | Excellent fit |
| 17088 | Normal, Lognormal, Weibull, Gamma, GEV | Weibull | 0.037 | 0.67 | Best among tested |
| 17033 | Normal, Lognormal, Weibull, Gamma, GEV | GEV | 0.031 | 0.86 | Strong fit |
| 17040 | Normal, Lognormal, Weibull, Gamma, GEV | Gamma | 0.020 | 0.998 | Excellent fit |
| 17038 | Normal, Lognormal, Weibull, Gamma, GEV | Gamma | 0.025 | 0.97 | Excellent fit |

According to the identified best-fit distribution, in Figure 5 the critical values corresponding to the MRLI risk levels were obtained, and the dataset was subsequently analyzed using the MRLI method.



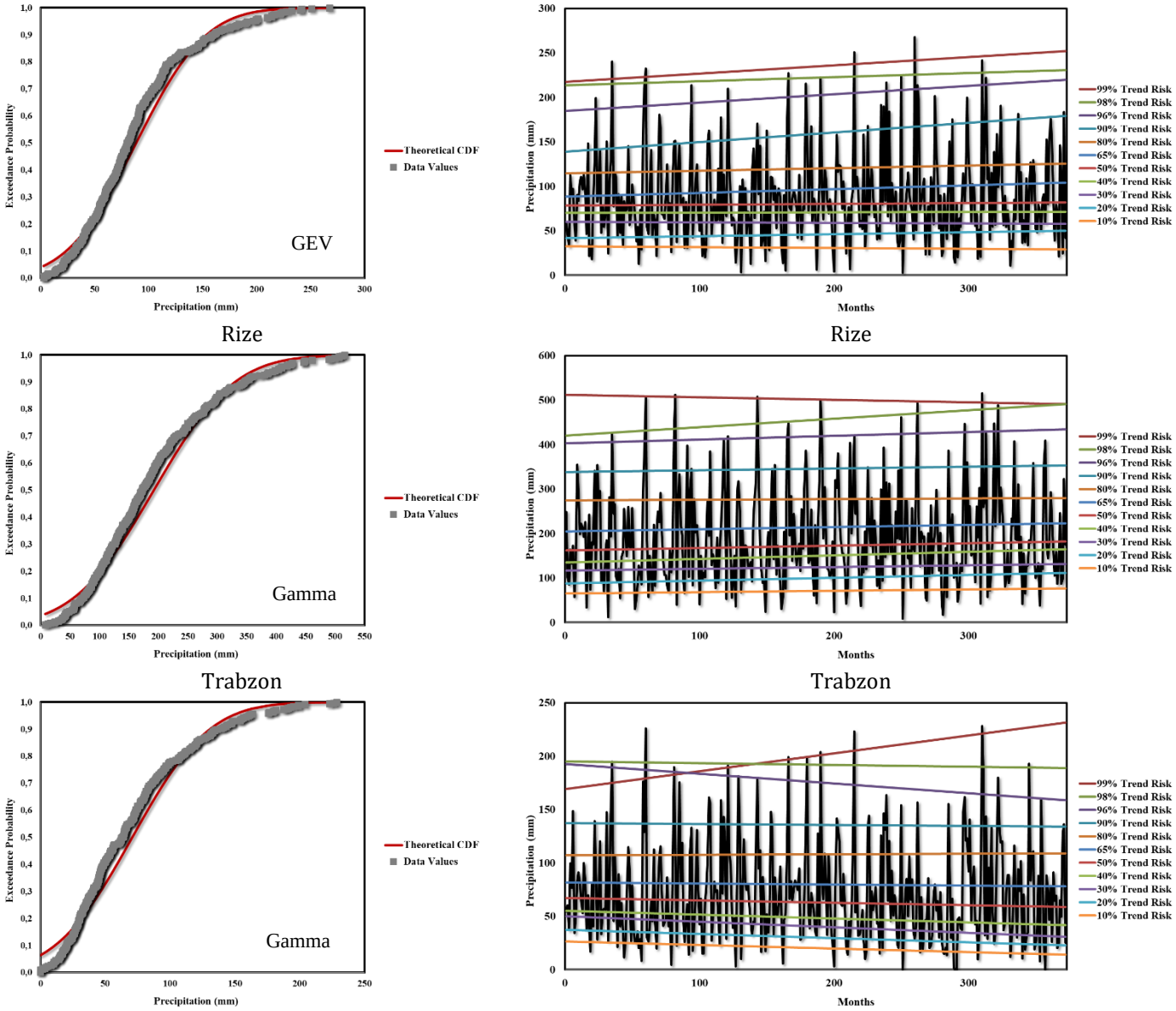



Figure 5. Analysis of precipitation data with CDF method and MRLI.

As illustrated in Figure 5, cumulative distribution functions (CDFs) were constructed for all provincial precipitation stations, and their goodness-of-fit was assessed using the (K–S) test. Within the MRLI framework, five commonly applied theoretical probability distributions—Normal, Log-Normal, Weibull, Gamma, and Generalized Extreme Value (GEV)—were fitted to the precipitation datasets of each station using maximum likelihood estimation. The best-fit model for each location was identified based on the lowest K–S statistic and the highest p-value. The results reveal noteworthy spatial variability in the probabilistic behavior of precipitation across the study area. Specifically, the Log-Normal distribution exhibited the best performance for Artvin, whereas the Weibull distribution provided the closest fit for Gümüşhane. Giresun and Ordu showed more distinct tail behavior, making the GEV distribution the most appropriate choice. Conversely, the Gamma distribution demonstrated excellent agreement with the empirical data at Rize and Trabzon. Overall, these outcomes emphasize that risk-based trend evaluations should consider station-specific distributional characteristics rather than adopting a uniform probability model for the entire region.

Furthermore, an examination of the MRLI analysis results for Artvin Province revealed increasing trends at the 99% and 40% risk levels, while decreasing trends were identified at the remaining risk levels of 10%, 20%, 30%, 50%, 65%, 80%, 90%, 96%, and 98%. For Giresun Province, the analysis indicated increasing trends across all risk levels. In Gümüşhane, decreasing trends were detected at the 10% and 20% risk levels, whereas increasing trends were observed across the remaining nine risk levels. In Ordu Province, decreasing trends were found at the 10% and 30% risk levels, while the remaining nine risk levels exhibited increasing trends. For Rize, the analysis showed a decreasing trend only at the 99% risk level, with increasing trends at all other risk levels. Lastly, in Trabzon Province, increasing trends were identified at the 99% and 80% risk levels, while decreasing trends were observed at the 10%, 20%, 30%, 40%, 50%, 65%, 90%, 96%, and 98% risk levels. Based on the overall assessment of all stations, approximately 65% of the identified

trends exhibit increasing behavior, while 35% indicate decreasing tendencies. Furthermore, the provincial distribution of trend directions, expressed as percentage ratios, is summarized and presented in Figure 6.

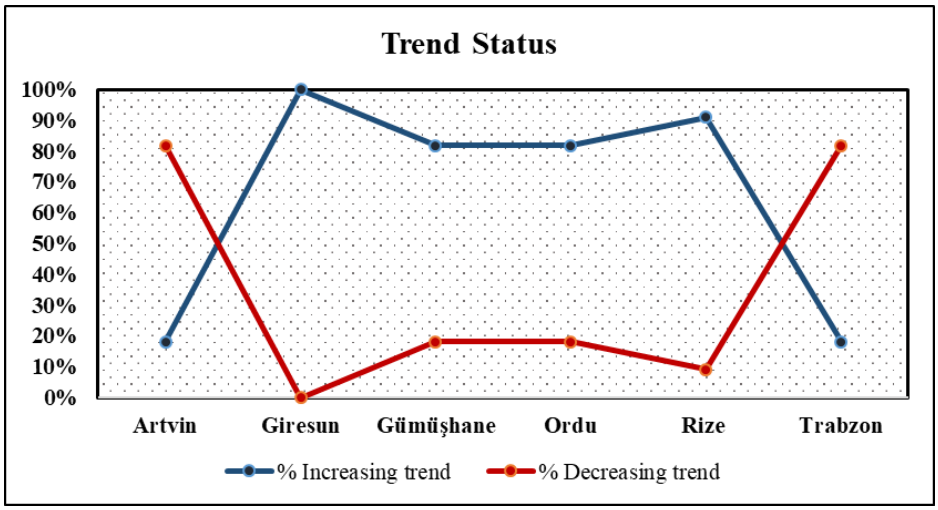
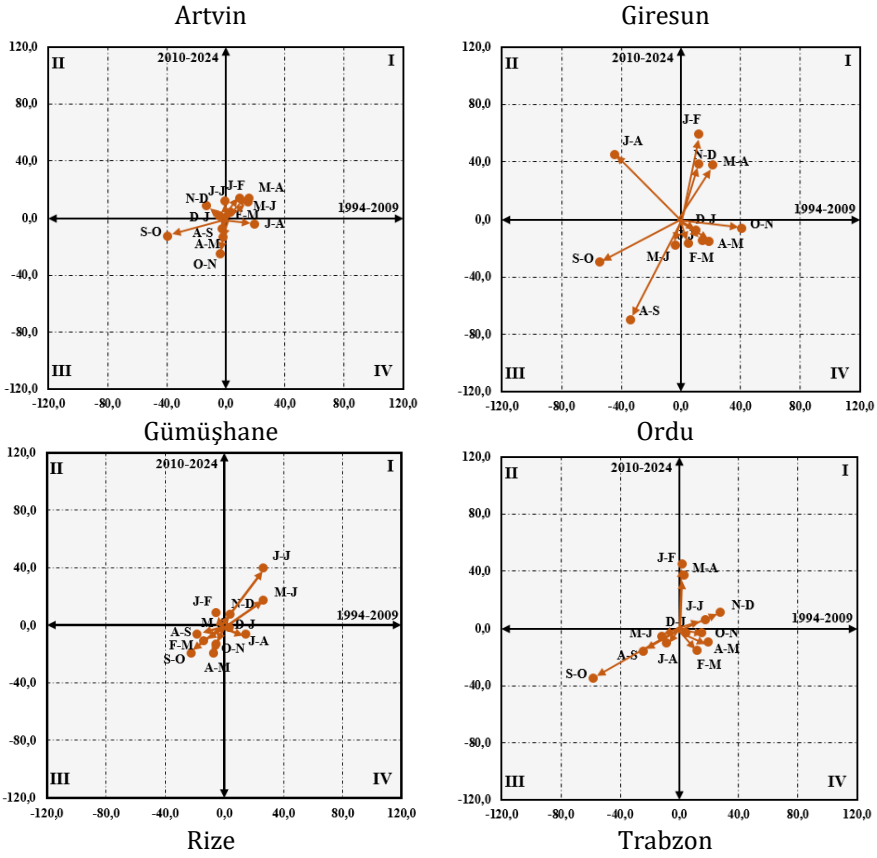



Figure 6. The provincial distribution of trend directions.

Figure 7 presents the results of the (TPSCM) for Artvin, Giresun, Gümüşhane, Ordu, Rize, and Trabzon.



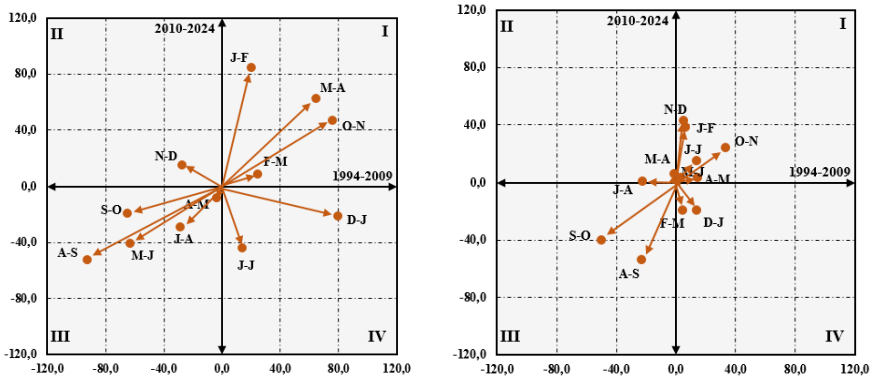



Figure 7. Analysis of precipitation data with TPSCM.

When Figure 7 is examined, it is observed that for Artvin, the monthly precipitation transitions J–F, M–A, J–J, and J–A fall within Region 1, while the transitions M–J, N–D, and D–J fall within Region 2. The transitions A–M, A–S, S–O, and O–N are located in Region 3, and the F–M transition lies within Region 4. For Giresun, the precipitation transitions J–F, M–A, and N–D are situated in Region 1, the transitions between J–A fall within Region 2, the M–J, A–S, and S–O transitions occur in Region 3, and the F–M, A–M, J–J, O–N, and D–J transitions are located in Region 4. For Gümüşhane, the transitions M–J, J–J, and N–D appear in Region 1, while J–F and J–A transitions lie in Region 2. The transitions F–M, M–A, A–M, A–S, and S–O fall within Region 3, and the O–N and D–J transitions are positioned in Region 4. For Ordu, the transitions J–F, M–A, J–J, and N–D are located in Region 1, whereas M–J, J–A, A–S, and S–O fall within Region 3. The transitions F–M, A–M, O–N, and D–J are placed in Region 4. For Rize, the transitions J–F, F–M, M–A, and O–N are found in Region 1, while the N–D transition lies in Region 2. The transitions A–M, M–J, J–A, A–S, and S–O are located in Region 3, and J–J and D–J transitions fall within Region 4. For Trabzon, the transitions J–F, M–A, A–M, J–J, O–N, and N–D occur in Region 1, while M–J and J–A are found in Region 2. The transitions A–S and S–O lie in Region 3, and the transitions F–M and D–J are positioned in Region 4.

These transition patterns, when evaluated collectively, reveal distinct seasonal signals across the provinces of the Eastern Black Sea Basin. Transitions located in Region 1 generally indicate strengthening precipitation from the early to late period, predominantly occurring during winter and early spring (e.g., J–F, F–M, M–A). This pattern reflects the basin's pronounced exposure to cyclonic activity and enhanced moisture transport from the Black Sea during colder months. Region 2 transitions, although less frequent, suggest moderate increases typically associated with late-autumn or early-winter adjustments (e.g., N–D, D–J), capturing early seasonal shifts in atmospheric circulation. Region 3 transitions commonly appear during late spring and summer (e.g., A–S, S–O), signaling changes in the timing or magnitude of convective rainfall as synoptic-scale systems weaken. In contrast, Region 4 transitions represent decreasing precipitation tendencies, often emerging during transitional periods between seasons (e.g., F–M, O–N, D–J), which may indicate evolving storm dynamics, reduced frontal activity, or shifts in seasonal moisture availability. Overall, the spatially varying distribution of transitions suggests that the Eastern Black Sea Basin is experiencing not only long-term changes in precipitation magnitude but also alterations in the timing and seasonal distribution of rainfall, consistent with the region's complex orography and the strong influence of changing Black Sea atmospheric conditions.

The precipitation characteristics of the Eastern Black Sea Basin for the period 1994–2024 were evaluated using both the Multi-Risk Level Identification method and the Trend Polygon Star Concept method, providing a comprehensive assessment of long-term trends and intra-annual variability. The MRLI analysis revealed that precipitation trends across the basin vary considerably among provinces and across risk percentiles. Artvin and Trabzon exhibited mixed behaviors with both increasing and decreasing trends depending on the risk level, while Giresun showed consistently increasing trends across all percentiles. In contrast, Ordu and Gümüşhane demonstrated decreasing trends at lower risk levels but increasing tendencies at most other levels. Rize displayed predominantly increasing trends except at the 99% risk level, where a decreasing tendency was detected. These findings highlight the spatial heterogeneity of precipitation responses within the basin as well as the importance of multi-risk evaluation for understanding long-term hydrological dynamics.

The (TPSCM) further expanded this assessment by revealing clear spatial differences in month-to-month precipitation transitions. For each province, the distribution of transitions across the four quadrants provided insight into seasonal evolution and shifts between the early and late periods of the dataset. While certain months (e.g., J-F, M-A) frequently appeared in the first region across multiple provinces—indicating consistent increases between periods—other transitions (e.g., F-M, D-J) were frequently located in the fourth region, representing decreasing tendencies. Together, the MRLI and star-polygon analyses indicate that the Eastern Black Sea Basin exhibits substantial temporal and seasonal variation, with some stations experiencing intensification of precipitation at specific risk levels or during certain seasonal transitions

Several previous studies conducted in the Eastern Black Sea region have reported mixed or weak precipitation trends due to strong orographic influences and high spatial variability. In contrast, the present analysis demonstrates that more

than half of the stations exhibit an increasing tendency in precipitation, particularly at high-risk percentiles. This finding suggests an intensification of wet conditions, which is consistent with recent observations reporting an increase in short-duration extreme rainfall events along the Black Sea coastal zones. Additionally, while earlier regional assessments predominantly relied on a single non-parametric trend test, the MRLI-based approach applied in this study provides a more detailed perspective by capturing the trend behavior across different risk levels, highlighting localized hydrometeorological changes that may not be detectable through traditional methods. (Koycegiz & Buyukyildiz, 2024).

Although traditional trend detection techniques such as the Mann–Kendall test provide valuable insights into the overall direction of long-term hydrological variability, they are limited to a single aggregated trend estimate and cannot represent how trends change across different portions of the distribution. The MRLI approach complements these classical methods by revealing percentile-dependent, nonlinear, and extreme-value-oriented behaviors that conventional tests may overlook. This risk-sensitive perspective allows for a more comprehensive interpretation of precipitation dynamics, particularly in regions with strong spatial heterogeneity such as the Eastern Black Sea Basin (Şen, 2024).

The combined application of the MRLI and Trend Polygon Star Concept methods provides a multidimensional understanding of precipitation variability in the Eastern Black Sea Basin. The MRLI results emphasize the significance of assessing trends across multiple risk percentiles rather than relying on single-threshold trend evaluations. Provinces such as Artvin and Trabzon, which show contrasting behaviors between high-risk (extreme) and moderate-risk precipitation levels, illustrate the complexity of hydrological responses in mountainous coastal basins. Such behavior could be linked to changes in moisture transport, atmospheric circulation patterns over the Black Sea, or evolving storm dynamics influenced by warming sea-surface temperatures. Giresun's uniformly increasing trend across all risk classes may signal a basin sub-region particularly sensitive to intensified hydrological cycles, potentially increasing the likelihood of floods and landslides (Simsek et al., 2024; Ceribasi et al., 2026).

The (TPSCM) complements these findings by offering insights into how seasonal transitions have evolved over time. The placement of specific month-to-month transitions into regions indicating increasing, decreasing, or changing variability demonstrates shifts in the seasonal distribution of precipitation. Provinces such as Rize and Trabzon, where several transitions fall into regions representing strong inter-period changes, may be experiencing alterations in the timing and intensity of rainfall events—possibly reflecting broader climatic changes in the Eastern Black Sea's humid ecosystem. Such modifications in monthly transitions can affect agricultural planning, hydropower management, and flood preparedness. Both methods collectively highlight that precipitation in the Eastern Black Sea Basin is neither temporally uniform nor spatially consistent. Instead, each province exhibits unique hydrological behavior shaped by local topography, proximity to the coast, and broader climatic influences. Importantly, the combination of risk-based and seasonal-transition analyses provides a more reliable understanding of precipitation trends than traditional linear trend approaches. This dual-method framework can support regional water resource management by identifying areas where extreme precipitation is intensifying, where low-risk precipitation is diminishing, and where seasonal rainfall cycles may be shifting.

## IV. CONCLUSION

This study evaluated long-term and intra-annual precipitation trends in the Eastern Black Sea Basin using the Multi-Risk Level Identification and Trend Polygon Star Concept methods. The MRLI results revealed that precipitation trends exhibit substantial spatial variability across the six provinces, with some stations demonstrating increases across nearly all risk levels and others showing mixed or decreasing tendencies. The Trend Polygon Star Concept analysis further highlighted the temporal complexity of precipitation variability by identifying month-to-month transition patterns and potential shifts in seasonal rainfall cycles.

The combination of these two advanced techniques provided a comprehensive assessment of precipitation dynamics, offering valuable insights for regional water resource management, climate adaptation planning, and hazard mitigation efforts. Given the basin's vulnerability to hydrological hazards such as floods and landslides, understanding precipitation behavior at both risk-based and seasonal scales is essential. The findings demonstrate that climate-related changes are already influencing precipitation patterns in the region, emphasizing the need for continuous monitoring and the integration of such analytical approaches into regional climate resilience strategies.

In summary, the MRLI-based assessment indicated that approximately 65% of the stations exhibited increasing precipitation trends, while 35% showed decreasing tendencies, highlighting a general intensification of wet conditions in the basin. These spatially heterogeneous patterns, combined with the seasonal transition insights revealed by the TPSCM analysis, underscore the complex hydrological response of the basin to evolving climatic influences. Although the limited number of stations may constrain full spatial representation, the combined use of MRLI and TPSCM offers high-resolution diagnostic capability for identifying risk-based and intra-annual changes. This dual-method framework has strong potential for broader hydrometeorological applications and can support future climate impact assessments, regional water management planning, and hazard mitigation strategies.

## DECLARATIONS

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**Author Contributions:** A.I.C.; "All parts of the study were conducted by the Author.

**Conflict of Interest:** The author declare no conflict of interest.

**Supporting Institutions:** This research received no external funding.

**Ethical Approval:** This study does not involve human or animal participants. All procedures followed scientific and ethical principles, and all referenced studies are appropriately cited.

**Plagiarism Statement:** This article has been evaluated for plagiarism and no instances of plagiarism were detected.

**Data Availability**: Data sharing is not applicable to this study.

**Use of AI Tools:** The author/authors declare that no Artificial Intelligence (AI) tools were used in the creation of this article.

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