



Original Research

Meteorological associations with out-of-hospital cardiac arrest: A national population-based time-series analysis

Ádám Pál-Jakab ^a, Patrik Pesti ^c, Zsuzsanna Horti-Maricza ^a, Bettina Nagy ^a, Boldizsár Kiss ^a, Botond Biebel ^c, György Pápai ^b, Gábor Csató ^b, Nora Boussoussou ^a, Béla Merkely ^a, András Gelencsér ^f, Péter Sóttonyi ^a, Brigitta Szilágyi ^{c,d}, Endre Zima ^{a,e,*}

^a Heart and Vascular Centre, Semmelweis University, Városmajor utca 68, Budapest, 1122, Hungary

^b Hungarian National Ambulance Service, Markó Street 22, Budapest, 1055, Hungary

^c Budapest University of Technology and Economics, Műgyetem rkp. 3, Budapest, 1111, Hungary

^d Corvinus University of Budapest, Fővám tér 8, Budapest, 1093, Hungary

^e Institute of Anesthesiology and Perioperative Patient Care, Semmelweis University, Üllői út 78/B, Budapest, 1082, Hungary

^f Research Institute of Biomolecular and Chemical Engineering, Air Chemistry Research Group, University of Pannonia, Egyetem út 10, Veszprém, 8200, Hungary

ARTICLE INFO

Keywords:

Out-of-hospital cardiac arrest (OHCA)

Weather

Environmental exposure

Time factors

Population surveillance

Epidemiology

ABSTRACT

Objectives: Meteorological factors may influence cardiovascular emergency incidence, but comprehensive national evidence for out-of-hospital cardiac arrest (OHCA) associations remains limited. We investigated meteorological associations with OHCA occurrence using complete national population data.

Study design: Population-based time-series retrospective, non-interventional analysis.

Methods: We conducted a population-based time-series analysis using the Hungarian National Ambulance Service registry from November 2018 to December 2023. After excluding COVID-19 disruption period, 114830 OHCA cases across 1584 days were analysed. Meteorological parameters included temperature, wind speed, atmospheric pressure, humidity, and air quality. Associations were assessed using negative binomial regression models with temporal lag structures (0–3 days). We used a rolling 30-day z-score to detect outlier days with high OHCA cases and identified their unique weather conditions. Machine learning validation was performed with XGBoost and SHAP interpretation.

Results: Daily OHCA incidence averaged 60.9 ± 14.3 cases, peaking in winter (17.8 % higher than summer, $p < 0.001$). Each 1 °C temperature decrease was associated with a 1.4 % increase in daily OHCA incidence (IRR 0.986). Wind speed demonstrated inverse association (7.9 % decrease in OHCA incidence per-IQR effect; IRR 0.928). The highest-incidence days saw 31.9 % more cases, equivalent to 19 additional cases daily, linked to adverse weather.

Conclusion: Meteorological factors demonstrate strong, predictable associations with OHCA incidence, with extreme weather increasing rates by nearly one-third. The 3-day lag patterns enable weather-based early warnings, supporting the integration of meteorological data into emergency response to reduce preventable deaths.

1. Introduction

Out-of-hospital cardiac arrest (OHCA) remains a significant public health challenge, with an estimated yearly incidence of 67–170 cases per 100,000 people across Europe and survival rates consistently below 10 %.^{1,2} While emergency medical service response times, bystander cardiopulmonary resuscitation, and healthcare system factors are

well-established determinants of OHCA outcomes,^{2–5} environmental influences represent an increasingly recognised yet understudied and potentially underestimated dimension of cardiovascular emergency epidemiology.

Emerging evidence suggests that meteorological conditions significantly influence OHCA incidence through complex pathophysiological mechanisms.^{6–10} Observational studies have documented marked

* Corresponding author. Heart and Vascular Centre Semmelweis University, Városmajor utca 68, Budapest, 1122, Hungary.

E-mail address: zima.endre.istvan@semmelweis.hu (E. Zima).

<https://doi.org/10.1016/j.puhe.2026.106145>

Received 28 August 2025; Received in revised form 25 November 2025; Accepted 8 January 2026

Available online 16 January 2026

0033-3506/© 2026 The Authors. Published by Elsevier Ltd on behalf of The Royal Society for Public Health. This is an open access article under the CC BY license (<http://creativecommons.org/licenses/by/4.0/>).

seasonal variations in OHCA occurrence, with winter months showing 20–70 % higher incidence compared to summer periods.^{11–13} However, most investigations have examined single meteorological parameters in isolation, potentially missing important interaction effects and confounding relationships. Existing research has predominantly focused on single-city analyses or limited regional populations, constraining generalizability and preventing a comprehensive assessment of population-level patterns.^{14–20} The lack of sophisticated temporal analysis of weather and extreme weather conditions, particularly regarding lagged effects of the latter, warrants further limited translation of meteorological associations into actionable clinical and public health interventions.

Climate change intensifies the importance of understanding weather-cardiovascular associations for emergency preparedness.^{21–24}

Hungary provides an ideal setting for addressing these research gaps, with its centralised National Ambulance Service ensuring complete OHCA case ascertainment across 9.7 million inhabitants without the selection biases inherent in multi-provider healthcare systems. This unique organisational structure enables unprecedented examination of meteorological influences on OHCA incidence while controlling for healthcare system variations that confound international comparisons.

This study aimed to comprehensively investigate meteorological associations with OHCA occurrence using complete national population data. Specifically, we sought to quantify associations between atmospheric conditions and daily OHCA incidence, characterise temporal lag patterns, validate findings through machine learning approaches, and assess the impact of extreme weather events on cardiovascular emergency burden. These findings aim to provide evidence for developing weather-based early warning systems and support targeted prevention strategies in the context of measurable changes in climate patterns.

2. Methods

2.1. Study Design and data sources

We conducted a population-based time-series analysis utilising the complete Hungarian National Ambulance Service (HNAS) registry from November 1, 2018, to December 31, 2023. OHCA cases were identified from the national registry using standardised emergency response codes with daily aggregation by occurrence date. Meteorological and air quality data were obtained from the Hungarian Meteorological Service as nationwide daily averages. Although event-location-specific measurements would be ideal, preliminary spatial correlation analyses demonstrated consistently high inter-station agreement for daily temperature (mean Pearson $r > 0.85$), indicating that national averages reliably reflect country-wide meteorological conditions in the examined study period. To capture rapid atmospheric changes and relevant temperature gradients, daily maximum temperature change was included as a covariate.

2.2. Environmental exposure assessment

Meteorological parameters were systematically evaluated for multicollinearity using variance inflation factors (VIF). Weather index (composite atmospheric stability measure) and global radiation sum demonstrated VIF values > 10 and were excluded to ensure model stability and parameter interpretability. Primary parameters included daily average temperature ($^{\circ}\text{C}$), Air Quality Index (AQI), wind speed (m/s), diurnal temperature range (DTR), daily maximum temperature change, atmospheric pressure (hPa), weather index (WEI), relative humidity (%), and global radiation sum (J/cm^2). Additional day-to-day difference variables were calculated for AQI, wind speed, atmospheric pressure, WEI, and relative humidity (Supplementary Table 1).

2.3. Temporal classification and covariate definition

The analysis period was stratified according to COVID-19 pandemic phases based on documented healthcare utilisation patterns and national emergency declarations. Pre-pandemic conditions were defined as the period preceding March 3, 2020; the acute pandemic phase encompassed March 4, 2020, through December 31, 2020; and the post-acute phase commenced January 1, 2021, based on Hungarian national legal regulations.^{25,26}

While there were two distinct COVID-19 mortality peaks in Hungary (November 2020–March 2021 and November 2021–March 2022), we excluded only the acute pandemic phase for the following reasons: (1) the first wave created unprecedented healthcare system disruption including fundamental changes to emergency medical service protocols and population mobility restrictions that fundamentally confounded OHCA epidemiology; (2) by January 2021, substantial vaccination coverage and healthcare system adaptation had normalized emergency service operations; (3) including the 2021–2023 period provided essential multi-year winter observations while also minimized confounding.

Statistical analyses included 1584 days after the COVID-19 period exclusion. Temporal lag analysis utilised 1581 days (accounting for 3-day maximum lag), while machine learning models required complete feature matrices across all lag periods analysed, total of 1526 days. The exclusion of the COVID-19 period minimized confounding from pandemic-related mortality excess, healthcare utilisation changes, and altered population behavioural patterns. Seasonal classifications followed established cardiovascular epidemiological conventions, with winter defined as October through March and summer encompassing April through September, corresponding to documented temperate climate cardiovascular risk periodicity.²⁷

2.4. Statistical analysis framework

Primary analysis employed negative binomial regression models with logarithmic link functions to model daily OHCA counts. Temporal lag analysis incorporated weather exposures from 0 to 3 days prior to OHCA occurrence. Incidence rate ratios (IRR) and 95 % confidence intervals were calculated for clinical interpretation.^{28–31} The 0–3-day lag window reflects established cardiovascular physiological responses to environmental stimuli, encompassing immediate sympathetic activation (0-day), inflammatory responses (1–2 days), and cumulative physiological stress (3-day) as documented in cardiovascular environmental epidemiology.^{32–36}

2.5. Extreme OHCA incidence days analysis

Days with exceptional OHCA case numbers were identified using rolling 30-day z-scores, with values > 1.28 and < -1.28 defining high and low OHCA incidence days (top/bottom 10th percentiles). Two-dimensional Gaussian kernel density estimation (KDE) employing a bandwidth parameter of 0.4 was utilised to assess meteorological parameter distributions on extreme OHCA days through density ratio mapping techniques.

2.6. Machine Learning Validation and predictive modelling

Gradient boosting regression (XGBoost) provided independent methodological validation capturing non-linear exposure-response relationships. Weather predictors incorporated 0–3 day lag structures, while antecedent OHCA patterns used 1–7 day lags. SHAP analysis quantified individual parameter contributions to predictions.

2.7. Missing data management

Missing environmental observations were addressed through complete case deletion following temporal data alignment to ensure analytical robustness. Temperature measurements with minimal missing values (<0.2 %, missing completely at random) underwent median imputation using daily averages from the complete observation period. All statistical analyses were restricted to days with complete environmental exposure and OHCA outcome data to prevent bias from differential missingness patterns.

2.8. Convergence validation

Model performance evaluation utilised the coefficient of determination, mean squared error, and root mean squared error metrics applied to holdout testing datasets. Statistical significance was defined as $p < 0.05$. Bonferroni correction was applied specifically to the three seasonal comparison tests (adjusted $\alpha = 0.017$). Primary scientific inference was based on the comprehensive multivariate meteorological model representing a single confirmatory analysis, while exploratory univariate analyses served hypothesis generation consistent with established environmental epidemiological practice. Temporal autocorrelation in daily count data was assessed through residual analysis.

All analyses were implemented using Python (Python Software Foundation. (2022). Python Language Reference, version 3.9), with specialised libraries including pandas for data manipulation, scikit-learn for machine learning implementations, XGBoost for gradient boosting, statsmodels for generalised linear modelling, and SHAP for model interpretability assessment.

3. Results

3.1. Study population and temporal distribution

During the study period, a total of 132,065 OHCA cases were recorded. After excluding the COVID-19 period to minimise confounding from pandemic-related mortality excess and healthcare system disruptions, the final analysis included 114,830 cases across 1584 days. The overall mean age was 69.7 ± 14.2 years, with 58.5 % male

predominance. Daily OHCA incidence ranged from 27 to 130 cases per day (mean: 60.9 ± 14.3 cases/day).

3.2. Seasonal variation in OHCA incidence

Pronounced seasonal variation was observed in daily OHCA incidence (Fig. 1). Winter months demonstrated consistently higher OHCA rates compared to summer months, with a mean daily incidence of 65.6 ± 15.1 versus 55.7 ± 11.4 cases (difference: 9.9 cases/day, 95 % CI: 8.6–11.2; Supplementary Table 2). Median daily incidence showed similar patterns (winter: 63.0 cases [IQR 55.0–74.0] vs summer: 54.0 cases [IQR 48.0–62.0], difference: 9.0 cases [95 % CI 7.0–12.0]). This seasonal difference represents a 17.8 % relative increase in winter OHCA incidence.

Statistical testing confirmed robust seasonal differences across multiple analytical approaches. The Mann-Whitney *U* test ($U = 434.874$, $p < 0.001$) and Kolmogorov-Smirnov test ($D = 0.289$, $p < 0.001$) all remained highly significant after Bonferroni correction for multiple testing (Supplementary Table 2).

3.3. Meteorological associations with OHCA incidence

WEI and global radiation sum demonstrated VIF values exceeding 10 and were excluded from the final analytical framework to ensure model stability and interpretability.

3.4. Univariate weather parameter analysis

Univariate negative binomial regression analysis identified several meteorological parameters significantly associated with daily OHCA incidence (Table 1). Daily mean temperature demonstrated the strongest association, with each 1 °C decrease associated with a 1.4 % increase in OHCA incidence (IRR = 0.990, 95 % CI: 0.988–0.991, $p < 0.001$), relative to baseline. When expressed in clinically interpretable units, each interquartile range increase in temperature (14.5 °C) corresponded to a 13.6 % decrease in daily OHCA incidence (Table 2).

Diurnal temperature range showed a significant association, with each 1 °C increase associated with a 1.2 % decrease in OHCA incidence (IRR = 0.988, 95 % CI: 0.986–0.991, $p < 0.001$) (Supplementary

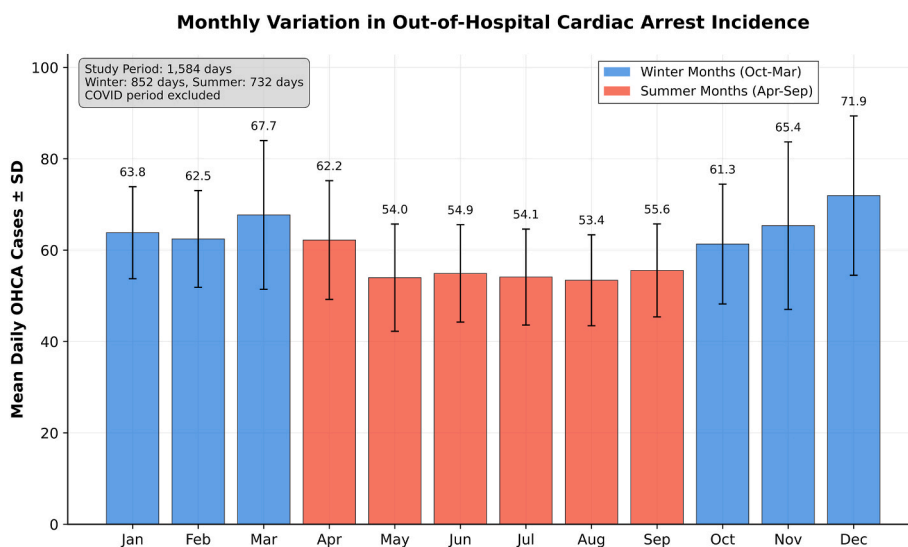


Fig. 1. Monthly Variation in OHCA Incidence Monthly distribution of daily OHCA incidence demonstrating pronounced seasonal variation across the study period. Bars represent mean daily cases ± standard deviation for each calendar month, with winter months (October–March) shown in blue and summer months (April–September) shown in red. Winter months consistently demonstrate higher OHCA incidence compared to summer months, with peak incidence occurring during December and January. $N = 1584$ total days (852 winter days, 732 summer days) with complete data. Seasonal definitions: Winter months = October through March; Summer months = April through September, following established cardiovascular epidemiological conventions for temperate climate regions. Abbreviations: OHCA = Out-of-Hospital Cardiac Arrest; SD = Standard Deviation.

Table 1
Primary meteorological associations with daily OHCA incidence.

Parameter	Observed Range (Mean ± SD)	Univariate Models			Multivariate Model			% Change per IQR‡
		IRR	95 % CI	p-value	IRR	95 % CI	p-value	
Primary temperature associations								
Mean temperature (°C)	−6.8 to 30.6 (12.2 ± 8.4)	0.990	0.988-0.991	<0.001	0.986	0.984-0.987	<0.001	−20.0 %
Diurnal temperature range (°C)	0.7 to 21.4 (8.9 ± 4.0)	0.988	0.986-0.991	<0.001	0.998	0.994-1.001	0.185	−1.5 %
Atmospheric dynamics								
Wind speed (m/s)	0.6 to 7.0 (2.1 ± 0.9)	0.989	0.979-0.999	0.033	0.928	0.912-0.943	<0.001	−7.9 %
Barometric pressure (hPa)	981.4 to 1042.1 (1013.2 ± 10.1)	1.000	0.999-1.001	0.840	0.998	0.996-0.999	0.001	−3.8 %
Relative humidity (%)	31.2 to 97.8 (71.2 ± 12.4)	1.003	1.002-1.004	<0.001	0.998	0.997-0.999	<0.001	−3.9 %
Air quality and variability								
AQI	25.8 to 88.6 (36.0 ± 7.0)	0.999	0.998-1.001	0.213	0.994	0.992-0.995	<0.001	−5.0 %
Wind speed daily difference	−4.7 to 4.3 (−0.0 ± 1.0)	1.006	0.996-1.017	0.230	1.049	1.032-1.066	<0.001	+4.8 %
Pressure daily difference	−18.5 to 19.8 (−0.0 ± 4.7)	0.998	0.996-1.000	0.061	0.998	0.996-1.001	0.265	−0.8 %

The table presents associations between retained meteorological parameters and daily OHCA incidence using negative binomial regression models. Univariate models assess individual parameter associations, while the multivariate model includes all retained meteorological parameters simultaneously to identify independent associations while controlling for variable confounding. Parameters were systematically evaluated for multicollinearity using variance inflation factors, with weather index and global radiation excluded due to VIF >10 to ensure model stability. Analysis excluded the COVID-19 disruption period (March 4, 2020–December 31, 2020) to minimise healthcare system confounding effects. All models account for overdispersion using a negative binomial distribution with dispersion parameter $\alpha = 0.030$. Clinical effect sizes (% change per IQR) represent population-level risk changes during typical seasonal meteorological variation. **Abbreviations:** CI, confidence interval; COVID-19, coronavirus disease 2019; hPa, hectopascals; IQR, interquartile range; IRR, incidence rate ratio; OHCA, out-of-hospital cardiac arrest; VIF, variance inflation factor. **Notes:** IRR values of parameters achieving statistical significance in multivariate models shown in bold. Six independent meteorological predictors were identified: mean temperature, wind speed, barometric pressure, relative humidity, air quality index, and wind speed daily variability. ‡Multivariate model represents a single comprehensive test of meteorological associations with OHCA incidence, including all retained parameters simultaneously. §Clinical interpretation calculated as: $(IRR - 1) \times 100$, where IQR represents the interquartile range for each parameter during the study period. IRR <1.0 indicates decreased OHCA risk (negative association), while IRR >1.0 indicates increased OHCA risk (positive association). N = 1584 days with complete meteorological and outcome data. Multivariate model goodness-of-fit: pseudo-R² = 0.213, dispersion parameter = 0.943, indicating appropriate model specification and overdispersion control.

Table 2
Clinical effect size translation and absolute daily case impact at the national level.

Parameter	Parameter IQR	IRR per Unit	IRR per IQR	% Change per IQR	Population Impact†	Multivariate IRR per IQR	Multivariate % Change	Multivariate Impact
Temperature Parameters								
Mean temperature	14.5 °C (IQR)	0.990	0.864	−13.6 %	8.3 fewer cases/day	0.799	−20.0 %	12.2 fewer cases/day
Per 10 °C increase	10.0 °C (reference)	0.990	0.900	−10.0 %	6.1 fewer cases/day	0.859	−14.1 %	8.6 fewer cases/day
Diurnal temperature range	6.2 °C (IQR)	0.988	0.928	−7.2 %	4.4 fewer cases/day	0.985	−1.5 %	0.9 fewer cases/day
Atmospheric Dynamics								
Wind speed	1.1 m/s (IQR)	0.989	0.988	−1.2 %	0.7 fewer cases/day	0.921	−7.9 %	4.8 fewer cases/day
Barometric pressure	12.9 hPa (IQR)‡	1.000	1.005	+0.5 %	0.3 more cases/day	0.962	−3.8 %	2.3 fewer cases/day
Relative humidity	18.8 % (IQR)	1.003	1.056	+5.6 %	3.4 more cases/day	0.961	−3.9 %	2.4 fewer cases/day
Air Quality and Variability								
Air quality index	7.9 units (IQR)	0.999	0.993	−0.7 %	0.4 fewer cases/day	0.950	−5.0 %	3.0 fewer cases/day
Wind speed daily difference	1.0 m/s (IQR)	1.006	1.006	+0.6 %	0.4 more cases/day	1.048	+4.8 %	2.9 more cases/day
Seasonal Comparison								
Winter vs Summer	9.9 cases/day difference	–	–	+17.8 %	9.9 more cases/day	–	–	–

Clinical interpretation of meteorological associations translated into population-level health impacts, comparing univariate and multivariate model results. Effect sizes expressed as per cent change in daily OHCA incidence per interquartile range (IQR) change in meteorological parameters. IQR values represent the interquartile range width (Q3–Q1) for each meteorological parameter. Population impact calculated as absolute change in daily case counts based on study period mean incidence (60.9 cases/day) and observed effect sizes. Multivariate effects demonstrate substantial strengthening for most parameters when controlling for confoundings. Abbreviations: IQR, interquartile range; IRR, incidence rate ratio; OHCA, out-of-hospital cardiac arrest. **Notes:** †Population impact calculated as: (Study mean daily cases × % change per IQR). Negative values indicate protective effects (fewer cases). ‡Barometric pressure IQR calculated from daily pressure values. IQR values derived from study period meteorological data (November 2018–December 2023, excluding the COVID-19 period). Clinical interpretation assumes causality and population-level exposure changes. Dramatic differences between univariate and multivariate effects highlight the importance of controlling for meteorological confounding.

Table 5). Relative humidity demonstrated a small but significant positive association (IRR = 1.003, 95 % CI: 1.002-1.004, p < 0.001). Wind speed showed a modest but statistically significant protective association (IRR = 0.989, 95 % CI: 0.979-0.999, p = 0.033), while barometric pressure daily differences demonstrated a non-significant protective trend (IRR = 0.998, 95 % CI: 0.996-1.000, p = 0.061).

3.5. Multivariate weather parameter analysis

Multivariate negative binomial models, simultaneously revealed six parameters with statistically significant independent associations with daily OHCA incidence, indicating substantial confounding and interaction effects among atmospheric variables (Table 1). The final

multivariate model demonstrated excellent fit characteristics (dispersion parameter = 0.943, pseudo- $R^2 = 0.213$), indicating appropriate model specification and over-dispersion control.

Temperature associations strengthened in multivariate analysis, with each 1 °C increase associated with a 1.4 % decrease in OHCA incidence (IRR = 0.986, 95 % CI: 0.984-0.987, $p < 0.001$).

Wind speed demonstrated the most dramatic change, with multivariate analysis revealing a strong protective association (IRR = 0.928, 95 % CI: 0.912-0.943, $p < 0.001$) representing a 7.2 % decrease in OHCA incidence per 1 m/s increase.

Additional parameters achieving significance in multivariate models included barometric pressure (IRR = 0.997, 95 % CI: 0.996-0.999, $p = 0.001$), relative humidity (IRR = 0.998, 95 % CI: 0.997-0.999, $p < 0.001$), and wind speed daily variability (IRR = 1.049, 95 % CI: 1.032-1.066, $p < 0.001$). Notably, diurnal temperature range effects were attenuated and became non-significant in multivariate analysis (IRR = 0.998, 95 % CI: 0.994-1.001, $p = 0.185$).

Clinical translations of effect sizes and population-level impact estimates are presented in Table 2.

3.6. Temporal lag structure analysis

Comprehensive lag structure analysis (0–3 days) revealed distinct temporal patterns for different meteorological parameters

(Supplementary Table 6). Temperature showed strongest associations at a 3-day lag in univariate analysis (IRR = 0.991, 95 % CI: 0.986-0.996, $p < 0.001$), with multivariate models showing tendentially similar, but non-significant delayed effects (IRR = 0.991, 95 % CI: 0.981-1.000, $p = 0.062$).

Wind speed demonstrated increasingly strong protective effects with longer lag periods, particularly in multivariate analysis. The 3-day lagged wind speed showed the strongest association (IRR = 0.959, 95 % CI: 0.946-0.972, $p < 0.001$), suggesting cumulative benefits from sustained atmospheric circulation rather than acute protective effects.

Diurnal temperature range exhibited immediate effects with same-day exposure showing significant associations in univariate (IRR = 0.993, 95 % CI: 0.990-0.997, $p < 0.001$) models, but non-significant multivariate models (IRR = 0.995, 95 % CI: 0.989-1.000, $p = 0.059$). Barometric pressure showed significant delayed effects at a 3-day lag in univariate analysis (IRR = 1.003, 95 % CI: 1.000–1.006, $p = 0.027$), while multivariate models demonstrated significant immediate effects only (IRR = 0.998, 95 % CI: 0.997-0.999, $p = 0.001$) (Supplementary Table 6).

3.7. Seasonal patterns in extreme OHCA days

Seasonal stratification of extreme OHCA incidence days revealed distinct temperature patterns. During winter months, days with high

Meteorological Parameter Distribution Analysis on Extreme OHCA Days Winter Period (October–March)

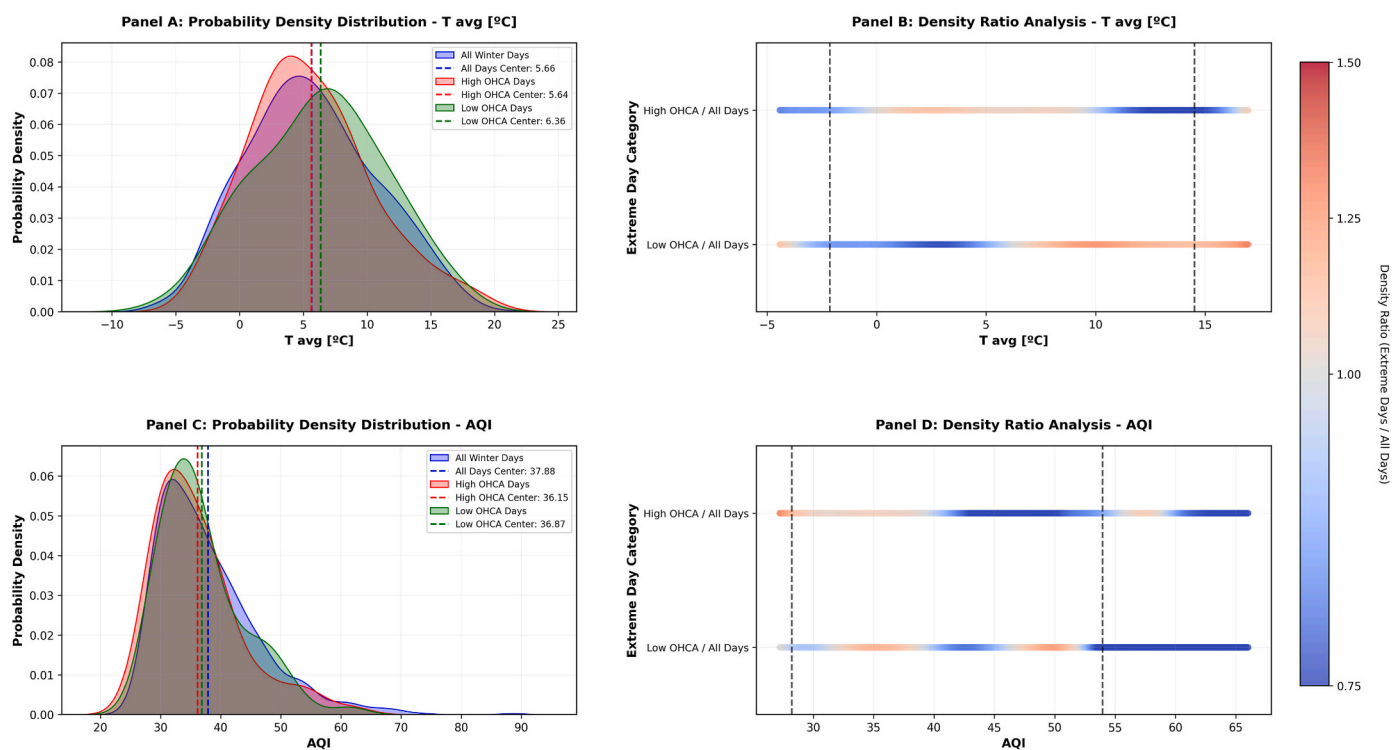


Fig. 2. Meteorological Parameter Distributions on Extreme Out-of-Hospital Cardiac Arrest Incidence Days During Winter Months Distribution analysis of meteorological parameters on days with extreme out-of-hospital cardiac arrest (OHCA) incidence during winter months (October–March). Extreme OHCA days were identified using rolling 30-day z-scores within the winter period, with the top and bottom 10th percentiles representing high and low OHCA incidence days, respectively. Panel A: Kernel density estimation of daily mean temperature distributions demonstrates that high OHCA days occurred at colder temperatures (mean: 5.64 °C) compared to low OHCA days (mean: 6.36 °C), representing a 0.72 °C difference. Vertical dashed lines indicate distribution centers of mass. Panel B: One-dimensional density ratio heatmaps illustrate the relative density of extreme OHCA days compared to all winter days across the temperature spectrum. Colors represent density ratios, with red indicating higher relative occurrence and blue indicating lower relative occurrence of extreme days. Vertical dashed lines represent the 5th and 95th percentiles of temperature distributions. Panel C: Air Quality Index (AQI) kernel density distributions show high OHCA days occurred on days with slightly better air quality (mean: 36.15) compared to low OHCA days (mean: 36.87). Panel D: AQI density ratio heatmaps across the air quality spectrum. Analysis period: November 2018–December 2023, excluding COVID-19 disruption period (March 2020–December 2020). N = 852 winter days; high OHCA days n = 85; low OHCA days n = 85. Abbreviations: AQI, Air Quality Index; OHCA, out-of-hospital cardiac arrest.

OHCA incidence occurred at mean temperatures of 5.64 °C compared to 6.36 °C for days with low OHCA incidence (difference: 0.72 °C). This difference was reflected in the full temperature distributions, where the kernel density curve for high OHCA days was shifted toward colder conditions, with a clear separation between the centers of the distributions (mean 5.64 °C vs 6.36 °C for high vs low OHCA days). The density ratio analysis further showed disproportionate concentration of high OHCA days at temperatures below 4 °C (red regions) and underrepresentation at warmer winter temperatures above 8 °C (blue regions). Air quality patterns showed an opposite tendency and were consistent with a meteorological mechanism in which cold, dry air masses produce both lower temperatures and clearer conditions. Consistent with this pattern, air quality index values during winter high OHCA days were slightly lower than during low OHCA days (mean 36.15 vs 36.87 AQI; Fig. 2).

During summer months, high OHCA incidence days occurred under slightly warmer and more polluted conditions, with mean temperatures of 19.37 °C compared to 19.17 °C for low OHCA days (difference: +0.20 °C). Air quality index values were higher during summer high OHCA days (34.06 units) compared to low OHCA days (33.39 units) (Supplementary Fig. S1).

Analysis across all seasons showed only minimal differences in

average temperature between high and low OHCA incidence days, with mean values of 12.13 °C versus 12.21 °C (difference: 0.08 °C) (Supplementary Table 7). AQI values were higher on days with extreme OHCA incidence (36.08 units) compared with low-incidence OHCA days (35.05 units), indicating slightly poorer air quality on days characterised by unusually high OHCA case numbers (Supplementary Fig. S2).

During winter, high-incidence OHCA days occurred at slightly colder temperatures (mean 5.64 °C vs. 6.36 °C) and at marginally lower AQI values compared with low-incidence days (Fig. 2). Density-ratio heat-maps demonstrated a disproportionate clustering of high-OHCA days at temperatures below 4 °C.

3.8. Machine Learning Validation and predictive modelling

XGBoost models incorporating all meteorological parameters and their temporal lags achieved moderate predictive performance ($R^2 = 0.22$ on test data, RMSE = 13.2 cases/day) (Table 3). SHAP value analysis confirmed temperature and wind speed parameters as the most influential environmental predictors of daily OHCA incidence (Fig. 3).

The SHAP analysis revealed that lower temperatures and reduced wind speeds consistently contributed to increased OHCA risk

Table 3
Summary of key findings: Meteorological associations with OHCA incidence.

Finding Category	Parameter/Comparison	Key Values	Interpretation
Seasonal Variation	Winter vs Summer	Winter: 65.6 ± 15.1 cases/day Summer: 55.7 ± 11.4 cases/day Difference: 9.9 cases/day (95 % CI: 8.6–11.2)	17.8 % relative increase in winter OHCA incidence
	Statistical significance	Mann-Whitney U: 434.874 (p < 0.001) Kolmogorov-Smirnov: D = 0.289 (p < 0.001)	Highly significant after Bonferroni correction
	Study period	1584 days total Winter: 852 days Summer: 732 days	Nov 2018–Dec 2023, COVID-19 period excluded
Primary Meteorological Associations (Multivariate)	Mean temperature	IRR: 0.986 (95 % CI: 0.984-0.987) p < 0.001	1.4 % increase in OHCA per 1 °C decrease; 20.0 % change per IQR
	Wind speed	IRR: 0.928 (95 % CI: 0.912-0.943) p < 0.001	7.9 % decrease in OHCA per IQR increase; protective association
	Barometric pressure	IRR: 0.998 (95 % CI: 0.996-0.999) p = 0.001	3.8 % change per IQR; significant association
	Relative humidity	IRR: 0.998 (95 % CI: 0.997-0.999) p < 0.001	3.9 % change per IQR; protective in multivariate model
	Air Quality Index (AQI)	IRR: 0.994 (95 % CI: 0.992-0.995) p < 0.001	5.0 % change per IQR; significant protective effect
	Temporal lag pattern	Strongest effects at 3-day lag	Cumulative physiological stress rather than acute triggering
Extreme Weather Day Characteristics	High-risk days (top 10 %)	Mean: 79.7 ± 15.3 cases/day Range: 55–130 cases	31.9 % increase vs normal days; ~19 additional cases/day
	Normal weather days	Mean: 60.4 ± 12.2 cases/day Range: 33–103 cases	Reference baseline (80 % of all days)
	Low-risk days (bottom 10 %)	Mean: 47.1 ± 9.8 cases/day Range: 28–78 cases	22.1 % decrease vs normal days
	Temperature patterns (winter)	High OHCA days: 5.64 °C Low OHCA days: 6.36 °C Difference: 0.72 °C	High OHCA days associated with colder temperatures
Model Performance Metrics	Multivariate negative binomial model	Pseudo-R ² : 0.213 Dispersion parameter: 0.943	Excellent fit, appropriate overdispersion control
	Enhanced lag structure model	Pseudo-R ² : 0.269 Dispersion parameter: 0.903	Improved performance with optimal lag structures
Machine Learning Validation	XGBoost (meteorological only)	R ² : 0.22 RMSE: 13.2 cases/day	Temperature and wind speed most influential predictors
	Enhanced XGBoost (with OHCA history)	R ² : 0.50 RMSE: 10.1 cases/day	Substantial improvement with 1–7 day antecedent OHCA patterns

The table consolidates all primary quantitative findings from the study, enabling rapid reference to key meteorological associations, seasonal patterns, extreme weather impacts, and model validation results. All analyses excluded the COVID-19 disruption period (March 4, 2020–December 31, 2020). Statistical significance defined as p < 0.05 with Bonferroni correction applied to seasonal comparisons (adjusted $\alpha = 0.017$). Extreme OHCA days identified using rolling 30-day z-score methodology ($z > 1.28$ or $z < -1.28$ representing top/bottom 10 %). Multivariate models include all meteorological parameters simultaneously to control for confounding. Abbreviations: AQI, Air Quality Index; CI, confidence interval; COVID-19, coronavirus disease 2019; IRR, incidence rate ratio; IQR, interquartile range; OHCA, out-of-hospital cardiac arrest; RMSE, root mean square error.

predictions, corroborating the parametric regression findings. Among lagged effects, 3-day temperature and wind speed parameters ranked highest in feature importance, confirming the temporal patterns identified in negative binomial models.

Enhanced XGBoost models incorporating 1-7-day antecedent OHCA occurrence patterns alongside statistically significant meteorological parameters achieved improved predictive performance ($R^2 = 0.50$, RMSE = 10.1 cases/day) compared to meteorological-only models ($R^2 = 0.22$, RMSE = 13.2 cases/day).

3.9. Model diagnostics and statistical validation

Negative binomial regression models appropriately addressed overdispersion evident in preliminary Poisson models (Supplementary Table 8). Univariate models showed dispersion parameters ranging from 0.99 to 1.24, with several parameters exceeding the overdispersion threshold. The multivariate model achieved excellent fit characteristics of the combined meteorological model explaining 21.3 % of daily OHCA variation. Enhanced models incorporating lag structures demonstrated further improvement, achieving a pseudo- R^2 of 0.269 with a dispersion parameter of 0.903.

4. Discussion

This national analysis demonstrates significant associations between meteorological factors and OHCA incidence. Each 1 °C decrease in daily temperature was associated with a 1.4 % increase in OHCA incidence. Pronounced seasonal variation was observed, with winter months demonstrating 17.8 % higher daily OHCA incidence compared to summer months. Independent validation through extreme case day analysis confirmed these associations: days with the highest OHCA case numbers were characterized by meteorological patterns consistent with regression findings, particularly lower temperatures and reduced atmospheric circulation. The 3-day lag pattern enables weather-based prediction and intervention strategies.

These associations suggest potential clinical applications. Weather forecasts provide a 1-3-day advance warning for healthcare resource allocation and emergency preparedness.^{37–39} The 31.9 % increased incidence during extreme weather suggests potential for burden reduction through targeted interventions, pending confirmation of causal relationships. Emergency medical services can optimise staffing and equipment distribution based on meteorological forecasts. Healthcare providers could implement enhanced monitoring for vulnerable populations during high-risk weather periods, particularly elderly patients and those with cardiovascular disease, following temperature drops.^{21,40–43}

The 17.8 % winter increase in cardiac arrest incidence supports systematic seasonal risk stratification. Community outreach programs can deliver targeted prevention messages during high-risk periods, emphasising thermal protection and medication adherence and support for those who need it. These predictable associations warrant future automated early warning systems integrating meteorological data with population health surveillance.^{21,23,44–47}

Cold exposure triggers sympathetic activation, vasoconstriction, and increased cardiac workload.^{7,8,48,49} The 3-day lag suggests cumulative physiological stress rather than acute triggering. The inverse wind speed association may reflect enhanced atmospheric circulation and air quality, with cumulative benefits from sustained circulation.^{50–53}

Although multiple studies describe a J-shaped temperature relationship, our findings showed that linear models for assessment of cold-related association were consistent with several non-linear exposure-response specifications, including cubic spline transformations, higher-order polynomial fits, and fully non-linear machine learning models (XGBoost with SHAP interpretation). Hungary's temperate climate provides limited exposure to extreme heat, reducing the visibility of the upper "heat-related" limb of the J-curve.

Our national approach eliminates selection bias while contributing novel extreme weather quantification consistent with international studies.^{10,13,40,54–57}

Our extreme weather validation addresses a critical gap in health-related environmental epidemiology, where traditional analyses assume linear associations without examining meteorological outlier impacts. Demonstrating that extreme conditions account for disproportionate cardiovascular burden provides crucial evidence for emergency preparedness.^{10,58,59} Convergent validation across negative binomial regression, machine learning, and temporal analyses establishes methodological standards while confirming result robustness.

Daily OHCA incidence exhibited marked short-term variability during the study period. Our multivariate meteorological model explained 21.3 % of this variability, indicating that while weather contributes meaningfully, additional temporal, behavioral, and healthcare factors likely influence daily fluctuations. Extreme-day analysis further showed that the highest 10 % of incidence days averaged approximately 19 additional cases relative to typical days, underscoring the operational importance of anticipating sudden surges. These findings support the potential utility of early warning systems that combine meteorological forecasts with recent OHCA patterns to enhance emergency preparedness.

The substantial performance improvement when incorporating historical OHCA patterns demonstrates that while meteorological factors provide meaningful predictive information for cardiovascular emergency preparedness, antecedent case patterns represent stronger short-term predictors. This finding supports the development of hybrid forecasting systems that combine meteorological monitoring with epidemiological surveillance.

Several aspects strengthen this investigation. Our statistical approach, incorporating negative binomial modelling, comprehensive lag analysis, and multiple validation methods, provides robust evidence within observational constraints.^{28,31,60}

The generalizability of these findings warrants careful consideration. While Hungary's temperate continental climate and centralised EMS provide ideal conditions for comprehensive meteorological-health relational research, extrapolation to regions with different climatic patterns, healthcare infrastructures, or population characteristics requires appropriate confounding handling and validation. The magnitude of associations may vary in populations with different baseline cardiovascular risk profiles, EMS adaptive capacities, or environmental exposure patterns.

Our rolling z-score methodology for extreme weather event detection represents a broadly applicable framework extending beyond cardiovascular epidemiology. This approach enables identification of meteorological conditions associated with health outcome surges while maintaining statistical rigor across diverse parameter ranges. The technique's ability to generate meaningful insights across the complete meteorological spectrum, combined with its adaptability to various health outcomes and geographic contexts, establishes a generalizable tool for environmental health surveillance and early warning system development.

Limitations include the population-level design's inability to account for individual factors, potential microenvironmental variations.^{61,62} Area-level meteorological measurements using national daily averages may not fully capture spatial heterogeneity during extreme weather events such as cold fronts, which can create temperature gradients across the country. While preliminary correlation analysis indicated high spatial consistency for typical weather patterns ($r > 0.85$), individual extreme events may affect regional OHCA risk differently than captured by national averages. Single-country analysis may limit generalizability to different climates, healthcare systems, or populations.^{10,11,21,26,55,56,63–65}

This national analysis provides evidence that meteorological factors have significant associations with OHCA incidence. Each 1 °C decrease in daily mean temperature was associated with a 1.4 % increase in daily

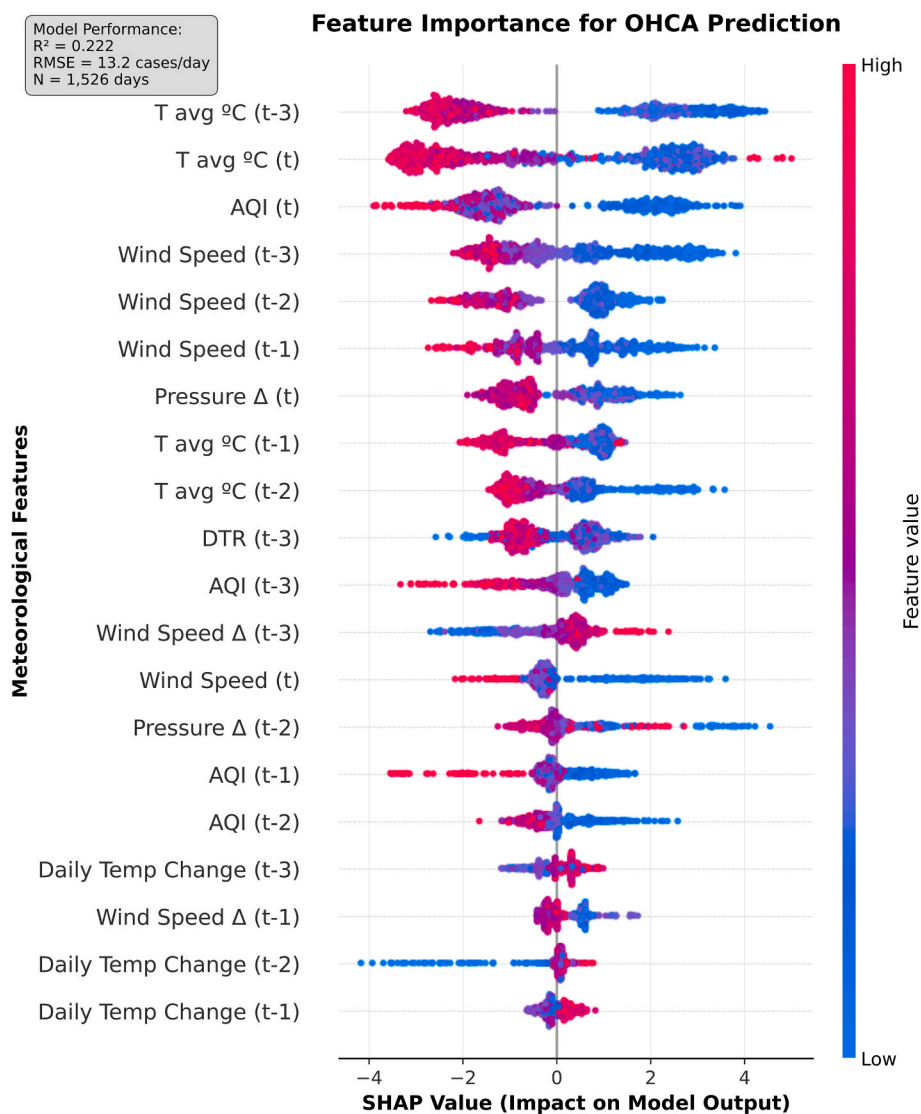


Fig. 3. Machine Learning Validation of Meteorological Associations with OHCA Incidence SHAP feature importance analysis from XGBoost regression demonstrating the relative predictive contribution of meteorological parameters to daily OHCA incidence. Features are ranked by absolute mean SHAP value, indicating each parameter's average impact on model predictions across all observations. The model incorporated meteorological parameters with temporal lag structures (0–3 days prior to OHCA occurrence) to capture delayed physiological responses to atmospheric conditions. Model performance: $R^2 = 0.222$, $RMSE = 13.2$ cases/day. Analysis validates primary statistical findings through independent machine learning methodology, demonstrating temperature and wind speed parameters as dominant environmental predictors. Data points represent individual predictions coloured by feature value magnitude (red = high values, blue = low values). Each dot represents the SHAP value for a specific observation, with horizontal spread indicating the distribution of feature impacts across the dataset. $N = 1526$ days with complete meteorological and outcome data. Abbreviations: AQI = Air Quality Index; DTR = Diurnal Temperature Range; OHCA = Out-of-Hospital Cardiac Arrest; RMSE = Root Mean Square Error; SHAP = SHapley Additive exPlanations; Δ = daily difference (day-to-day change). Temporal notation: (t) = same day as OHCA occurrence; (t-1) = 1 day prior to OHCA; (t-2) = 2 days prior to OHCA; (t-3) = 3 days prior to OHCA.

OHCA incidence, while reduced wind speed showed strong protective associations (7.9 % decrease in OHCA incidence per interquartile range increase). Pronounced seasonal variation demonstrated 17.8 % higher winter incidence compared to summer months. The predictable 3-day lag patterns and robust seasonal variations enable the practical implementation of weather-based early warning systems and targeted prevention strategies.

For clinical implementation, we recommend monitoring five key meteorological parameters: (1) daily mean temperature with 3-day lag consideration, (2) wind speed patterns, (3) barometric pressure changes, (4) relative humidity levels, and (5) air quality indices. Early warning systems should trigger enhanced emergency preparedness when daily temperature drops exceed 5 °C, wind speeds fall below 2 m/s, or

combined adverse meteorological conditions are forecast.

These findings translate to substantial population health impact, with seasonal variation alone representing approximately 10 additional daily cases during peak winter months nationally. Through meteorologically informed emergency preparedness and clinical interventions, healthcare systems can anticipate and respond to predictable increases in cardiovascular emergency burden. As climate change increases extreme weather frequency, integrating meteorological monitoring with cardiovascular emergency response represents a promising approach, warranting further investigation.⁶⁶ The development and implementation of weather-responsive healthcare systems should become a priority for targeted population health initiatives aimed at reducing preventable cardiovascular mortality.

Ethical statement

This investigation received approval from the Hungarian Medical Research Council (approval numbers: IV/3043/2021/EKU and IV/3043-3/2021/EKU) and was conducted in full accordance with the principles of the Declaration of Helsinki and applicable institutional and national ethical standards. All procedures complied with the General Data Protection Regulation (GDPR). Individual consent was waived for this non-interventional retrospective registry analysis.

Funding

Semmelweis University provided funding of open-access publication. Research support was received through the PhD Excellence Program of Semmelweis University via grant EFOP-3.6.3-VEKOP-16-2017-00009 ("Semmelweis 250+ Excellence Scholarship"). Project no. RRF-2.3.1-21-2022-00014 received implementation support from the European Union through the Hungarian Climate Change National Laboratory. Additional support was provided by RRF-2.3.1-21-2022-00003 under the National Cardiovascular Laboratory Artificial Intelligence Core Lab framework. B.M. acknowledges institutional funding to the Heart and Vascular Centre of Semmelweis University from Biotronik, Boehringer Ingelheim, DUKE Clinical Institute, Eli Lilly, and Novartis, along with personal consulting fees from Boehringer Ingelheim, Daiichi Sankyo, DUKE Clinical Institute, and Novartis, all unrelated to the current research. B.S. participated in project no. TKP2021-EGA-02, supported through funding from the Ministry of Culture and Innovation of Hungary via the National Research, Development and Innovation Fund under the TKP2021-EGA funding scheme. E.Z. acknowledges personal consulting relationships with Biotronik, Abbott, AstraZeneca, Innomed, Boston Scientific, and Medtronic, all independent of this research. The funding organisations maintained no involvement in study conception, data collection and analysis, manuscript preparation, or publication decisions. All other authors declare that they have no financial or non-financial competing interests related to the work presented in this manuscript.

Declaration of competing interest

The authors declare no competing interests.

Data availability statement

The original datasets analysed in this investigation are not accessible for public distribution in accordance with privacy protection requirements and institutional guidelines established by the Hungarian National Ambulance Service. Aggregated data that support the study findings may be obtained from the corresponding author upon reasonable academic request and after obtaining necessary authorizations.

Author contributions (CRediT)

Conceptualisation, Á.P.-J., B.S. and E.Z.; methodology, P.P., B.B., Á.P.-J., B.S., and E.Z.; validation, Á.P.-J., B.S. and E.Z.; formal analysis, P.P., B.B., Á.P.-J., B.S.; investigation, Á.P.-J., B.S., G.P., G.C. and E.Z.; resources, A.G., G.P., N.B., B.M., G.C., P.S. and E.Z.; data curation, Á.P.-J., B.N., B.K., B.S., and P.P.; writing-original draft preparation, Á.P.-J.; writing-review and editing, Á.P.-J., Z.H.-M., B.N., B.K., N.B., G.P., B.M., A.G., G.C., P.S., P.P., B.B., B.S., and E.Z.; visualisation, Á.P.-J., B.B., B.S., and P.P.; project administration, E.Z.; funding acquisition, E.Z. All authors have read and agreed to the published version of the manuscript.

Data sharing statement

The original datasets analysed in this investigation are not accessible for public distribution, in accordance with privacy protection

requirements and institutional guidelines established by the Hungarian National Ambulance Service and Semmelweis University. Aggregated data that support the study findings may be obtained from the corresponding author upon reasonable academic request with appropriate institutional approvals.

Declaration of generative AI and AI-assisted technologies in the writing process

In the development of this manuscript, the authors utilised Anthropic Claude Sonnet 4, OpenAI ChatGPT 5, and Grammarly to improve linguistic precision and enhance grammatical structure and stylistic presentation. Following the application of these technological tools, the authors conducted a comprehensive review and manual modification of all content and assume complete accountability for the final publication.

Acknowledgements

The authors express gratitude to the team at MedCode Ltd., Hungary, for their valuable data science, statistical expertise and methodological support provided during the development and completion of this research manuscript.

Glossary

AIC -	Akaike Information Criterion
AQI -	Air Quality Index
CI -	Confidence Interval
COVID-19 -	Coronavirus Disease 2019
DTR -	Diurnal Temperature Range
hPa -	Hectopascals (unit of atmospheric pressure)
IRR -	Incidence Rate Ratio
IQR -	Interquartile Range
J/cm ² -	Joules per square centimetre (unit of solar radiation)
KDE -	Kernel Density Estimation
m/s -	Metres per second (unit of wind speed)
OHCA -	Out-of-Hospital Cardiac Arrest
R ² -	Coefficient of Determination
RMSE -	Root Mean Square Error
SD -	Standard Deviation
SHAP -	SHapley Additive exPlanations
VIF -	Variance Inflation Factor
WEI -	Weather Index (composite atmospheric stability measure)
XGBoost -	eXtreme Gradient Boosting

Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.puhe.2026.106145>.

References

- Empana JP, Lerner I, Valentin E, et al. Incidence of sudden cardiac death in the European Union. *J Am Coll Cardiol*. 2022;79(18):1818–1827.
- Gräsner JT, Wnent J, Herlitz J, et al. Survival after out-of-hospital cardiac arrest in Europe: results of the EuReCa TWO study. *Resuscitation*. 2020;148:218–226.
- Amacher SA, Bohren C, Blatter R, et al. Long-term survival after out-of-hospital cardiac arrest: a systematic review and meta-analysis. *JAMA Cardiol*. 2022;7(6):633–643.
- Berdowski J, Berg RA, Tijssen JG, Koster RW. Global incidences of out-of-hospital cardiac arrest and survival rates: systematic review of 67 prospective studies. *Resuscitation*. 2010;81(11):1479–1487.
- Gowens P, Smith K, Clegg G, Williams B, Nehme Z. Global variation in the incidence and outcome of emergency medical services witnessed out-of-hospital cardiac arrest: a systematic review and meta-analysis. *Resuscitation*. 2022;175:120–132.
- Priya A, Mol N, Singh AK, Aditya AK, Ray AK. Unveiling the impacts of climatic cold events on the cardiovascular health in animal models. *Sci Total Environ*. 2025;971, 179028.
- Sun Z. Cardiovascular responses to cold exposure. *Front Biosci*. 2010;2(2):495–503.

8. Ikäheimo TM. Cardiovascular diseases, cold exposure and exercise. *Temperature (Austin)*. 2018;5(2):123–146.
9. Fan JF, Xiao YC, Feng YF, et al. A systematic review and meta-analysis of cold exposure and cardiovascular disease outcomes. *Front Cardiovasc Med*. 2023;10, 1084611.
10. Alahmad B, Khraishah H, Royé D, et al. Associations between extreme temperatures and cardiovascular cause-specific mortality: results from 27 countries. *Circulation*. 2023;147(1):35–46.
11. El Sibai RH, Bachir RH, El Sayed MJ. Seasonal variation in incidence and outcomes of out-of-hospital cardiac arrest: a retrospective national observational study in the United States. *Medicine (Baltim)*. 2021;100(18), e25643.
12. Szczerbiński S, Ratajczak J, Jasiewicz M, Kubica A. Observational analysis of out-of-hospital cardiac arrest occurrence and temporal variability patterns in a subpopulation of Southern Poland from 2006 to 2018: OSCAR-POL registry. *Cardiol J*. 2023;30(4):567–575.
13. Wu Q, Yang M, Wu K, et al. Abnormal ambient temperature change increases the risk of out-of-hospital cardiac arrest: a systematic review and meta-analysis of exposure types, risk, and vulnerable populations. *Sci Total Environ*. 2023;861, 160554.
14. Kim Y, Kim Y. Explainable heat-related mortality with random forest and Shapley additive explanations (SHAP) models. *Sustain Cities Soc*. 2022;79, 103677.
15. Alari A, Chen C, Schwarz L, et al. The role of ozone as a mediator in the relation between heat waves and mortality in 15 French urban agglomerations. *Am J Epidemiol*. 2023;192(6):949–962.
16. Anenberg SC, Haines S, Wang E, Nassikas N, Kinney PL. Synergistic health effects of air pollution, temperature, and pollen exposure: a systematic review of epidemiological evidence. *Environ Health*. 2020;19(1):130.
17. Chen S, Zhao J, Lee SB, Kim SW. Estimation of relative risk of mortality and economic burden attributable to high temperature in Wuhan, China. *Front Public Health*. 2022;10, 839204.
18. Demoury C, Aerts R, Vandeninden B, Van Schaeuybroeck B, De Clercq EM. Impact of short-term exposure to extreme temperatures on mortality: a multi-city study in Belgium. *Int J Environ Res Publ Health*. 2022;19(7):3763.
19. Gasparrini A, Masselot P, Scortichini M, et al. Small-area assessment of temperature-related mortality risks in England and Wales: a case time series analysis. *Lancet Planet Health*. 2022;6(7):e557–e564.
20. Guo C, Lanza K, Li D, et al. Impact of heat on all-cause and cause-specific mortality: a multi-city study in Texas. *Environ Res*. 2023;224, 115453.
21. De Vita A, Belmusto A, Di Perna F, et al. The impact of climate change and extreme weather conditions on cardiovascular health and acute cardiovascular diseases. *J Clin Med*. 2024;13(3):759.
22. Caldeira D, Dores H, Franco F, et al. Global warming and heat waves risks for cardiovascular diseases: a position paper of the Portuguese Society of Cardiology. *Rev Port Cardiol*. 2023;42(12):1017–1024.
23. Kazi DS, Katznelson E, Liu CL, et al. Climate change and cardiovascular health: a systematic review. *JAMA Cardiol*. 2024;9(8):748–757.
24. Alahmad B, Khraishah H, Royé D, et al. Associations between extreme temperatures and cardiovascular cause-specific mortality: results from 27 countries. *Circulation*. 2023;147(1):35–46.
25. Szocska M, Pollner P, Schizler I, et al. Countrywide population movement monitoring using mobile devices generated (big) data during the COVID-19 crisis. *Sci Rep*. 2021;11(1):5943.
26. Wikipedia. COVID-19 pandemic in Hungary. Updated https://en.wikipedia.org/wiki/COVID-19_pandemic_in_Hungary; 2025.
27. Trenberth KE. What are the seasons? *Bull Am Meteorol Soc*. 1983;64(11):1276–1282.
28. Mirjani Arjenan M, Askarshahi M, Vakili M. Comparison between efficiency of Poisson regression model and negative binomial regression in the analysis of factors affecting mortality from cardiovascular diseases in Yazd Province in 2017. *J Toloobehdasth*. 2021;19(5):55–67.
29. Hilbe JM. *Negative Binomial Regression*. Cambridge, UK: Cambridge University Press; 2007.
30. Tiara Y, Aidi M, Erfiani E, Rachmawati R. Overdispersion handling in Poisson regression model by applying negative binomial regression. *BAREKENG J Ilmu Mat Apl*. 2023;17(1):417–426.
31. Stoklosa J, Blakey RV, Hui FKC. An overview of modern applications of negative binomial modelling in ecology and biodiversity. *Diversity*. 2022;14(5):320.
32. Münzel T, Hahad O, Sørensen M, et al. Environmental risk factors and cardiovascular diseases: a comprehensive expert review. *Cardiovasc Res*. 2022;118(14):2880–2902.
33. Wang H, Jing ZC. Inflammation and cardiovascular diseases. *Chronic Dis Transl Med*. 2020;6(4):215–218.
34. Liu C, Yavar Z, Sun Q. Cardiovascular response to thermoregulatory challenges. *Am J Physiol Heart Circ Physiol*. 2015;309(11):H1793–H1812.
35. Ni W, Areal AT, Lechner K, et al. Low and high air temperature and cardiovascular risk. *Atherosclerosis*. 2025;406, 119238.
36. Jingsi M, Yin Z, Huang S, et al. Cardiovascular morbidity risk attributable to thermal stress: analysis of emergency ambulance dispatch data from Shenzhen, China. *BMC Public Health*. 2024;24(1):2861.
37. Wong HT, Lai PC. Weather inference and daily demand for emergency ambulance services. *Emerg Med J*. 2012;29(1):60–64.
38. Curtis S, Fair A, Wistow J, Val DV, Oven K. Impact of extreme weather events and climate change for health and social care systems. *Environ Health*. 2017;16(suppl 1): 128.
39. PoshtMashhadi A, Ijadi Maghsoodi A, Wood LC. The impact of extreme temperatures on emergency department visits: a systematic review of heatwaves, cold waves, and daily temperature variations. *Sci Total Environ*. 2025;970, 178869.
40. Ryti NRI, Nurmi J, Salo A, Antikainen H, Kuisma M, Jaakkola JJK. Cold weather and cardiac arrest in 4 seasons: helsinki, Finland, 1997–2018. *Am J Publ Health*. 2022; 112(1):107–115.
41. Ashraf M, Sulaiman S, Alyami B, Bhatia A, Jahangir A. Seasonal variation in the incidence of in-hospital cardiac arrest. *JACC Clin Electrophysiol*. 2023;9(8 pt 3): 1755–1767.
42. El Sibai RH, Bachir RH, El Sayed MJ. Seasonal variation in incidence and outcomes of out-of-hospital cardiac arrest: a retrospective national observational study in the United States. *Medicine (Baltim)*. 2021;100(18), e25643.
43. Pell JP, Sirel J, Marsden AK, Cobbe SM. Seasonal variations in out-of-hospital cardiopulmonary arrest. *Heart*. 1999;82(6):680–683.
44. Aitken WW, Brown SC, Comellas AP. Climate change and cardiovascular health. *J Am Heart Assoc*. 2022;11(24), e027847.
45. Ang SP, Chia JE. Climate change and cardiovascular risk. *Curr Opin Cardiol*. 2025;40(4):244–250.
46. Katznelson E, Malkani K, Zhang R, Patel S. Impact of climate change on cardiovascular health. *Curr Atheroscler Rep*. 2024;27(1):13.
47. Gostimirovic M, Novakovic R, Rajkovic J, et al. The influence of climate change on human cardiovascular function. *Arch Environ Occup Health*. 2020;75(7):406–414.
48. Papanek PE, Wood CE, Fregly MJ. Role of the sympathetic nervous system in cold-induced hypertension in rats. *J Appl Physiol*. 1991;71(1):300–306.
49. Greaney JL, Kenney WL, Alexander LM. Sympathetic function during whole-body cooling is altered in hypertensive adults. *J Appl Physiol (1985)*. 2017;123(6): 1617–1624.
50. Yamazaki S, Michikawa T. Association between high and low ambient temperature and out-of-hospital cardiac arrest with cardiac etiology in Japan: a case-crossover study. *Environ Health Prev Med*. 2017;22(1):60.
51. Hensel M, Geppert D, Kersten JF, et al. Association between weather-related factors and cardiac arrest of presumed cardiac etiology: a prospective observational study based on out-of-hospital care data. *Prehosp Emerg Care*. 2018;22(3):345–352.
52. Dohmen LME, Spigt M, Melbye H. The effect of atmospheric pressure on oxygen saturation and dyspnea: the Tromsø study. *Int J Biometeorol*. 2020;64(7):1103–1110.
53. Cabeli A, Shuka N, Dado E, et al. The impact of atmospheric pressure changes on patients with acute coronary syndrome. *Eur Heart J Acute Cardiovasc Care*. 2022;11(suppl 1).
54. Moghadamnia MT, Ardalan A, Mesdaghinia A, Keshtkar A, Naddafi K, Yekaninejad MS. Ambient temperature and cardiovascular mortality: a systematic review and meta-analysis. *PeerJ*. 2017;5, e3574.
55. Riahi P, Khorsandi B. Temperature-related mortality and future health risks from climate change in a Middle Eastern metropolis. *Urban Clim*. 2025;59, 102327.
56. Kephart JL, Sánchez BN, Moore J, et al. City-level impact of extreme temperatures and mortality in Latin America. *Nat Med*. 2022;28(8):1700–1705.
57. Hundessa S, Huang W, Zhao Q, et al. Global and regional cardiovascular mortality attributable to nonoptimal temperatures over time. *J Am Coll Cardiol*. 2024;83(23): 2276–2287.
58. Singh N, Areal AT, Bretnier S, et al. Heat and cardiovascular mortality: an epidemiological perspective. *Circ Res*. 2024;134(9):1098–1112.
59. Weilhhammer V, Schmid J, Mittermeier I, et al. Extreme weather events in Europe and their health consequences: a systematic review. *Int J Hyg Environ Health*. 2021; 233, 113688.
60. Gasparrini A, Leone M. Attributable risk from distributed lag models. *BMC Med Res Methodol*. 2014;14:55.
61. Bhatnagar A. Environmental determinants of cardiovascular disease. *Circ Res*. 2017; 121(2):162–180.
62. Weisskopf MG, Sparrow D, Hu H, Power MC. Biased exposure-health effect estimates from selection in cohort studies: are environmental studies at particular risk? *Environ Health Perspect*. 2015;123(11):1113–1122.
63. Tzoulaki I, Elliott P, Kontis V, Ezzati M. Worldwide exposures to cardiovascular risk factors and associated health effects: current knowledge and data gaps. *Circulation*. 2016;133(23):2314–2333.
64. Liu C, Luo B, Wang B, et al. Global spatiotemporal trends of cardiovascular diseases due to temperature in different climates and socio-demographic index regions from 1990 to 2019. *Environ Sci Pollut Res Int*. 2023;30(2):3282–3292.
65. Mann ME, Rahmstorf S, Kornhuber K, et al. Projected changes in persistent extreme summer weather events: the role of quasi-resonant amplification. *Sci Adv*. 2018;4(10):eaat3272.
66. Lange S, Volkholz J, Geiger T, et al. Projecting exposure to extreme climate impact events across six event categories and three spatial scales. *Earths Future*. 2020;8(12).