ISSN: 3067-0144
Iris Journal of Astronomy and Satellite Communications
DOI: 10.33552/IJASC.2024.01.000518
Iris Publishers

Research Article

Using a Distributed Lag Non-Linear Model to Forecast the Impact of Temperature on Cardiovascular Admissions: Implications for Meteorology and Health Systems

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Received Date: October 21, 2024

Published Date: November 04, 2024

Abstract

This study explores the application of the Distributed Lag Non-Linear Model (DLNM) to predict cardiovascular hospital admissions in relation to daily average air temperature fluctuations. With increasing concerns about weather-driven health risks, our aim is to analyse the delayed and non-linear effects of temperature changes on hospital admissions over time. By utilizing advanced statistical modelling techniques and historical weather data, we uncover critical insights into the sensitivity of cardiovascular admissions to temperature variations, particularly highlighting peak impacts occurring two days post-exposure. This research not only contributes to the understanding of temperature-health relationships but also enhances the development of health surveillance systems. Additionally, the integration of visual aids facilitates a clearer comprehension of weather-induced health risks, offering valuable implications for public health politics preparedness and the effective use of meteorological and satellite data in health forecasting.

Keywords: Distributed Lag Non-Linear Model (DLNM); Cardiovascular Hospital Admissions; Temperature fluctuations; Faial (Azores) Island

Introduction

The interplay between environmental factors and human health has garnered increasing attention in recent years, particularly considering climate changes and its associated impacts on extreme weather events. Among various meteorological variables, air temperature has emerged as a crucial predictor of health outcomes, especially concerning cardiovascular diseases (CVDs). The relationship between temperature fluctuations and health effects is often complex, characterized by both lagged and non-linear dynamics. The rising frequency and severity of extreme weather events is a significant concern, as highlighted in studies from regions such as the Northeast Atlantic and the Azores Islands. Carvalho et al. [1] emphasize that climate change intensifies these occurrences, which have broader implications for public health politics. In addition to cardiovascular diseases, evidence suggests that climatic factors significantly contribute to hospital admissions for respiratory conditions, underscoring the need to understand how climate variability affects overall health [2]. This understanding is particularly vital for vulnerable populations, who may experience heightened risks from these fluctuations.

In other latitudes, like in China, a study has demonstrated that temperature changes can significantly affect mortality rates, revealing non-linear relationships between daily temperature variations and health outcomes [3]. Specifically, increases in temperature have been linked to higher mortality rates from both non-accidental and cardiovascular diseases. Similarly, research conducted in Cyprus has utilized a Distributed Lag Non-Linear Model (DLNM) to investigate the relationship between air temperature and cardiovascular mortality [4]. This approach has revealed critical insights into the risks posed by increasing heat waves in the Eastern Mediterranean and Middle East regions, where warming trends exceed the global average. These findings highlight the importance of examining temperature fluctuations on both regional and national scales to gain a comprehensive understanding of their health impacts.

Previous studies have identified peak impacts on mortality occurring days after extreme temperature exposure, reinforcing the need for comprehensive assessments of such delayed effects [5]. It is widely recognized that variations in ambient temperature correlate with fluctuations in mortality and morbidity over time, and recent studies have shown that these effects can persist for several days after exposure [6]. This growing body of research underscores the importance of examining how sudden temperature changes impact health, particularly for individuals with existing chronic conditions. Despite the increasing interest, there remains a limited understanding of the specific health effects of temperature changes between adjacent days, particularly in the context of cardiovascular health. This understanding is crucial, as it emphasizes the need for a nuanced approach in evaluating the relationship between temperature fluctuations and health outcomes, particularly for vulnerable populations.

Overall, climate variability has long been associated with health outcomes, particularly cardiovascular disease events. This study explores how air temperature variations affect cardiovascular admissions using a DLNM framework. DLNM allows for detailed exploration of delayed effects by identifying lag periods and non-linear relationships between temperature and hospital admissions. Furthermore, integrating meteorological and satellite-derived temperature data into public health planning through DLNM offers promising opportunities for enhancing preparedness in the face of climate variability. This study not only advances the understanding of temperature-related health risks but also emphasizes the importance of developing robust health surveillance systems capable of anticipating the impacts of extreme weather.

Methodology

Study Area

This study was conducted on the island of Faial, part of the Atlantic Azores archipelago in Portugal. Faial is characterized by its unique subtropical climate, which significantly influences both the local environment and health outcomes. The island's varied topography and maritime influences create a distinctive context for examining the impacts of temperature fluctuations on cardiovascular health. For additional details about the study area, refer to sources [1,2].

Model and Data

The analysis is based on a comprehensive dataset comprising 658 days of hospital admission records and corresponding daily average air temperatures from 2010 to 2020. The statistical modeling was performed using the Stats models module in Python. In this analysis, we exclusively utilized mean temperature as the sole predictor for hospital admissions. This approach implies that any additional factors represented in the equation, specifically the third term on the right side, were excluded and effectively set to zero. This methodology enables us to isolate the effect of mean temperature on hospital admissions, eliminating the influence of other potential variables.

Data for this research was sourced from the local hospital in Faial, provided by the Statistics Service of the Hospital of Horta. The dataset includes information on the number of hospitalized individuals, encompassing both those admitted and those who visited the Emergency Department with a cardiovascular diagnosis. Additionally, meteorological data were collected from the automated weather station at the Meteorological Observatory Príncipe Alberto de Monaco (Faial), which is part of the surface meteorological network of the Instituto Português do Mar e da Atmosfera (IPMA) (https://www.ipma.pt).

DLNM Overview

For this analysis, we employed the Distributed Lag Non-linear Model (DLNM) due to its capacity to assess both the lagged and non-linear effects of temperature on hospital admissions. The model is represented as follows:

$$g(\mu_t) = \alpha + \sum_{(j=1)}^{J} s_j(x_{tj};\eta_j) + \sum_{(k=1)}^{K} \gamma_k u_{tk}$$

Where: μ_t = Daily Cardiovascular Admissions; $x_{t\ j}$ = Mean Air Temperature on day *t-j*; J = Number of lags; S_j = Spline function for lag *j*; η_j = Estimated parameter or coefficient for lag *j*; α = Constant

Descriptive Analysis

This descriptive analysis provides a detailed overview of the dataset, focusing on both daily cardiovascular hospital admissions and mean air temperatures. Summary statistics, including measures of central tendency (mean, median) and variability (standard deviation, range), were employed to reveal the fundamental characteristics of the data. These basic metrics serve as a foundation for understanding patterns, trends, and potential relationships. The dataset comprised daily cardiovascular admissions, where most days saw between 0 and 2.5 admissions, and the daily mean air temperatures ranged from 10°C to 24.5°C, with most days falling between 15°C and 19°C. Tables 1 and 2 (supplementary material) provide detailed descriptive statistics for both these variables. Additionally, Table 3 presents the results of a Generalized Linear Model (GLM) regression, which helps expand upon the initial descriptive statistics by exploring the relationship between temperature and admissions in greater depth. These results, while still descriptive, offer a preliminary perspective on the potential influence of air temperature on cardiovascular admissions, providing a statistical snapshot of the strength and direction of this association.

Results and Discussion

Building upon the descriptive analysis, the results presented here aim to deepen our understanding of how daily temperature fluctuations are associated with cardiovascular hospital admissions. The mean number of daily admissions was 1.61 (SD = 1.40), and the mean daily temperature was 17.46°C (SD = 3.04°C). The progression of the figures highlights the analytical journey, moving from basic data exploration to more sophisticated model-driven analysis. The initial step in the analysis involved exploring the data distributions for both daily admissions and air temperatures through visual representations, such as scatter plots. These plots serve as the foundation for understanding the general patterns within the dataset. They illustrate that a simple, linear relationship between temperature and admissions is not immediately evident, suggesting the need for more advanced modeling techniques.

Subsequent analyses focused on the lagged effects of temperature, demonstrating how admissions respond to temperature changes not just on the same day, but also across several subsequent days. This progression reveals that the relationship between temperature and admissions is not immediate, and that delayed responses are crucial for grasping the full scope of the interactions. Finally, a comprehensive integration of temperature-lag relationships was achieved through advanced modeling techniques. This culminated in a detailed visual representation of both temperature extremes and their lagged effects on hospital admissions. Collectively, these analyses offer a complete picture of the dynamic interactions between environmental factors and health outcomes.

Exploratory Analysis

The analysis of daily cardiovascular admissions and average air temperatures during the study period reveals significant patterns, as depicted in Figure 1, which includes three visual components: the histogram of daily admissions (top-left), the histogram of air temperature frequency (top-right), and the scatter plot illustrating the relationship between daily admissions and air temperature (bottom).

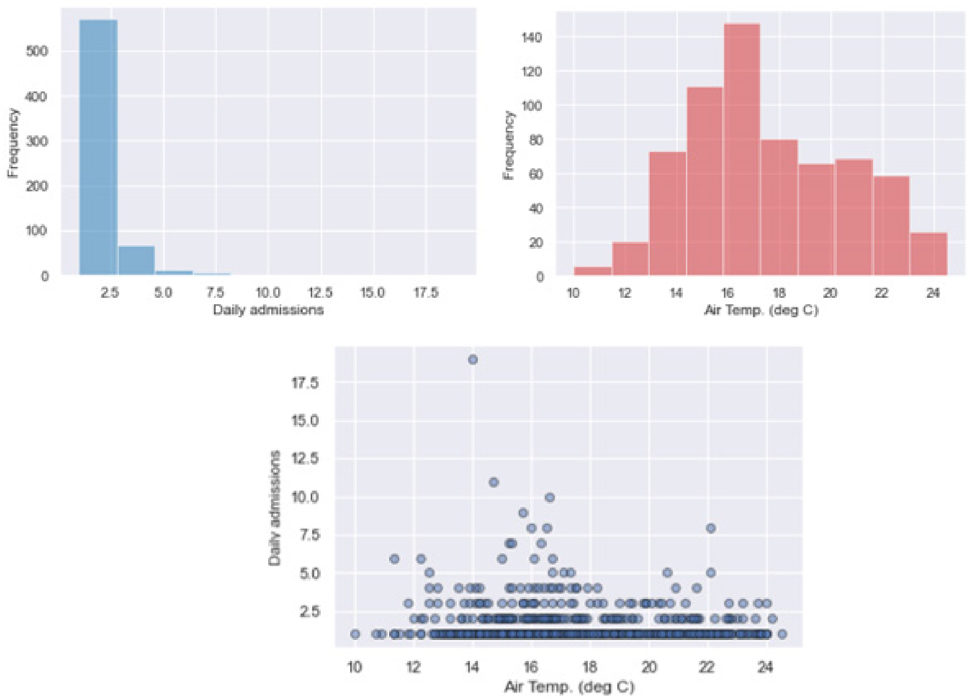

Figure 1: Histogram of Daily Admissions Frequency (Top-Left), Histogram of Air Temperature Frequency (Top-Right), and Scatter Plot of Daily Admissions vs. Air Temperature (Bottom).

The top-left histogram demonstrates that most days show very few admissions (most days have between 0 and 2.5 admissions). A much smaller number of days show more than 5 admissions, and the number of days with higher admissions diminishes rapidly. This is an indicative that cardiovascular admissions are relatively rare events on most days, as shown by the high frequency of low admission counts. The skewed distribution suggests that extreme spikes in admissions (e.g., more than 7.5 admissions) are uncommon, highlighting the sporadic nature of high-burden events.

In the top-right histogram, the frequency distribution of average daily air temperatures (in °C) shown that temperatures between 15°C and 19°C are the most frequent, peaking around 16°C to 18°C. Very few days had temperatures below 12°C or above 22°C. This histogram illustrates the typical temperature range experienced in the study area, with most days experiencing moderate temperatures. The central tendency around 16-18°C suggests that extreme temperature events (either very hot or very cold) were relatively rare during the study period.

The bottom scatter plot presents the relationship between air temperature and the number of daily cardiovascular admissions. Most data points cluster between 0 and 2.5 admissions, indicating a lack of a clear linear correlation. Nevertheless, several outlier points display higher admissions (up to 17.5) at temperatures ranging from 10°C to 20°C. While moderate temperatures (12°C–22°C) are generally associated with low admissions (≤ 2.5), there are instances of significantly higher admissions, particularly within the 12°C–20°C range. The lack of a direct, visible pattern suggests a potentially non-linear relationship between temperature and admissions, indicating that extreme weather might lead to spikes in hospitalizations, but these effects are not immediately apparent from this scatter plot alone. The outliers could indicate that other factors besides temperature contribute to high admissions, or that the effect of temperature on admissions may involve lagged effects (as proposed by the DLNM). This bottom plot attempts to show the relationship between daily admissions and air temperature. It highlights the lack of a strong, immediate correlation, suggesting that a simple direct comparison might not be sufficient, thus motivating more complex analysis.

The histograms the histograms provide valuable insights into the distribution of daily temperatures and cardiovascular admissions, revealing that most days are characterized by moderate temperatures and low admission counts. The scatter plot highlights the complex dynamics between temperature and admissions, suggesting that extreme admissions can occur across a range of temperatures. Together, these visualizations emphasize the variability in both temperature and health outcomes, highlighting the necessity for more sophisticated modelling, such as the Distributed Lag Non-Linear Model (DLNM), to explore potential lagged or non-linear effects of temperature on cardiovascular admissions. This foundational analysis sets the stage for deeper investigations into the intricate relationships between temperature fluctuations and hospital admissions, which will be further elucidated in the following section on DLNM outcomes.

DLNM Outcomes

The analysis shifts from exploratory insights in Figure 1 to a more refined statistical modelling approach. This section aims to compare observed daily admissions with those estimated based on temperature, while also evaluating the role of lagged effects in this relationship.

Figures 2 and 3 illustrate four plots that elucidate the relationship between observed and estimated daily cardiovascular admissions in relation to air temperature. These visual representations are based on a Distributed Lag Non-Linear Model (DLNM), which enhances the understanding of the delayed and non-linear effects of air temperature on hospital admissions.

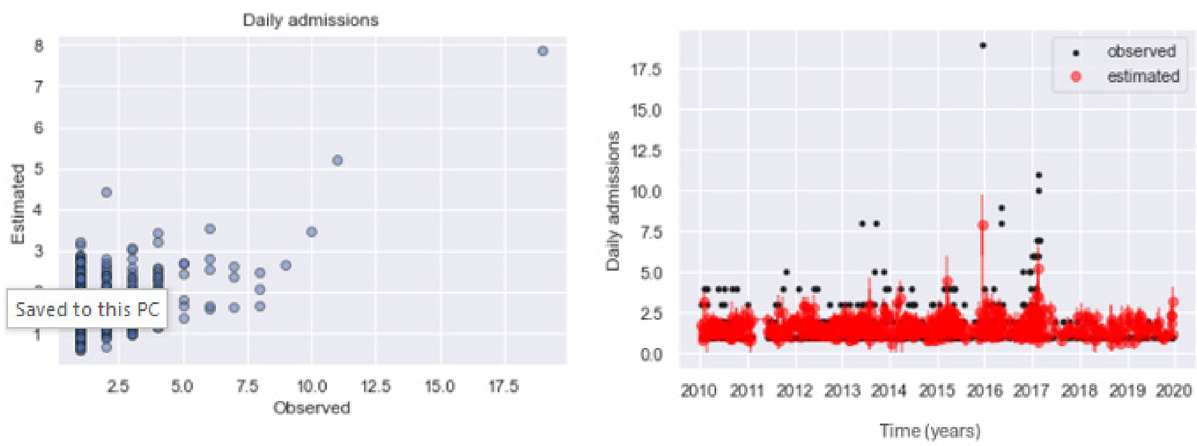

Figure 2: Scatter Plot of Observed vs. Estimated Admissions (Left), Time Series Plot of Observed vs. Estimated Admissions (Right).

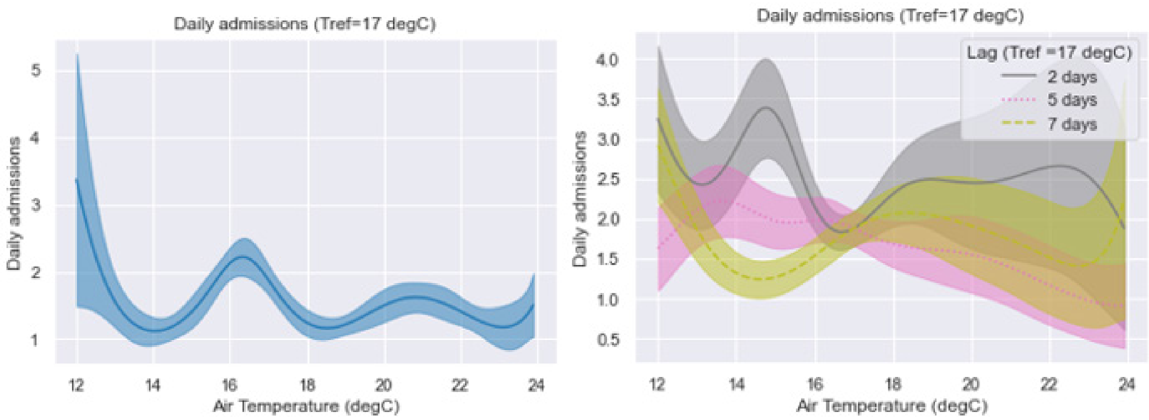

Figure 3: Daily admissions as a function of air temperature (reference temperature = 17°C), showing a clear relationship between temperature and hospital admissions, with confidence intervals around the trend (Left). Daily admissions vs. air temperature with varying lag periods (2, 5, and 7 days), demonstrating how temperature-related admissions respond over time with different lag effects (Right).

Figure 2 consists of two plots: a scatter plot on the left and a time series plot on the right, both of which elucidate the relationship between observed and estimated daily cardiovascular admissions. The scatter plot (left) compares the actual daily admissions with the model's estimated values. A significant clustering of values is observed at the lower end (between 1 and 5 daily admissions), alongside some outliers exceeding 7 admissions. Generally, there is alignment between observed and estimated values, particularly for lower admissions (around 2–5). However, the model appears to underestimate higher observed admissions (greater than 7.5), indicating potential limitations in capturing extreme spikes in admissions. Nevertheless, the model performs adequately for predicting daily admissions, especially for common lower counts. This clustering reinforces the earlier trend that most days witness low admissions, underscoring the model's robustness in capturing such patterns.

The time series plot (right) displays observed (black dots) and estimated (red dots) admissions from the model over time (2010-2020). Both observed and estimated values generally follow a stable trend, with noticeable spikes in specific years (e.g., around 2016 and 2017). While the model effectively captures the broader trends in daily admissions, there are instances where it underestimates or overestimates the magnitude of certain peaks and valleys. Notably, the larger spikes in admissions, particularly those observed in 2016, are not fully represented in the model. This time series plot emphasizes the cyclical nature of admissions over time and indicates potential temporal patterns that may correlate with seasonal variations or extreme weather events. Furthermore, it provides a comparative analysis of actual observed admissions versus model-estimated admissions during the same timeframe, highlighting periods of divergence that suggest influences beyond temperature alone. Figure 3 builds on Figures 1 and 2 by incorporating the notion of lag in temperature effects and refining the exploratory results with a statistical model. The time series comparison of observed and estimated admissions further demonstrates the model's effectiveness in capturing patterns over time.

The left plot illustrates the modelled relationship between air temperature and daily admissions with 95% confidence intervals (shaded region). There is a sharp rise in daily admissions when temperatures are low (12°C). There is another peak at around 14°C, followed by a dip in admissions, and then a gradual increase as the temperature rises above 20°C. The confidence intervals suggest more uncertainty in the admissions predictions at higher and lower temperatures. The non-linear relationship between temperature and daily admissions is evident here. There seems to be an increase in cardiovascular admissions at both lower temperatures (around 12°C) and higher temperatures (above 20°C), with a dip in admissions around the mid-range temperatures (17–19°C). This indicates a potential "U-shaped" relationship between air temperature and admissions, where both colder and hotter temperatures may increase cardiovascular stress and result in more admissions. The peaks at low temperatures are likely due to cold stress, while the increase at higher temperatures may be due to heat stress.

The right plot depicts how the lag effect of temperature (with a reference temperature of 17°C) impacts daily admissions over varying lag times (2, 5, and 7 days). Each curve represents a different lag period, with corresponding confidence intervals. The plot shows how the effect of temperature changes with time after the initial exposure (2, 5, and 7 days). The curves demonstrate variability in the temperature-admissions relationship, with the highest daily admissions occurring after a 2-day lag at lower temperatures (around 12°C). The temperature-admission relationship smooths out at longer lags (5 and 7 days), particularly at higher temperatures (20–24°C). This plot highlights the importance of considering lag effects when modelling temperature impacts on health. The immediate effect of colder temperatures (lag of 2 days) is most pronounced, while the impact of higher temperatures becomes more apparent after longer lags (5 to 7 days). The curves show that cold temperatures tend to result in more immediate increases in admissions, while heat may have a more delayed effect. The overlapping confidence intervals suggest that these trends are not sharply different, but the model does detect some degree of variation in the temperature effect over time. While Figure 2 provides an overview of the model's performance in estimating daily cardiovascular admissions using historical data, it indicates that the model effectively captures overall trends but encounters challenges with extreme values. In contrast, the two plots in Figure 3 explore the relationship between air temperature and admissions, revealing a non-linear, potentially U-shaped relationship where both cold and hot temperatures contribute to increased admissions. The lag plot further demonstrates that temperature effects are not immediate and vary over time, with colder temperatures producing more immediate impacts and higher temperatures exhibiting delayed effects. These findings suggest that cardiovascular admissions are influenced by temperature in complex ways, necessitating the consideration of both immediate and delayed effects to fully understand and predict health outcomes. Figure 4 extends the analysis by examining the lagged effects of temperature on admissions, comparing lagged admissions at specific thresholds of 12°C, 15°C, and a reference temperature (Tref= 17°C), which illustrates how various air temperatures influence daily cardiovascular admissions across a 9-day lag period.

Lag (days) represents the number of days after the initial exposure to a specific air temperature. It spans from 0 to 9 days, indicating a delayed or lagged effect of temperature on daily admissions. Daily admissions show the predicted number of daily cardiovascular admissions based on the given air temperatures (12°C, 15°C, and 20°C). The three curves represent daily admissions for different air temperatures. The shaded areas around each curve represent the 95% confidence intervals, showing the uncertainty around these predictions. The blue curve shows the effect of colder temperatures (12°C) on admissions. There is a sharp increase in admissions immediately after exposure (at lag 0 days), with daily admissions spiking to approximately 3.5. The admissions then rapidly decrease by day 2, followed by smaller oscillations in the days that follow. This pattern suggests that colder temperatures have an immediate and pronounced effect on cardiovascular admissions. For temperatures of 15°C, the effect is less extreme than 12°C. The pattern shows an initial peak around day 1, followed by fluctuating daily admissions between 1 and 2 over the next 9 days. The confidence intervals indicate a moderate level of certainty about this pattern. At 20°C, there is a more gradual and less pronounced effect on admissions. Unlike 12°C, where admissions spike rapidly, at 20°C, the admissions rise more steadily, reaching a peak of about 2.5 around day 2 or 3. After that, there is a slight dip, followed by relatively stable levels of admissions for the remainder of the lag period. The interpretation of Lag effects suggest:

- *Immediate Effects* (Day 0-2): The effect of colder temperatures (12°C) is more immediate and intense, leading to a spike in admissions almost instantly. On the other hand, warmer temperatures (20°C) have a slower and less dramatic effect.
- *Mid-term Effects* (Day 3-6): Around day 3, the effect of temperatures tends to stabilize, with colder temperatures showing more variability (larger fluctuations) and warmer temperatures (20°C) showing a more consistent, gradual effect.
- *Longer-term Effects* (Day 6-9): Over longer lag times, all temperatures exhibit more stable patterns, but colder temperatures (12°C) still show more variation in admissions, while 20°C leads to a slight increase at the end of the period.

The widening confidence intervals (shaded areas) as the lag days increase indicate greater uncertainty in predictions over time. For colder temperatures (12°C), the intervals are broader, especially in the initial days, reflecting heightened variability and potentially less predictability regarding the impact of cold weather on admissions. Conversely, the confidence intervals for warmer temperatures (20°C) are narrower, suggesting a more predictable influence of warmer temperatures on admissions.

In summary, colder temperatures (12°C) exert a more immediate and pronounced influence on cardiovascular admissions, resulting in an initial spike that diminishes but continues to fluctuate throughout the 9-day period. In contrast, warmer temperatures demonstrate a slower, more moderate effect, with admissions gradually increasing and remaining relatively stable over time. Intermediate temperatures (15°C) exhibit a balanced pattern, displaying moderate fluctuations in admissions during the 9-day lag.

Our results indicate that exposure to cold leads to an acute rise in admissions, whereas exposure to warmth results in a more gradual yet steady increase. Both temperature extremes distinctly affect cardiovascular admissions. The graph in Figure 4 reinforces the concept of lagged health impacts due to temperature fluctuations, illustrating that colder temperatures prompt a quicker and more intense response, particularly regarding cardiovascular events. Moreover, Figure 4 complements Figure 3 by focusing on the effects of specific temperature thresholds. It clarifies how different temperature ranges (cold, moderate, hot) influence health outcomes over time, offering a more nuanced understanding of temperature-related risks. This also reinforces the U-shaped risk curve observed in Figure 3, highlighting that both cold and hot extremes lead to higher admissions. Figure 5 expands on these findings by offering a thorough examination of the temperature-lag interaction. It integrates all previous insights into a unified analysis of how temperature affects cardiovascular admissions across a broad spectrum of temperatures (ranging from 12°C to 24°C) and different lag periods (from 0 to 9 days). Featuring both a heatmap and a 3D surface plot, this figure provides a dynamic visualization of the relationship between daily admissions and temperature variations over time.

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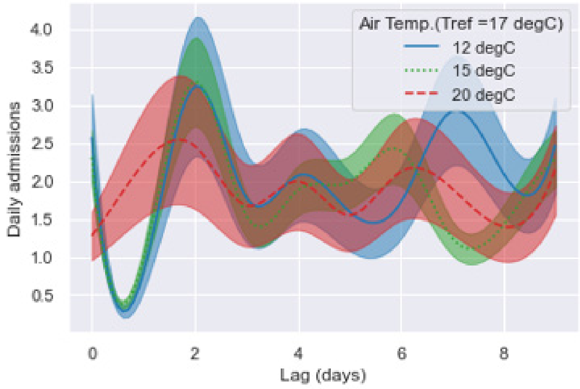

Figure 4: Effect of air temperature (with a reference temperature of 17°C) on daily admissions over a lag period (measured in days).

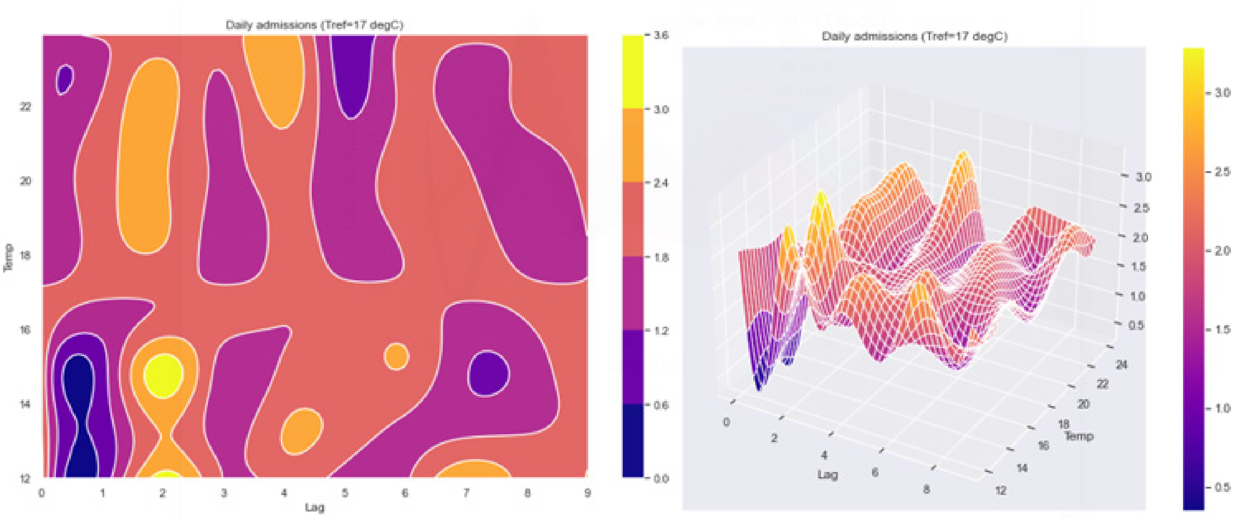

Figure 5: Heatmap of daily admissions as a function of air temperature and lag (Tref = 17°C), illustrating the intensity of hospital admissions across different temperature ranges and lag times (Left). 3D surface plot of daily admissions (Tref = 17°C), providing a visual representation of the interaction between temperature, time lag, and hospital admissions (Right).

Two distinct plots in Figure 5 illustrate daily admissions in relation to air temperature, using a reference temperature of 17°C across various lag periods (measured in days). Each plot conveys similar information through different visual formats. The left plot is a heatmap where the colour gradient represents the daily admissions, while the x-axis represents the lag period (days after temperature exposure), that indicates the number of days after exposure, ranging from 0 to 9 days. It suggests the lagged effect of temperature on daily admissions, and the y-axis represents air temperatures, ranging from approximately 12°C to 24°C. The reference temperature (17°C) serves as a benchmark. The heatmap uses a colour gradient from yellow (high admissions) to purple (low admissions). The admissions scale is visible on the right, with values from 0.5 to over 3.5 daily admissions. Yellow patches represent areas of higher admissions, while purple regions represent lower admissions. At higher temperatures (around 22°C or higher), the heatmap remains mostly purple, indicating lower daily admissions. This suggests that warmer weather leads to relatively fewer admissions. For mid-range these temperatures, especially around 14°C to 16°C, there are pockets of yellow early in the lag period (lag 0 to 2 days). This indicates that mid-range cooler temperatures may lead to a spike in admissions, particularly shortly after exposure. These fluctuations are also evident during lag days 5-6, indicating that mid-range temperatures have delayed effects on hospital admissions. At colder temperatures (around 12°C), localized yellow patches appear in the initial lag days, signalling higher daily admissions shortly after exposure to cold. This observation aligns with findings from previous graphs, which

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demonstrated that colder temperatures have both an acute and immediate impact on admissions.

Colder temperatures, particularly in the range of 12°C to 14°C, are associated with both immediate and delayed spikes in cardiovascular admissions, as reflected by localized yellow patches in the heatmap. These spikes are most pronounced during the initial lag days (0-3) and again around lag days 5-6, indicating that the effects of cold exposure are both acute and prolonged. In contrast, higher temperatures (above 20°C) tend to correlate with fewer admissions, as shown by the predominantly purple areas in the heatmap, especially during extended lag periods. The heatmap presents a detailed view of how different temperatures, over varying lag days, impact admissions. Yellow regions represent higher admissions, while purple indicates lower admissions. This visualization helps identify the most critical temperature ranges and lag periods that lead to increased admissions, emphasizing both immediate and delayed effects of colder weather.

The right plot in Figure 5 is a 3D surface representation of the same data, showcasing the relationship between daily admissions, temperature, and lag days in a more dynamic format. The x-axis indicates the number of days after temperature exposure, ranging from 0 to 9 days, while the y-axis displays the temperature range from 12°C to 24°C. The z-axis represents the predicted number of daily admissions, spanning from below 1 to over 3, illustrated through the peaks and valleys of the surface.

In this 3D visualization, peaks correspond to higher daily admissions (depicted in yellow to pink areas on the z-axis), while troughs represent lower admissions (shown in purple). Notably, at lower temperatures (12°C-14°C), multiple peaks emerge within the first 2-3 lag days, confirming that cold exposure significantly increases daily admissions. A secondary peak is observed around lag days 5-6. For mid-range temperatures (16°C-18°C), the peaks and valleys are more evenly distributed, indicating moderate fluctuations in admissions. In contrast, at higher temperatures (above 20°C), there are fewer peaks, and the surface remains relatively low, reflecting a stable trend of decreased admissions, even across longer lag days.

Our study reveals that higher admissions predominantly occur at lower temperatures (12°C to 14°C) during the initial lag days (0-3) and again around lag days 5-6. Warmer temperatures (20°C and above) are associated with fewer admissions, represented by flatter regions on the surface. This 3D plot enhances the heatmap by providing a tangible representation of the peaks and valleys in admissions based on temperature-lag combinations. Both plots in Figure 5 consistently illustrate the relationship between temperature and hospital admissions over lag periods:

- *Colder temperatures* (12°C - 14°C) are associated with higher admissions, with both immediate effects (lag 0-2 days) and delayed effects (around lag days 5-6).
- *Mid-range temperatures* (16°C - 18°C) show moderate fluctuations in admissions.
- *Warmer temperatures* (above 20°C) are associated with lower admissions, showing a more stable and less reactive pattern over the lag period.

The combination of the heatmap and the 3D surface plot effectively conveys the complex interactions between temperature, time, and health impacts, emphasizing the increased cardiovascular risk associated with colder weather while showing fewer effects from warmer temperatures.

Synthesis of Findings

Figure 5 brings together the patterns identified in Figures 3 and 4, offering a comprehensive view of how temperature and lag influence hospital admissions. It confirms earlier observations, such as the immediate spike in admissions due to colder temperatures, while also highlighting the delayed effects seen with moderate to warm temperatures. Each figure plays a role in progressively deepening the understanding of temperature's impact on admissions:

- *Figure 1* introduces basic data exploration, pointing to the need for more detailed analysis by showing that a simple relationship between temperature and admissions is not obvious.
- *Figures 2 and 3* incorporate lag effects and present comparisons between observed and modelled data, providing a clearer picture of how temperature affects admissions over time.
- *Figure 4* further explores the temperature-lag relationship by isolating the effects of specific temperature ranges.
- *Figure 5* unifies these patterns into a single, comprehensive visualization, capturing the full scope of lagged effects and temperature extremes.

Through the findings provided from Figures 1 to 5 serve to illustrate the relationship between temperature variations and daily hospital admissions over time, with a particular focus on how changes in temperature impact health outcomes, especially related to hospitalizations. The study's findings highlight a significant relationship between air temperature and cardiovascular admissions, suggesting that weather patterns could serve as early indicators of potential health risks. Our model identifies a two-day lag as a critical period for hospital admissions following changes in temperature, particularly for temperatures above 17°C.

Relevance to Meteorology and Health Forecasting

These results offer promising applications in meteorology and satellite communications. By integrating satellite-derived temperature data and DLNM forecasting, public health systems could benefit from early warning systems that predict spikes in hospital admissions during extreme weather events. For instance, meteorological agencies could collaborate with health authorities to develop systems that alert hospitals of potential surges in admissions based on real-time weather forecasts and temperature data.

Health and Climate Implications

With the increasing frequency of heatwaves and other temperature extremes due to climate change, this research demonstrates the importance of weather forecasting not only for environmental monitoring but also for public health preparedness. Hospitals and emergency services could use temperature forecasts to anticipate periods of high admissions, adjusting staffing and resources accordingly.

Future Directions

Future studies should incorporate additional meteorological variables such as humidity and pollution, along with satellite data, to refine the DLNM's accuracy in predicting health outcomes. Furthermore, the integration of meteorological and health data could lead to the development of sophisticated forecasting models that account for multiple weather parameters simultaneously, enhancing the resilience of public health systems in the face of climate change.

Conclusions

This study highlights the effectiveness of Distributed Lag Non-linear Models (DLNM) in predicting the impact of temperature on cardiovascular admissions. The findings indicate that, overall, the influence of temperature on hospitalizations decreases as the average air temperature rises. In the case of this study, using a reference temperature of 17°C, admissions tend to increase two days after exposure (Lag = 2). However, the relationship between temperature and lag time is notably complex, showing an almost periodic behaviour for temperatures exceeding 17°C.

By incorporating meteorological data, such as temperature, into public health strategies, authorities can better anticipate health risks and take preventive measures. The integration of satellite-based weather forecasts with health data offers an opportunity to improve early warning systems and health preparedness, particularly during extreme weather events. As climate change continues to alter weather patterns, models like this will become increasingly vital for protecting public health in the future.

Supplementary Material

Table 1: Daily Admissions.

Statistic	Value
Number of Observations (nobs)	658
Missing Data	0
Mean	1.607903
Standard Error	0.054771
Upper Confidence Interval	1.715251
Lower Confidence Interval	1.500554
Standard Deviation (SD)	1.404948
Interquartile Range (IQR)	1
Normalized IQR	0.741301
Median Absolute Deviation (MAD)	0.849955
Normalized MAD	1.065261
Coefficient of Variation	0.873777
Range	18
Maximum	19
Minimum	1
Skewness	5.130777
Kurtosis	46.336742
Jarque-Bera Statistic	54377.4681
Jarque-Bera p-value	0
Mode	1
Mode Frequency	0.699088
Median	1
1st Percentile	1
5th Percentile	1
10th Percentile	1
25th Percentile	1
50th Percentile	1

75th Percentile	2
90th Percentile	3
95th Percentile	4
99th Percentile	7.43

Table 2: Mean Daily Temperature.

Statistic	Value
Number of Observations (nobs)	658
Missing Data	0
Mean	17.457143
Standard Error	0.118324
Upper Confidence Interval	17.689054
Lower Confidence Interval	17.225232
Standard Deviation (SD)	3.035195
Interquartile Range (IQR)	4.6
Normalized IQR	3.409985
Median Absolute Deviation (MAD)	2.530221
Normalized MAD	3.171162
Coefficient of Variation	0.173865
Range	14.5
Maximum	24.5
Minimum	10
Skewness	0.316935
Kurtosis	2.256725
Jarque-Bera Statistic	26.162311
Jarque-Bera p-value	0.000002
Mode	16.5
Mode Frequency	0.024316
Median	16.8
1st Percentile	11.671
5th Percentile	13.185
10th Percentile	13.9
25th Percentile	15.2
50th Percentile	16.8
75th Percentile	19.8
90th Percentile	21.9
95th Percentile	22.7
99th Percentile	23.8

Table 3: Generalized Linear Model Regression Results.

Dependent Variable: Y	Method: PIRLS
No. Observations: 658	Log-Likelihood: -928.69
Model: GLMGam	Deviance: 363.56
Df Residuals: 567.00	Pearson chi^2: 452
Model Family: Poisson	No. Iterations: 6
Df Model: 90.00	Pseudo R-squ. (CS): 0.1643
Link Function: Log	Covariance Type: nonrobust
Scale: 1.0000	

	coef	std err	z	P>|z|	[0.025	0.975]
Intercept	-3.44	1.906	-1.805	0.071	-7.175	0.295
D0	-0.0813	0.088	-0.928	0.353	-0.253	0.09
D1	-0.0771	0.067	-1.154	0.249	-0.208	0.054
D2	-0.0332	0.117	-0.284	0.776	-0.262	0.196
D3	-0.0125	0.093	-0.135	0.893	-0.194	0.169
D4	0.0425	0.193	0.22	0.826	-0.336	0.421
D5	-0.0856	0.158	-0.541	0.588	-0.396	0.224
D6	0.0537	0.099	0.543	0.587	-0.14	0.247
D7	0.0703	0.099	0.708	0.479	-0.124	0.265
D8	0.0469	0.094	0.498	0.618	-0.137	0.231
D9	0.0333	0.086	0.386	0.7	-0.136	0.202
D0_s0	0.3434	1.61	0.213	0.831	-2.812	3.498
D0_s1	0.3789	0.796	0.476	0.634	-1.181	1.939
D0_s2	0.3039	0.799	0.38	0.704	-1.263	1.871
D0_s3	0.6769	0.517	1.308	0.191	-0.337	1.691
D0_s4	-0.0139	0.541	-0.026	0.98	-1.075	1.047
D0_s5	0.4079	0.629	0.648	0.517	-0.826	1.642
D0_s6	0.3451	0.78	0.442	0.658	-1.183	1.874
D0_s7	1.0386	0.828	1.254	0.21	-0.584	2.662
D0_s8	0.3312	0.748	0.443	0.658	-1.135	1.797
D1_s0	-2.0014	1.034	-1.936	0.053	-4.027	0.024
D1_s1	-0.1979	0.527	-0.375	0.707	-1.231	0.835
D1_s2	-1.1828	0.551	-2.148	0.032	-2.262	-0.104
D1_s3	0.2161	0.396	0.546	0.585	-0.559	0.991
D1_s4	0.4267	0.525	0.813	0.416	-0.602	1.456
D1_s5	0.7494	0.707	1.06	0.289	-0.636	2.135
D1_s6	0.7282	0.97	0.751	0.453	-1.173	2.629
D1_s7	0.2869	0.879	0.326	0.744	-1.437	2.011
D1_s8	1.6005	0.667	2.401	0.016	0.294	2.907
D2_s0	1.9754	1.773	1.114	0.265	-1.499	5.45
D2_s1	-1.2532	0.808	-1.551	0.121	-2.836	0.33
D2_s2	1.8241	0.866	2.106	0.035	0.126	3.522
D2_s3	-0.2552	0.543	-0.47	0.638	-1.32	0.809
D2_s4	0.775	0.571	1.358	0.175	-0.344	1.894
D2_s5	0.3678	0.697	0.527	0.598	-0.999	1.735
D2_s6	0.9024	0.817	1.105	0.269	-0.699	2.504
D2_s7	0.7509	0.916	0.82	0.412	-1.044	2.545
D2_s8	0.0611	0.836	0.073	0.942	-1.577	1.699
D3_s0	0.6993	1.555	0.45	0.653	-2.348	3.747
D3_s1	0.3678	0.669	0.55	0.583	-0.944	1.679
D3_s2	-0.0812	0.746	-0.109	0.913	-1.544	1.382
D3_s3	0.916	0.462	1.981	0.048	0.01	1.822
D3_s4	0.0182	0.531	0.034	0.973	-1.023	1.059
D3_s5	0.9241	0.716	1.291	0.197	-0.479	2.327
D3_s6	0.0202	0.83	0.024	0.981	-1.607	1.647
D3_s7	1.0912	0.901	1.211	0.226	-0.675	2.857
D3_s8	0.4205	0.836	0.503	0.615	-1.217	2.058

D4_s0	-1.1398	3.301	-0.345	0.73	-7.61	5.33
D4_s1	1.8403	1.89	0.974	0.33	-1.863	5.544
D4_s2	0.3048	1.436	0.212	0.832	-2.51	3.119
D4_s3	0.2913	0.885	0.329	0.742	-1.444	2.026
D4_s4	0.3344	0.683	0.49	0.624	-1.004	1.673
D4_s5	0.0276	0.717	0.038	0.969	-1.378	1.434
D4_s6	0.6321	0.864	0.732	0.464	-1.061	2.325
D4_s7	0.5462	1.032	0.529	0.597	-1.477	2.569
D4_s8	0.0109	1.169	0.009	0.993	-2.28	2.302
D5_s0	-0.8571	2.589	-0.331	0.741	-5.931	4.217
D5_s1	-0.7397	1.255	-0.589	0.556	-3.199	1.72
D5_s2	-0.5523	1.308	-0.422	0.673	-3.116	2.011
D5_s3	0.4791	0.749	0.64	0.522	-0.99	1.948
D5_s4	0.4205	0.755	0.557	0.578	-1.059	1.9
D5_s5	0.6001	1.006	0.596	0.551	-1.372	2.572
D5_s6	0.2864	1.12	0.256	0.798	-1.909	2.482
D5_s7	1.4415	1.186	1.215	0.224	-0.883	3.766
D5_s8	-0.2641	1.115	-0.237	0.812	-2.448	1.92
D6_s0	-1.6191	2.301	-0.704	0.481	-6.129	2.891
D6_s1	-0.0097	1.171	-0.008	0.993	-2.305	2.285
D6_s2	1.5668	1.354	1.157	0.247	-1.087	4.221
D6_s3	0.0066	0.792	0.008	0.993	-1.547	1.56
D6_s4	-0.17	0.854	-0.199	0.842	-1.843	1.503
D6_s5	-0.3611	1.032	-0.35	0.726	-2.383	1.661
D6_s6	-0.4518	1.081	-0.418	0.676	-2.571	1.667
D6_s7	0.1426	1.331	0.107	0.915	-2.466	2.751
D6_s8	-0.227	1.248	-0.182	0.856	-2.673	2.219
D7_s0	-1.6947	2.204	-0.769	0.442	-6.014	2.624
D7_s1	-0.3954	1.151	-0.344	0.731	-2.652	1.861
D7_s2	-0.4781	1.179	-0.406	0.685	-2.788	1.831
D7_s3	-0.1632	0.801	-0.204	0.838	-1.733	1.407
D7_s4	0.0576	0.748	0.077	0.939	-1.409	1.524
D7_s5	0.7191	1.05	0.685	0.493	-1.34	2.779
D7_s6	0.118	1.154	0.102	0.919	-2.144	2.38
D7_s7	0.0837	1.393	0.06	0.952	-2.647	2.814
D7_s8	-0.6743	1.308	-0.516	0.606	-3.238	1.889
D8_s0	-2.0252	2.394	-0.846	0.397	-6.717	2.667
D8_s1	-0.0743	1.232	-0.06	0.952	-2.49	2.342
D8_s2	-0.1173	1.332	-0.088	0.93	-2.728	2.494
D8_s3	0.0091	0.788	0.012	0.991	-1.536	1.554
D8_s4	-0.0574	0.723	-0.079	0.937	-1.475	1.36
D8_s5	1.1969	1.057	1.132	0.257	-0.875	3.268
D8_s6	0.77	1.281	0.601	0.548	-1.74	3.28
D8_s7	-0.3791	1.272	-0.298	0.766	-2.872	2.114
D8_s8	1.5526	1.156	1.343	0.179	-0.713	3.818
D9_s0	0.1866	2.116	0.088	0.93	-3.96	4.333
D9_s1	-0.7511	1.173	-0.64	0.522	-3.05	1.548
D9_s2	-1.6695	1.282	-1.302	0.193	-4.183	0.844

D9_s3	0.0714	0.783	0.091	0.928	-1.464	1.607
D9_s4	-0.3785	0.808	-0.469	0.639	-1.962	1.205
D9_s5	-0.334	1.031	-0.324	0.746	-2.355	1.687
D9_s6	-0.7865	1.104	-0.713	0.476	-2.951	1.378
D9_s7	0.0182	1.346	0.014	0.989	-2.62	2.657
D9_s8	-0.5924	1.166	-0.508	0.611	-2.877	1.692

Conflicts of Interest

The authors declare no conflicts of interest.

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Citation: Maria Meirelles, Fernanda Carvalho, Ana Catarina Ferreira and Helena Cristina Vasconcelos*. Using a Distributed Lag Non-Linear Model to Forecast the Impact of Temperature on Cardiovascular Admissions: Implications for Meteorology and Health Systems. Iris Jour of Astro & Sat Communicat. 1(4): 2024. IJASC.MS.ID.000518. **DOI:** 10.33552/IJASC.2024.01.000518.