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Assessing environmental and pandemic influences on mortality through seasonal time series models☆

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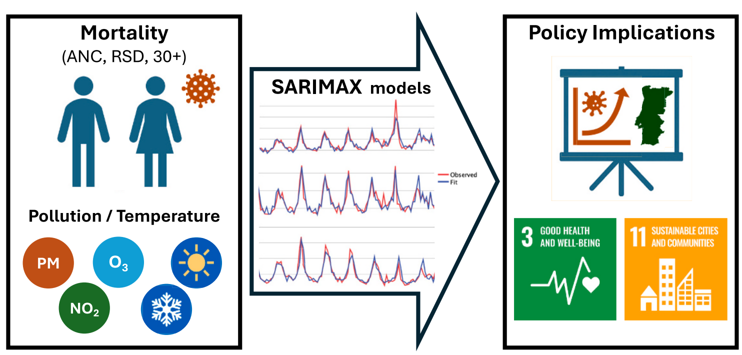
HIGHLIGHTS

- Winter mortality was ≈19 % higher, with elevated NO_2 (+24 %) and PM_{10} (+12 %).
- SARIMAX models identified lagged mortality effects for PM_{10} and temperature.
- COVID-19 disrupted seasonal mortality patterns, masking environmental effects.
- Cold-related mortality risks persisted with nonlinear, delayed responses.
- Findings highlight the need for stronger winter air quality and targeted health measures.

GRAPHICAL ABSTRACT



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ABSTRACT

Understanding the interplay between air pollution, climate variables, and mortality is essential for developing evidence-based public health policies and mitigating environmental health risks. Seasonal mortality patterns, particularly winter peaks, are often associated with increased air pollution and low temperatures. However, understanding the combined associations of these factors, especially under global disruptions such as the COVID-19 pandemic, poses a challenge for public health research and policy.

This study shows that the monthly number of deaths from all-natural causes in Portugal from 2010 to 2022 exhibits a pronounced seasonal pattern, with winter mortality about 19 % higher than the annual mean. In the same period, air pollutant concentrations show clear seasonality, with NO_2 (+24 %) and PM_{10} (+12 %) peaking in winter, while minimum temperatures fall about 42 % below the mean. Conversely, ozone exposure (SOMO35) reaches highest levels in summer, reflecting distinct seasonal burden. Using Seasonal Autoregressive Integrated Moving Average models with Predictor Variables (SARIMAX), the analysis identifies complex and lagged associations: PM_{10} exhibits a delayed effect at four months, while NO_2 is associated with immediate increases on mortality. Temperature acts as a nonlinear and oscillatory predictor, with both acute effects and delayed cold-related risks over several months.

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The findings indicate that pandemic-related mortality disrupted typical seasonal patterns and hindered the detectability of subtler environmental effects. Comparing models that include or exclude COVID-19 mortality reveals clearer environmental associations in the non-COVID model, highlighting the value of distinguishing acute shocks from long-term conditions.

Overall, the results underscore the need for stricter air quality standards during colder months and for adaptive public health strategies that consider cumulative and lagged environmental effects. While this study focused on adults aged 30 years and older, the findings suggest that older adults, individuals with chronic respiratory or cardiovascular conditions, and those in disadvantaged settings may be more susceptible to environmental stressors.

1. Introduction

Long-term patterns in mortality provide essential insights into public health, reflecting how the combined effects of disease, environmental stressors, and socioeconomic conditions influence the number of deaths in a population over time. Analysing such temporal patterns enables policymakers and researchers to quantify temporal variations in mortality rates and identify underlying trends, evaluate the influence of environmental and health-related interventions, and design strategies to reduce population vulnerability (HEI, 2024).

Air pollution has emerged as a major contributor to premature mortality, ranking as the second leading global risk factor for early death in 2021, surpassed only by high blood pressure (HEI, 2024). Recognizing this, the Sustainable Development Goal (SDG) indicator 3.9.1 monitors mortality attributed to pollutants such as fine particulate matter ($PM_{2.5}$) and nitrogen dioxide (NO_2) (WHO, 2024). According to the World Health Organization (WHO), ambient air pollution caused approximately 4.2 million deaths in 2019, predominantly due to non-communicable diseases such as ischemic heart disease, chronic obstructive pulmonary disease, stroke, and lung cancer (WHO, 2024). These figures underscore the urgent need for stronger regulatory action to reduce exposure.

The 2021 WHO Air Quality Guidelines (AQG) (WHO, 2021) provide updated recommendations for safe exposure levels, emphasizing the urgency of minimizing population exposure to harmful pollutants. Beyond driving morbidity, air pollution shortens global life expectancy by an average of 1 year and 8 months – an impact comparable to that of tobacco use (WHO, 2024). The latest State of Global Air (SoGA) report, based on Global Burden of Disease (GBD) 2021 estimates (GBD 2021 Risk Factors Collaborators, 2024), further identified air pollution as the second leading global risk factor for premature mortality, contributing to 8.1 million deaths in 2021 (HEI, 2024). Despite this evidence, the combined long-term effects of air quality and climate factors on mortality patterns remain poorly characterized (Pozzer et al., 2024; Ruchiraset and Tantrakarnapa, 2018).

Climate change further amplifies these health risks. Rising global temperatures are projected to cause an additional 2.3 million deaths in Europe by the end of the century under high-emission scenarios (Masselot et al., 2025). Beyond the well-established cardiovascular and respiratory effects of air pollution, growing evidence suggests associations with cognitive decline and neurodegenerative conditions such as Alzheimer's disease and dementia (Meo et al., 2024), reinforcing the need for more comprehensive mitigation policies.

To address such complex interactions, advanced statistical and modelling approaches are essential. Time series analysis, particularly using Seasonal Autoregressive Integrated Moving Average (SARIMA) models, is effective for capturing seasonality, lag effects, and external influences (Gudziunaite et al., 2023). SARIMA models with predictor variables – often referred to as SARIMAX – have been widely applied to examine the effects of air pollution and weather on mortality (Gudziunaite et al., 2023). Recent advances, including machine learning techniques, have further improved the accuracy of mortality forecasts (Amer et al., 2024). However, the objective of the present study was not to develop a new forecasting algorithm but rather to evaluate mortality patterns using SARIMAX as a transparent and policy-relevant framework integrating environmental and pandemic-related exposures.

While long-term exposures shape mortality trends, acute disruptions can reveal critical dynamics. The COVID-19 pandemic served as a natural experiment, as lockdowns sharply reduced traffic and industrial activity, leading to short-term declines in pollutants such as NO_2 and $PM_{2.5}$. These reductions were captured by the Portuguese Environment Agency (APA) through the Online Database on Air Quality (QualAr) (APA, 2025) monitoring stations, which remained operational during lockdowns.

In Portugal, understanding these interactions has become increasingly relevant for public-health assessment. Recent evidence underscores the importance of jointly assessing air pollution and temperature when evaluating mortality risks. National and regional studies have highlighted the complex interplay between these environmental stressors, with temperature acting as a key modifier of pollution-related health outcomes (Duarte et al., 2025; Martins et al., 2021). Concurrent episodes of extreme heat and elevated pollution are expected to increase in frequency, with higher levels of PM_{10} and ozone amplifying all-cause and non-accidental mortality during hot periods (Duarte et al., 2025).

Historical data further demonstrate significant mortality fluctuations during heatwaves and wildfire seasons. For example, in the Alentejo region, mortality rose sharply beyond a minimum mortality temperature of 19 °C, and the severe 2003 heatwave resulted in 289 excess deaths (Neto and Araújo, 2024). Similarly, the 2017 wildfire season – one of the most destructive on record – was linked to acute spikes in mortality coinciding with peaks in PM_{10} and high temperatures, with up to 100 natural cause deaths and 38 cardiorespiratory deaths attributable to smoke exposure (Augusto et al., 2020). Wildfire-related $PM_{2.5}$ exposure contributed to an estimated 189 deaths and 3092 years of life lost in 2017 alone (Barbosa et al., 2024). Long-term estimates also suggest that more than 5000 annual deaths in Portugal may be attributable to NO_2 and $PM_{2.5}$ exposure (Simões et al., 2025), and that heat accounts for approximately 2.3 % of total mortality in Alentejo, potentially rising to 15.9 % by the end of the century under high-emission scenarios (Neto and Araújo, 2024). Together, these findings indicate that the combined and interacting effects of air pollution and temperature remain insufficiently quantified, particularly under extreme events. The present study addresses this gap through an integrated national analysis of long-term mortality, air pollution, and climatic variables in Portugal.

In this context, the study analyses all-natural cause and respiratory mortality among adults aged 30 years and older in Portugal between 2010 and 2022, complementing earlier national assessments (Bernardo et al., 2019; Brito et al., 2022, 2021; Simões et al., 2025). It extends prior SARIMA-based analyses of air pollution (e.g., Dey et al., 2021) by integrating persistent environmental exposures with acute shocks such as the COVID-19 pandemic into a comprehensive SARIMAX time series framework. The modelling strategy explicitly compares mortality trends with and without COVID-19 deaths, incorporates predictors such as SOMO35 (ozone exposure) to capture both winter and summer health burdens, and accounts for acute disruptions alongside background environmental risks. The hypotheses tested are that: (i) winter mortality peaks are partly driven by lagged effects of particulate matter (PM_{10})

and low temperatures; (ii) nitrogen dioxide (NO_2) exerts immediate effects on mortality; (iii) ozone (SOMO35) contributes primarily to summer respiratory mortality; and (iv) inclusion of COVID-19 mortality disrupts the detection of these environmental associations, while exclusion reveals clearer long-term effects.

By linking mortality dynamics to both environmental exposures and pandemic-related disruptions, this analysis provides empirical evidence to support targeted public-health interventions and strengthen population resilience to environmental stressors.

2. Materials and methods

2.1. Dataset

2.1.1. Health and population data sources

Data on population and health outcomes were obtained from Statistics Portugal (INE) (INE, 2024a) and PORDATA, the Database of Contemporary Portugal (PORDATA, 2024). Mortality data included the number of deaths from all-natural causes (ANC), defined as deaths attributed to disease processes, as opposed to external causes such as accidents, injuries, or violence. The dataset also included the number of deaths due to respiratory system diseases (RSD) (ICD-10: J00–J99). Only individuals aged 30 years and older were considered. Data on COVID-19 related mortality, categorised by month of death from 2020 to 2022, was sourced from INE databases (INE, 2024b). COVID-19 deaths are included within the all-natural causes (ANC) category as reported by INE. To construct the non-COVID mortality series (ANC_NONCOVID), the monthly number of COVID-19 deaths (2020−2022) was subtracted from the ANC dataset. All mortality data were available as monthly and yearly counts, and the analysis was therefore conducted at a monthly temporal resolution, since daily or weekly mortality data are not publicly available from INE/PORDATA. All data refer to the total number of registered deaths in Portugal, including the Autonomous Regions of the Azores and Madeira.

2.1.2. Air pollution data

Air pollution data, including hourly concentrations of NO_2, PM_{10}, $PM_{2.5}$ and O_3 were obtained from the Portuguese Environment Agency (APA) via the Online Database on Air Quality (QualAr) (APA, 2025). The dataset spans from 1 January 2010 to 31 December 2022 and includes monitoring stations across various municipalities in Portugal. Only datasets from stations reporting at least 75 % of hourly observations, as approved by APA, were included. For each pollutant, hourly observations were first aggregated into daily averages at each monitoring station, and daily values were then aggregated into monthly means. National monthly pollutant indicators were calculated as the arithmetic mean across all stations reporting valid data for that month. Urban, suburban, rural, and traffic stations were included to capture national-scale variability, and stations with insufficient valid data for a given month (>25 % missing) were excluded from that month's national average. No population-weighting was applied, consistent with the national-scale focus of the study and previous national assessments. The geographical distribution of monitoring stations can be accessed through the APA database (QualAr) (APA, 2025).

Given that most stations measure PM_{10}, while only a subset measure $PM_{2.5}$, PM_{10} was selected as the primary pollutant variable for assessing particulate matter concentration, due to its more complete and continuous time series. This choice also avoids reliance on estimated values derived from correction factors used to convert PM_{10} into $PM_{2.5}$. Additional details are provided in the Supplementary Material (Section 2).

To assess health risks associated with ozone exposure, the SOMO35 (Sum of Ozone Means Over 35 ppb (70 $\mu g/m^3$)) indicator was used, following the WHO recommendations. SOMO35 was defined as the monthly sum of the daily maximum 8-h running average ozone concentration exceeding 70 $\mu g/m^3$. The unit of measurement is $\mu g/m^3 \cdot$ days.

The study follows the European Air Quality Directive (2008/50/EC) (OJEU, 2008), which sets the number of required monitoring stations based on population and pollution levels. Since most of Portugal's urban and industrial pollution sources are along the Atlantic coast, the western regions have more monitoring stations than the east.

2.1.3. Temperature data

Temperature data were collected from Instituto Português do Mar e Atmosfera (IPMA), using in-situ observations of 2-m air temperature (Tair2m) from weather stations across Portugal. The dataset includes daily mean, maximum, and minimum air temperatures from 1 January 2010 to 31 December 2022, and weather stations were selected based on data availability from IPMA (IPMA, 2024). For the purposes of this study, daily values were aggregated into monthly averages for each station. National monthly temperature indicators (T_{min}, T_{mean}, T_{max}) were then calculated as the arithmetic mean across all weather stations with valid data for the corresponding month.

2.1.4. Key variables for analysis

Mortality variables (All-Natural Causes Mortality (ANC), Non-COVID Natural Causes Mortality (ANC_NONCOVID), and Mortality from Respiratory System Diseases (RSD) [ICD-10: J00–J99]) were defined in Section 2.1.1.

Air Pollutants included PM_{10} ($\mu g/m^3$), NO_2 ($\mu g/m^3$), and SOMO35 ($\mu g/m^3$·days), as described in Section 2.1.2. PM_{10} was selected as the primary measure of particulate matter concentration due to its more complete dataset, as detailed in Section 2.1.2.

Temperature variables (monthly averages of T_{mean}, T_{max} and T_{min}) were sourced from IPMA, as described in Section 2.1.3.

A binary event variable named COVID-19 [E] (binary) (coded as 0 = *pre-pandemic period*, 1 = *pandemic period*, covering all months from 2020 to 2022) was included in the model to distinguish between pre- and post-pandemic periods and to capture pandemic-related variations in mortality and environmental conditions. This classification was based on official COVID-19 death records from INE, as detailed in Section 2.1.1.

2.2. Statistical methods

The Seasonal Autoregressive Integrated Moving Average with covariates, predictors or exogenous variables (SARIMAX) model was employed to analyse and predict mortality cases in Portugal. This model is particularly suited for time series data exhibiting seasonality and the inclusion of predictor variables, making it an appropriate choice for this study. The SARIMAX$(p,d,q)(P,D,Q)_s$ model is an extension of the SARIMA$(p,d,q)(P,D,Q)_s$ model, where p,d,q represent the autoregressive (AR) order, differencing order, and moving average (MA) order, respectively; P,D,Q represent the seasonal AR, seasonal differencing, and seasonal MA terms, respectively; s denotes the number of periods in each season.

The SARIMAX$(p,d,q)(P,D,Q)_s$ model can be expressed as:

$$\Phi_P(B^s)\phi_p(B)\nabla_s^D\nabla^d Y_t = \delta + \Theta_Q(B^s)\theta_q(B)\epsilon_t + \sum_{i=1}^{n}\beta_i X_t^i$$

where the ordinary autoregressive and moving average components are represented by polynomials $\phi_p(B)$ and $\theta_q(B)$ of orders p and q, respectively, and the seasonal autoregressive and moving average components by $\Phi_P(B^s)$ and $\Theta_Q(B^s)$ of orders P and Q, and ordinary and seasonal difference components by $\nabla^d = (1-B)^d$ and $\nabla_s^D = (1-B^s)^D$. B is the backshift operator, defined by $BY_t = Y_{t-1}$ and extended to powers by $B^k Y_t = Y_{t-k}$; Y_t is the observed time series; ϵ_t is white noise; δ is an intercept term; and X_t^i represents the predictor variables with their respective coefficients β_i.

The SARIMAX model is widely used in environmental epidemiology for analysing and forecasting health-related time series data, particularly in cases where seasonality and exogenous influences play a significant role (Gudziunaite et al., 2023). Time series analysis has been instrumental in assessing the effects of air pollution and meteorological factors on health outcomes, such as mortality and hospital admissions (Gudziunaite et al., 2023). The ability of SARIMAX to explicitly account for seasonal trends and incorporate covariate variables makes it a robust choice for studying epidemiological time series data (Gudziunaite et al., 2023).

The modelling process was conducted using the Expert Modeler function in IBM SPSS Statistics (v.29.0.2) (IBM Corp., 2023), which automates model selection by evaluating multiple SARIMAX configurations. The Expert Modeler also accounts for stationarity and seasonality by applying necessary transformations such as differencing and natural log scaling. The SARIMAX models were designed to incorporate different combinations of predictor variables, including air pollution indicators (NO_2, PM_{10}, SOMO35), temperature metrics (T_{min}, T_{mean}, T_{max}), and the COVID-19 binary variable. The mortality categories analysed included All-Natural Causes Mortality (16 models: ANC_1 to ANC_16), Non-COVID Natural Causes Mortality (15 models: ANC_NONCOVID_1 to ANC_NONCOVID_15), and Diseases of the Respiratory System Mortality (19 models: RSD_1 to RSD_19).

Candidate models were evaluated using the Normalized Bayesian Information Criterion (BIC) and the coefficient of determination (R^2). Lower BIC values indicated better model parsimony, while higher R^2 values reflected stronger explanatory power. Model robustness was assessed using the Ljung–Box test to verify residual independence. Complete results (BIC, R^2, and Ljung–Box p-values) are reported in Supplementary Table S5.

To minimise potential multicollinearity, temperature indicators (minimum, mean, and maximum) were not included simultaneously in the same model, as they were found to be highly correlated. Instead, each temperature metric was tested in separate model specifications. Pairwise correlations among predictors were examined only for variables considered together within a given model to ensure that no highly correlated variables were retained. Additionally, for selected models, interaction terms between pollutants, as well as pollutant–temperature combinations, were tested to assess potential synergistic effects. Final SARIMAX models were selected by minimizing Normalized BIC, maximizing R^2, and confirming the absence of significant autocorrelation in residuals. This approach aligns with the Box–Jenkins principle of identifying adequate yet parsimonious models (Box et al., 2016; Yaffee and McGee, 2000).

Finally, to evaluate the sensitivity of model performance to particulate matter indicators, an alternative specification using a derived $PM_{2.5}$ variable instead of PM_{10} was tested. Results of this comparison are presented in Table S6 (Supplementary Material).

3. Results and discussion

3.1. Univariate time series analysis and seasonal decomposition

Summary statistics for mortality, air pollution, and temperature in Portugal during 2010–2022 are presented in Tables S1 and S2 (Supplementary Material). Figs. 1 and 2 display the monthly time series of key variables in Portugal from 1 January 2010 to 31 December 2022. Fig. 1 shows the monthly mortality series by cause, illustrating seasonal patterns and long-term variation; winter months (December–February) are shaded in grey. Fig. 2 presents the monthly evolution of air pollution and temperature variables, highlighting their fluctuations over time and suggesting potential environmental trends.

To characterise underlying temporal components, multiplicative time series decomposition was applied to each variable. This classical decomposition method separates the observed series into trend, seasonal, and irregular components, allowing quantification of seasonal patterns through Seasonal Adjustment Factors (SAF) (see Table S3, Supplementary Material).

The decomposition results confirm clear and consistent seasonal effects. Mortality due to all-natural causes (ANC) was 19 % higher than the annual mean in winter and 11 % lower in summer, representing a seasonal contrast of about 30 percentage points between the two extremes. Respiratory disease mortality (RSD) exhibited an even stronger amplitude, with winter values 38 % above and summer values 20 % below the mean (≈58-point contrast). Air pollutants followed a similar pattern: NO_2 (+24 %) and PM_{10} (+12 %) peaked in winter, coinciding with markedly lower minimum temperatures (−42 %), whereas ozone (SOMO35) displayed the opposite pattern, with pronounced peaks in spring (+60 %) and summer (+35 %). These findings reinforce the strong winter burden of mortality associated with cold weather and primary pollutants, while highlighting ozone as a distinct summer-related risk factor.

The mortality patterns in Portugal from January 2010 to December 2022 illustrated in Fig. 1 reveal consistent seasonal patterns, with higher mortality rates during winter and lower rates in summer across all categories. All-natural causes mortality exhibits seasonal variation, with higher mortality in winter and lower in summer, which aligns with previous findings attributing winter mortality peaks to cold weather and flu season effects (INE, 2024c). The all-natural causes (non-COVID) mortality (Jan 2020 – Dec 2022) also exhibits a similar pattern but with reduced variability. Specifically, the standard deviation decreased from approximately 1262 (pre-pandemic period) to 1105 (during the pandemic), and the coefficient of variation decreased from 14.7 % to

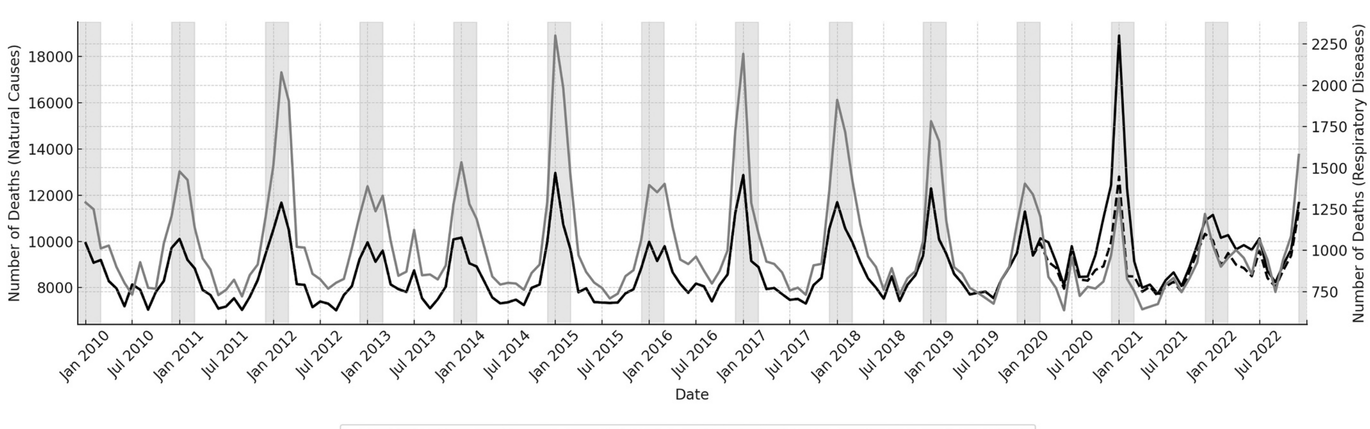

Fig. 1. Time series of monthly mortality by cause in Portugal from January 2010 to December 2022. Grey-shaded areas correspond to winter months (December–February).

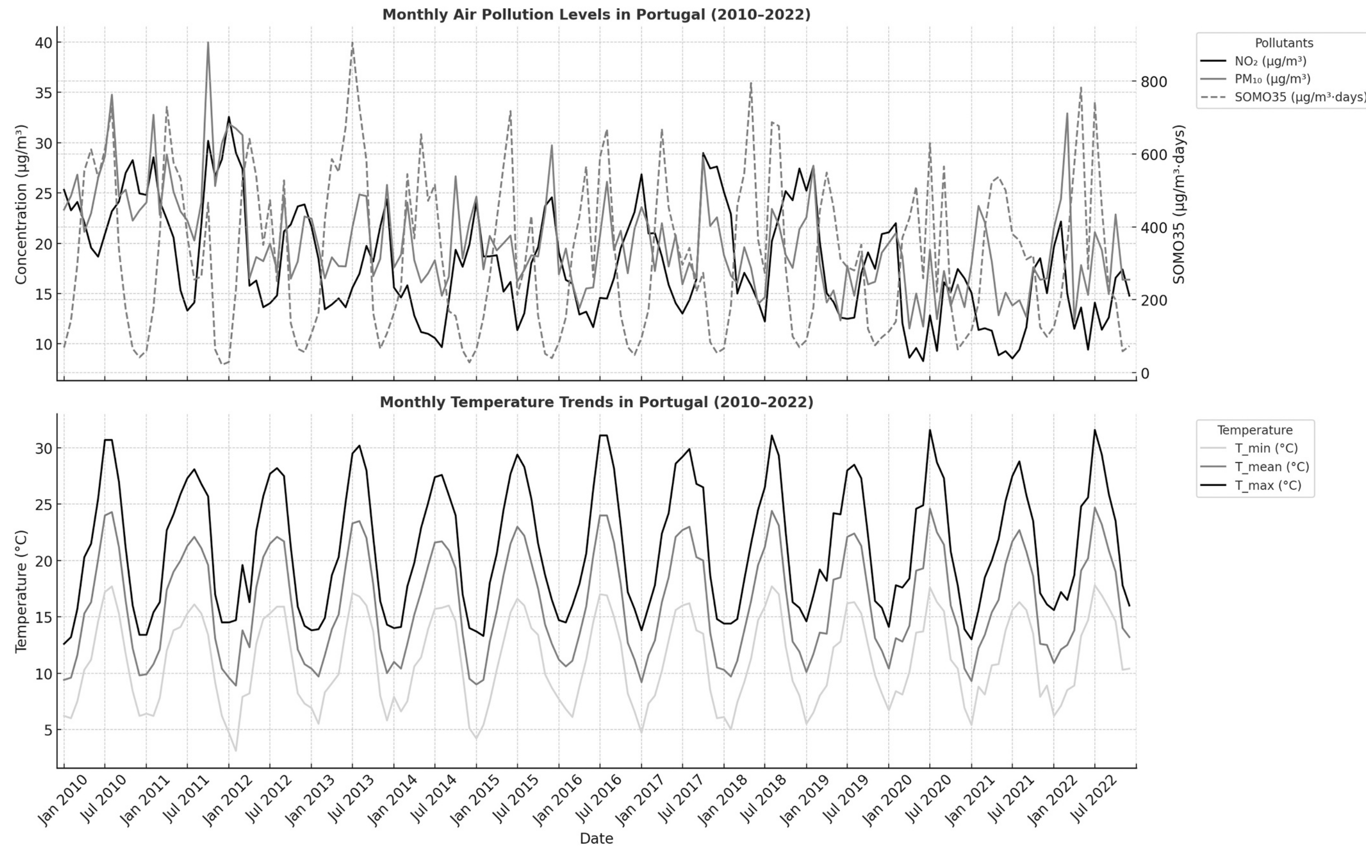

Fig. 2. Time series plots of monthly air pollution variables and temperature variables from January 2010 to December 2022 in Portugal.

12.2 %. This reduction in variability may reflect the indirect effects of public health measures such as lockdowns and improved hygiene practices. This is supported by data indicating a decrease in non-COVID respiratory infections and other seasonal illnesses due to pandemic-related precautions (INE, 2024c).

The data on mortality from diseases of the respiratory system highlights significant winter spikes, reinforcing the impact of seasonal flu and respiratory infections, with a notable increase in pneumonia-related deaths in specific years. In 2022, for example, deaths from diseases of the respiratory system increased by 18 % compared to 2021, largely due to a rise in pneumonia cases, which accounted for nearly 40 % of this increase (INE, 2024c). During 2020–2022, respiratory mortality rates declined slightly, likely due to pandemic-related interventions that reduced the spread of airborne infections (INE, 2024c).

The air pollution and temperature time series in Portugal from January 2010 to December 2022 reveal important patterns, as illustrated in Fig. 2 and Table S1 (Supplementary Material). NO_2 and PM_{10} concentrations in Portugal have generally declined, with more pronounced reductions observed during the COVID-19 years (2020−2021), when mobility was restricted. In 2022, NO_2 levels rose slightly compared to 2021, although they remained below pre-pandemic levels. PM_{10} concentrations, however, increased more substantially in 2022, reaching values comparable to those recorded before 2016, suggesting a short-term rebound linked to resumed economic and traffic activity (APA, 2024).

SOMO35 levels, reflecting ozone pollution, show high interannual variability with no consistent long-term pattern, suggesting episodic peaks influenced by temperature and atmospheric conditions. In 2022, the average ozone concentration increased by 7 % in rural areas and 17 % in urban and suburban areas, reinforcing the link between high temperatures and ozone formation (APA, 2024).

Even though NO_2 and PM concentrations in Portugal have generally declined, they continue to exceed the strictest WHO 2021 air quality guidelines. The annual WHO limit for NO_2 is 10 μg/m^3, while levels in Portugal ranged from 12.33 μg/m^3 in 2021 to 23.45 μg/m^3 in 2010, meaning that the recommended limit was exceeded (WHO, 2021). Similarly, the WHO-recommended annual PM_{10} guideline is 15 μg/m^3, while Portugal's PM_{10} levels ranged from 15.86 μg/m^3 in 2020 to 26.58 μg/m^3 in 2011, exceeding WHO recommendations (WHO, 2021). For $PM_{2.5}$, the WHO 2021 guideline is 5 μg/m^3, but $PM_{2.5}$ levels in Portugal fluctuated between 6.49 μg/m^3 in 2021 and 10.21 μg/m^3 in 2015, meaning air quality did not fully meet WHO's stricter recommendations (WHO, 2021). However, the European Union's air quality limit for $PM_{2.5}$ is 25 μg/m^3, which Portugal remained well below. The WHO 2021 guideline for peak season average 8-h ozone (O_3) concentration is 60 μg/m^3. However, O_3 levels in Portugal have consistently exceeded this threshold, ranging from 75.83 μg/m^3 in 2019 to 89.24 μg/m^3 in 2013, meaning air quality failed to meet WHO's stricter recommendation in every recorded year (WHO, 2021) (see Table S4 in the Supplementary Material).

In terms of temperature, Portugal has experienced a steady warming pattern, with 2022 being the hottest year on record, exceeding the historical average (1971–2000) by 1.38 °C (IPMA, 2023). This trend is particularly evident in T_{min}, which has increased over the years, suggesting that nighttime temperatures are rising faster, a common sign of climate change. The last 10 years have consistently recorded temperatures above historical norms, with 2022 ranking as the hottest year since 1931 (APA, 2024).

The alignment of air pollution and temperature trends highlights their interplay. Higher temperatures contribute to ozone formation, particularly during summer months, leading to periodic peaks in pollution levels. This reinforces the need for sustained monitoring and policy interventions to mitigate air pollution, reduce greenhouse gas emissions, and adapt to climate change impacts (APA, 2024).

3.2. SARIMAX models

The modelling process was conducted using the Expert Modeler function in SPSS, as described in Section 2.2. To determine the most suitable SARIMAX model, various models were tested under different scenarios, as outlined in Table S5 (Supplementary Material).

The final models selected were ANC_12 for all-natural causes mortality, ANC_NONCOVID_2 for non-COVID natural causes mortality, and RSD_14 for respiratory system disease mortality. ANC_12 incorporated COVID-19 as a predictor variable, along with PM_{10} and T_{mean}, capturing both direct pandemic effects and environmental influences on mortality. ANC_NONCOVID_2 included NO_2, PM_{10}, and T_{min}, demonstrating that air pollution and cold temperatures are significant drivers of non-COVID mortality. The RSD_14 model included SOMO35 and T_{min}, reflecting the strong link between ozone exposure, cold stress, and respiratory mortality. The selection of these models was based on their superior performance in terms of BIC and R^2, as well as their ability to capture seasonal mortality patterns and environmental influences effectively. The details for chosen models are provided in Table 1.

3.2.1. All-natural causes model (ANC_12)

This model incorporates a moving average (MA) component that smooths short-term fluctuations, helping to prevent sudden mortality spikes from distorting long-term trends. It also includes a seasonal autoregressive (AR, Seasonal) component that captures the recurring nature of mortality peaks, particularly during winter months.

The model identifies COVID-19 as a significant predictor factor, indicating a strong statistical association with elevated mortality during pandemic-affected periods. The estimated effect of COVID-19 suggests an increase of approximately 1268 excess deaths per month during pandemic-affected periods ($p < 0.001$). This finding aligns with global research indicating that excess mortality during the pandemic period far exceeded expected levels, often surpassing official COVID-19 death counts due to indirect health impacts, such as delayed medical care and pressure on healthcare systems (Karlinsky and Kobak, 2021).

The model indicates that seasonally differenced PM_{10} exposure has a significant delayed effect on mortality, suggesting that its association accumulates over time rather than causing immediate mortality spikes. Specifically, for each 1 $\mu g/m^3$ increase in the seasonal difference in PM_{10} – meaning the change compared to the same month in the previous year – there is an estimated increase of 33 deaths per month, occurring four months later ($p = 0.007$). For example, if PM_{10} levels in January 2022 were 1 $\mu g/m^3$ higher than in January 2021, the model predicts that there would be approximately 33 additional deaths in May 2022. This is consistent with findings from multi-city time series studies showing that prolonged exposure to PM_{10} increases cardiovascular and respiratory mortality, often with a delay of several weeks to months (Pope et al., 2020).

Temperature also plays a complex role. The model uses a second-order transfer function with a one-month delay to assess how temperature changes – relative to the same month in the previous year – influence mortality. This approach captures not only the immediate effects of temperature but also the delayed and ongoing impact.

The transfer function reflects both short-term reactions and longer-term "memory" effects. In practical terms, this means that a period of colder-than-usual weather may lead to more deaths not only that month but also in the months that follow, with the effect gradually diminishing in a wave-like pattern. This behaviour mirrors known biological responses to cold, such as increased physical stress, reduced immune function, and respiratory complications. While this pattern is particularly relevant in winter, when cold-related mortality tends to be highest, the model also captures the impact of warmer-than-usual conditions.

Table 1
SARIMAX model description and parameters.

Time series	SARIMAX model	Parameter	Lag	Estimate	SE	t	p
All-natural causes	$(0,0,1)(1,1,0)_{12}$	MA	1	−0.474	0.078	−6.084	<0.001
ANC_12		AR, seasonal	1	−0.798	0.068	−11.788	<0.001
		Seasonal difference		1			
PM_{10}		Delay		4			
		Numerator	0	33.263	12.218	2.722	0.007
		Seasonal difference		1			
T_{mean}		Delay		1			
		Numerator	0	−174.891	44.534	−3.927	<0.001
			1	−284.588	82.477	−3.451	<0.001
			2	128.211	49.338	2.599	0.010
		Denominator	1	1.874	0.029	65.301	<0.001
			2	−1.000	0.030	−33.838	<0.001
		Seasonal difference		1			
COVID-19 [E] (binary)		Numerator	0	1267.574	237.207	5.344	<0.001
		Seasonal difference		1			
All-Natural Causes (NON-COVID)	$(1,0,0)(1,1,0)_{12}$	Constant		124.630	49.442	2.521	0.013
ANC_NONCOVID_2		AR	1	0.408	0.084	4.884	<0.001
		AR, seasonal	1	−0.684	0.070	−9.742	<0.001
		Seasonal difference		1			
NO_2		Numerator	0	39.181	13.648	2.871	0.005
		Seasonal difference		1			
PM_{10}		Delay		4			
		Numerator	0	31.643	9.893	3.199	0.002
		Seasonal difference		1			
T_{min}		Delay		1			
		Numerator	0	−162.867	38.522	−4.228	<0.001
		Seasonal difference		1			
Diseases of the Respiratory System	$(1,0,0)(0,1,1)_{12}$	AR	1	0.623	0.070	8.908	<0.001
RSD_14 (*)		Seasonal difference		1			
		MA, seasonal	1	0.830	0.103	8.043	<0.001
SOMO35 (*)		Numerator	0	0.100	0.024	4.095	<0.001
		Seasonal difference		1			
T_{min} (*)		Numerator	0	−0.234	0.071	−3.305	0.001
			1	0.402	0.073	5.542	<0.001
		Seasonal difference		1			

(*) Variables marked with an asterisk (*) were log-transformed (natural logarithm).

The recursive structure allows for both cold- and heat-related effects to emerge, depending on seasonal context, baseline climate, and population vulnerability. A full discussion and example of summer-period effects is provided in the Supplementary Material (Section 3, Table S7).

The model also exhibits oscillatory behaviour, driven by the internal dynamics of the transfer function. This was confirmed by fitting a cosine curve to the modelled temperature effect, which revealed a cyclical pattern with a period of approximately 17.6 months. A full mathematical characterisation and visualisation of this oscillatory structure, including the fitted cosine curve, is provided in the Supplementary Material (Section 3.1).

Overall, the model highlights the significant but delayed health associations of air pollution and temperature, as well as the strong contemporaneous association with COVID-19. These findings underscore the importance of public health policies that account for time-lagged effects – particularly in the areas of air quality regulation, climate adaptation, and pandemic preparedness.

3.2.2. All-natural causes (NON-COVID) model (ANC_NONCOVID_2)

This model exhibits autoregressive and seasonal patterns, capturing how past mortality levels continue to shape current trends. The seasonal peaks in mortality, particularly during colder months, indicate that winter-related illnesses and environmental stressors are key drivers. The inclusion of NO_2 and PM_{10} as significant predictors aligns with well-established evidence linking air pollution to increased mortality risks (APA, 2024).

NO_2 had a statistically significant immediate effect. Specifically, a 1 $\mu g/m^3$ increase in the seasonal difference of NO_2 (i.e., compared to the same month in the previous year) was associated with 39 additional deaths per month ($p = 0.005$). For instance, if average NO_2 concentrations in March 2022 were 1 $\mu g/m^3$ higher than in March 2021, the model predicts approximately 39 excess deaths occurring in March 2022 because of that increase. This aligns with prior research linking NO_2 exposure to respiratory and cardiovascular stress, leading to increased mortality risk (APA, 2024).

PM_{10} showed a significant delayed effect. A 1 $\mu g/m^3$ increase in the seasonal difference of PM_{10} (i.e., the interannual change) with a lag of four months was associated with approximately 32 additional deaths per month ($p = 0.002$). For example, if PM_{10} levels in February 2021 were 1 $\mu g/m^3$ higher than in February 2020, the model predicts around 32 additional deaths occurring in June 2021 due to that increase in exposure. This suggests that PM_{10} exposure contributes to long-term health deterioration, particularly through respiratory and cardiovascular complications. The findings align with previous research showing that prolonged exposure to particulate matter increases the risk of chronic lung disease, systemic inflammation, and cardiovascular stress, ultimately leading to higher mortality rates (APA, 2024; Pope et al., 2020).

Minimum temperature (T_{min}) also exhibited a statistically significant delayed effect. A 1 °C decrease in the seasonal difference of T_{min} – indicating that a given month was colder than the same month in the previous year – was associated, on average, with approximately 163 additional deaths one month later ($p < 0.001$). This finding underscores the substantial health burden of colder-than-usual conditions, particularly during the winter season when baseline vulnerability is higher. For instance, if January 2021 was 1 °C colder than January 2020, the model estimates around 163 additional deaths in February 2021 attributable to that temperature drop. However, this estimate reflects a modelled average applied uniformly across the year; the actual health impact of a 1 °C drop may vary depending on the season, with smaller effects likely during warmer months. The observed delay supports the understanding that cold exposure can impair immune function and exacerbate cardiovascular and respiratory conditions over time, contributing to elevated mortality weeks after the initial temperature decline. These results are consistent with broader climate-health evidence showing that prolonged exposure to cold significantly increases the risk of hypothermia, respiratory infections, and cardiovascular events, and that cold-related mortality continues to outnumber deaths linked to extreme heat (Masselot et al., 2025).

Taken together, these findings highlight the need of implementing public health strategies to mitigate cold-related risks, including ensuring adequate heating, improving early warning systems, and strengthening healthcare responses to cold-induced illnesses.

3.2.3. Diseases of the respiratory system model (RSD_14)

This model shows that deaths from respiratory diseases tend to persist over time, with autoregressive effects indicating that current mortality is influenced by recent trends. Respiratory deaths follow a clear seasonal cycle, peaking during colder months due to a combination of flu outbreaks, low temperatures, and increased air pollution. These patterns highlight how environmental stressors can exacerbate respiratory vulnerabilities and lead to sustained health impacts.

One of the most significant environmental drivers identified by the model is ozone pollution, measured using the seasonal difference in the SOMO35 index. The results show that a 1 % increase in SOMO35 compared to the same month in the previous year is associated with approximately a 0.1 % increase in respiratory mortality ($p < 0.001$). For example, if SOMO35 levels in July 2022 were 10 % higher than in July 2021, the model predicts about a 1 % increase in respiratory deaths in July 2022. Unlike particulate matter, which accumulates over time, ozone exerts its harmful effects rapidly, leading to higher hospital admissions for respiratory diseases (Pozzer et al., 2024).

Minimum temperature (T_{min}) also plays a critical role. The model includes both immediate (lag 0) and short-term delayed (lag 1) effects, indicating that colder-than-usual months have a compounding adverse association on respiratory mortality.

The immediate association (lag 0) is likely driven by direct cold exposure, which increases the incidence of respiratory infections such as influenza, pneumonia, and bronchitis (EEA, 2024). Cold conditions also encourage indoor crowding and reduced ventilation, facilitating the transmission of airborne pathogens. Physiological responses to cold, such as bronchoconstriction and reduced immune function, further elevate respiratory risk (EEA, 2024).

The additional effect at lag 1 suggests that the consequences of colder-than-usual weather can continue into the following month, possibly due to complications from earlier infections or delayed health outcomes. It may also reflect environmental continuity, where extended exposure to low temperatures increases vulnerability over time.

Seasonal temperature fluctuations reinforce the link between cold weather and respiratory vulnerability. Cold temperatures contribute to higher viral infections, increased indoor air pollution from heating systems, and temperature inversions that trap pollutants close to the ground. Conversely, rising temperatures may worsen respiratory risks through ozone formation and placing additional strain on the cardiovascular system. Vulnerable populations, including the elderly, children, and individuals with chronic respiratory diseases, may be particularly affected, highlighting the need for targeted public health interventions (Gasparrini et al., 2015).

Overall, the model confirms that respiratory mortality exhibits strong seasonal patterns, with colder months showing a sharp increase in deaths. The presence of autoregressive effects further highlights the persistence of respiratory-related mortality, emphasizing the ongoing impact of environmental factors on respiratory health.

3.3. SARIMAX model charts

Fig. 3 illustrates the fitted and observed values for All-Natural Causes (ANC_12), All-Natural Causes (NON-COVID) (ANC_NONCOVID_2), and Diseases of the Respiratory System (RSD_14) over the period from 2010 to 2022. The SARIMAX models effectively capture the seasonal trends and fluctuations in mortality, with fitted values closely following the observed mortality cases in all three panels.

In the top panel, the ANC_12 model reflects overall mortality

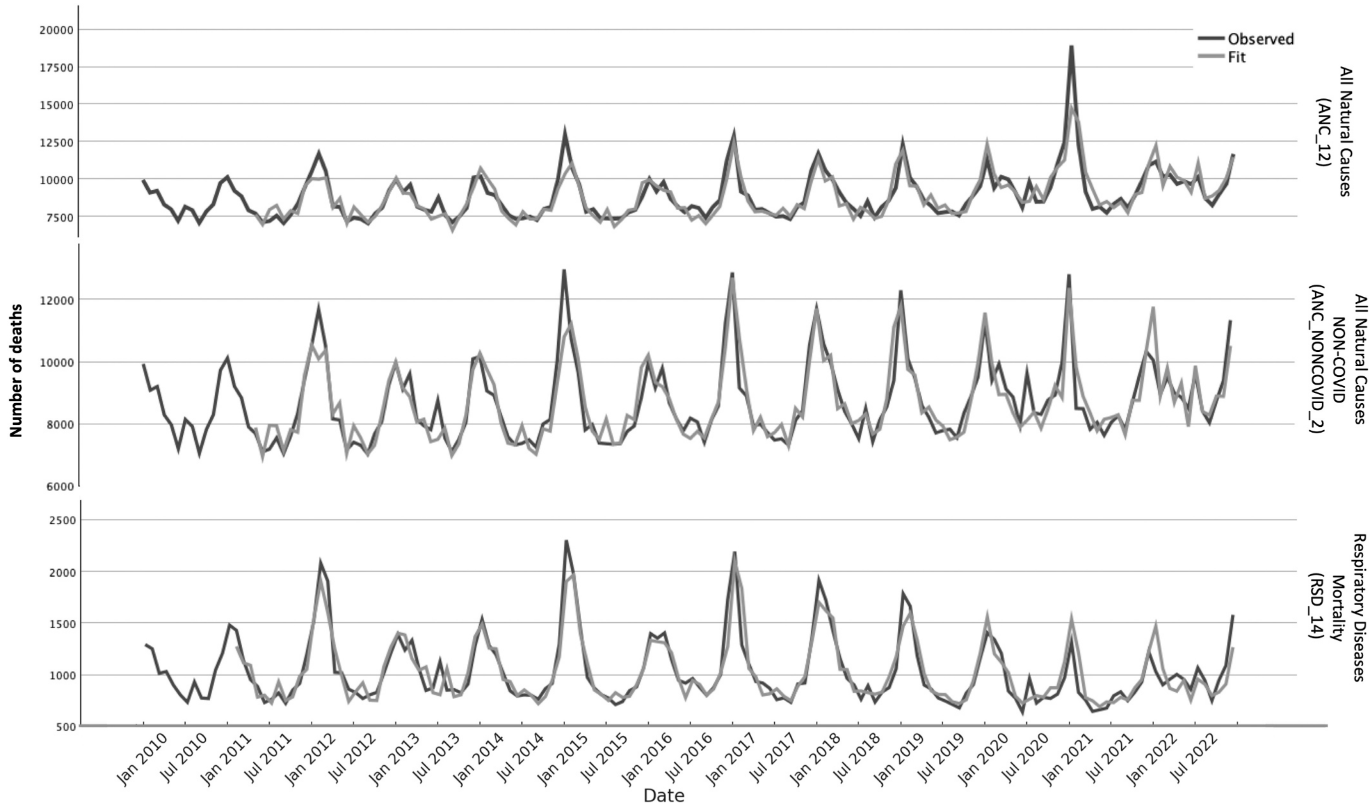

Fig. 3. Observed and fitted mortality for ANC_12, ANC_NONCOVID_2, and RSD_14, Portugal (2010−2022).

patterns, with consistent winter peaks and summer troughs. The sharp spike in early 2021 corresponds to the peak of the COVID-19 pandemic, illustrating its profound and immediate impact on all-natural causes mortality.

The middle panel (ANC_NONCOVID_2), which excludes COVID-19-related deaths, displays similar seasonal trends but with reduced variability in recent years. This may reflect the indirect effects of pandemic responses, such as lockdowns and enhanced medical care, which likely helped reduce deaths from other causes.

In the bottom panel, the RSD_14 model shows pronounced seasonal peaks in respiratory mortality, especially during colder months. These are consistent with well-documented drivers such as cold-related immune suppression, indoor air pollution from heating, and outdoor pollutant buildup during temperature inversions. The immediate effect of SOMO35 (ozone exposure) in the model supports its role in triggering acute respiratory distress, contributing to these peaks.

Overall, these SARIMAX models offer a robust framework for monitoring and forecasting mortality trends. By incorporating key predictors – including temperature, air pollution, and COVID-19 impacts – they provide a more integrated view of environmental and public health risks. Nevertheless, the results also highlight that the abrupt mortality surges observed during the pandemic exceed the structural capacity of SARIMAX models to capture short-term, nonlinear epidemic dynamics. This limitation suggests that future analytical frameworks may benefit from hybrid approaches that complement traditional time series modelling with mechanistic epidemic models able to represent the underlying transmission and recovery processes that drive sudden epidemic peaks. For example, SIR-type compartmental models, which structure the population into susceptible, infectious, and removed groups (S, I, R) and describe their temporal evolution through transmission and recovery equations, offer a principled way to capture the nonlinear infection dynamics that generate rapid surges in cases or deaths (Kalachev et al., 2023; Tavares, 2017). These models also incorporate epidemiologically meaningful parameters such as the transmission rate β, the recovery/removal rate γ, and the basic reproduction number R_0 – which determines whether an epidemic expands or decays – allowing them to simulate short-term epidemic behaviour that purely statistical models cannot anticipate. Integrating such mechanistic information with SARIMAX-based seasonal baselines and real-time epidemiological inputs would enable a modelling framework that remains sensitive to long-term environmental determinants while responding adaptively to emerging infectious threats, ultimately enhancing its usefulness for strategic public health interventions such as air-quality regulation, seasonal vaccination planning, and climate-adaptive healthcare preparedness.

3.4. Comparative evaluation of ANC_12 and ANC_NONCOVID_2 models

The ANC_12 and ANC_NONCOVID_2 models provide complementary perspectives on mortality tendencies in Portugal from 2010 to 2022. While both use the SARIMAX framework and incorporate environmental predictors, they differ in how they handle pandemic mortality and detect environmental effects.

The ANC_12 model, which includes a moving average component and a COVID-19 event variable, is designed to capture sudden mortality surges, such as those during the pandemic. It also detects delayed effects from PM_{10} and complex, oscillating temperature influences. However, the inclusion of pandemic deaths may obscure smaller environmental effects like those from NO_2, possibly due to signal overlap during extreme mortality spikes.

In contrast, the ANC_NONCOVID_2 model excludes pandemic-related deaths and follows a more stable autoregressive structure. This allows it to reveal clearer links between mortality and environmental exposures. It identifies NO_2 as an immediate and significant factor, alongside consistent effects from PM_{10} and low temperatures (T_{min}), especially during winter.

Structurally, ANC_12 smooths short-term fluctuations, which helps during crises but may mask slower environmental impacts.

ANC_NONCOVID_2 preserves temporal continuity, making it better suited to detecting persistent environmental risks and informing long-term public health planning.

Rather than choosing one model over the other, using both offers a fuller understanding. The ANC_12 model answers the question "What happened?", while the ANC_NONCOVID_2 model approximates "What might have happened without the pandemic?". This distinction is particularly important as climate change, urban pollution shifts, and recurrent respiratory epidemics require leaders to prepare for both extraordinary crises and ongoing fluctuations.

4. Conclusions

This study confirms that air pollution and climate variability are major drivers of seasonal mortality in Portugal. Analysis using SARIMAX models indicates that mortality consistently peaks during colder months, closely associated with lower temperatures and elevated levels of pollutants such as PM_{10} and NO_2.

In the ANC_12 model, which includes COVID-19 mortality, a 1 μg/m^3 increase in the seasonal difference of PM_{10} was associated with 33 additional deaths per month after a four-month lag, reflecting the effects of accumulated exposure. Temperature effects showed a nonlinear and oscillatory pattern. Instead of fading quickly, cold-related mortality risks persisted and recurred over time. COVID-19 itself appeared as a major mortality shock, contributing around 1268 excess deaths per month during peak periods.

The ANC_NONCOVID_2 model, which excludes pandemic-related deaths, offered clearer estimates of environmental risks. A 1 μg/m^3 increase in the seasonal difference of NO_2 was associated with 39 additional deaths in the same month, while PM_{10} retained its delayed effect (+32 deaths/month at lag 4). A 1 °C drop in the seasonal difference of minimum temperature – meaning the month was colder than the same month in the previous year – was associated, on average, with 163 additional deaths one month later. This finding highlights the health burden of colder-than-usual conditions, particularly during the winter season. However, it is important to note that this estimate reflects an average modelled effect applied uniformly across the year. In practical terms, the health impact of a 1 °C temperature drop may differ substantially between colder and warmer months and may not result in the same mortality burden during summer as during winter. Further research is needed to explore whether the association between cold and mortality varies by season or is modified by baseline climatic conditions.

Comparing both models shows the value of a dual approach. The ANC_12 model captures the full mortality burden, including shocks like the COVID-19 pandemic, which is essential for healthcare planning. The ANC_NONCOVID_2 model, in contrast, isolates long-term environmental effects more clearly by filtering out pandemic-related mortality. Using both models together allows for a better understanding of how crises interact with underlying, modifiable risk factors like air pollution and cold weather.

The respiratory diseases model (RSD_14) showed that deaths from respiratory causes respond more immediately to environmental conditions. A 1 % increase in SOMO35 compared to the same month in the previous year is associated with approximately a 0.1 % increase in respiratory mortality. Cold temperatures also contributed through both immediate and one-month delayed effects. These delays may reflect complications following respiratory infections. Warmer months may also bring increased risk due to ozone formation, reinforcing the need for year-round air quality interventions.

While SARIMAX models are effective for capturing seasonal mortality patterns and long-term environmental associations, they are structurally limited in their ability to represent abrupt and unpredictable shocks such as pandemic-driven mortality spikes. The COVID-19 pandemic functioned as an acute disturbance that obscured more subtle environmental effects, underscoring the need for methodological approaches capable of integrating stable seasonal dynamics with rapidly evolving epidemiological conditions. Future research should therefore progress beyond retrospective time series analysis toward hybrid predictive frameworks that combine SARIMAX-based seasonality modelling with real-time epidemiological and environmental data. In particular, incorporating mechanistic epidemic models such as SIR or SEIR – capable of explicitly modelling transmission and recovery processes – may allow these frameworks to capture the nonlinear dynamics underlying sudden epidemic surges. Such integration would strengthen early-warning capacity, improve detection of emerging disruptions, and enhance preparedness for future health and environmental emergencies. Incorporating data-assimilation methods that continuously update these hybrid models with new surveillance data offers a particularly promising way to enhance prediction accuracy during rapidly evolving public health crises.

This study also reveals limitations that should be acknowledged. The use of monthly data may mask short-term fluctuations and acute environmental effects occurring at daily or weekly scales. The estimated cold-related mortality effects represent average annual associations and may vary seasonally; future research should examine how impacts differ between winter and non-winter periods. SARIMAX models also have limited capacity to represent abrupt or extreme events, further supporting the need for hybrid modelling strategies. In addition, modelling mortality counts without an explicit population offset may introduce confounding by demographic change. However, the resident population aged 30 years and older remained essentially stable throughout the study period, with annual variations between −0.2 % and +0.9 %. This near-constancy implies that mortality rates would closely mirror the temporal patterns observed in the raw counts, meaning that the practical impact of omitting an offset is likely to be small. Nonetheless, gradual shifts in age structure within this group may contribute to long-term background trends and therefore represent a potential source of residual confounding. A further limitation relates to the aggregation of environmental data to national monthly averages, which may introduce exposure misclassification due to spatial heterogeneity in pollution and temperature levels across Portugal.

These findings can be used to support urgent public health action. Stricter air quality regulations – especially during winter – can help reduce deaths linked to PM_{10} and NO_2. Seasonal flu vaccinations, improved respiratory care, and targeted protection for vulnerable groups (such as the elderly and those with chronic illnesses) can further reduce risk. Strengthening early-warning systems and real-time environmental monitoring will be essential to manage both heatwaves and cold spells.

By integrating environmental and pandemic-related data into a forecasting framework, this study contributes to a growing body of evidence supporting proactive health policies. Addressing the combined effects of air pollution, climate variability, and mortality will require coordinated strategies across health, environmental, and urban planning sectors. A resilient healthcare system, strong pollution controls, and climate adaptation measures are critical to protect public health in the face of ongoing and future challenges.

CRediT authorship contribution statement

João Simões: Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Alexandra Bernardo:** Writing – review & editing, Data curation. **Luísa Lima Gonçalves:** Writing – review & editing, Data curation. **José Brito:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Investigation, Formal analysis, Conceptualization.

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

During the preparation of this work, the authors used ChatGPT

(OpenAI) to assist in improving the language and clarity in specific parts of the text. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.scitotenv.2025.181274.

Data availability

Data will be made available on request.

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