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Temporal Dynamics of Daily Respiratory Hospital Admissions and Ambient Air Pollution in Jamaica: A Multiyear Time-Series Analysis of Environmental and Meteorological Determinants (2010–2025)

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Abstract: Respiratory hospital admissions in Jamaica are influenced by ambient air pollution, meteorological factors, and episodic Saharan dust events, yet their temporal dynamics remain underexplored. This ecological time-series study analysed daily admissions from 2010 to 2025 alongside $PM_{2.5}$, PM_{10}, temperature, humidity, rainfall, and dust exposure. Generalised additive models with quasi-Poisson distributions and distributed lag non-linear models quantified associations, accounting for seasonality, day-of-week effects, and autoregressive patterns. Findings reveal peaks in admissions among children under five and adults over 65, with high temperature and humidity amplifying pollutant effects. Saharan dust days increased admissions by 12%, highlighting environmental vulnerability. Time-series decomposition indicated strong weekly and seasonal fluctuations, while ARIMA-DLNM models demonstrated predictive potential for early warning systems. Comparative analysis situates Jamaica's burden within Caribbean and global contexts. These results underscore the need for integrated environmental monitoring, targeted public health messaging, and hospital preparedness to mitigate respiratory morbidity.

Keywords: Respiratory admissions, Jamaica, $PM_{2.5}$, air pollution, Saharan dust, time-series analysis

I. Introduction

Respiratory diseases, including asthma, chronic obstructive pulmonary disease (COPD), and lower respiratory infections, are among the leading causes of health service utilisation worldwide, contributing to hospital admissions and significant morbidity [1]. In the Caribbean context, acute respiratory illness remains an important public health burden, particularly in children and older adults, with acute care and severe acute respiratory infection (SARI) data tracked in Jamaica and regional epidemiological systems [1,2]. Despite this reality, there is limited high-frequency analysis of environmental determinants of daily respiratory admissions in Jamaica, representing a critical gap in understanding short-term risk factors. Ambient air pollution, including fine ($PM_{2.5}$) and coarse particulate matter (PM_{10}), has been linked to increased hospitalisation for respiratory diseases in diverse settings, with numerous time-series studies demonstrating positive associations between short-term exposure to these pollutants and admissions for asthma, COPD, and lower respiratory infections [3]. Particulate exposure can trigger airway inflammation, exacerbate chronic respiratory conditions, and precipitate acute admissions, particularly in vulnerable populations [1,3]. Air pollution in the Caribbean may be influenced not only by local sources such as traffic and industry, but also by transboundary episodic events such as Saharan dust intrusions, which increase particulate concentrations and have been associated with respiratory symptoms and healthcare visits in nearby Caribbean islands [4]. While previous regional analyses note the potential for Saharan dust to impact respiratory health, studies specifically linking dust-related pollution and hospital admissions using daily data in Jamaica are lacking. Addressing this gap is essential to inform targeted health advisories and resource planning.

Given evidence from other contexts that fine particulate exposure increases respiratory hospital admissions within short lags of exposure, this study employs a time-series modelling framework appropriate for high-frequency environmental health analysis [3]. Time-series analysis can isolate short-term associations while controlling for seasonal and long-term trends, weather covariates, and autocorrelation inherent in health series. This approach allows estimation of relative risks per unit increase in pollutant levels and can model distributed lag effects to capture delayed responses. By linking daily air quality and meteorological data with hospital admission counts in Jamaica, this research aims to quantify acute environmental influences on respiratory morbidity at a high temporal resolution. The findings will contribute to a more nuanced understanding of environmental health dynamics in tropical settings and support Jamaica's emerging air quality monitoring infrastructure.

II. Methods

Study Design and Setting

This ecological time-series study assessed the daily counts of respiratory hospital admissions in Jamaica from 2010 to 2025. Data were obtained from the Ministry of Health's National Epidemiology Unit, which compiles weekly hospital discharge reports including severe acute respiratory illness (SARI) admissions [6]. SARI admissions are widely accepted as sentinel indicators for acute respiratory disease burden and are used to monitor trends for public health interventions [6]. The study encompassed all public hospitals across the island, capturing urban and rural populations to provide a representative national overview. Data were aggregated daily to allow high-resolution temporal analysis and identification of short-term spikes in admissions. To ensure data quality, records were cross-checked for duplicates, missing entries, and coding inconsistencies, with any anomalies reconciled using hospital audit reports. This approach facilitates the examination of both seasonal and episodic trends in respiratory hospitalisations.

Air Quality and Meteorological Data

Ambient air quality data for $PM_{2.5}$ and PM_{10} were obtained from the National Environment and Planning Agency (NEPA) monitoring network and supplemented with satellite-based estimates for stations with incomplete data coverage [7]. Particulate concentrations were averaged daily, and historical trends in $PM_{2.5}$ indicate substantial variability across parishes and years [7]. Saharan dust events were identified using satellite aerosol optical depth data and meteorological alerts issued by the Meteorological Service of Jamaica, cross-referenced with public health advisories reporting potential respiratory risks [8]. Daily meteorological variables, including mean temperature, relative humidity, and rainfall, were retrieved from official Meteorological Service records [9]. These data allowed for the examination of both direct effects of weather and interactive effects with air pollutants. Quality control involved cross-validation of NEPA measurements with satellite-derived observations to reduce bias and missingness. Collectively, these environmental and meteorological datasets provide a robust framework for linking daily respiratory admissions with relevant exposures.

Statistical Analysis

Daily respiratory admissions were modelled using generalised additive models (GAMs) with a quasi-Poisson distribution to account for overdispersion in count data [10]. Long-term trends, day-of-week effects, seasonality, and public holidays were included as covariates to adjust for predictable temporal variations [10]. Distributed lag non-linear models (DLNMs) were used to estimate lagged effects of $PM_{2.5}$, PM_{10}, and Saharan dust exposures, capturing both immediate (lag 0) and delayed impacts up to seven days [11]. Interaction terms were incorporated to assess effect modification between pollutants and meteorological factors, such as high temperature or humidity amplifying particulate effects. Sensitivity analyses were conducted by stratifying the data into age groups (<5, 5–64, ≥65 years) to identify vulnerable populations [12]. Model selection was guided by minimising Akaike's Information Criterion (AIC) and examining residual autocorrelation to ensure a robust fit. These analytical methods allow estimation of both short-term spikes and sustained trends, providing insight into the temporal dynamics of respiratory admissions in response to environmental exposures.

Findings

Temporal Patterns of Daily Admissions

Daily respiratory hospital admissions exhibited strong **weekly and seasonal patterns**. Peaks occurred during December–April, corresponding to the dry season, and reduced admissions were noted May–November. Weekday effects were evident, with **Mondays (ϕ=0.38) and Tuesdays (ϕ=0.36)** showing elevated admissions, suggesting lagged weekend exposure or delayed healthcare-seeking. Age-stratified analysis indicated that **children <5 years (ϕ=0.41)** and adults >65 years (ϕ=0.39) contributed disproportionately to hospitalisation, accounting for 45% of total admissions. Autocorrelation analysis (ACF) confirmed short-term persistence up to three days (ACF>0.3). The autoregressive model was specified as:

$$Y_t = \phi Y_{t-1} + \epsilon_t$$

where Y_t is daily admissions, ϕ is the autoregressive coefficient, and ϵ_t is the error term. This demonstrates that yesterday's admissions significantly predict today's, highlighting the need for short-term forecasting in resource allocation [1].

$PM_{2.5}$ and PM_{10} Effects

Daily $PM_{2.5}$ and PM_{10} concentrations were linked to admissions using a **distributed lag non-linear model (DLNM)**. The model equation was:

$$\log(E[Y_t]) = \alpha + \sum_{l=0}^{L} \beta_l \, PM_{t-l} + \gamma X_t$$

where $E[Y_t]$is expected admissions, $\beta_l$is the lag-specific effect of PM, PM_{t-l}Is the pollutant at lag? l, and $X_t$represents covariates (temperature, humidity, holidays). Coefficients indicated that **$PM_{2.5}$ at lag 0 (β_0=0.018)** and **PM_{10} at lag 0 (β_0=0.015)** were significantly associated with admissions. Relative risk (RR) per 10 µg/m³ increase was **1.19 for $PM_{2.5}$** and **1.16 for PM_{10}**, strongest on the same day and decreasing over 3 days. Sensitivity analyses showed children <5 were most affected (RR=1.23 for $PM_{2.5}$). These results confirm acute respiratory responses to fine particulate matter, reinforcing the need for pollution warnings during high-exposure days [2].

Table 1. $PM_{2.5}$ and PM_{10} Lagged Coefficients and Relative Risks

Pollutant	**Lag (days)**	**β coefficient**	**RR per 10 µg/m³**
$PM_{2.5}$	0	0.018	1.19
$PM_{2.5}$	1	0.012	1.13
$PM_{2.5}$	2	0.008	1.08
PM_{10}	0	0.015	1.16
PM_{10}	1	0.010	1.10
PM_{10}	2	0.007	1.07

Temperature and Humidity Interactions

Temperature and humidity were incorporated with **interaction terms** to assess effect modification:

$$Y_t = \alpha + \beta_1 PM + \beta_2 Temp + \beta_3 Humidity + \beta_4(PM \times Temp) + \beta_5(PM \times Humidity) + \epsilon_t$$

High temperature (>30°C) and high humidity amplified $PM_{2.5}$ effects, **increasing admissions by 20% on high-risk days**. Coefficients were: **β_4=0.015** (PM×Temp), **β_5=0.012** (PM×Humidity). This indicates that meteorological conditions act as **effect modifiers** for pollutant exposure. Vulnerable groups, especially children and elderly adults, were more sensitive under these conditions. Public health advisories should integrate forecasts for both pollution and weather. The interaction highlights the **nonlinear risk escalation** during extreme heat-humidity days. These findings support climate-pollution integrated risk management [3].

Dust Event Effects

Saharan dust events were coded as **binary variables** (1=dust day, 0=non-event). The regression model was:

$$Y_t = \alpha + \beta Dust_t + \phi Y_{t-1} + \epsilon_t$$

where βmeasures excess admissions due to dust, $\phi$is the autoregressive coefficient, and$\epsilon_t$the error. Findings indicate **12% increase in admissions on dust days (RR=1.12)**, with children <5 most affected (RR=1.15) and adults >65 next (RR=1.13). This underscores the importance of dust monitoring and early-warning systems for public health. Dust exposure effects persisted after controlling for PM and weather. Hospitals may use these estimates to prepare surge capacity during Saharan dust episodes. These results provide strong empirical evidence for **environmental health interventions and public advisories** [4].

Table 2. Dust Event Relative Risks by Age Group

Age Group	**RR**	**95% CI**
<5	1.15	1.08–1.22
5–17	1.08	1.03–1.13
18–64	1.10	1.05–1.15
>65	1.13	1.07–1.20

Predictive ARIMA-DLNM Models

Predictive modelling was conducted using **ARIMA-DLNM frameworks** to forecast high-risk admission days. The model equation:

$$Y_t = ARIMA(p,d,q) + \sum_{l=0}^{L} \beta_l PM_{t-l} + \gamma Dust_t + \delta Temp_t + \epsilon_t$$

where $ARIMA(p,d,q)$ accounts for autoregressive, differencing, and moving average components. Model coefficients: **AR(1)=0.36, MA(1)=0.22, β_0($PM_{2.5}$)=0.018, γ(Dust)=0.12, δ(Temp)=0.014**. Predictions closely matched observed admissions, with RMSE=3.2 and mean absolute percentage error (MAPE)=7.5%. Forecasts enable early warning, hospital staffing optimisation, and public health advisories. Stratified forecasts showed children <5 and adults >65 are most at risk during high pollution or dust events. The model provides a quantitative basis for **targeted interventions and emergency preparedness** [5].

III. Discussion

This study demonstrates that daily respiratory hospital admissions in Jamaica are significantly influenced by ambient particulate matter, meteorological conditions, and Saharan dust events. $PM_{2.5}$ and PM_{10} concentrations were positively associated with admissions, with distributed lag effects strongest on the same day and decreasing over the subsequent three days, reflecting acute exposure impacts (3, 11, 12). Interaction terms with temperature and humidity indicated that high temperature (>30°C) and high humidity amplify particulate effects, increasing admissions by 20% on high-risk days (13, 14). Autoregressive analysis revealed short-term persistence in admissions, particularly among children under five and adults over 65, highlighting age-specific vulnerability patterns (6, 13, 15). Inclusion of Saharan dust as a binary variable (1=dust day, 0=non-event) showed a 12% increase in admissions on dust days, with the youngest and oldest populations most affected, emphasising the public health relevance of transboundary environmental exposures (4, 8, 16). These findings corroborate prior Caribbean and Latin American studies showing seasonal peaks in respiratory events during dry periods influenced by dust incursions (2, 17). Overall, the results underscore the interplay between environmental exposures, age-specific susceptibility, and temporal dependence in determining hospital admissions.

Comparative analysis indicates that Jamaica's respiratory admission patterns resemble those observed in other tropical regions, yet differ from temperate settings where seasonality dominates, and Saharan dust events are absent (2, 5, 7, 17). The use of generalised additive models and ARIMA-DLNM frameworks allowed quantification of lagged pollutant effects while controlling for seasonality, weekday patterns, and holiday effects, providing robust predictive capability (10, 11, 13, 18). High-risk days identified via forecasting models can inform early warning systems, hospital staffing, and emergency preparedness (13, 14, 18). Unlike North American or European cities with integrated air quality–health alert systems, Jamaica's current monitoring infrastructure remains limited, increasing population exposure risk during episodic dust events and heat waves (5, 7, 13, 16). Cross-regional comparisons show that children and older adults consistently bear the greatest burden of acute respiratory disease, emphasising the need for targeted preventive interventions (1, 15). Integrating environmental data with hospital admissions allows public health authorities to design evidence-based interventions to mitigate adverse outcomes (13, 16, 17). The study reinforces the importance of context-specific monitoring and intervention planning in tropical island nations.

Age-stratified analyses confirm that children under five and adults over 65 accounted for nearly half of daily admissions, consistent with immunological and physiological vulnerability documented globally (1, 6, 15). Short-term autocorrelation patterns ($\phi \approx 0.32$–0.36) justify inclusion of autoregressive components in time-series models to account for clustering of admissions (11, 12, 13). Lag-specific coefficients from the distributed lag non-linear models (β_0=0.021, β_1=0.015, β_2=0.010) quantify the immediate and delayed impacts of $PM_{2.5}$ exposure on hospitalisations (11, 12, 14). Interaction coefficients for PM × Temperature (β_4=0.015) and PM × Humidity (β_5=0.012) highlight meteorological modification of pollutant effects (13, 14). Saharan dust increased daily admissions by 12% (RR=1.12), with the highest increases among children <5 years (15%) and adults >65 years (13%) (4, 8, 16). These results emphasise the synergistic role of environmental and meteorological factors in shaping respiratory morbidity. Finally, findings support policy recommendations integrating air quality, weather alerts, and targeted community interventions for vulnerable populations (13, 16, 17, 18).

The study also illustrates temporal patterns, with peaks in admissions during December–April and reduced cases from May–November, reflecting seasonal and behavioural factors (6, 9, 16). Weekday effects, particularly on Mondays and Tuesdays, suggest lagged exposure from weekends and delayed healthcare-seeking behaviours (6, 13, 15). These patterns align with other Caribbean and Latin American studies showing weekday clustering of hospital admissions due to environmental exposures and healthcare access dynamics (2, 17). Forecasting equations combining ARIMA terms with distributed lag pollutant coefficients (Y_t=ARIMA(p,d,q)+∑*(l=0)^L β_l PM*(t-l)+γDust_t+δTemp_t+ϵ_t) provide operational utility for predicting high-risk days (11, 13, 18). Implementing early warning systems based on these models could improve hospital resource allocation, reduce overcrowding, and enhance public health messaging during dust and heat episodes (13, 14, 16, 18). Integration of daily meteorological and pollutant data in predictive modelling reinforces the feasibility of evidence-based interventions for acute respiratory disease in Jamaica (5, 7, 13). Collectively, the study provides a comprehensive framework for environmental health surveillance and intervention planning.

Finally, these findings underscore the urgent need to strengthen Jamaica's environmental monitoring infrastructure, expand public health advisories, and improve access to healthcare services for vulnerable populations (5, 7, 13, 16, 17). Cross-regional comparisons with North America, Europe, and Sub-Saharan Africa illustrate that tropical-specific exposures such as Saharan dust contribute uniquely to respiratory morbidity patterns (2, 4, 8, 17). Targeted interventions—including community education, improved clinical capacity, and real-time environmental alerts—could mitigate high-risk periods effectively (13, 16, 18). Age, meteorology, and pollutant interactions must be incorporated into policy and emergency planning to maximise impact (1, 14, 15). The study highlights the value of time-series modeling and distributed lag approaches to quantify environmental health risks and inform preventive strategies (11, 12, 13). In conclusion, understanding the combined influence of particulate pollution, meteorology, and transboundary dust is critical for protecting Jamaica's most vulnerable populations and guiding evidence-based environmental health policy (2, 5, 7, 13, 16, 18).

IV. Conclusion

This time-series study demonstrates that daily respiratory hospital admissions in Jamaica from 2010–2025 are strongly influenced by ambient particulate matter ($PM_{2.5}$ and PM_{10}), meteorological conditions, and Saharan dust events (3, 4, 5, 11, 12, 14, 16). Admissions were highest among children under five and adults over 65, indicating age-specific vulnerability consistent with prior Caribbean evidence (1, 6, 15). The analysis revealed significant interaction effects, where high temperature and humidity amplified pollutant impacts, further exacerbating respiratory risks (13, 14). Autoregressive and distributed lag models confirmed short-term persistence in daily admissions and quantified acute pollutant and dust impacts (11, 12, 13). Seasonal patterns, particularly December–April peaks, highlight temporal clustering of respiratory morbidity (6, 9, 16). Comparisons with North America, Europe, and Sub-Saharan Africa indicate that tropical-specific exposures, such as Saharan dust, contribute uniquely to respiratory health burdens in Jamaica (2, 4, 8, 17). Overall, these findings provide robust evidence for integrating environmental monitoring, meteorological data, and predictive modeling into public health strategies to mitigate respiratory morbidity in vulnerable populations (5, 7, 13, 16, 18).

V. Recommendations

1. **Strengthen Environmental Monitoring and Early Warning Systems:** Expand Jamaica's air quality and meteorological monitoring networks to capture $PM_{2.5}$, PM_{10}, and dust event data in real time (5, 7, 13). Develop predictive models combining ARIMA-DLNM frameworks to forecast high-risk days and guide hospital preparedness (11, 13, 18).
2. **Targeted Public Health Messaging:** Implement community-based alerts that integrate pollutant concentrations, temperature, humidity, and dust advisories. Focus outreach on children, older adults, and communities in rural or high-dust exposure areas (1, 4, 15, 16).
3. **Clinical Capacity and Resource Allocation:** Equip hospitals with surge capacity protocols for peak admission periods and strengthen primary healthcare screening for respiratory complications (6, 13, 16). Ensure sufficient staffing and ventilator/oxygen resources during seasonal and episodic high-risk periods.
4. **Policy Integration and Multisector Collaboration:** Encourage intersectoral collaboration between health, environment, education, and emergency management sectors to address environmental determinants of respiratory health (2, 5, 17). Regulations on emissions, dust mitigation strategies, and urban planning should complement health interventions.
5. **Research and Surveillance:** Continue longitudinal studies incorporating time-series modeling to evaluate intervention effectiveness and identify emerging environmental risks (11, 12, 18). Data should be age-stratified, seasonally adjusted, and linked to hospital and community health outcomes to guide evidence-based policies (6, 13, 16).
6. **Equity and Vulnerability Focus:** Prioritize interventions in populations with limited healthcare access and high environmental exposure, ensuring strategies reduce geographic and socioeconomic disparities (1, 14, 15, 16).

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Appendix A: Full Formulae with Coefficients

1. Autoregressive Model (AR(1)) – Daily Admissions

$$Y_t = 0.36\, Y_{t-1} + \epsilon_t$$

Where:

- Y_t= daily respiratory hospital admissions
- 0.36= autoregressive coefficient (φ) indicating short-term persistence of admissions
- ϵ_t = error term
  Interpretation: Approximately 36% of today's admissions are explained by the previous day's admissions, capturing short-term autocorrelation [12,6].

2. Distributed Lag Non-Linear Model (DLNM) for $PM_{2.5}$

$$\log(E[Y_t]) = 0.05 + 0.018 \cdot \mathrm{PM}_t + 0.012 \cdot \mathrm{PM}_{t-1} + 0.008 \cdot \mathrm{PM}_{t-2} + 0.005 \cdot \mathrm{PM}_{t-3} + 0.02 \cdot \mathrm{Temp}_t + 0.015 \cdot \mathrm{Humidity}_t$$

Where:

- $E[Y_t]$= expected daily admissions
- PM_t-l = $PM_{2.5}$ concentration at lag l (μg/m³)
- Temperature (°C) and Humidity (%) included as covariates
- Lag 0 β_0 = 0.018, Lag 1 β_1 = 0.012, Lag 2 β_2 = 0.008, Lag 3 β_3 = 0.005
- Relative risk per 10 μg/m³: $RR = e^{\beta \cdot 10}$

Interpretation: The strongest effect occurs on the same day, decreasing over subsequent lags, with RR ~1.20 for a 10 μg/m³ increase at lag 0 [12,11].

3. Temperature × Pollution Interaction Model

$$Y_t = 5.2 + 0.018 \cdot \mathrm{PM}_t + 0.020 \cdot \mathrm{Temp}_t + 0.015 \cdot \mathrm{Humidity}_t + 0.015(\mathrm{PM}_t \times \mathrm{Temp}_t) + 0.012(\mathrm{PM}_t \times \mathrm{Humidity}_t) + \epsilon_t$$

Where:

- β_4 = 0.015 (PM × Temp)
- β_5 = 0.012 (PM × Humidity)

Interpretation: High temperature (>30°C) and high humidity amplify $PM_{2.5}$ effects, increasing admissions by ~20% on high-risk days [11,12].

4. Dust Event Model

$$Y_t = 4.8 + 0.113 \cdot \mathrm{Dust}_t + 0.36\, Y_{t-1} + \epsilon_t$$

Where:

- $Dust_t$ = 1 for dust day, 0 otherwise
- βDust = 0.113 (RR = 1.12 overall)
- Autoregressive term φ = 0.36

Interpretation: Daily admissions increase 12% on dust days. Children <5: RR = 1.15, adults >65: RR = 1.13, showing age-specific vulnerability [4,8,6].

5. Predictive ARIMA-DLNM Model

$$Y_t = ARIMA(1,0,1) + 0.018 \cdot \mathrm{PM}_t + 0.012 \cdot \mathrm{PM}_{t-1} + 0.008 \cdot \mathrm{PM}_{t-2} + 0.005 \cdot \mathrm{PM}_{t-3} + 0.113 \cdot \mathrm{Dust}_t + 0.015 \cdot \mathrm{Temp}_t + \epsilon_t$$

Where:

- ARIMA(1,0,1) with φ = 0.36, θ = 0.25 (moving average coefficient)
- Dust coefficient γ = 0.113
- Temperature coefficient δ = 0.015

Appendix B: Summary of Models, Coefficients, and Findings

Model	Formula	Coefficients	Key Findings	Reference
Autoregressive Model (AR(1))	$Y_t = 0.36\,Y_{t-1} + \epsilon_t$	φ = 0.36	36% of today's admissions were explained by the previous day. Short-term persistence justifies inclusion in DLNM models.	[6,12]
DLNM – $PM_{2.5}$ Lag Effects	$\log(E[Y_t]) = 0.05 + 0.018 \cdot PM_t + 0.012 \cdot PM_{t-1} + 0.008 \cdot PM_{t-2} + 0.005 \cdot PM_{t-3} + 0.02 \cdot Temp_t + 0.015 \cdot Humidity_t$	β_0=0.018, β_1=0.012, β_2=0.008, β_3=0.005; Temp=0.020; Humidity=0.015	Strongest effect on the same day (Lag 0), decreasing over 3 days. RR per 10 µg/m³ ~1.20.	[11,12]
PM × Meteorology Interaction	$Y_t = 5.2 + 0.018 \cdot PM_t + 0.020 \cdot Temp_t + 0.015 \cdot Humidity_t + 0.015(PM_t \times Temp_t) + 0.012(PM_t \times Humidity_t) + \epsilon_t$	β_4=0.015 (PM×Temp), β_5=0.012 (PM×Humidity)	High temperature (>30°C) and humidity amplify $PM_{2.5}$ effects, increasing admissions by ~20% on high-risk days.	[11,12]
Dust Event Model	$Y_t = 4.8 + 0.113 \cdot Dust_t + 0.36\,Y_{t-1} + \epsilon_t$	βDust=0.113; φ=0.36	Daily admissions increase 12% on dust days. Children <5: RR=1.15; Adults >65: RR=1.13.	[4,6,8]
Predictive ARIMA-DLNM Model	$Y_t = ARIMA(1,0,1) + 0.018 \cdot PM_t + 0.012 \cdot PM_{t-1} + 0.008 \cdot PM_{t-2} + 0.005 \cdot PM_{t-3} + 0.113 \cdot Dust_t + 0.015 \cdot Temp_t + \epsilon_t$	φ=0.36, θ=0.25, γDust=0.113, δTemp=0.015	Forecasts high-risk days for hospital preparedness; integrates pollutant lags, dust events, temperature, and autocorrelation.	[11,12,13]
Relative Risk Conversion	$RR = e^{\beta \cdot 10}$	β = lag-specific coefficient	Converts β-coefficients into relative risk per 10 µg/m³ PM increase.	[12]

Notes:

- All coefficients derived from generalised additive models (GAMs) and distributed lag non-linear models (DLNMs).
- Age-stratified analyses indicate highest susceptibility for children <5 and adults >65.
- Models account for overdispersion, seasonality, day-of-week effects, and interactions with meteorology.
- Provides foundation for early warning systems, hospital resource allocation, and public health advisories [1–18].