Long-term assessment of cold stress in Tabriz: Temporal analysis of sensible temperature and heat loss indices

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Abstract

The wind chill phenomenon plays a significant role in thermal comfort and cold stress in cold climates. This study evaluates the long-term evolution of cold stress in Tabriz by analysing daily mean temperature and wind speed data from the Tabriz synoptic station over 63 years (1961–2023). The Wind Chill Equivalent Temperature (WCET) and Heat Loss indices were calculated using standard meteorological models. Trend and mutation analyses were conducted utilising the Mann–Kendall test, Sen's slope estimator, and Sequential Mann–Kendall (SMK) analysis, following autocorrelation pre-processing. The results indicate a gradual warming trend in annual mean WCET, alongside a general, though statistically non-significant, decreasing trend in the persistence of prolonged cold spells. SMK analysis suggests a structural shift around 1975, after which the duration of cold spells exhibited a downward trajectory characterised by strong interannual and temporal fluctuations. While the frequency and intensity of extreme cold events have diminished compared to the 1960s and 1970s, the potential for severe cold waves remains. The findings provide empirical data that can inform regional climate change adaptation strategies and urban infrastructure planning.

Keywords: Wind Chill, Wind Chill Equivalent Temperature (WCET), Heat Loss, Climate Change, Tabriz.

Introduction

Human thermal comfort, as a key pillar in bioclimatological studies, plays a vital role in public health, urban quality of life, and patterns of energy consumption. A precise understanding of climatic conditions, especially in urban environments that host a major portion of the world's population, is essential for sustainable planning and human-centred design. (Tamaskani Esfahankalateh et al., 2020). In cold climates, the assessment of cold stress goes beyond simple air temperature measurements, since the simultaneous effect of wind can dramatically intensify the sensation of cold and the rate of heat loss from the body. This phenomenon, known as wind chill, is a crucial ergonomic index for evaluating the actual conditions of human exposure to cold and holds strategic importance in various fields, including urban safety, public health, and even passive defence. The Wind Chill Index (WCI) has recently been employed at a regional scale, for example, across Eastern Anatolia in Türkiye to map perceived winter temperatures and identify areas at moderate to high risk of frostbite and cold-weather shock, demonstrating its continued relevance for public health planning in topographically complex cold regions. (Elmastas et al., 2025). Accurately understanding climatic threats and the vulnerability of infrastructure and populations to cold waves is a fundamental principle of passive defence for building urban resilience against environmental hazards.

The concept of wind chill was first introduced in polar studies by Siple and Passel in 1945 to quantify the cooling rate of the atmosphere. (Siple & Passel, 1945) It has since become one of the most important applied meteorological indices worldwide. (Lankford & Fox, 2021). This concept is quantified in two main forms: one as the Wind Chill Equivalent Temperature (WCET), which expresses the equivalent wind chill temperature and is widely used in modern meteorological standards. (Osczevski, 1995)The other is the Heat Loss index, which measures the physical rate of energy loss from the skin surface in watts per square meter (W/m^2) and serves as a direct indicator of the stress imposed on the body. (Brauner & Shacham, 1995). Both indices are essential for a comprehensive understanding of cold stress. Research examining intraseasonal variations of WCT across North America has shown that January consistently exhibits the coldest mean WCTs and the highest frequency of severe WCT hours (≤ -32°C), with air temperature rather than wind speed acting as the primary driver of WCT variability. (Howarth & Laird, 2017). The significance of these indices is not limited to humans; they are also used in other life sciences, such as veterinary medicine, to assess the survival risk of animals under harsh environmental conditions. (Swarnkar et al., 2018).

Despite the importance of this topic, many climate studies in Iran (Fallah-Ghalhari et al., 2019; Farajzadeh et al., 2015; Roshan et al., 2010) have focused on monthly averages or short-term statistical periods. While studies have examined temperature trends and climate change in Iran (Fallah-Ghalhari et al., 2019) or have assessed thermal indices at broad scales (Farajzadeh et al., 2015), there is a distinct research gap concerning a long-term, daily, high-resolution analysis of wind chill indices for the cold-climate metropolises of Iran. Furthermore, recent systematic reviews of outdoor thermal comfort research (1980–2024) indicate that the field has predominantly focused on heat stress in tropical and subtropical regions, pointing to a clear gap in comprehensive cold-stress assessments in continental climates. (Liu et al., 2025). The city of Tabriz, as one of Iran's coldest metropolises with a cold and semi-arid climate, is an ideal case study for evaluating historical changes in cold stress patterns. A recent study projected that the cooling effect of wind will decrease over time in Tabriz under climate change scenarios, further emphasising the need to understand past and future trends in wind-chill conditions. (Roshan et al., 2022). Understanding whether the intensity, frequency, and persistence of cold waves in this city have changed over the past six decades is vital for future planning in the fields of energy, health, and urban design. (Roshan et al., 2010).

Accordingly, the present study aims to address this research gap by conducting a quantitative analysis of the WCET and Heat Loss indices in Tabriz over a 63-year statistical period. Using daily meteorological data, this study pursues the following objectives: (1) calculating daily time series for WCET and Heat Loss using standard models; (2) analysing long-term trends and decadal variations; (3) identifying the frequency and duration of cold waves; and (4) visualising the temporal patterns of cold stress. The findings are intended to provide an empirical baseline for understanding the evolution of Tabriz's winter climate, offering practical insights for urban planning and cold-risk adaptation.

Materials and Methods

This research employs a quantitative and analytical approach to evaluate human-centred bioclimatic conditions in the cold climate of Tabriz. The main research framework is based on the calculation and analysis of reliable thermal comfort indices.

Study Area

The study area is the Tabriz Synoptic Station, with the international ID 40706. This station is located at 38.12° N latitude and 46.23° E longitude, at an altitude of 1345 meters above sea level (Figure 1). The selection of this station is due to the strategic location of Tabriz in northwestern Iran and its cold, semi-arid climate, characterised by harsh and long winters. As noted in previous studies (Tamaskani Esfahankalateh et al., 2020), in such climates, airflow management and cold-adapted design play a vital role in ensuring the thermal comfort of residents.

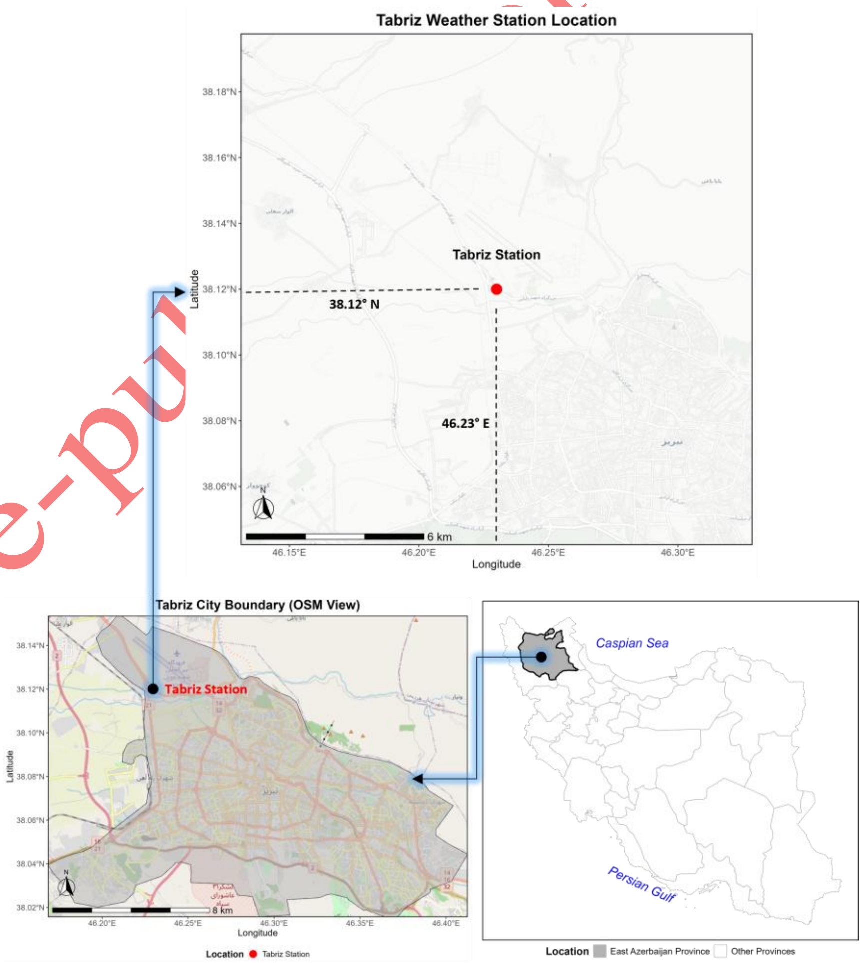

Fig 1. Location of the Tabriz Synoptic Station.

Daily statistical data, including mean temperature in degrees Celsius and average wind speed in meters per second, were obtained from the Iran Meteorological Organisation for a long-term 63-year statistical period (1961–2023). The selection of this long-term period enables a precise analysis of trends, the identification of anomalies, and the examination of climate change on multi-decadal scales, an approach that has also been emphasised in similar studies in Iran (Fallah-Ghalhari et al., 2019).

Quality Control and Data Preprocessing

Following the guidelines of the World Meteorological Organisation (WMO, 2008) regarding the screening of climatic data, a two-stage quality control procedure was implemented:

a) Identification and removal of anomalous data:

In alignment with the standard deviation-based approaches recommended in various meteorological guidelines, the 3-sigma rule was applied. For each month separately, the mean (μm) and standard deviation (σm) were calculated, and values falling outside the range ($\mu m \pm 3\sigma m$) were flagged as anomalous data and converted to empty cells. The theoretical basis of this method is the central limit theorem and the normal distribution, according to which approximately 99.7% of valid data fall within this range; therefore, any value outside this range is statistically highly improbable ($p \approx 0.003$) and is a strong candidate for a measurement error or an unrealistic event. Nevertheless, two measures were taken to avoid common pitfalls:

- **Mitigating the masking effect:** By performing the calculations separately for each month, the influence of seasonal cycles on the mean and standard deviation was neutralised (Hawkins, 1980)ensuring that anomalous data were only compared with values from the same month.

- **A conservative approach:** Choosing a threshold of 3 (as opposed to 2) minimised the probability of inadvertently removing a valid climate record that could represent a rare extreme event (Barnett & Lewis, 1994).

b) Management of missing data:

After the removal of anomalous data, the resulting gaps were filled using the median of the same month from the entire statistical period. This non-parametric approach, which is widely used in climate data processing (Frich et al., 2002; WMO, 2011), is more robust than the mean against distributional skewness and better preserves the overall structure of the time series.

Together, these measures ensured the complete homogeneity of the input time series, which is a critical prerequisite for validating extreme climate indices. (Farajzadeh et al., 2015).

Computational Models and Bioclimatic Indices

In this research, to accurately assess cold stress, two complementary indices were employed, each illustrating a different aspect of the impact of cold on human physiology.

a) Wind Chill Equivalent Temperature (WCET) Index

This index estimates the apparent temperature, i.e., the temperature perceived by human skin when exposed to wind. In this study, the current standard model jointly developed by the U.S. National Weather Service (NWS) and the Meteorological Service of Canada (MSC) was used. This model, which replaced older formulations in 2001, is founded on advanced heat transfer principles and wind tunnel experiments on a human face model. (Osczevski & Bluestein, 2005). The model is also recognised as a reliable method in reputable regional studies. (Roshan et al., 2010). The calculation was implemented in the R programming environment as follows: According to Equ. 1, the computational formula (originally designed for imperial units) was applied after converting units to the International System (SI):

$$WCET = 13.12 + 0.6215\, T_a - 11.37\, V^{0.16} + 0.3965\, T_a\, V^{0.16} \quad (1)$$

where T_a is the air temperature (*°C*) and *V* is the wind speed at the standard 10-m height (*km/h*). A key aspect of this model is that the formula inherently incorporates the height adjustment from 10 m to the face level (about 1.5 m) within its coefficients. Thus, no separate wind-height correction factor is required. In accordance with the index definition, the formula is valid only when the air temperature is below 10 *°C* and the wind speed exceeds 4.8 *km/h* (Lankford & Fox, 2021; Osczevski & Bluestein, 2005). This condition was strictly enforced during computation; on days when the validity criteria were not met ($T_a \geq 10°C$ or $V \leq 4.8$ *km/h*), the index value was set to undefined and these days were classified as Not Applicable in cold-stress analyses. This approach adheres more rigorously to the scientific definition of the index and prevents physically invalid data from entering the stress analyses.

b) Heat Loss Index

This index, rooted in the classic studies of Siple and Passel (Doğan et al., 2020; Siple & Passel, 1945), quantifies the physical rate of energy loss from exposed skin. Unlike WCET, which is a temperature quantity, the Heat Loss Index is a physical quantity and provides a direct measure of the burden placed on the body's thermoregulatory system. The formula used in this research is the modified version by Brauner and Shacham. (Brauner & Shacham, 1995), which yields results directly in watts per square meter (*W/m²*); accordingly, a conversion factor of 1.163 was incorporated into the formula to directly convert the output from kilocalories per square meter per hour (*kcal/m²/h*) to watts per square meter (*W/m²*), consistent with the aforementioned modifications (Equ. 2)

$$H = \left(10.45 + 10\sqrt{V} - V\right)(33 - T_a) \times 1.163 \quad (2)$$

where *V* is the wind speed in meters per second (*m/s*), and 33 is the average skin surface temperature (°C). Note that unlike the WCET index (Equation 1), which utilises wind speed in km/h, the modified Siple-Passel Heat Loss index (Equation 2) mathematically requires wind speed to be expressed in m/s. Employing this index alongside WCET enables comparisons with biological and veterinary studies. (Swarnkar et al., 2018) and affords a more comprehensive perspective on cold severity. It should be recalled that the validity domain of this index was likewise restricted, analogous to WCET, to days with temperatures below 10°C and wind speeds above 4.8 km/h.

Both formulas are well-established in the literature and continue to be used in contemporary operational and research settings (Lankford & Fox, 2021; Mekis et al., 2015). The foundational references from the 1990s are therefore cited as the original derivations, while the enduring validity of the equations is evidenced by their current official use.

Trend and Mutation Analysis

To examine the significance and magnitude of trends in the time series of the longest annual cold periods, in addition to ordinary least squares (OLS) regression, the non-parametric Mann–Kendall test (MK) (Kendall, 1949; Mann, 1945) and Sen's slope estimator (Sen, 1968) were employed. Owing to their freedom from distributional assumptions and robustness to anomalous values, these methods are widely accepted for trend analysis of climatic variables. (Güçlü, 2020). It must be noted, however, that the presence of first-order autocorrelation in time series can inflate the Type I error rate of the classical MK. (von Storch, 1995). Therefore, in the first step, for each time series, the null hypothesis of independence was tested using the Ljung–Box test with one lag (*lag-1*) (Ljung & Box, 1978). Based on the outcome, one of two paths was selected:

• If no significant autocorrelation was detected ($p \geq 0.05$), the classical MK and Sen's slope estimator were used.

• If significant autocorrelation was present ($p < 0.05$), to remove its effect, the modified version of the MK known as the (Hamed & Rao, 1998) method was applied using the **mmkh** function from the **modifiedmk** package in R. This method corrects the variance of the S statistic, thereby returning the test's error rate to its nominal level.

In the Mann–Kendall test, the S statistic is calculated as in Equ. 3:

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} \operatorname{sgn}(x_j - x_i) \tag{3}$$

where n is the length of the time series and $sgn(\theta)$ is the sign function, equal to 1, 0, or −1 for positive, zero, or negative θ, respectively. For sufficiently long time series ($n \geq 10$), S is normally distributed and its variance, accounting for possible ties, is estimated from Equ. 4:

$$Var(S) = \frac{n(n-1)(2n+5) - \sum_{i=1}^{g} t_i(i-1)(2t_i+5)}{18} \tag{4}$$

where g is the number of tied groups and t_i is the size of the i-th group. Subsequently, the standardised test statistic Z, with continuity correction, is defined by Equ. 5:

$$Z = \begin{cases} \frac{S-1}{\sqrt{Var\,(S)}} & S > 0 \\ 0 & S = 0 \\ \frac{S+1}{\sqrt{Var\,(S)}} & S < 0 \end{cases} \tag{5}$$

If $|Z| > Z_{(1-\alpha/2)}$, the trend is significant at the α level. This test was implemented using the **Mann-Kendall** function from the **Kendall** package in R, which automatically applies tie and continuity corrections. The magnitude and direction of the trend were estimated using Sen's slope estimator. (Sen, 1968), which is the median of the slopes of all possible data pairs, as given in Equ. 6:

$$\beta = median\left(\frac{x_j - x_i}{j - \mathrm{i}}\right). \qquad \forall \mathrm{i} < j \tag{6}$$

According to this equation, positive β values indicate an upward trend, while negative values indicate a downward trend.

Furthermore, to identify abrupt change points (mutations) in the behaviour of the time series, the Sequential Mann–Kendall test (SMK) (Sneyers, 1991) was applied. In this approach, the progressive (UF_k) and retrograde (UB_k) statistics are computed. For each k from 2 to n, the statistic S_k is calculated. Under the null hypothesis, the expected value of S_k is zero, and its variance is obtained from Equ. 7:

$$Var(Sk) = \frac{k(k-1)(2k+5)}{18} \quad (7)$$

Then, the progressive standardised statistic ($UF_1 = 0$) is defined, with continuity correction, according to Equ. 8:

$$UF_k = \frac{sk - sgn(S_k)}{\sqrt{Var(S_k)}} \quad (8)$$

To obtain the retrograde statistic UB_k, the same computation is performed on the reversed time series, and the result is sign-reversed as $UB_k = -UF'_{n+1-k}$. The intersection of the *UF* and *UB* curves within the 95% confidence limits (approximately ± 1.96) may indicate the year of a significant abrupt change in the trend. (Güçlü, 2020; Sneyers, 1991). Additionally, whenever a series exhibited significant autocorrelation, the Trend-Free Pre-Whitening (TFPW) method, based on (Yue & Wang, 2004), was applied before the sequential test. In this method, the autocorrelation component is first removed from the series, and the sequential test is then performed on the whitened residuals. This procedure was carried out using the **pwmk** function from the **modifiedmk** package with the appropriate parameter activated in R.

Classification and Stress Evaluation

To aid in the qualitative interpretation of the WCET values reported in this study and to illustrate potential cold-stress warning levels for public health and passive defence purposes, Table 1 summarises a set of risk categories based on internationally recognised thresholds for severe cold weather alerts. These thresholds are consistent with those used by Environment and Climate Change Canada in issuing public wind chill warnings, as documented by (Mekis et al., 2015). The classification is grounded in physiological limits of frostbite and hypothermia risk. It should be noted that some studies have proposed different classifications for specific regions. (Doğan et al., 2020)The use of this internationally accepted framework allows the reader to contextualise the measured WCET values. The table is provided here as a general reference and was not employed for any quantitative frequency analysis in this work.

Table 1. Risk level classification based on WCET

Temperature	Risk Level	Description
> 0 °C	No Risk	Safe conditions.
0 to −10 °C	Low Risk	Slight discomfort. Warm clothing recommended.
−10 to −28 °C	Moderate Risk	Risk of frostbite with prolonged exposure. Protective layers needed.
−28 to −40 °C	High Risk	Exposed skin freezes in 10–30 min. Serious risk for outdoor activities.
−40 to −55 °C	Very High Risk	Exposed skin freezes in < 10 min. Critical conditions.
≤ −55 °C	Extreme Risk	Frostbite in < 2 min. Immediate danger to life.

Definition of cold spells

For the purpose of this study, a cold spell (cold wave) is defined as any uninterrupted sequence of days on which WCET ≤ –10 °C, without imposing a minimum duration. This absolute threshold corresponds to the (Cool) category in the standard risk classification (Table 1) and reflects physiologically relevant cold stress (Roshan et al., 2010). The analysis focuses on the longest such spell in each calendar year, exactly as it occurs in the observational record, since the WCET index itself is a daily value and its validity depends only on air temperature and wind speed thresholds; no external persistence criterion is required.

Software Tools

All stages of data processing, formula implementation, and statistical analyses were carried out using the R programming language within the RStudio development environment.

- The **dplyr** package was used for managing the large dataset (over *22,000* daily records).
- The **ggplot2** package, together with the scientific colour palettes **viridis** and **RColorBrewer**, was employed to produce high-resolution climatic fingerprints and heatmaps.
- Trend and anomaly analyses were performed using statistical methods of linear regression and the calculation of deviations from the long-term mean.

This comprehensive methodology, combining reliable physical models (Brauner & Shacham, 1995; Osczevski & Bluestein, 2005; Osczevski, 1995) with advanced data analysis tools, provides scientifically robust results that can inform decision-making in urban management and passive defence.

For a better understanding of the computation process, a schematic flowchart is presented in Figure 2, which sequentially illustrates the workflow from the input of initial variables to the final outputs.

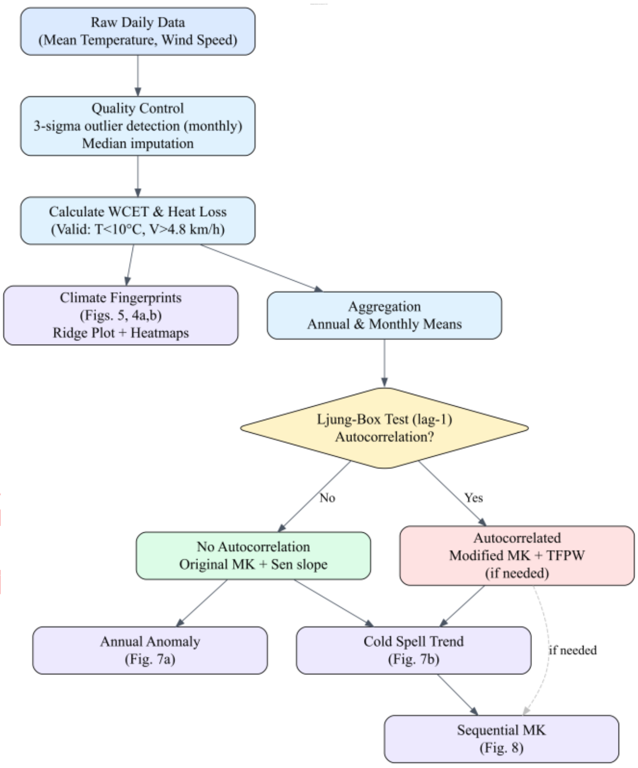

Fig 1. Schematic flowchart of the research methodology and computations

Results and Discussion

Data quality overview

Following the 3-sigma rule, 109 outliers were removed from the temperature series and 270 from the wind speed series (representing ~0.82% of all records). Visual inspection indicated that these anomalous values were randomly distributed across the temporal record rather than systematically clustered, reducing the likelihood of instrument-drift bias. The resulting gaps were filled using the long-term monthly median of the respective month. This non-parametric approach is more robust than the mean against skewed distributions and is commonly used in climate data processing (Frich et al., 2002; WMO, 2011). It is important to note that a maximum consecutive gap threshold was monitored; the longest consecutive gap was only 7 days (occurring once), with most being isolated single days. This justifies the use of median imputation without introducing artificial biases. The procedure ensured complete and homogeneous time series, a prerequisite for reliable analysis of extreme climate indices (Farajzadeh et al., 2015).

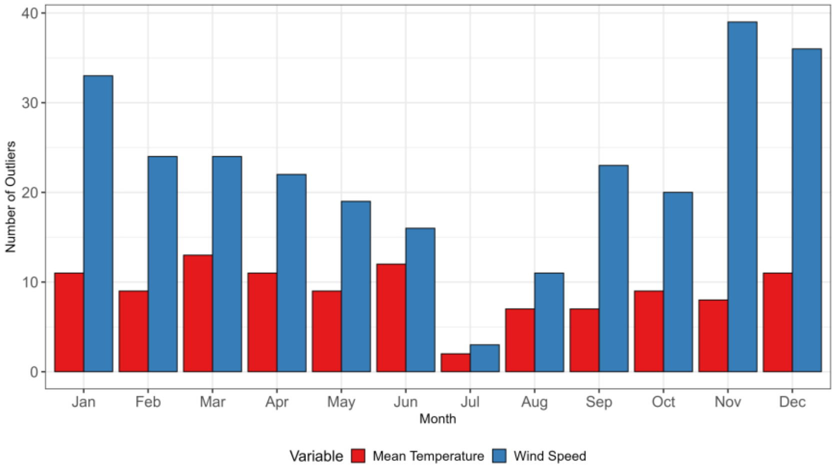

Fig 2. Quality control of anomalous data in the studied time series (1961–2023)

Seasonal Patterns and Long-term Trends

In accordance with Figure 4, a distinct seasonal pattern of cold stress in Tabriz is revealed. For both the cold stress and heat loss indices, the months of January, February, and December consistently show the lowest mean WCET (dark blue colours in Figure 4a) and the highest mean Heat Loss rates (yellow and orange colours in Figure 4b). Conversely, a complete absence of data from June through September is observed in both plots, stemming from the non-fulfilment of the index validity conditions during the warm months of the year, which correctly focuses the analysis on the cold seasons, although this time span has extended since the mid-2000s. A visual comparison of the map columns confirms that the spatial patterns of WCET and Heat Loss are completely inverse to each other; in other words, any month that exhibits colder colours in Figure 4a correspondingly shows a higher energy loss rate in Figure 4b. This visual consistency in turn reflects the physical validity of the indices. From a decadal change perspective, an overall look at the aforementioned plots indicates that the winters of the 1960s and 1970s (upper rows) recorded a higher density of intensely cold grid cells, whereas in recent decades (lower rows) the intensity and expanse of the cold colours have diminished, and the winter months have gradually appeared milder. This gradual colour shift can serve as evidence for the progressive moderation of winter cold in Tabriz over the past six decades.

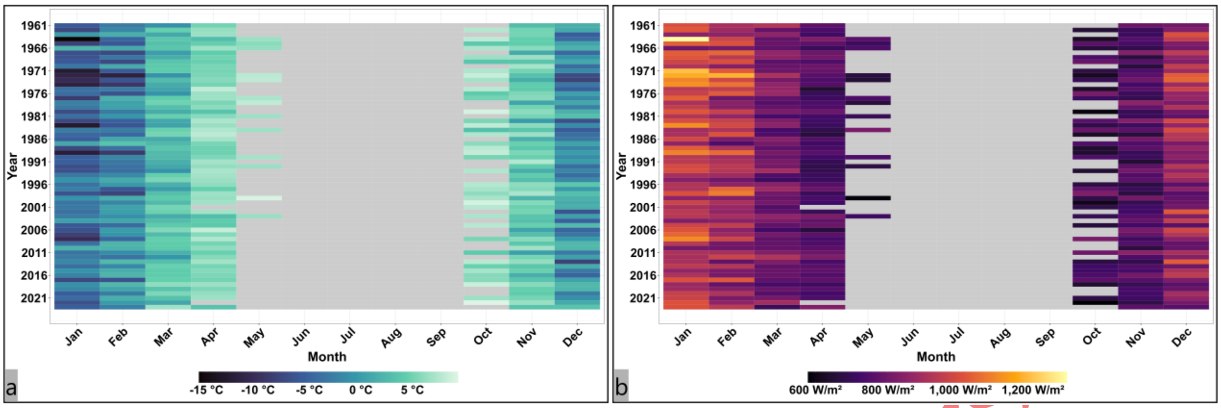

Fig 3. Annual and monthly variations of cold stress in Tabriz; (a) mean WCET in degrees Celsius, and (b) mean Heat Loss in watts per square metre at Tabriz station for the period 1961–2023

Decadal Changes in the Distribution of WCET

As illustrated in Figure 5, which depicts the frequency distribution of daily WCET for each decade of the 1961–2023 period, the most prominent feature of this plot is the gradual shift of the distribution peak to the right across successive decades. In the 1960s, the distribution exhibits a wide range and a long tail extending toward very cold temperatures (below −15°C), reflecting the abundance of days with extreme wind chill during that decade. This pattern persists into the 1970s. From the 1990s onward, the centre of the distribution visibly moves to the 0 to 5 °C range, and the spread of the distribution narrows. Concurrently, the left tail of the distribution (representing very cold days) noticeably shortens in the 2000s, 2010s, and 2020s, indicating a decline in the frequency of severe cold events. It should be noted that the 2020s decade comprises only the first four years (2020–2023), and its pattern must therefore be interpreted with caution. Overall, although days with wind chill still occur in Tabriz's climate, their frequency and intensity have decreased, particularly over the past two decades. This change is fully consistent with the pattern of gradual moderation of winter cold that was also observed in the monthly and annual variations of the studied indices (Figure 4).

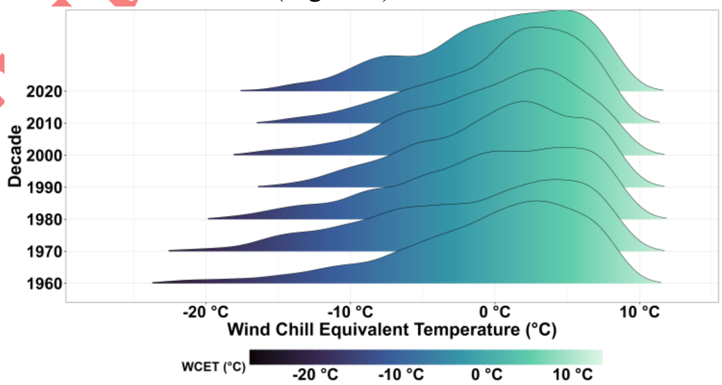

Fig 4. Distribution of daily WCET (°C) for each decade from 1961 to 2023 at Tabriz station

Analysis of Extreme Events and Anomalies

Before conducting trend analyses, the presence of first-order autocorrelation in all time series (annual and monthly) was examined using the Ljung–Box test (lag-1). At the annual scale, the mean temperature and wind speed series exhibited significant autocorrelation ($p < 0.05$), and their trend analysis was therefore performed using the modified Hamed–Rao method, whereas the WCET and Heat Loss series showed no significant autocorrelation and were analysed using the classical Mann–Kendall test. At the monthly scale, a similar procedure was followed for each series, based on the outcome of the Ljung–Box test. Full details of all test results are presented in Figure 6.

Looking at Figure 7a, the analysis of the annual anomaly of the mean WCET shows that the 1960s and 1970s exhibit a noticeable frequency of years with negative anomalies (colder than average); the peak of this extreme cold occurred in 1964 with an anomaly of approximately –3.2 °C. From the 1990s onward, the frequency of positive anomalies increased, with most years experiencing milder winters than the long-term average.

This pattern is complemented by the trend of the longest annual consecutive cold spells (Figure 7b). A cold spell is defined as any uninterrupted sequence of days on which WCET ≤ –10 °C, without imposing an arbitrary minimum duration – a definition that follows directly from the daily nature of the index itself. Under this definition, a total of 57 years contained at least one qualifying event. The most extreme and prolonged cold spells were recorded during the earlier decades of the study period, with 1964 ranking first (18 consecutive days), followed closely by 1971 (17 days). While notable persistent events were also observed in 1997 (15 days) and 2008 (12 days), the overall duration of these events has shown a clear decline in recent years. In fact, over the past two decades, the duration of cold spells has markedly decreased, with no single event exceeding 12 days.

The ordinary least squares (OLS) regression indicates a slight downward trend over time:
Duration = 90.53 – 0.0433 · Year (i.e., an average decrease of about 0.043 days per year, or roughly 2.7 days over the entire 63-year period).

However, the Mann–Kendall test yields a tau of –0.122 with a p-value of 0.213, which is far from the 95 % significance level. The Sen's slope estimate is 0 days yr^{-1}. Therefore, the apparent decrease in cold spell duration over time is not statistically significant.

Overall, while both panels of Figure 7 show a general tendency toward milder winters, the high interannual variability and the absence of a statistically significant trend in cold spell persistence indicate that Tabriz's winter climate remains capable of producing severe, prolonged cold waves despite the long-term warming in mean temperatures.

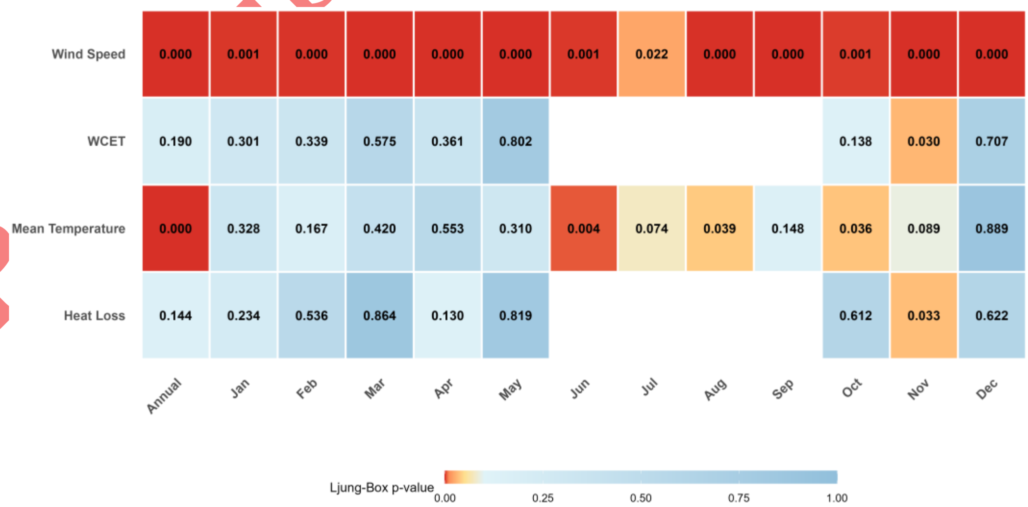

Fig 5. Autocorrelation status among the input data and the studied indices

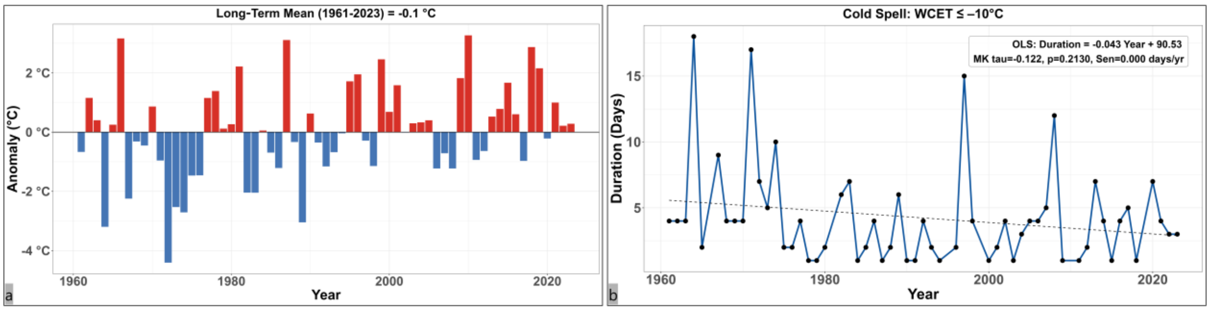

Fig 6. (a) Annual anomaly of mean WCET relative to the long-term mean, (b) Duration of the longest annual cold spell (WCET ≤ –10°C) in Tabriz during the 1961–2023 period.

SMK Trend Analysis of Cold Stress in Tabriz

The SMK plot (Figure 8), with its two curves UF (progressive, red) and UB (retrograde, blue) alongside the 95% confidence limits, traces the variations in the persistence of the longest annual cold spells from 1961 to 2023. The initial fluctuations of the series, which are mainly due to the short length of the series and the impact of extreme events such as the winter of 1964, gradually subside as the series lengthens. From the early 1970s, UF begins a downward trend, and around 1975 the two curves intersect within the confidence limits. This intersection, which is the only lasting crossing point in the entire period, thereafter keeps UF consistently in the negative half and below UB, thus indicating a gradual departure of cold duration from earlier conditions. However, this trend never becomes a persistent, fully significant structural change. In the mid-1990s and early 2000s, UF temporarily exceeds –1.96, making the decrease in cold duration momentarily significant, but on both occasions it returns to within the confidence bounds. This behaviour shows that although a general declining trend has existed since 1975, it has not progressed uniformly but has appeared in the form of temporary episodes. Overall, the SMK analysis confirms that winters in Tabriz have undergone a kind of gradual moderation since the mid-1970s, yet this moderation has occurred not as a sudden shift but as a gradual change interspersed with periods of short-lived intensification, a conclusion that is fully consistent with the monthly patterns in Figure 4 and the anomaly and trend diagrams in Figure 7.

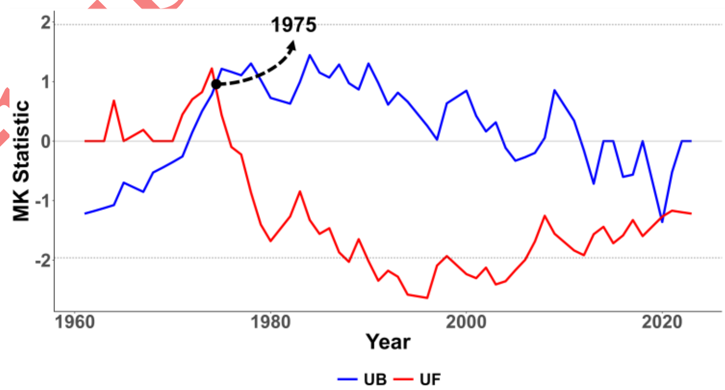

Fig 7. SMK for the longest annual cold spell in Tabriz (1961–2023)

The results of this 63-year study paint a clear picture of the transformation of cold stress in Tabriz. The key findings, including a decrease in the intensity and persistence of extreme cold and a warming trend in winters, align remarkably well with global and regional literature.

Interpretation of Findings and Comparison with Previous Studies

The significant decline in very cold days in recent decades is in complete agreement with the results of the study by Roshan et al. (2010), which points to an overall reduction in cold intensity at stations across Iran. These findings also corroborate the results of Fallah-Ghalhari et al. (2019) concerning the warming trend in minimum and maximum temperatures over Iran. A noteworthy point in the SMK analysis is that the shift of the UF curve toward negative values began with a structural intersection around 1975, after which, despite fluctuations, it never returned to its pre-1975 state. However, the fact that this trend became statistically significant only intermittently in the mid-1990s and early 2000s, without gaining lasting stability, indicates that the moderation of Tabriz winters has not been a sudden, uniform change but rather a gradual, non-linear process accompanied by periods of temporary intensification. In other words, this study demonstrates that this warming is not confined to thermometer readings but is also reflected in the WCET and thermal stress on the human body. The observed inverse relationship between WCET and Heat Loss confirms the physical validity of the models employed in this research, which are founded on heat-transfer principles (Brauner & Shacham, 1995; Osczevski & Bluestein, 2005).

Significance of the Indices for Passive Defence

One of the analytical innovations of this study is the interpretation of the results from a passive defence standpoint. The reduction in long-lasting cold waves should not encourage complacency. Historical extremes, such as the 18-day cold spell in 1964, demonstrate that Tabriz's climate retains the capacity for severe cold events. For infrastructure planning, WCET values below (–25 °C) may increase the risk of natural gas pipeline freezing and transit disruptions, while Heat Loss rates exceeding 800 W/m² are associated with rapid body cooling and outdoor work hazards. The Very Cold (≤ –45 °C) and Extremely Cold (≤ –60 °C) categories should trigger emergency protocols for heating systems and public shelters. Given the SMK-revealed instability of the moderation trend, resilience strategies must be designed for the worst historical scenarios, not merely for the recent warmer averages. The indices calculated in the present study provide precise tools for estimating these strategies and assessing population vulnerability to atmospheric threats. (Lankford & Fox, 2021).

Discordances and Practical Implications

While this study used the state-of-the-art NOAA formulas (Osczevski & Bluestein, 2005), some works, such as Swarnkar et al. (2018), still employ older models for specific applications (e.g., veterinary medicine), highlighting the applied diversity of these indices. Moreover, the findings of the present research on the reduction in cold intensity have direct consequences for building design. As shown by Tamaskani Esfahankalateh et al. (2020), window design in the cold climate of Tabriz plays a vital role in comfort; the results of this study suggest that design strategies should become more flexible and be optimised not only for protection against cold but also for taking advantage of longer periods of milder winter weather.

Conclusion

This study provided a long-term empirical assessment of winter cold stress in Tabriz using a comprehensive 63-year dataset (1961–2023). By simultaneously analysing the Wind Chill Equivalent Temperature (WCET) and Heat Loss indices, the research demonstrated a gradual transition of Tabriz's winter climate toward milder conditions. The frequency, intensity, and persistence of extreme cold events have systematically declined compared to the 1960s and 1970s, with the Sequential Mann-Kendall analysis identifying a distinct structural shift starting around 1975. However, this warming trend is characterised by strong interannual variability rather than a linear trajectory, indicating that severe, prolonged cold spells remain a recurring feature of the local climate system.

The practical value of these findings lies in their integration into urban planning, municipal winter infrastructure design, and passive defence strategies. The dual application of the WCET and Heat Loss indices offers distinct administrative tools: while the WCET helps define safety and operational thresholds for outdoor labour and transit systems, the Heat Loss rate serves as a critical indicator for municipal energy demand forecasting and thermal building designs. The reality of a changing, non-linear climate necessitates that urban planning in cold regions transitions away from static historical baselines toward adaptive, risk-based resilience strategies that account for extreme, low-probability climatic events.

The present study relies on data from a single synoptic station over 63 years. While this provides a valuable long-term temporal record, the findings should be interpreted with the following limitations in mind:

1. **Urbanisation and the UHI Effect:** Over the past six decades, Tabriz has experienced significant urban expansion. The associated Urban Heat Island (UHI) effect likely elevated minimum temperatures. Consequently, the observed moderation in cold stress might partially reflect local microclimatic warming rather than purely macro-climatic shifts.
2. **Surface Roughness and Wind Dynamics:** Urban densification increases surface roughness, which may artificially reduce local wind speeds recorded at the station over time, further contributing to the perceived reduction in cold severity.
3. **Spatial Representativeness and Threshold Sensitivity:** A single-station analysis limits the ability to generalise the spatial fingerprint of cold stress across the topographically diverse Tabriz metropolitan area. Furthermore, while standard physiological thresholds (e.g., WCET ≤ -10°C) were applied, human

thermal perception is highly subjective, and the vulnerability of infrastructure may vary depending on material sensitivity.

Therefore, future research should incorporate multi-station spatial analyses and homogenization techniques to better isolate the pure regional climate signal from local anthropogenic influences.

A comprehensive visual narrative of the study's analytical pathway, core empirical findings, and practical implications is presented in Figure 9, which synthesises the entire research framework from initial data processing to policy-oriented outcomes.

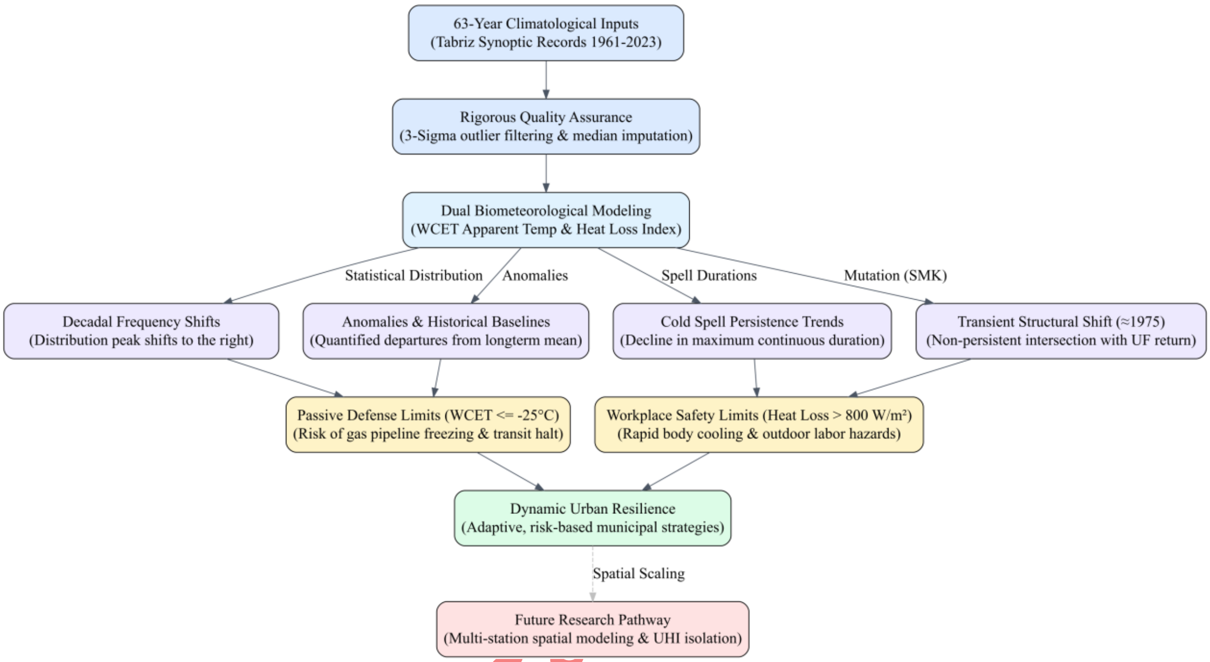

Fig 8. Synthesis framework of the Tabriz cold stress study (1961–2023), linking data, indices, findings, and practical implications

Acknowledgements

The authors gratefully acknowledge the Iran Meteorological Organisation for providing the data used in this study.

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