

Article

Temperature Extremes and Topographic Complexity: Validation, Correction, and Spatial Trends of Temperature Indices in Northern Carpathian (1980–2024)

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Abstract

While global climate change is fundamentally reshaping thermal regimes, capturing these shifts in topographically diverse regions remains a significant hurdle for standard gridded datasets. This study provides a comprehensive spatiotemporal analysis of 16 extreme temperature indices across Northern Carpathian from 1980 to 2024 using the E-OBS dataset. The QDM framework proved highly effective in neutralizing elevation-induced temperature biases, which reached up to 5.1 °C in raw E-OBS data. Beyond simple bias removal, the correction significantly improved the daily accuracy of the dataset, with RMSE values at high-altitude stations, such as the Chopok summit (1995 m), decreasing from 5.1 °C to 2.3 °C. Both Warm Days (TX90p) and Summer Days (SU) show near-perfect Field Coherence ($C_f = 100\%$ and 98% , respectively). A prominent feature of this temporal national average trend is its inherent asymmetry; the Annual Minimum (TNn) is climbing nearly twice as fast ($+1.1$ °C/decade) as the Annual Maximum (TXx) ($+0.6$ °C/decade), though the warming of these coldest nights is more localized (74.5% coherence). We also identified a clear signal of Elevation-Dependent Warming (EDW), with absolute maximums surging most aggressively in the Northern Carpathians at $+1.6$ °C/decade. Conversely, cold-tail indices like Ice Days are in a concurrent nationwide retreat ($C_f = 97\%$), a shift that significantly reduces the physical window for winter tourism and alters the climatic envelope for fragile mountain ecosystems. Ultimately, these results position Slovakia as a high-sensitivity climate region where observed trends often outpace broader Central European averages, highlighting the urgent need for localized, nature-based adaptation strategies.

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1. Introduction

The Earth's thermal regime is being drastically changed by anthropogenic climate change, which is mostly caused by greenhouse gas (GHG) emissions since the Industrial Revolution and became much more intense after 1950 [1]. Global temperatures are chang-

ing, and the frequency, duration, and intensity of extreme heat events are increasing non-linearly [2,3]. The most direct and serious risks to human health, agricultural productivity, and ecosystem stability are frequently posed by changes in the tails of the temperature distribution, such as extreme heat and cold events [4–7].

Due to its complicated topography, Slovakia, which is located in a moderate transitional climate zone in Central Europe, is extremely vulnerable to these global trends [8,9]. The orography of the area, which is dominated by the Western Carpathians, produces unique local microclimates that considerably alter regional warming signals. With mean air temperatures rising by about 2 °C in both the cold and warm half-years since 1981, observational data support the region's accelerating warming trend [8,9]. Warm extremes like Tropical Days ($T_{MAX} \geq 30$ °C) and Supertropical Days ($T_{MAX} \geq 35$ °C) are sharply increasing due to this warming, while cold extremes like Frost Days and Ice Days are decreasing [9]. Extreme heat is the most common climate hazard in the area, according to recent studies that indicate the hot tail of the temperature distribution is warming faster than changes in the cold tail [10,11].

While regional gridded datasets like E-OBS or CARPATCLIM provide essential continuous spatial fields, their resolution often fails to capture the localized extremes inherent to topographically diverse regions [12,13]. In the Western Carpathians, these products frequently smooth out critical orographic effects and complex lapse rates, leading to systematic elevation-induced biases [13]. Furthermore, existing research in Slovakia has often relied on simple mean temperatures, leaving a significant gap in the national-scale analysis of full ETCCDI that can statistically differentiate between duration-based, threshold-specific, and percentile-based extremes while accounting for temporal nonstationary across a broad altitudinal gradient [9,14]. This study addresses these gaps by offering a comprehensive spatiotemporal analysis of 16 standardized temperature extreme indices across Slovakia for the period 1980–2024. The specific scientific contribution of this work lies in the application of the Quantile Delta Mapping (QDM) framework, which effectively un-smooths gridded data by neutralizing systematic offsets while preserving the underlying climate change signal. By anchoring the E-OBS dataset to 13 high-precision meteorological stations spanning 98 m to 1995 m altitudinal gradients, this study provides the first statistically robust evidence of Elevation-Dependent Warming (EDW) and Field Coherence (C_f) at the national level.

The specific goals of this study are to: (1) Use Quantile Delta Mapping (QDM) to mitigate elevation-induced biases and assess the E-OBS high-resolution gridded dataset's performance against 13 meteorological stations covering a varied altitudinal gradient (98 m to 1995 m a.s.l.). (2) Measure long-term monotonic trends in ETCCDI, use Sen's Slope Estimator and the non-parametric Mann–Kendall test. (3) Determine which geographic regions are experiencing the fastest intensification of thermal extremes using geostatistical interpolation. This will provide a solid basis for proactive adaptation strategies in public health, agriculture, and water management.

2. Data and Methodology

2.1. Study Area

Slovakia, located in Central Europe (Figure 1), represents a significant area for climatic research because of its complex topography and its position within a moderate transitional climate zone. The Northern Carpathian Mountains, which dominate the northern and western regions, generate distinct local microclimates that substantially influence regional warming signals [9]. The country exhibits a broad altitudinal range, from 94 m above sea level in the southern lowlands to 2655 m at the highest mountain peaks. Approximately 60% of Slovakia's territory is situated above 300 m, while only 5.4% lies above

1000 m, rendering the region particularly sensitive to elevation-dependent climatic changes [15].

According to Konček and Petrovič's climate classification, the country is divided into three main regions (warm, moderately warm, and cold) based on temperature thresholds and moisture indices [16]. The warm region, mainly in the Danubian and Eastern Slovak Lowlands, is defined by at least 50 Summer Days per year with maximum temperatures of 25 °C or higher [17]. In contrast, high-altitude areas such as the High Tatras have a continental Dfc climate type, with cold, wet conditions and July temperatures below 16 °C [18]. Since 1981, Slovakia has experienced a significant warming trend, with mean air temperatures rising by about 2.0 °C [9]. Warming in this region is occurring at roughly twice the global average rate [19]. This change is evident in the sharp increase in extreme heat indicators, including Tropical Days, Supertropical Days, and Tropical Nights [20]. At the same time, cold indicators such as Frost and Ice Days are declining. These changing thermal patterns have significant effects on biodiversity, agriculture, and hydrological cycles, especially as the warm climate zone expands into colder mountainous basins [17].

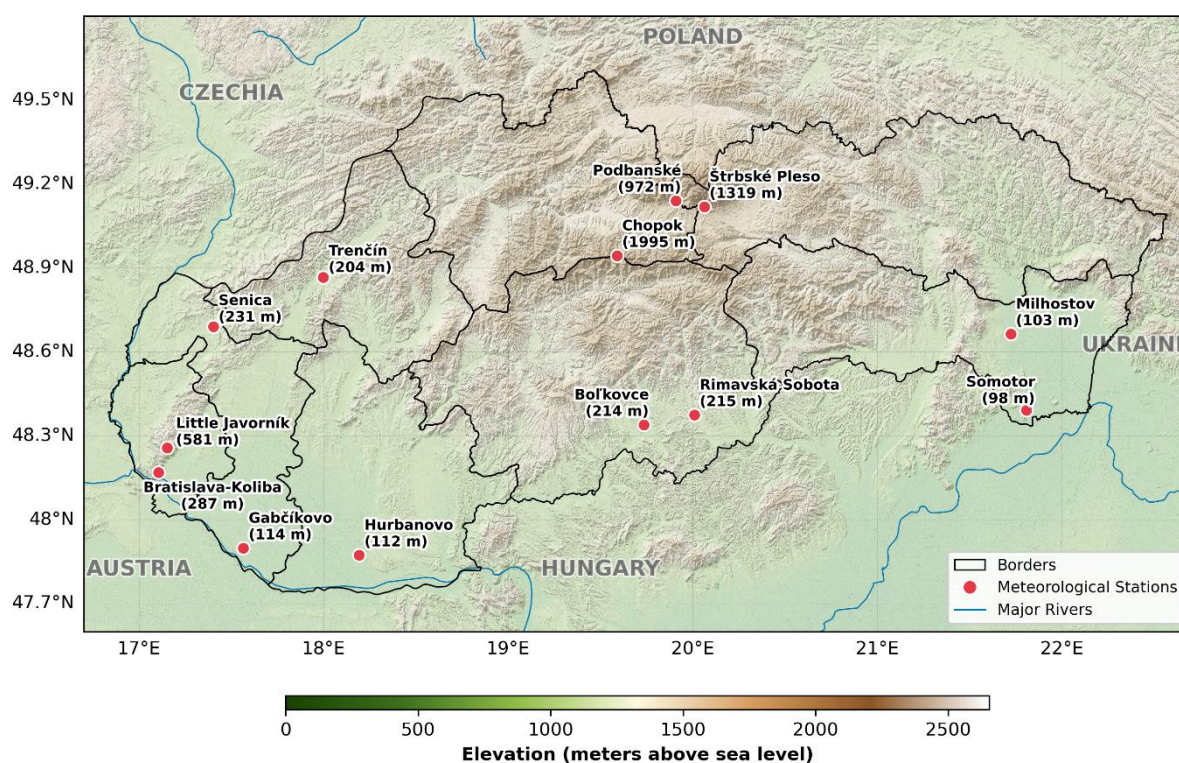


Figure 1. Topographic distribution of the 13 meteorological stations in Slovakia. The background represents elevation in meters above sea level (SRTM30 data) [21], and administrative boundaries from GADM, highlighting the complex Carpathian orography. Stations were selected to cover a vertical gradient from 98 m to 1995 m a.s.l. to anchor the 10 km E-OBS gridded dataset.

2.2. Data Sources

A dual-source data framework serves as the foundation for the spatiotemporal evaluation of temperature extremes in Slovakia (1980–2024). The European Climate Assessment and Dataset produced the E-OBS high-resolution gridded dataset (version 31.0e), which serves as the primary spatial field. The 0.1° regular grid (~11 km resolution), which provides daily maximum (TMAX) and minimum (TMIN) surface air temperatures, is used in this study [22]. High-precision records from 13 major weather stations (Table S1) supplied by the Slovak Hydrometeorological Institute (SHMU) were combined to act as the observed truth and anchor the gridded data. These stations ensure accurate representation

of the complex orographic effects and adiabatic lapse rates of the Western Carpathians, spanning a critical altitudinal gradient from 98 m a.s.l. (Somotor) to 1995 m a.s.l. (Chopok).

2.3. Calculation of Standardized Climate Indices

The xclim library [23] was used to calculate a suite of 16 climate indices to measure changes in thermal extremes and assess the effect of the bias correction on climatic trends. The Expert Team on Climate Change Detection and Indices (ETCCDI) established international standards that serve as the foundation for these indices [24]. The indices were calculated for the 1980–2024 period for both the original and the bias-corrected E-OBS datasets. The indices are divided into four groups: percentile-based, absolute, threshold-based, and duration-based (Table S2). Percentile-based indices (TX90p, TX10p, TN90p, and TN10p) describe relative extremes by comparing daily temperatures to the 10th and 90th percentiles (P10 and P90) of the 1981–2010 base period. Absolute indices, including TXx, TXn, TNx, and TNn, were utilized to investigate magnitude extremes. Threshold-based indices utilize fixed physical and biological thresholds (SU, TR, FD and ID). Notably, while analyzed alongside standard ETCCDI metrics, three specific indicators, Tropical Days (TD30), Supertropical Days (STD35), and Summer Nights (SN15), are implemented based on the regionally refined definitions of Lapin et al. [9]. In this study, TD30 and STD35 are measured as the annual count of days where TMAX is ≥ 30 °C and 35 °C respectively. SN15 is calculated as the annual count of days where the daily minimum temperature (TMIN ≥ 15 °C) and it serves as a critical indicator for tracking the expansion of the warm climate zone into topographically complex areas, as Summer Nights have become increasingly frequent in the mountains and valleys of northern Slovakia [9]. While the original regional definition by Lapin et al. [9] utilizes a specific nocturnal minimum window (21:00–07:00 h) to avoid distortions from morning cold fronts, this study employs the standard 24 h daily minimum to maintain methodological consistency with the E-OBS gridded framework. Finally, the Diurnal Temperature Range (DTR) was analyzed as the duration-based index. The comparison between datasets quantifies the impact of systematic interpolation errors and is detailed in Section 2.5.

2.4. Validation Metrics: MB and RMSE

Mean Bias (MB) and Root Mean Square Error (RMSE) are used to measure the degree of deviation between the E-OBS data and the station data. The average overestimation or underestimation of the model is represented by MB (Equation (1)). The E-OBS is too warm or wet if the MB is positive, and too cold or dry if the MB is negative. Large outliers are given more weight by RMSE (Equation (2)), which calculates the average magnitude of the error. RMSE is always positive, in contrast to MB. A lesser RMSE reveals that the gridded data directly tracks the everyday changeability of the station.

$$MB = \frac{1}{n} \sum_{i=1}^n (P_i - O_i) \quad (1)$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (P_i - O_i)^2} \quad (2)$$

where P_i = Gridded value (E-OBS), O_i = Observed value (Station).

2.5. Quantile Delta Mapping (QDM) Framework

Gridded observational products like E-OBS, while essential for regional climate studies, often contain systematic biases due to the spatial interpolation of sparse station networks particularly in topographically complex areas. Calculating climate indices directly from such data can lead to inaccurate representations of frequency and intensity for extreme events. We employ the Quantile Delta Mapping (QDM) framework to mitigate

these interpolation artifacts, ensuring that the gridded data aligns with ground-truth observations while preserving the underlying climate trends.

Standard Quantile Mapping (QM) corrects biases based on historical distributions but frequently distorts climate change signals in future projections [25,26]. To address this, Quantile Delta Mapping (QDM) was developed to preserve relative or absolute changes across all quantiles [27,28]. To correct systematic biases in the E-OBS gridded temperature data against local station observations, we employed the Quantile Delta Mapping (QDM) approach. QDM is preferred over standard Quantile Mapping because it preserves the trend in the E-OBS while correcting distributional biases. The process was implemented for the 1980–2024 period through the following steps:

- (1) Station observations were paired with the nearest E-OBS grid cell using nearest-neighbor extraction.
- (2) The QDM procedure was implemented independently for each variable (TMAX and TMIN) and each of the 13 meteorological stations
- (3) To account for the seasonal cycle of temperature bias, the QDM process was performed independently for each month. This ensures that the transfer function captures month-specific biases.
- (4) We defined the empirical cumulative distribution functions (CDFs) for both the observed station data and the E-OBS model data using 100 empirical quantiles ($n = 100$), which allows for a precise characterization of the temperature distribution shape, including the extreme tails, while maintaining stability against random noise.
- (5) For each month and quantile, the correction was calculated by mapping the E-OBS value to the observed distribution using the formulation (Equation (3)):

$$\hat{x}_m(t) = F_{o,h}^{-1}(F_{m,h}(x_{m,p}(t))) + (x_{m,p}(t) - F_{m,h}^{-1}(F_{m,h}(x_{m,p}(t)))) \quad (3)$$

where $\hat{x}_m(t)$ is the bias-corrected temperature value at time t , $x_{m,p}(t)$ is the raw E-OBS dataset, $F_{m,h}$ is the CDFs of the raw E-OBS dataset, and $F_{o,h}^{-1}$ is the inverse CDF of the 13 meteorological stations. Also, the term $(x_{m,p}(t) - F_{m,h}^{-1}(F_{m,h}(x_{m,p}(t))))$ is the relative change (delta) calculated between E-OBS current value and its own historical quantile. The transfer function was derived using the 1981–2010 climate normal period as the baseline. The resulting bias-correction parameters were then applied to the entire 1980–2024 period, ensuring consistency across the multi-decadal record.

The spatial interpolation of these residuals was performed using Inverse Distance Weighting (IDW) with a power parameter of $p = 2$ [29] (Equation (4)). This approach was chosen to ensure that the high-precision station data directly influenced the correction of the nearest 10 km grid cells. While the number of stations is limited to 13, their broad altitudinal range (98 m to 1995 m) ensures that the correction captures the primary source of error in the E-OBS dataset, which is the smoothing of extreme temperature contrasts across the Carpathian vertical gradient.

$$T_{corr}(i, j, t) = T_{obs}(i, j, t) + \Delta Bias_{month}(i, j) \quad (4)$$

where $T_{corr}(i, j, t)$ is the corrected daily temperature value (either TMAX or TMIN) for a specific grid cell at spatial coordinates (i, j) and time t , $T_{obs}(i, j, t)$ is the original observed temperature from the E-OBS dataset at the same grid cell (i, j) and time t , and $\Delta Bias_{month}(i, j)$ is the interpolated monthly bias-correction field at grid cell (i, j) .

The primary difference between the original and bias-corrected datasets lies in the distribution of temperature extremes. While the original E-OBS tends to exhibit a compressed probability distribution, an inherent effect of spatial smoothing, the bias-corrected data effectively recovers the variance and intensity of local extremes. By adjusting the cumulative distribution function (CDF) through the QDM approach, this dataset provides a more physically consistent basis for the temperature indices calculated in Section 2.3.

2.6. Statistical Trend Analysis: Mann–Kendall and Sen’s Slope

Monotonic trends in temperature extreme indices are evaluated using the non-parametric Mann–Kendall (MK) test [30,31], which is robust to outliers and does not require normality in the data. The MK test compares the null hypothesis of no trend (H_0) with the alternative hypothesis of a monotonic trend (H_1). The test statistic S (Equation (5)) is calculated based on the number of years (n) and index values (X).

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^n \text{sgn}(X_j - X_i) \quad (5)$$

The magnitude of change is estimated using Sen’s Slope Estimator [32], which is the median of the slopes between all pairs of data points (Equation (6)).

$$\beta = \text{median}(Q_k), \text{ where } Q_k = \frac{x_j - x_i}{j - i} \text{ for all } 1 \leq i < j \leq n \quad (6)$$

2.7. Coherence and Hotspot Identification

To assess regional consistency, Field Coherence (C_f) distinguishes between localized variability and unified regional shifts. The indicator function (I_i) is determined via a Mann–Kendall trend test, where $I_i = 1$ if the calculated p -value is < 0.05 , and $I_i = 0$ otherwise. The Field Coherence (C_f) is then the ratio of cells satisfying this significance criterion to the total number of grid cells (M) in the study area (Equation (7)). Physically, a value approaching 100% indicates that the observed trend is driven by large-scale atmospheric forcings such as the North Atlantic Oscillation or global warming, while a low value suggests local factors like land use or microclimates are more influential [33,34].

$$C_f = \left(\frac{\sum_{i=1}^M I_i}{M} \right) \quad (7)$$

Hotspot identification (Equation (8)) focuses on locating areas where changes are happening most quickly. To do this, the distribution of Sen’s Slope values (β) is examined across all grid cells. Each grid cell is then compared with the overall national distribution. If the slope value of a grid cell (i) falls within the highest 10% of all calculated slopes, that cell is classified as a Hotspot (H_i) [35].

$$H_i = \{\beta_i | \beta_i \geq P_{90}(\beta)\} \quad (8)$$

2.8. Methodological Limitations and Uncertainty

Despite the robustness of the QDM-IDW framework, several limitations must be acknowledged. First, the use of 13 meteorological stations to correct a nationwide 0.1° grid introduces spatial uncertainty, particularly in remote mountain massifs located far from the anchor stations. While the altitudinal representation is strong, and the stations meet climate station location standards, microclimates may not be fully captured within the grid cells between stations. Second, IDW interpolation assumes a smooth transition of biases, which may over-simplify the complex thermal topography of the Northern Carpathians during extreme events.

3. Results

3.1. Analysis of Systematic Bias and Elevation Dependency

An initial look at the bias original column shows a clear link between elevation and the accuracy of the E-OBS dataset (Table S3). Stations at higher elevations experience the largest systematic errors, with original biases reaching up to $+4.4^\circ\text{C}$ for TMAX at Chopok station (Figure 2a). For minimum temperature at Štrbské Pleso and Podbanské the bias was recorded about 5.1°C (Figure 2b). These differences suggest that the gridded interpolation used in E-OBS has difficulty capturing the complex lapse rates and local micro-

climates typical of the Tatra Mountains. In contrast, stations in lower-lying areas like Hurbanovo (112 m) and Boľkovce (214 m) show almost no original bias (around 0.1 °C), indicating that the gridded dataset represents flatter terrain much more accurately.

Applying Quantile Delta Mapping (QDM) largely removed the systematic Mean Bias across all stations and variables. The results show a consistent decrease in RMSE across the stations (Figure 3a,c), although the degree of improvement varies depending on location. The largest improvements appear at high-elevation sites. After the correction, the bias-corrected values for both TMAX and TMIN at the 13 stations were reduced to values very close to zero (Figure 3b,d). For example, at Podbanské, the bias decreased from −5.0 °C to −0.01 °C. Similarly, at Chopok, the bias was reduced from +2.0 °C to 0.0 °C. At the high-altitude station Chopok, the RMSE for TMAX dropped from 5.1 °C to 2.3 °C after correction. In contrast, stations in lower-lying areas show only minor changes. At Hurbanovo, the RMSE decreased slightly by about 0.01 °C. This small difference suggests that the original E-OBS dataset was already capturing the day-to-day temperature variability quite well in flatter terrain. These results show that QDM successfully adjusts the gridded data so that its meaning closely matches the station observations, which is an essential requirement when analyzing climate trends at the local scale. The validation of the bias-corrected E-OBS dataset shows a clear improvement in how regional temperature patterns are represented across Slovakia. In winter (illustrated by conditions on 15 January 2010 (Figure S1), the original E-OBS TMAX field covered a relatively narrow range, from −7.6 °C to 4.7 °C. After applying the correction factors, this range shifted to −5.1 °C to 4.5 °C. The spatial difference between the original and corrected fields reached about 6.0 °C (from −2.7 to +3.3 °C). This pattern indicates that the raw dataset contained a noticeable cold bias in high-elevation areas during winter. The correction process reduced this problem by warming the mountain grid cells, so they better matched the station observations.

Even stronger adjustments appeared in summer, particularly for TMAX on 15 July 2010 (Figure S3). Here, the difference between the original and corrected datasets reached a maximum span of 11.1 °C, with corrections ranging from −5.0 to +6.1 °C. Such large adjustments suggest that the 10 km × 10 km E-OBS grid struggles to capture intense local heating in the lowlands while also smoothing temperatures too much at higher elevations. By applying corrections of up to 6.1 °C, the hybrid approach restored the strong temperature contrast between the Danubian Lowlands and the peaks of the High Tatras.

Unlike the large adjustments observed for TMAX, the corrections applied to TMIN were generally more moderate throughout the year. In both autumn and spring (Figures S2 and S4), the differences between the original and corrected TMIN fields typically ranged from about −2.3 °C to +3.2 °C. This pattern suggests that systematic errors in the E-OBS minimum temperature data are less strongly influenced by topography than those affecting TMAX. The spring transition period provides a good example of how the correction improves the dataset. On 15 April 2010, the adjustment shifted the lower bound of the TMAX distribution from a positive 2.0 °C to −0.9 °C. This change is particularly important for studies of frost–thaw cycles and snowmelt processes, since it ensures that the critical 0 °C threshold is realistically represented in high-elevation areas of the Carpathian Mountains.

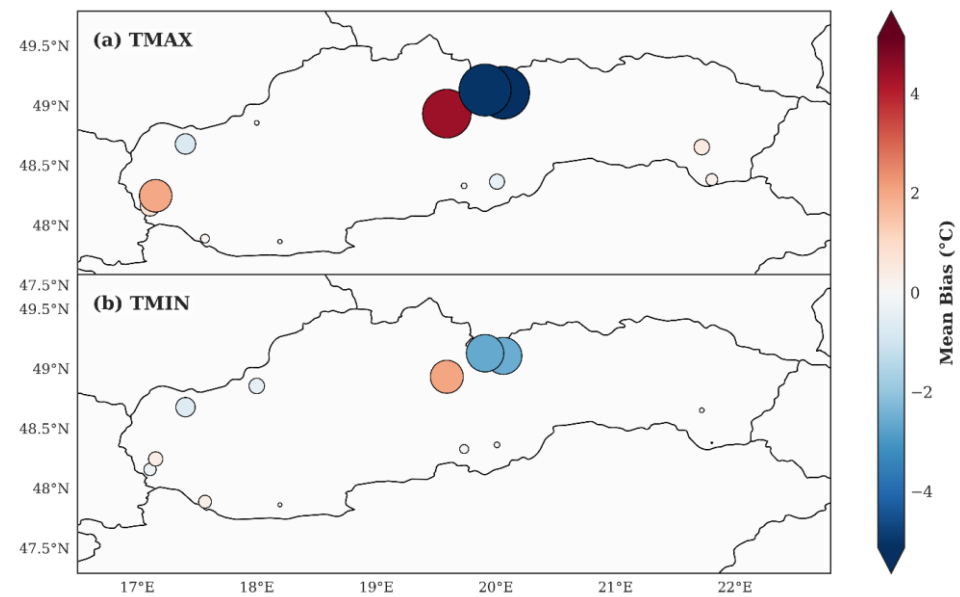


Figure 2. Spatial Mean Bias for the 13 weather stations across the study area for (a) maximum temperature and (b) minimum temperature. The radius of each circle is proportional to the absolute magnitude of the Mean Bias (MB) in °C.

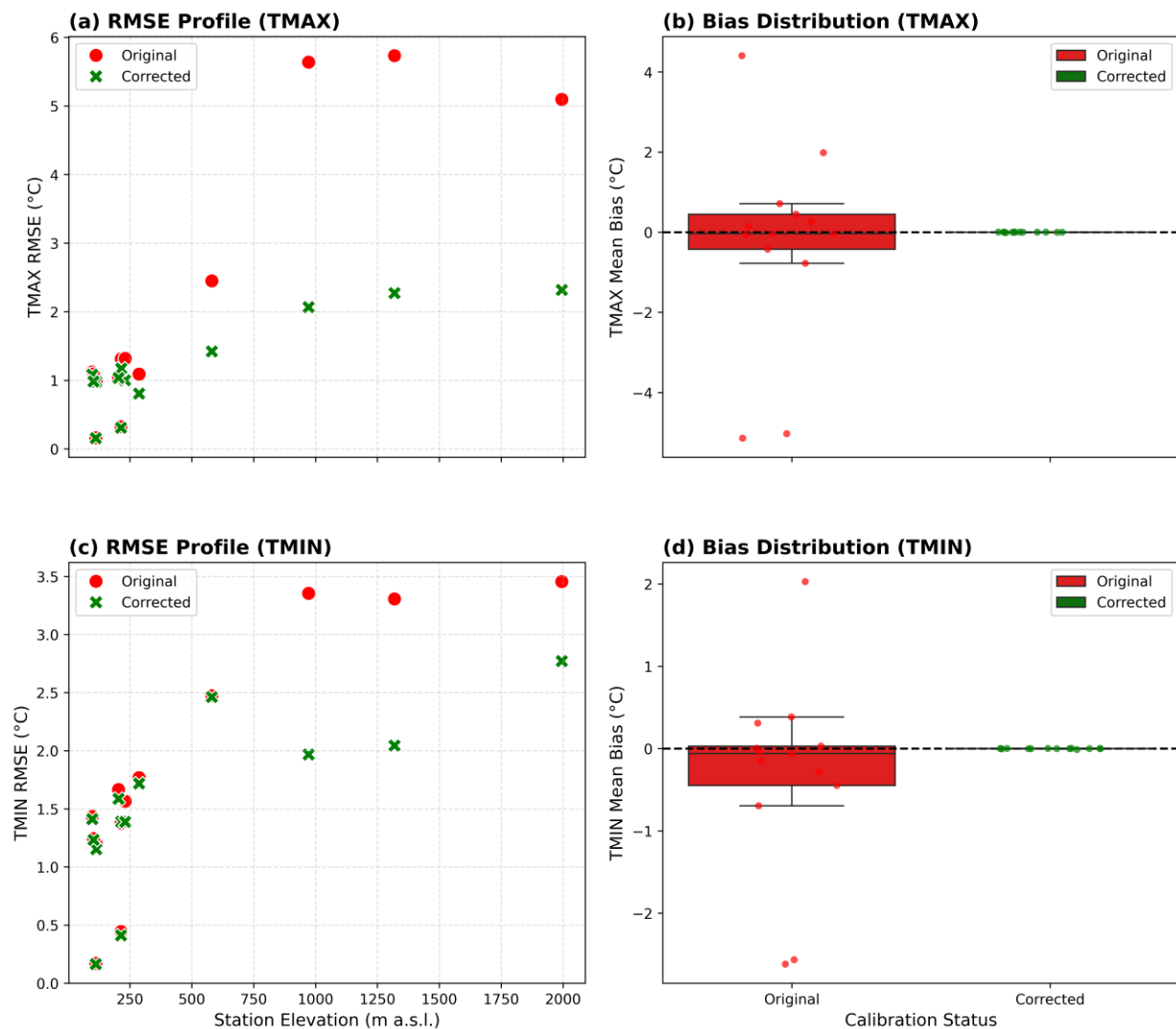


Figure 3. Comparative error profiles for TMAX (a,b) and TMIN (c,d) before and after QDM correction. Plots (a,c) show the RMSE regarding station elevation. Plots (b,d) display the Mean Bias (MB) distribution.

3.2. Temporal Trend Analysis

The Mann–Kendall trend analysis for 1980–2024 reveals a clear and statistically robust warming signal across Slovakia (Figures 4–7), and these represent the trends of the national average time series. To quantify the impact of the QDM bias correction on these signals, we compared the Sen’s slopes for the 16 analyzed indices (Table 1). While the correction largely preserved the trends of percentile-based indices, more significant adjustments occurred in threshold-based indices where the raw gridded data frequently smoothed out extreme values. Overall, the results point to a steady rise in heat-related extremes, accompanied by a consistent decline in cold events (Table S4). The strongest signals emerge from the percentile-based indices (Figure 4). The frequencies of Warm Days (TX90p) and Warm Nights (TN90p) increase by about 11.7% and 10.7% per decade, respectively. At the same time, cold-related indices show a steady decline, with Cool Days (TX10p) and Cool Nights (TN10p) decreasing by around 7–8% per decade.

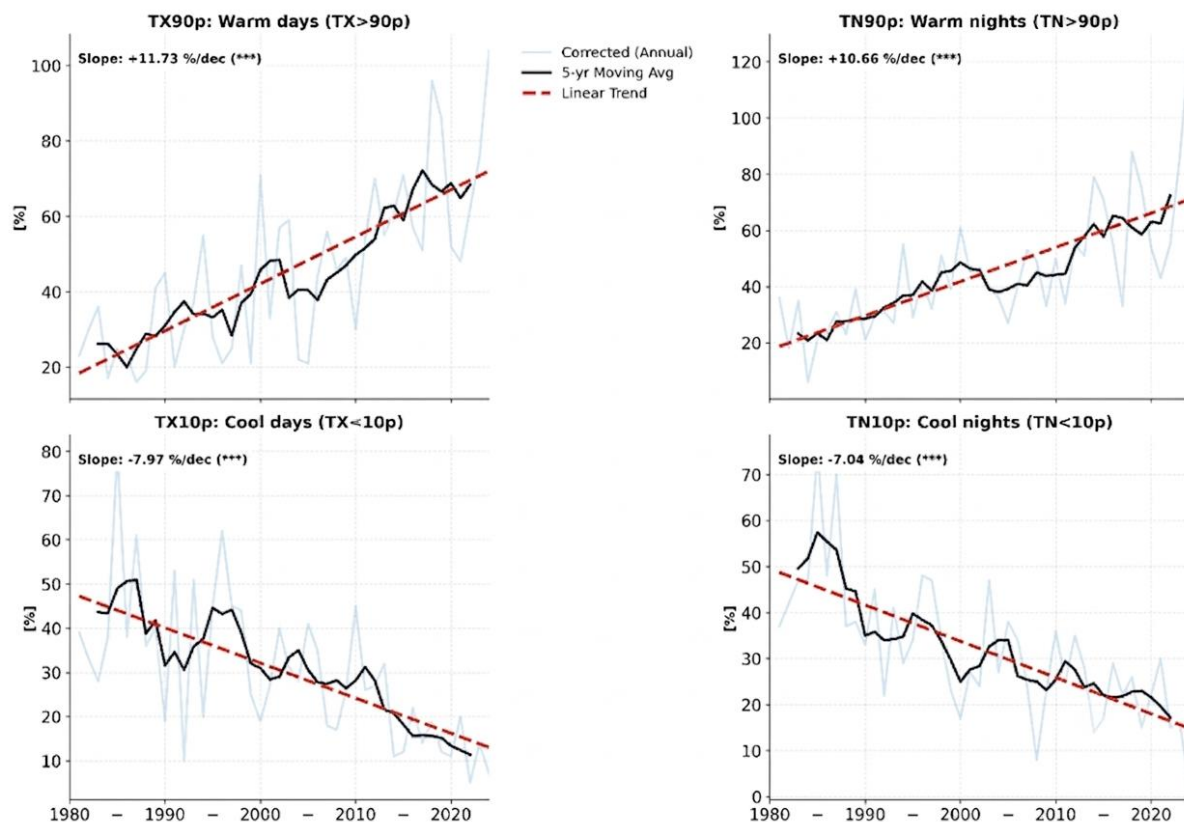


Figure 4. Corrected and original Temporal trend (%/decade) of percentile indices (TX90p, TN90p, TX10p and TN10p). Statistical significance is indicated by asterisks: *** $p < 0.001$.

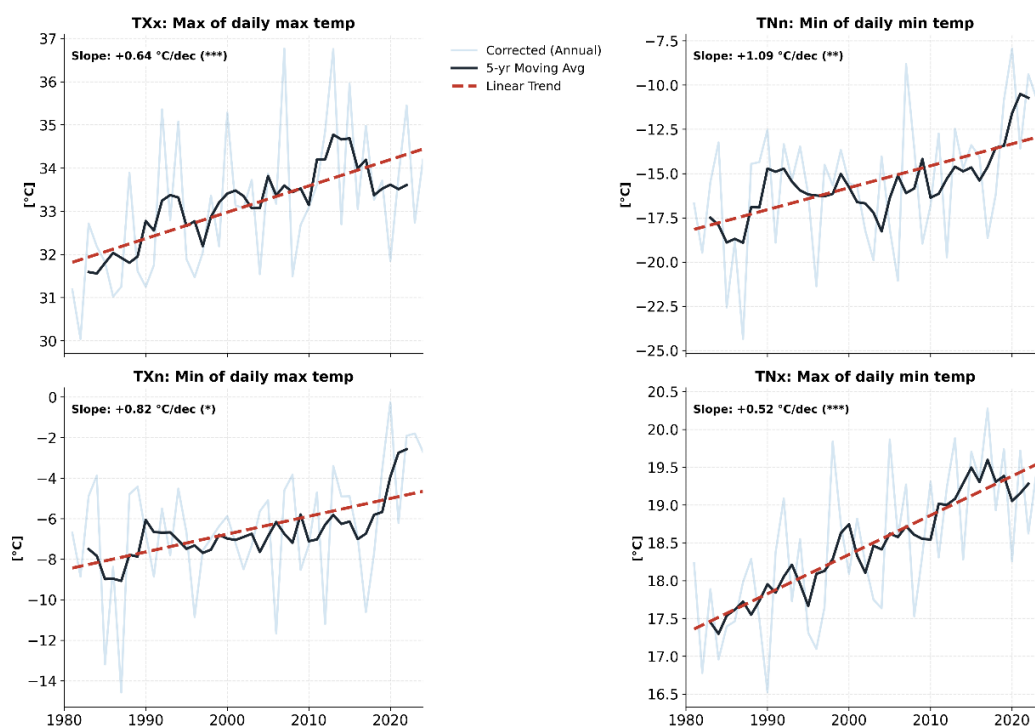


Figure 5. Corrected and original Temporal trend ($^{\circ}\text{C}/\text{decade}$) of absolute indices (TXx, TNx, TXn and TNn). Statistical significance is indicated by asterisks: * $p < 0.05$, ** $p < 0.01$ and *** $p < 0.001$.

Changes in absolute temperature extremes (Figure 5) further reinforce this warming signal. Both TXx (Annual Maximum temperature) and TNn (Annual Minimum temperature) show significant upward trends. Notably, after correction, TNn is increasing at 1.1°C per decade ($p < 0.01$), indicating that the coldest conditions are warming nearly twice as fast as the Annual Maximums (TXx at $0.6^{\circ}\text{C}/\text{decade}$). Meanwhile, the Diurnal Temperature Range (DTR) shows a modest but significant increase of about 0.17°C per decade.

The most significant quantitative impact of the bias correction is observed in the threshold-based indices (Figure 6 and Table 1). Notably, the frequency of Summer Nights (SN15) showed the largest correction-induced shift, increasing from $+6.9$ to $+7.6$ days/decade (a difference of $+0.69$). Similarly, Tropical Days (TD30) increased by $+0.3$ days/decade following correction. For cold-related extremes, the correction adjusted the Frost Day (FD) trend from -7.0 to -6.6 days/decade (a difference of $+0.47$). These shifts demonstrate that the hybrid QDM-IDW approach successfully restores the intensity of local thermal shifts in complex terrain that were previously underrepresented due to the smoothing effects of the 10 km raw grid. While Tropical Nights (TR) and the extreme heat index Supertropical Days (STD35) exhibit non-statistically significant trends at the national scale, the significant upward trends in TD30, SN15, and DTR suggest an escalating heat risk for the coming decades, particularly in the lowlands and mountain basins.

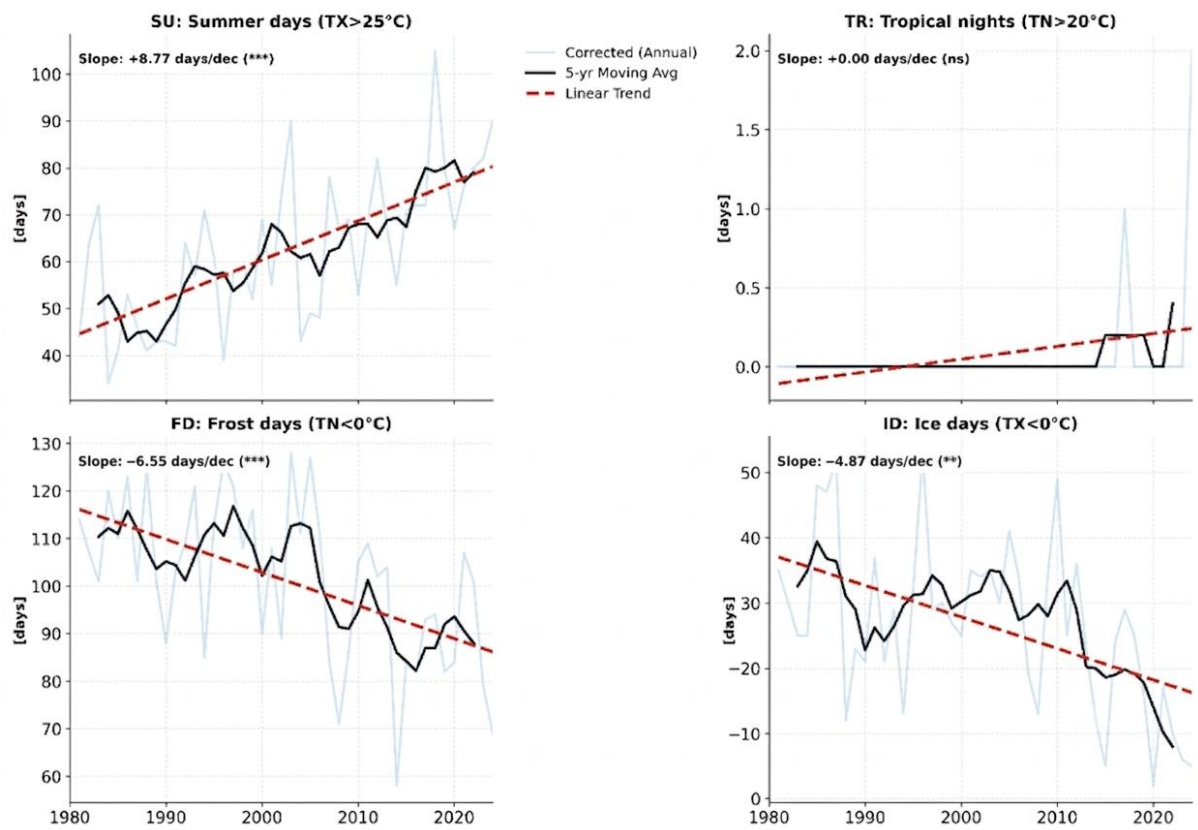


Figure 6. Corrected and original Temporal trend (day/decade) of standard indices (SU, TR, FD and ID). Statistical significance is indicated by asterisks: ** $p < 0.01$, *** $p < 0.001$, and (ns) indicates non-significance ($p \geq 0.05$).

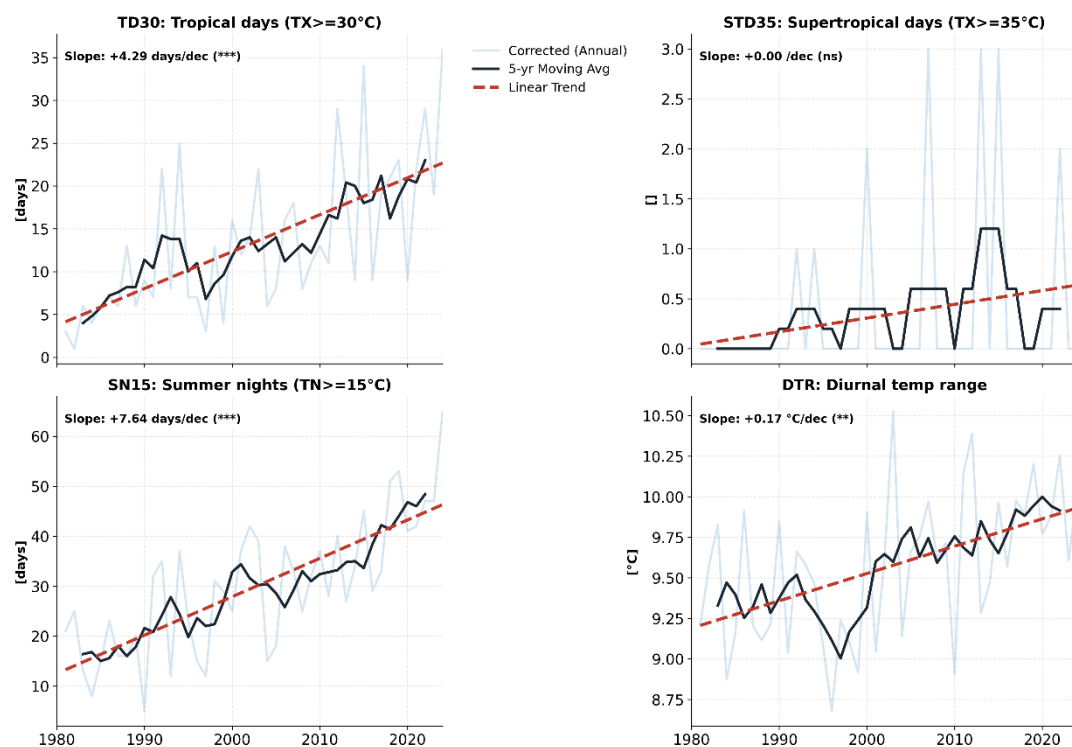


Figure 7. Corrected and original Temporal trend (day/decade) of tropical indices (TD30, STD35 and SN15), while trend (°C/decade) for DTR). Statistical significance is indicated by asterisks: ** $p < 0.01$, *** $p < 0.001$, and (ns) indicates non-significance ($p \geq 0.05$).

Table 1. Comparison of decadal trends (Sen’s slopes) for 16 temperature extreme indices before (Original) and after (Corrected) QDM bias correction across Slovakia (1980–2024). Note: Slopes are per decade. Sig: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$, ns: non-significant.

Index	Orig. Slope	Corr. Slope	Unit	Diff
TX90p	11.79 (***)	11.73 (***)	%	−0.06
TX10p	−7.94 (***)	−7.97 (***)	%	−0.03
TN90p	10.66 (***)	10.66 (***)	%	0.00
TN10p	−7.04 (***)	−7.04 (***)	%	0.00
TXx	0.65 (***)	0.64 (***)	°C	−0.01
TXn	0.81 (*)	0.82 (*)	°C	+0.01
TNx	0.52 (***)	0.52 (***)	°C	0.00
TNn	1.08 (*)	1.09 (**)	°C	0.00
SU	8.67 (***)	8.77 (***)	days	+0.09
TR	0.00 (ns)	0.00 (ns)	days	0.00
FD	−7.02 (***)	−6.55 (***)	days	+0.47
ID	−4.82 (**)	−4.87 (**)	days	−0.05
TD30	4.00 (***)	4.29 (***)	days	+0.29
STD35	0.00 (ns)	0.00 (ns)	days	0.00
SN15	6.95 (***)	7.64 (***)	days	+0.69
DTR	0.17 (**)	0.17 (**)	°C	0.00

3.3. Spatial Trend Analysis

The mean of the spatial trends analysis for 1980–2024 shows a strong and widespread warming signal over Slovakia with exceptionally high spatial agreement. As presented in Figure 8, the Annual Maximum temperature (TXx) exhibits a C_f of 96% demonstrating a near-universal exposure of the Northern Carpathians to intensifying peak heat. This high coherence suggests that daytime extremes are primarily governed by persistent atmospheric blocking, which affects the region regardless of altitude, with a spatial mean increase of +0.6 °C/decade. In contrast, the lower coherence of TNn (74.5%) indicates that while the coldest nights are warming faster on average (+1.12 °C/decade).

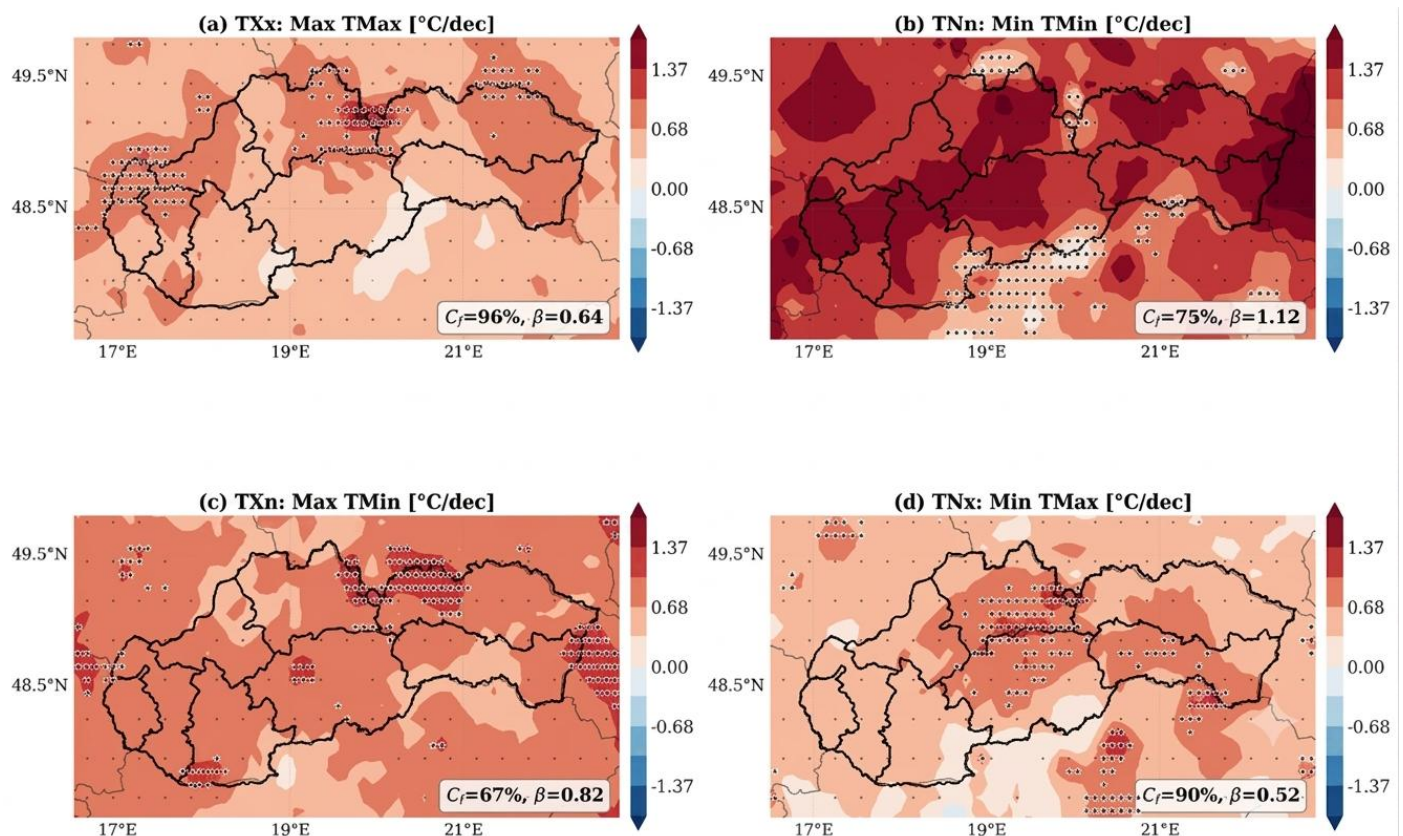


Figure 8. Spatial distribution of decadal trends (Sen's Slope) for absolute temperature indices (TXx, TNx, TXn, TNn) across Slovakia (1980–2024). Black stars indicate hotspots defined as grid cells in the top 10% of the slope distribution. Field Coherence (C_f) represents the percentage of the study area showing a statistically significant trend ($p < 0.05$).

The most significant changes are found in percentile-based indicators with the mean rates of increase in Warm Days (TX90p) and Warm Nights (TN90p) being +13.9 and +12.5% per decade, respectively. The spatial coherence of these indices is almost absolute with the TX90p reaching a Field Coherence (C_f) of 100% and TN90p reaching 96%. The Northern Carpathians and the Central Slovak Ore Mountains are prominent hotspots for such relative extremes, which confirms that high-altitude environments are experiencing faster intensifications than the national average (Figure 9).

The regional climate data reveals a striking contrast between the steady expansion of moderate heat and the rapid erosion of cold extremes (Figure 10). Summer Days (SU) are increasing by 7.7 days per decade with a C_f of 98%, which indicates a consistent warming signal across the region stretches from the Southern Basin to the Eastern Slovak Beskids. In contrast, Tropical Nights (TR) show much weaker spatial coherence (38%), remaining geographically confined compared to their daytime counterparts. Conversely, indices linked to cold conditions are experiencing a sharp and remarkably uniform decline across the study area. Frost Days (FD) and Ice Days (ID) are declining at mean rates of 6.2 and 4.9 days per decade, respectively, with ID showing a remarkably high coherence of 97%. This shift is most aggressive in the Central Slovakian Valleys and the Northern Carpathians, where localized declines reach nearly 15 days per decade.

From Figure 11, Tropical Days (TD30) are increasing by 4.2 days per decade with high spatial consistency (96%), and Summer Nights (SN15) are rising by 6.2 days per decade with high C_f (93.1%) creating hotspots along the southeastern regions while more intense Supertropical Days (STD35) show much lower Field Coherence (19%), remaining strictly confined to the Southern Basin and Danubian Lowlands. This spatial complexity is represented in the Diurnal Temperature Range (DTR), which shows a moderate coherence of 58% and high regional volatility. In specific hotspots like the Central Valleys, DTR slopes reach up to +1.2 °C per decade, suggesting that maximum temperatures are pulling away from minimums and potentially intensifying heat stress during peak daylight hours.

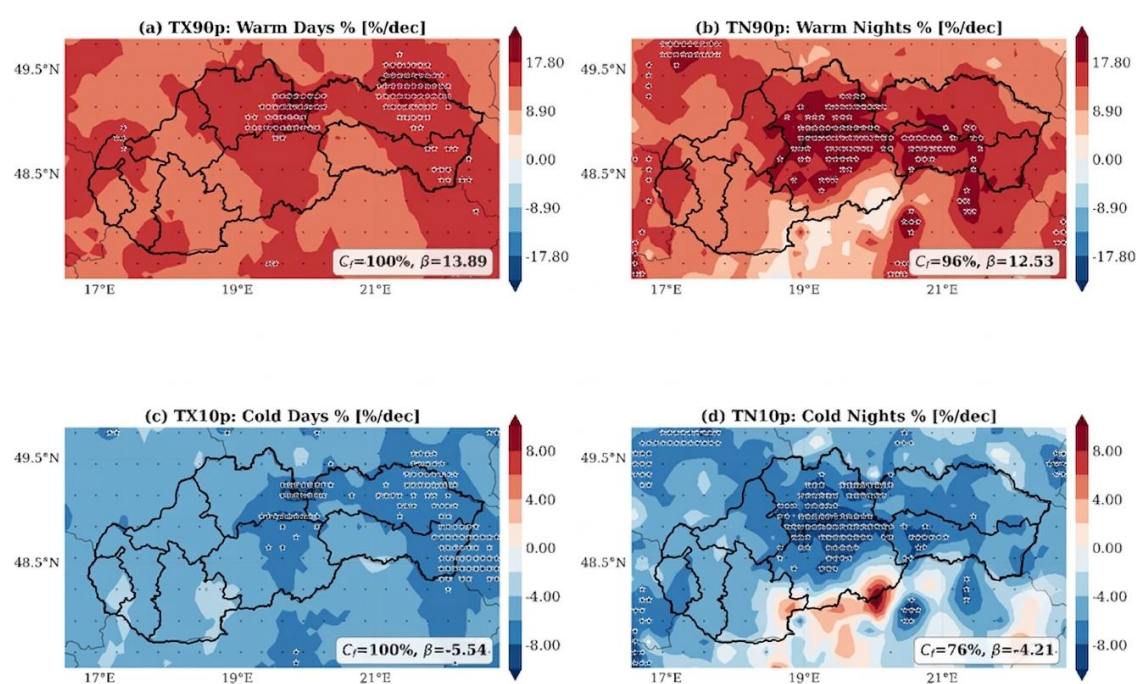


Figure 9. Spatial distribution of decadal trends (Sen's Slope) for percentile indices (TX90p, TN90p, TX10p and TN10p) across Slovakia (1980–2024). Black stars indicate hotspots defined as grid cells in the top 10% of the slope distribution. Field Coherence (C_f) represents the percentage of the study area showing a statistically significant trend ($p < 0.05$).

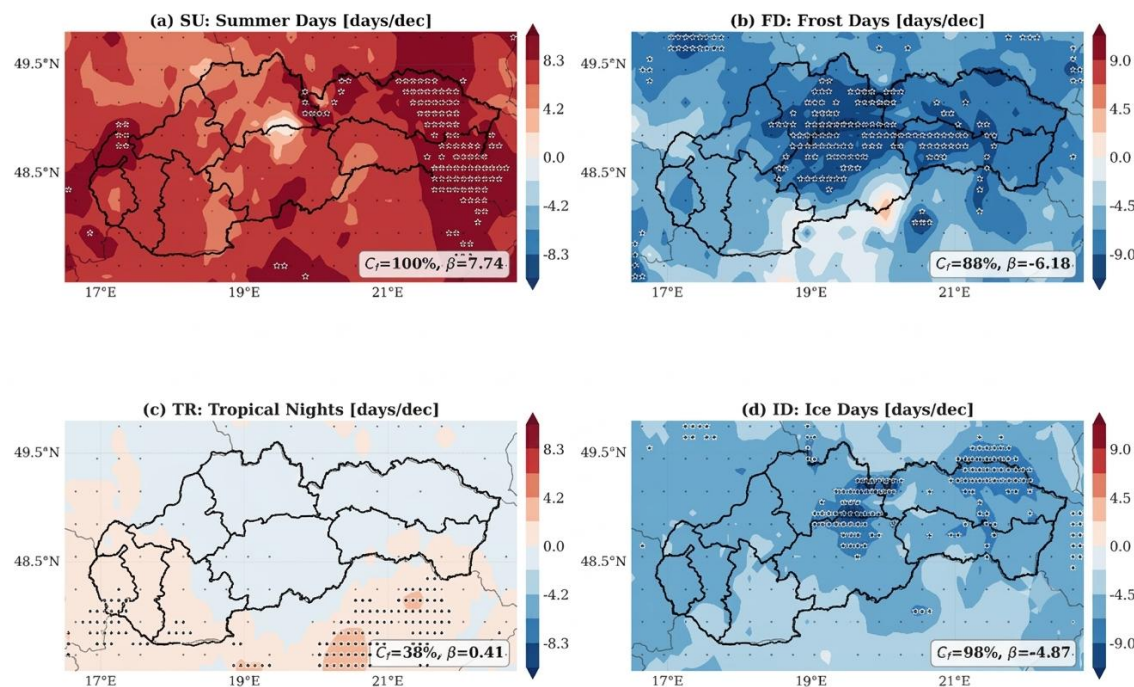


Figure 10. Spatial distribution of decadal trends (Sen's Slope) for standard indices (SU, TR, FD and ID) across Slovakia (1980–2024). Black stars indicate hotspots defined as grid cells in the top 10% of the slope distribution. Field Coherence (C_f) represents the percentage of the study area showing a statistically significant trend ($p < 0.05$).

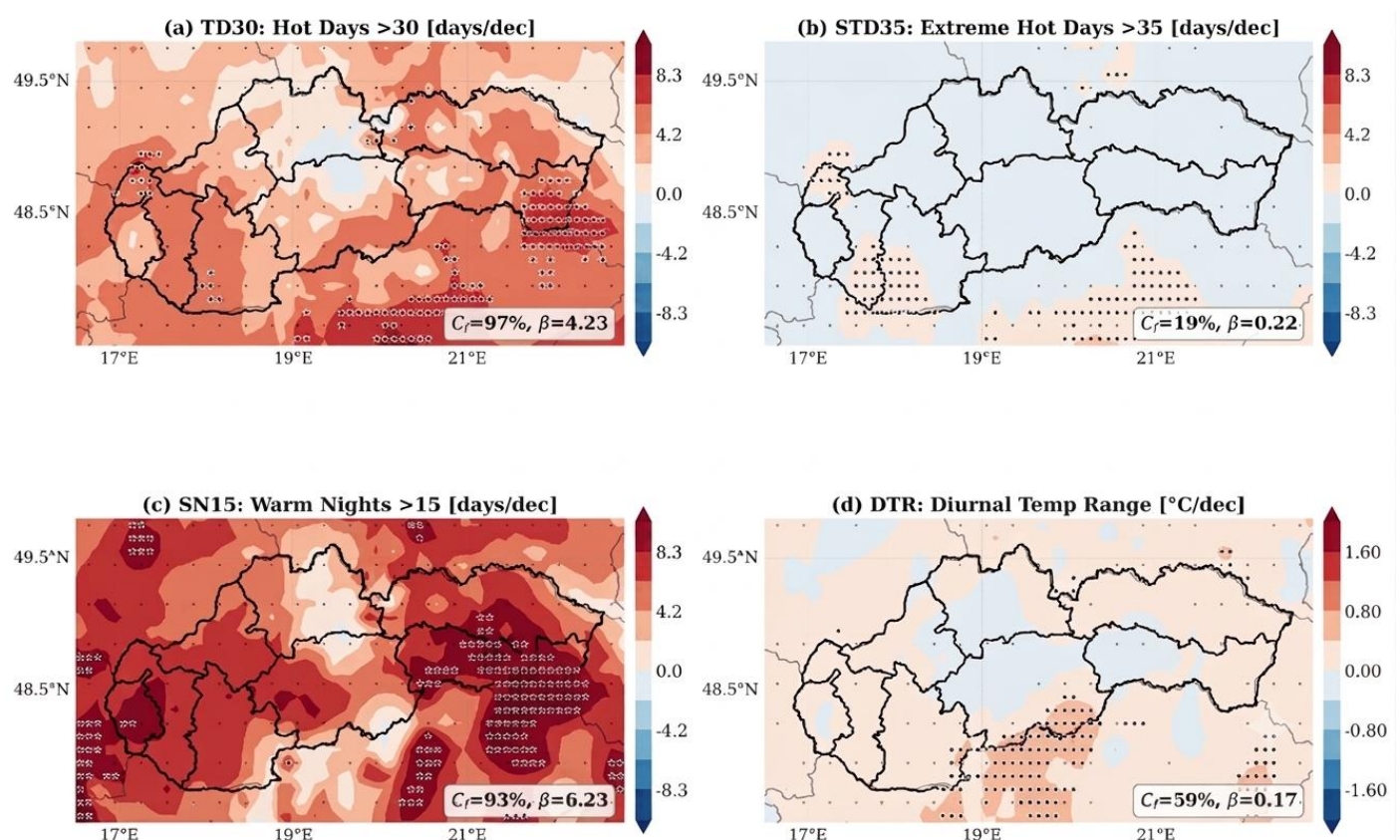


Figure 11. Spatial distribution of decadal trends (Sen's Slope) for tropical indices (TD30, STD35 and SN15) across Slovakia (1980–2024). Black stars indicate hotspots defined as grid cells in the top 10% of the slope distribution. Field Coherence (C_f) represents the percentage of the study area showing a statistically significant trend ($p < 0.05$).

4. Discussion

Scientific literature repeatedly describes Slovakia as systematically changing towards warmer conditions [15,19,20,36]. There is agreement among several studies about the increase in heat-related indices and the decrease in cold indicators. Our results provide new evidence of the extraordinary spatial homogeneity of the warming shift. The values of 100% for Warm Days (TX90p) and 97% for Ice Days (ID) are not merely high statistics; they represent a complete phase shift in the regional climate regime. The identified TXx hotspots (+1.6 °C/decade) in the high mountains are physically significant because they confirm that the Northern Carpathians are not just warming alongside the lowlands but are acting as high-sensitivity amplifiers of the broader Central European trend due to EDW mechanisms [37].

This kind of asymmetric warming is not only specific to Slovakia, as both global [38] and regional [39] studies indicate that changes in extreme temperatures are usually more significant during the night than during the day. Threshold indices (Summer Days (SU), and Tropical Days (TD30)) are increasing by +7.7 and +4.2 days/decade respectively. These values are higher than many historical averages reported for Central Europe; for example, research in the Czech Republic found an increase of around 4.4 Summer Days/decade [37]. This indicates that previous, uncorrected gridded analyses may have underestimated the true intensity of the warming shift in topographically complex areas.

The spatial analysis underscores a high degree of uniformity in SU trends ($C_f = 98\%$), with hotspots identified via Equation (8) stretching across a broad corridor from the Western Carpathians to the Eastern Slovak. While moderate heat is becoming ubiquitous, the most extreme events show a different geographic footprint. For instance, at the Hurbánovo station, the frequency of Supertropical Days (STD35) has surged by over 660% since 1991 [9]. Despite this intensity, our findings show a Field Coherence of only 19% for STD35, suggesting that these extreme thresholds are still largely confined to and expanding outward from core hotspots in the Southern Basin and the Danubian Lowland. Physically, these shifts are rooted in large-scale atmospheric changes, particularly an increase in anticyclonic circulation and persistent atmospheric blocking [37,40], which traps heat over the region for extended periods.

The correlation between temperature extremes and altitude in our data provides further evidence for Elevation-Dependent Warming (EDW) (Figure S5). Specifically, we observed that relative heat extremes (TX90p) are intensifying more rapidly at higher elevations, with the Northern Carpathians emerging as a primary hotspot for this trend. This vertical expansion of heat is clearly visible at the Skalnaté Pleso Observatory (1778 m), where Annual Maximum temperatures rose by approximately 1.2 °C between the 1961–1990 and 1991–2020 climate periods [41]. These shifts are mirrored in UTCI biometeorological analyses, which highlight southward-facing mountain slopes as increasing hotspots for human thermal stress [42], indicating that warming is now significantly impacting environments once considered cool-weather refuges.

Simultaneously, the steady decline of cold indicators has become statistically significant. In specific Central Slovakian hotspots, the frequency of Frost Days (FD) has decreased at a rate of 14.6 days per decade, evidencing a pronounced retreat of winter conditions. This trend converges with recent regional evidence indicating an accelerating expansion of the Slovakian growing season, a shift with profound implications for local phenology and agricultural cycles [43]. The Ice Day (ID) index exhibits a remarkably high

Field Coherence of 97%, confirming that the retreat of freezing conditions is a near-universal phenomenon across the country. This trend mirrors observations in the Alps, where winter warming has accelerated to +1.2 °C per decade at several high-elevation observatories [39]. These shifts are already fundamentally altering local ecosystems; in the Western Carpathians, for example, European beech trees (*Fagus sylvatica* L.) are showing increasing signs of physiological stress as summer conditions intensify and the historical climate envelope shifts [41,44]. Findings of ($C_f = 58\%$) for Diurnal Temperature Range (DTR) reveal significant regional variability, particularly in the Southern Basin. The data suggests that, in these specific areas, daytime maximums are outpacing nighttime minimums. This decoupling of day and night temperatures, coupled with declining snow cover, heightens the risk of false springs and subsequent late frost damage, as vegetation may be prompted to bloom prematurely only to be exposed to freezing nighttime temperatures [37,39].

5. Conclusions

This study highlights that while the E-OBS dataset is a valuable tool, it requires substantial correction via Quantile Delta Mapping (QDM) to be reliable for local-scale research in Slovakia. By neutralizing elevation-related biases, this corrected data provides a much clearer view of the 16 temperature indices, confirming a systematic and statistically significant shift toward warmer conditions. Beyond simple bias removal, the correction significantly improved the daily accuracy of the dataset, with RMSE values at high-altitude stations, such as the Chopok summit (1995 m), decreasing from 5.1 °C to 2.3 °C. This demonstrates the framework's capability to recover local climatic signals in complex mountainous terrain, where interpolated gridded products traditionally struggle.

The intensifying frequency of warm-tail events evidenced by the 98% coherence in Summer Days (SU) reflects broader trends across Central Europe [45]. The heat intensity documented here marked by the 100% Field Coherence of Warm Days (TX90p) provides a rigorous climatological basis for the escalating mortality risks identified in recent regional studies [46]. In addition, the strong cold-tail signal is where the Annual Minimum temperature (TNn) is rising nearly twice as fast as the Annual Maximum (TXx). While TXx shows high spatial agreement (96%), TNn is more localized (74.5%), suggesting that the warming of the coldest nights is particularly intense in specific mountain basins. From a climatological perspective, this rapid rise in TNn represents a significant shift in the regional thermal envelope that may serve as a proxy for reduced cold-related physical stressors [45]. Thermal hotspots in the Danubian and East Slovak Lowland isolate regions of heightened climatic vulnerability, where observed patterns align with the physical triggers for health, agricultural, and operational stressors documented in regional studies [47,48].

Furthermore, the near-universal decline in Ice Days (ID) marked by a 97% coherence indicates an expanding physical window for outdoor recreation and regional festivals [49]. Additionally, the Elevation-Dependent Warming (EDW) identified here with TXx hotspots climbing by +1.6 °C/decade represents a significant physical constraint for the winter tourism sector. Combined with localized Frost Day (FD) losses reaching 14.57 days/decade, our results quantify the accelerating climatic pressures that challenge the long-term viability of mountain resorts across the Northern Carpathians [48].

Collectively, these patterns underscore Slovakia's position as a region of heightened climatic sensitivity. The interplay between high Field Coherence indicating uniform shifts and the emergence of extreme mountainous hotspots makes the region climatically sensitive. This unique thermal profile highlights the importance of exploring localized, nature-based adaptation strategies to mitigate the physical impacts on regional ecosystems and infrastructure. Supporting such localized strategies requires continuous refinement of the

underlying spatial data. While this study utilized 13 meteorological stations to successfully neutralize elevation-induced biases, the bimodal distribution of these sites highlights a need for further spatial refinement. Future research will focus on integrating a broader network of meteorological stations, specifically at intermediate altitudes, to enhance the precision of the Quantile Delta Mapping (QDM) residuals and provide an even more granular assessment of local-scale climate hotspots.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/cli14070142/s1>, Figure S1. Spatial distribution of original vs. QDM-corrected daily maximum (TMAX) and minimum (TMIN) temperatures for 15 January 2010, during the winter season. This comparison highlights the framework's ability to neutralize systematic cold biases at high altitudes and recover the intricate thermal complexity of the Northern Carpathians that is often smoothed out in the raw 0.1° E-OBS grid; Figure S2. Spatial distribution of original vs. QDM-corrected daily maximum (TMAX) and minimum (TMIN) temperatures for 15 April 2010, during the spring season. This comparison demonstrates how the QDM-IDW framework restores critical thermal contrasts and elevational signals across Slovakia, correcting the systematic biases often present in the raw 0.1° E-OBS grid during transitional seasons; Figure S3. Spatial distribution of original vs. QDM-corrected daily maximum (TMAX) and minimum (TMIN) temperatures for 15 July 2010, during the summer season. This figure illustrates the framework's effectiveness in correcting the systematic warm bias over high-altitude peaks, effectively restoring the regional adiabatic lapse rates and thermal complexity of the Northern Carpathian that are often smoothed in the 0.1° E-OBS grid; Figure S4. Spatial distribution of original vs. QDM-corrected daily maximum (TMAX) and minimum (TMIN) temperatures for 15 October 2010, during the autumn season. This comparison serves as a representative example of how the QDM-IDW framework restores localized thermal gradients and elevation-induced contrasts across Slovakia that are frequently smoothed out in the raw 0.1° E-OBS grid; Figure S5. Elevation-Dependent Warming (EDW) profiles for selected 16 temperature indices across the 13 anchor stations (98 m to 1995 m a.s.l.). Trends are derived from the QDM-corrected E-OBS dataset for the 1980–2024 period. The correlation illustrates the relationship between station elevation and decadal trend magnitude (Sen's Slope), with significance levels indicated at $p < 0.05$; Table S1. Geographic and metadata attributes of the 13 anchor meteorological stations used for the QDM-IDW bias correction of the E-OBS dataset. Attributes include station names, coordinates, and elevation profiles (ranging from 98 m to 1995 m a.s.l.), which provide the essential altitudinal representation required to neutralize topographical biases across Slovakia; Table S2. Definitions, units, and calculation criteria for the temperature indices used in this study, based on the Expert Team on Climate Change Detection and Indices (ETCCDI) framework. These standardized metrics provide the objective basis for the trend analysis and spatial mapping of extremes across the Northern Carpathians; Table S3. Statistical evaluation of Mean Bias (MB) and Root Mean Square Error (RMSE) between the raw 0.1° E-OBS grid and the 13 anchor meteorological stations for the 1981–2010 historical baseline period. These values quantify the systematic elevation-induced errors that necessitated the application of the QDM-IDW correction framework to ensure local-scale reliability; Table S4. Summary of the Mann–Kendall trend test and Sen's Slope estimates for 16 temperature indices across Slovakia (1980–2024). These results are derived from the QDM-corrected E-OBS dataset. The table provides a nationwide assessment of decadal trend magnitudes, with statistical significance determined at the $p < 0.05$ level.

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Abbreviations

The following abbreviations are used in this manuscript:

E-OBS	Gridded dataset based on the station time series
QDM	Quantile Delta Mapping
EDW	Elevation-Dependent Warming
C_f	Field Coherence
GHG	greenhouse gas
CARPATCLIM	Climate of the Carpathian Region
ETCCDI	The Expert Team on Climate Change Detection and Indices
a.s.l.	above sea level
SRTM30	Shuttle Radar Topography Mission 30-arcsecond
GADM	The full name of GADM is Global Administrative Areas
SHMU	Slovak Hydrometeorological Institute
TX90p	Warm Days
TX10p	Cold days
TN90p	Warm Nights
TN10p	Cold nights
TXx	Annual maxima of daily maximum temperature
TXn	Annual minima of daily maximum temperature
TNx	Annual maxima of daily minimum temperature
TNn	Annual minima of daily minimum temperature
SU	Summer Days
TR	Tropical Nights
FD	Frost Days
ID	Icing days
TD30	Tropical Days
STD35	Super Tropical Days
SN15	Summer Night
DTR	Diurnal Temperature Range
MB	Mean Bias
RMSE	Root Mean Square Error
QM	Standard Quantile Mapping
CDF	cumulative distribution function
β	Sen's Slope

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