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Assessing the impact of climatic variability on acute respiratory diseases across diverse climatic zones in South Africa

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HIGHLIGHTS

- Johannesburg: Elevated respiratory disease risk linked to extreme cold and moderate winter temperatures.
- Cape Town: Stable respiratory risk across a moderate temperature range; increased risk with extreme heat.
- Gqeberha: Indistinct temperature-respiratory disease relationship due to moderate climate with year-round rainfall.
- Spikes in claims are closely associated with relative changes in weather patterns, rather than specific absolute thresholds.
- There are complex, non-linear interactions between climate and respiratory health risks for South Africa.

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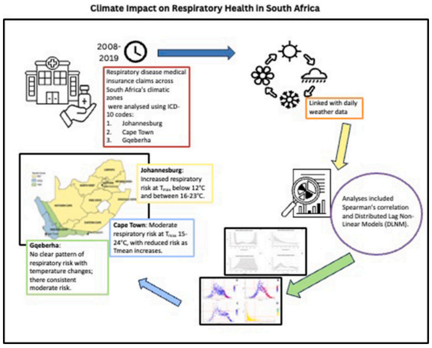
GRAPHICAL ABSTRACT



ABSTRACT

Acute respiratory diseases are a significant public health concern in South Africa, with climatic variables such as temperature and rainfall being key influencers. This study investigates the associations between these variables and the prevalence of acute respiratory diseases in Johannesburg, Cape Town, and Gqeberha (Port Elizabeth), representing distinct climatic zones. Spearman's correlation analyses showed negative correlations in Johannesburg for respiratory disease claims with maximum temperature ($r = -0.12$, $p < 0.0001$) and mean temperature ($r = -0.13$, $p < 0.0001$), and a negative correlation with daily rainfall ($r = -0.12$, $p < 0.0001$). Cape Town demonstrated a negative correlation with maximum temperature ($r = -0.18$, $p < 0.0001$) and a positive correlation with rainfall ($r = 0.08$, $p < 0.0001$). Utilizing Distributed Lag Non-linear Models (DLNM), the study revealed that in Johannesburg, the relative risk (RR) of respiratory claims increases notably at temperatures below 12 °C, and again at a T_{max} between 16 and 23 °C. The risk escalates further at >30 °C, although with a considerable error margin. For Cape Town, a stable level of moderate RR is seen from T_{max} 15–24 °C, with a significant increase in RR and error margin above 30 °C. In Gqeberha, the DLNM results are less definitive, reflecting the city's moderate climate and year-round rainfall. The RR of acute respiratory diseases did not show clear patterns with temperature changes, with increasing error margins outside the 22 °C threshold. These findings emphasize the imperative for region-specific public health strategies that account for the complex, non-linear influences of climate on respiratory health. This detailed understanding of the climate-health nexus

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provides a robust basis for enhancing public health interventions and future research directed at reducing the impacts of climate factors.

1. Introduction

Acute respiratory diseases have a marked impact on public health globally, with pronounced effects in South Africa, where socioeconomic conditions heighten the vulnerability of a large proportion of the population (Cohen et al., 2015a, 2015b; Wright et al., 2021). The intricate relationships between acute respiratory diseases and various environmental factors, especially weather conditions, have been observed worldwide (Tempia et al., 2017). Understanding these associations at local scales is crucial as they offer valuable insights into the determinants of disease prevalence, and the variations across different regions (Cannell et al., 2006). Studies have underscored specific associations between climate variables like temperature and humidity and respiratory diseases, highlighting the crucial role of localized research in effectively understanding and addressing these health impacts within particular regions or communities (Fuhrmann, 2010; Motlogeloa et al., 2023). In South Africa, the substantial disease burden and economic costs attributed to acute respiratory diseases necessitate an in-depth understanding of these dynamics to develop effective public health strategies and interventions (Van Noort et al., 2012).

Globally, weather conditions over periods of days to weeks have been demonstrated to significantly influence the incidence and severity of acute respiratory diseases (Roussel et al., 2016). These climatic factors influence the viability of respiratory pathogens and human behaviour, both crucial determinants of respiratory health outcomes. Weather conditions significantly influence the incidence and severity of acute respiratory diseases through two main pathways. First, they affect pathogen survival and transmission by altering the environment in which pathogens thrive (Harlan and Ruddell, 2011). Second, varying weather conditions impact human susceptibility and exposure to these pathogens, as they influence human behaviour and immune system performance (D'Amato et al., 2014). Given the intricate nature of these relationships, an investigation is imperative for developing effective and precise public health interventions aimed at alleviating the burden of acute respiratory diseases (Takaro et al., 2013; Vega et al., 2015). Maximum, minimum, and mean temperatures (T_{max}, T_{min} and T_{mean}), and rainfall, are vital meteorological parameters influencing the transmission and prevalence of acute respiratory diseases. (Roussel et al., 2016; Mirsaeidi et al., 2016; Weaver et al., 2022). Changes in these weather variables can directly alter the transmission rates and viability of respiratory pathogens, thereby affecting disease incidence and severity within various populations (Patz et al., 2003). South Africa presents a complex climate system characterized by a variety of rainfall regions and seasonality patterns, further complicating the relationship between weather and acute respiratory diseases (Engelbrecht and Landman, 2016; Roffe et al., 2019). Three distinct rainfall seasonality zones have been identified, namely the Winter Rainfall Zone (WRZ), Summer Rainfall Zone (SRZ), and Year-Round Rainfall Zone (YRZ; Tyson and Preston-Whyte, 2000; Engelbrecht and Landman, 2016; Roffe et al., 2021). These zones, resulting from South Africa's unique geographical position, exhibit different weather patterns and hence possess distinct implications for the transmission of acute respiratory diseases (Pica and Bouvier, 2012; Engelbrecht and Engelbrecht, 2016).

In an exploration of the interplay between meteorological variables and respiratory diseases, global studies have revealed nuanced insights (Alahmad et al., 2019; Zhang et al., 2022; Dumanoglu et al., 2021; de Sousa et al., 2019; Liu et al., 2021; Cui et al., 2003; Zhang et al., 2021; Shen et al., 2010; Stojanovic et al., 2019). For instance, Alahmad et al. (2019) performed a case-crossover analysis in Saudi Arabia, revealing a higher likelihood for the coronavirus linked to severe respiratory symptoms, formerly known as Middle East Respiratory Syndrome, to present predominantly under colder and drier conditions. Concurrently, studies emanating from China have underscored the susceptibility of paediatric populations to respiratory diseases amidst temperature extremes, elucidating a pronounced emphasis on the detrimental impacts of lower temperatures (Zhang et al., 2022; Liu et al., 2021).

Key meteorological variables, such as temperature, humidity, and air pollution metrics including PM10 and NOx concentrations, have been recurrently identified as pivotal influencers across these studies (Shen et al., 2010; Stojanovic et al., 2019; Cui et al., 2003; Dumanoglu et al., 2021; Liu et al., 2021). For instance, Dumanoglu et al. (2021) reported a nuanced interplay between weather parameters such as temperature and air pressure and the incidence of COVID-19 cases in Turkey. Furthermore, research from the Russian Far East has highlighted the modulation of immune responses in respiratory diseases by weather variations, thereby underscoring the intricate interplay between atmospheric conditions and respiratory health (Stojanovic et al., 2019).

The Distributed Lag Non-linear Models (DLNM) framework has been a crucial asset in epidemiological studies, enabling researchers to delve deeply into the intricate associations between environmental exposures, such as temperature and air pollution, and respiratory diseases (Bi et al., 2007; Alahmad et al., 2019; Chai et al., 2020). The DLNM is adept at capturing and modelling the nonlinear and delayed effects of these exposures, providing a comprehensive understanding of their impact on respiratory health outcomes over time (Gasparrini, 2011, 2014; Gao et al., 2023). Gasparrini (2011) utilized the DLNM to explore the exposure-response and lag-response associations, allowing for a detailed exploration of how health effects evolve over lagged times following exposure. For Lanzhou, China, the DLNM was applied to assess the effects of extreme temperatures on respiratory diseases, offering insights into temperature-related health risks (Meng et al., 2023). Another study, applied in São Paulo, Brazil, employed the DLNM to investigate the relationships between meteorological variables, air pollution, and paediatric respiratory disease hospitalizations, demonstrating the applicability of the model in various geographical and demographic contexts (de Sousa et al., 2019). Zhang et al. (2020a) applied the DLNM to explore the associations between sulphur dioxide exposure and respiratory disease hospitalizations in Ganzhou, China, highlighting its effectiveness in revealing relative risks essential for public health policymaking.

Through exploring univariate linear relationships and applying the DLNM, this study aims to illuminate the lagged and nonlinear relationships between maximum, minimum, and mean temperatures, rainfall, and the incidence of acute respiratory diseases in different climatic zones across South Africa. The insights garnered will be instrumental in informing targeted public health interventions, crafting climate-resilient healthcare strategies, and developing policy frameworks for mitigating acute respiratory diseases across various climate zones in South Africa.

2. Material and methods

2.1. Study site

South Africa, with coordinates ranging from 22 to 35°S in latitude and 16–33°E in longitude, covers an area of about 1,220,000 km^2 and exhibits a variety of climates due to its geographical diversity (Landman et al., 2017). The country is positioned where subtropical and mid-latitude climates converge, resulting in different rainfall patterns such as the Summer Rainfall Zone (SRZ) and Winter Rainfall Zone (WRZ; Fitchett and Bamford, 2017; Sousa et al., 2018; Roffe et al., 2021). These patterns are influenced by the seasonal latitudinal displacement of the

Intertropical Convergence Zone (ITCZ) and the Southern Hemisphere Westerlies (Lennard, 2019; Landman et al., 2017; Roffe et al., 2021).

The study focuses on three cities: Johannesburg, Cape Town, and Gqeberha (formerly Port Elizabeth), each with distinct climatic characteristics (Fig. 1). Johannesburg, located in the north-eastern part of South Africa, experiences a subtropical highland climate, characterized by dry winters and rainy summers (Crétat et al., 2012). Cape Town, situated in the southwestern part, has a Mediterranean climate with mild, wet winters and warm, dry summers (Favre et al., 2016). Gqeberha, on the south-eastern coast, experiences an oceanic climate, receiving a more evenly distributed rainfall throughout the year (Roffe et al., 2019). These cities were selected to represent different climatic conditions in South Africa, providing a diverse range of environments to study the impact of weather on acute respiratory diseases. The focus on cities relates to the data requirements to run the DLNM, which would not be met for smaller towns.

2.2. *Data sources*

2.2.1. *Medical insurance scheme claims*

The study utilized data from the Discovery Health Medical Scheme (DHMS), South Africa's leading private medical insurance provider, which covers approximately 3.3 million clients. DHMS has a comprehensive database of medical claims, each classified by an International Classification of Diseases ICD-10 code corresponding to the diagnosed condition (Hohl et al., 2014). These codes are assigned by medical practitioners based on patient symptoms during consultations, often without the need for laboratory confirmation (Stausberg and Hasford, 2010). For our analysis, we focused on claims linked to ICD-10 codes for acute respiratory diseases: J00 (acute nasopharyngitis), J110 (influenza with pneumonia), J111 (influenza with other respiratory manifestations), and J118 (influenza with other manifestations). While the dataset spans claims from 2008 to 2019, our study specifically targeted claims from Johannesburg (28,114), Cape Town (11,372), and Gqeberha (3888) to represent three distinct rainfall zones. Claims from smaller regions within these cities, such as spatially contiguous but discretely named suburbs, were aggregated to provide a holistic view of the data for each city.

2.2.2. *Meteorological data*

Daily resolution meteorological data were sourced from the South African Weather Services for the period 2008–2019. The dataset included daily maximum, minimum, and mean temperatures (T_{max}, $T_{min,}$ T_{mean}), and rainfall, recorded at ground-based meteorological stations located in Johannesburg, Cape Town, and Gqeberha. During the data cleaning process, the initial step involved exploratory data analysis, checking for inconsistencies, errors, and outliers in the dataset, ensuring that the data were accurate and reliable for analysis. The data were then processed to manage missing values. In cases where data were missing, various imputation methods could be applied, such as mean imputation or interpolation, to maintain the dataset's integrity and usability (Ding et al., 2010). We employed imputation methods best suited to the characteristics of the missing data, selecting the most appropriate technique based on the proportion and the observed pattern of the missing values (Scheffer, 2002). The cleaned and processed meteorological data were then added to the database containing the medical aid claims data, ensuring consistency and accuracy in the temporal matching of the two datasets.

3. Data analysis

Integrating the meteorological and claims data, Spearman's correlation coefficients were calculated to identify simplistic linear correlations between meteorological variables and occurrences of acute

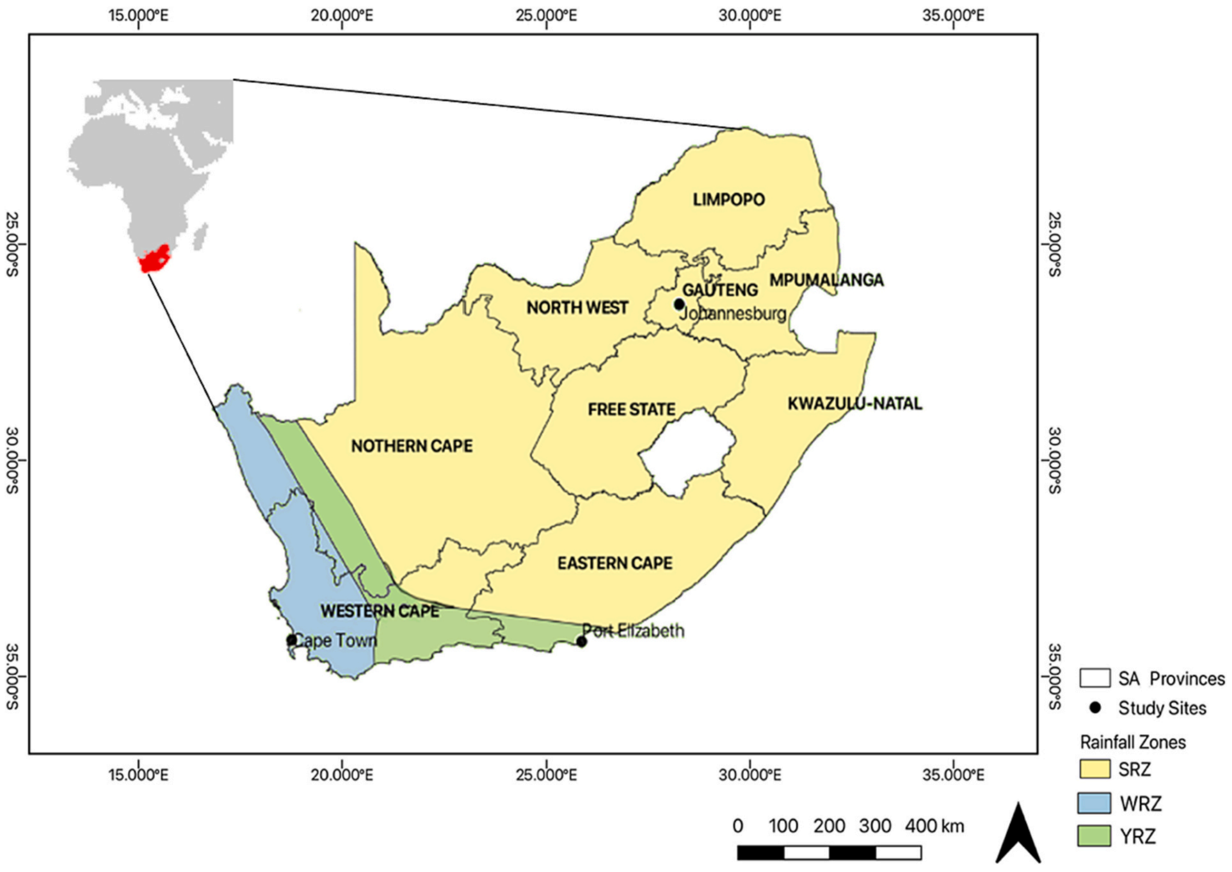

Fig. 1. Spatial distribution of rainfall season zones (Roffe et al., 2019) across South Africa with locations of Cape Town, Johannesburg and Gqeberha.

respiratory diseases (Pica and Bouvier, 2012; Jackson et al., 2021; Motlogeloa et al., 2023) in Johannesburg, Cape Town, and Gqeberha. Scatter plots were produced to graphically represent the distribution of acute respiratory disease incidences in relation to temperature and precipitation data. Points exceeding two standard deviations from the mean were marked to denote significant anomalies from expected values, indicative of potential extreme weather effects on health outcomes.

Subsequently, a time series quasi-Poisson regression and the DLNM were applied using the 'dlnm' package in R. In the DLNM, a quadratic B-spline was used for temperature, and a natural cubic spline was applied for the lag-response curve (Gasparrini and Leone, 2014; Zhao et al., 2018). The model was adjusted for time-varying confounders such as weekdays and holidays. Following the approach by Zhao et al. (2018), three degrees of freedom were assigned to exposure variables within the model, and a maximum lag of fourteen days (0–14 days) was incorporated to assess the meteorological impacts on respiratory disease-related claims in each city (Ozeki et al., 2015; Motlogeloa et al., 2023), which are delayed from infection by the period of incubation of the disease, the onset and worsening of symptoms, and delays in accessing healthcare (Lessler et al., 2009).

The output from the DLNM was primarily focused on the relative risk of acute respiratory diseases associated with meteorological variables. This approach is consistent with several studies that have utilized the DLNM outputs to assess and visualize the relative risks associated with environmental exposures (Armstrong et al., 2014; Phung et al., 2016). The relative risks were plotted against each meteorological variable to provide a clear representation of the associations between weather variables and the likelihood of respiratory disease occurrences, facilitating a nuanced interpretation of the potential health risks posed by varying meteorological conditions (Zhang et al., 2016; Sera et al., 2019). Recent applications of DLNM in the field (Li et al., 2023; Crank et al., 2023; Lam et al., 2024) support its continued relevance and suitability for our study. The DLNM is calculated by:

$$\begin{aligned} RR =& exp.\big(\alpha + CBmin\_\text{temp}\ (Tmin, t, lt) + CBmax\_\text{temp}\ (Tmax, t, lt) \\ &+ CB\text{mean\_temp}\ (T\text{mean}, t, lt) + CB\text{rain}\ (Rt, lt) + \gamma 1\cdot\text{Weekday} \\ &+ \gamma 2\cdot\text{Holiday} + NS\ (\text{Time}, df) + \epsilon \end{aligned}$$

where:

- *RR*: Relative Risk. This is the outcome of interest, often representing the risk of an event (like respiratory disease) occurring. In the context of the model, it's the expected count of the outcome given the predictors, relative to a baseline count.
- exp.(): Exponential function. It's used to ensure that the model's predictions are positive, as counts cannot be negative. This is the link function for the quasi-Poisson regression model.
- α: Intercept. This is the log-relative risk when all predictors are at their reference levels (typically zero for continuous variables).
- *B*: Cross-basis function. This is used to model the relationship between a predictor (like temperature or rainfall) and the outcome across different lags. It's a combination of two functions: one for the relationship at each time point (like a B-spline) and one across lags (like a natural cubic spline).
- *T*min,*t*, *T*max,*t*, *T*mean,*t*: These represent the minimum, maximum, and mean temperature values at time *t*, respectively.
- *Rt*: This represents the rainfall value at time *t*.
- *lt*: Lag time at time *t*, indicating how many days in the past the model looks to assess the effect of temperature and rainfall on the current risk.
- $\gamma 1$, $\gamma 2$: Coefficients for categorical variables. These are the parameters estimated for the effects of weekdays and holidays, respectively.
- $\cdot$: Multiplication sign. It's used to indicate that the coefficient (like $1\gamma 1$) multiplies the predictor (like Weekday).
- *NS*(Time, *df*): Natural spline function of time with a specified degree of freedom. This is used to control for time-varying confounders and trends that are not captured by other variables in the model.
- ϵ: Error term. It accounts for the variation in the outcome that is not explained by the model.
- $+$: Plus sign. It's used to indicate that terms are added together in the model.

4. Results

In Johannesburg, the average daily maximum summer temperature registered at 27.19 °C, and the winters, while wettest, reached up to 171.09 mm of rain per day, which is less than expected for a summer rainfall zone (Fig. 2a). Cape Town, however, exhibited a daily maximum summer average of 27.34 °C and a cooler winter daily maximum average of 19.84 °C, with the highest rainfall in summer, not winter, averaging 171.46 mm per day, challenging the typical Mediterranean climate pattern (Fig. 2b). Gqeberha experienced minor temperature fluctuations year-round — the summer and winter daily maximum averages were 26.09 °C and 20.59 °C, respectively, with a more uniform rainfall distribution, peaking at 29.77 mm in winter (Fig. 2c). These findings illustrate the distinct climatic dynamics within South African regions, as influenced by their specific geographical and topographical features (Fig. 2).

4.1. *Correlation between meteorological variables and respiratory disease claims*

Spearman's correlation coefficients (Table 1) reveal relatively weak, but statistically significant, linear univariate relationships between meteorological variables and acute respiratory disease claims across Johannesburg, Cape Town, and Gqeberha. T_{max} and T_{mean} consistently show statistically significant negative correlations with disease claims across all cities, with coefficients ranging from $r = -0.10$ to $r = -0.18$ ($p < 0.0001$). Conversely, T_{min} displays varied associations; a weak but statistically significant positive correlation is observed in Johannesburg $r = 0.10$, $p < 0.0001$, while in the other two cities analyzed, the relationships are either slight or statistically insignificant (Table 1). An interesting observation is the decrease in respiratory disease risk with colder T_{min}, necessitating further exploration (Table 1). Daily rainfall correlations also vary, with significant relationships observed in some cities, such as Johannesburg and Cape Town, and non-significant correlations in others like Gqeberha (Table 1).

4.2. *Meteorological influences on acute respiratory diseases*

The second stage of analysis explores non-linear relationships between meteorological variables and medical aid claims, exploring the distribution of total claims at each given temperature or daily total rainfall amount. In Johannesburg, the highest number of claims are recorded from at a T_{max} of 18–23 °C, T_{min} of 3–8 °C, and T_{mean} of 11–15 °C (Fig. 3), meteorological conditions which dominate during the winter season and during autumn, spring and early summer season cold snaps associated with cut-off low systems. The rainfall data (Fig. 3d) exhibit a right-skewed distribution, due to the large number of days with no rainfall in Johannesburg; with many dry days and no clear increase in claims on days with higher rainfall totals or extreme events.

In Gqeberha, the largest number of claims are recorded for T_{max} of 17–24 °C, T_{min} of 5–13 °C, and T_{mean} of 12–18 °C, again consistent with conditions during the winter season, and cooler conditions during the autumn and spring (Fig. 4). For rainfall, although the data remain right skewed, there is a greater variation in rainfall totals associated with heightened claims. This is likely due to the position of Gqeberha in the year-round rainfall zone, where the winter months are not characterized by an absence of rainfall that is common in Johannesburg.

For Cape Town, the peak in respiratory disease claims is associated

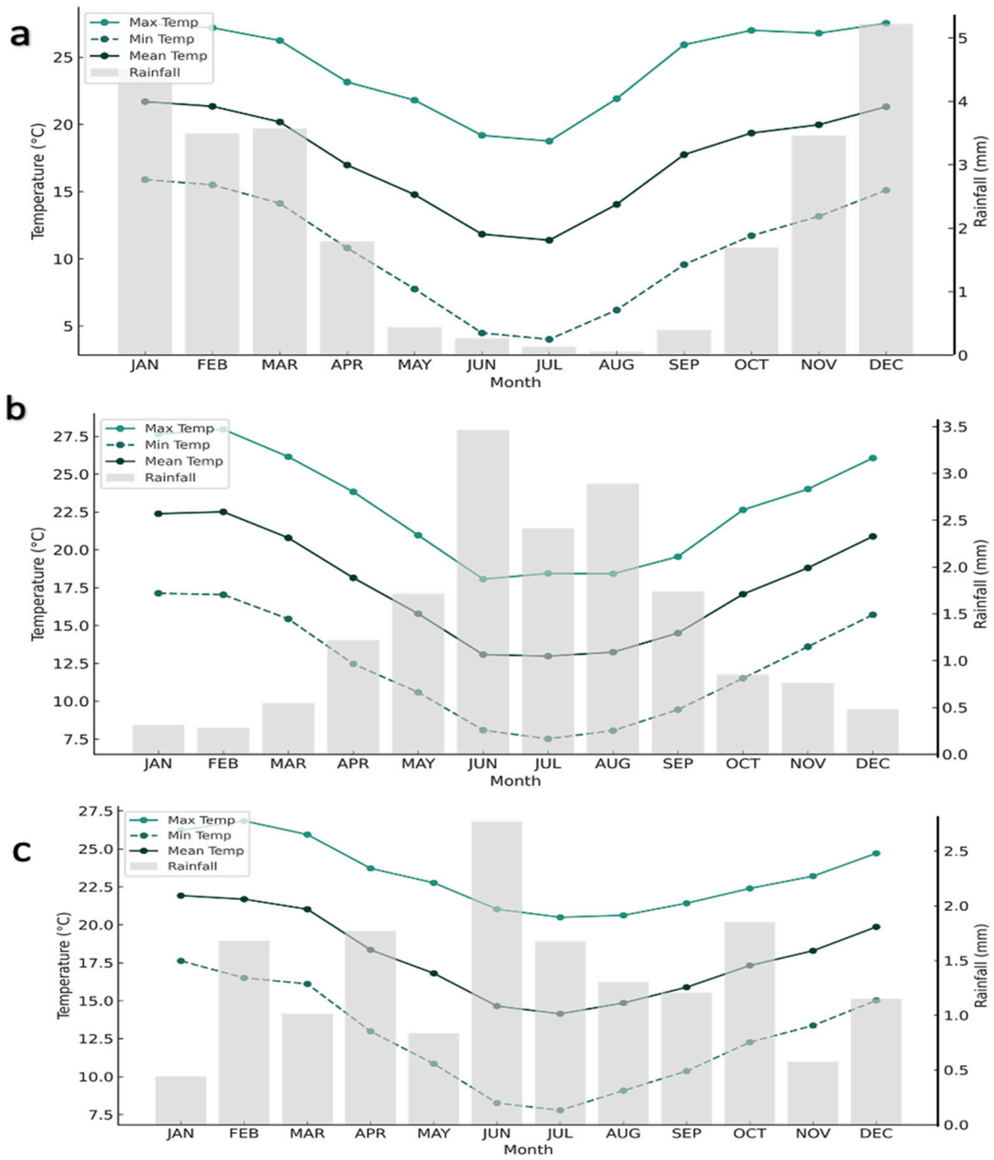

Fig. 2. Comparative monthly climate trends – Illustration of the monthly variations in temperature and rainfall for Johannesburg (a), Cape Town (b), and the Gqeberha(c) in South Africa.

Table 1
Spearman correlation coefficients and *P*-values for weather variables and medical insurance claims in Johannesburg, Cape Town, and Gqeberha.

City	Variable	Correlation (r)	P-value
Johannesburg	T_{max}	−0.12	$p < 0.0001$
	T_{min}	0.10	$p < 0.0001$
	Daily Rainfall	−0.12	$p < 0.0001$
	T_{mean}	−0.13	$p < 0.0001$
Cape Town	T_{max}	−0.18	$p < 0.0001$
	T_{min}	0.02	0.1836
	Daily Rainfall	0.08	$p < 0.0001$
	T_{mean}	−0.17	$p < 0.0001$
Gqeberha+	T_{max}	−0.10	$p < 0.0001$
	T_{min}	0.02	0.4428
	Daily Rainfall	−0.01	0.8743
	T_{mean}	−0.13	$p < 0.0001$

with T_{max} ranging from 18 to 2215 °C, T_{min} ranging from 5 to 14 °C, and T_{mean} from 12 to 16 °C (Fig. 5), again characteristic of the winter months. In Cape Town, the analysis of rainfall data reveals a wider spread in the volume of rainfall compared to Gqeberha and Johannesburg. This aligns with Cape Town's winter rainfall climate, where periods of higher rainfall coincide with lower temperatures. The seasonal temperature shifts and their impact on medical claims highlight the need for a non-linear statistical model that accounts for lag time between weather exposure and claims. Hence, the DLNM is applied to dissect these intricate relationships further.

4.3. Nonlinear associations between meteorological variables and acute respiratory disease incidence

The outputs of the DLNM do not dispute the broad relationships between meteorological variables and medical aid claims for acute upper respiratory disease demonstrated previously, but provide more nuanced non-linear reflections in light of the influence of lags and influencing periods such as holidays. In Johannesburg, the relative risk (RR) of respiratory claims increases significantly at T_{max} below 12 °C, which corresponds to extremely cold events. There is also a notable peak in RR at T_{max} between 16 and 23 °C, aligning with typical winter daytime temperatures. Above 30 °C, the RR increase is less certain, as indicated by a larger error margin (Fig. 6a). T_{min} shows the highest RR

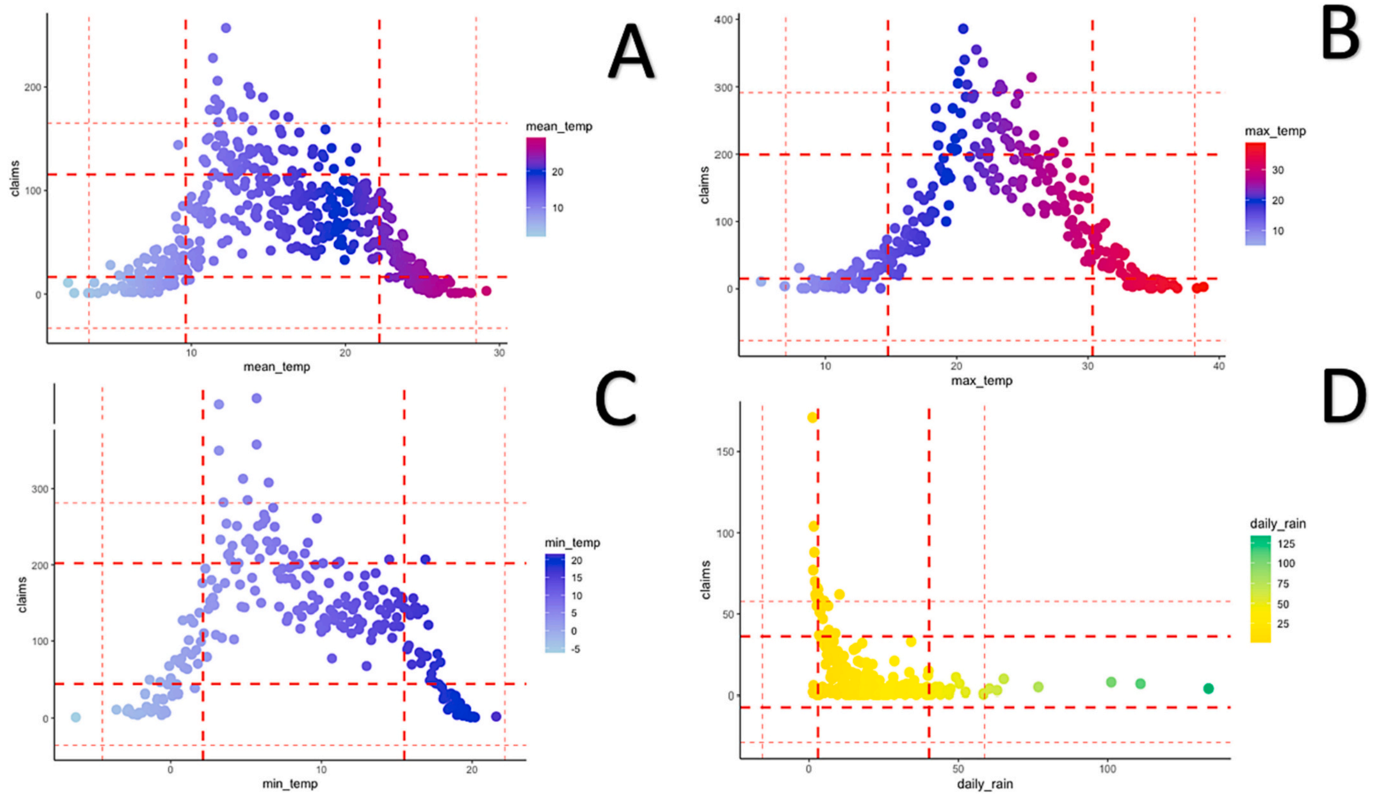

Fig. 3. Acute respiratory claims plotted against daily a) mean temperature, b) maximum temperature, c) minimum temperature and d) daily rainfall in Johannesburg, South Africa. The thick red bars indicate one standard deviation from the mean and the thin red bars indicate two standard deviations from the mean.

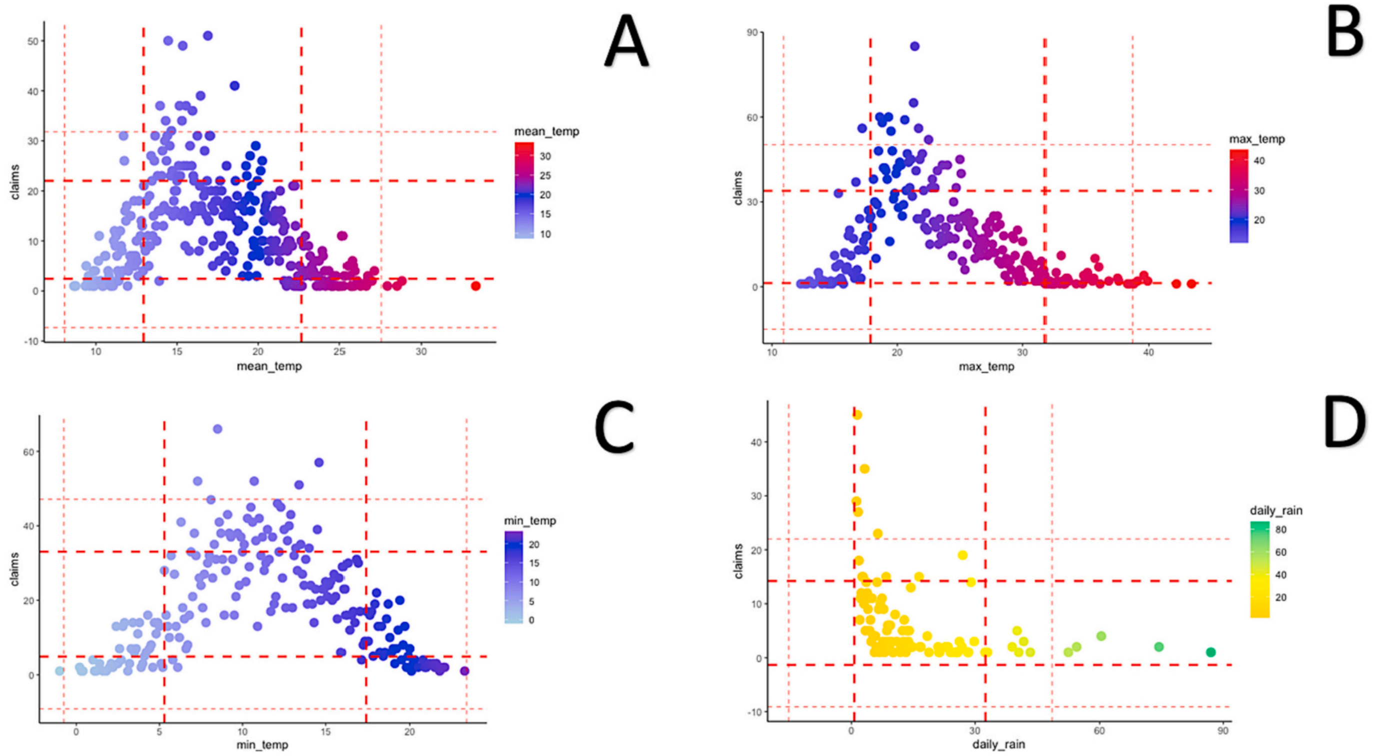

Fig. 4. Acute respiratory claims plotted against daily a) mean temperature, b) maximum temperature, c) minimum temperature and d) daily rainfall in Gqeberha, South Africa. The thick red bars indicate one standard deviation from the mean and the thin red bars indicate two standard deviations from the mean.

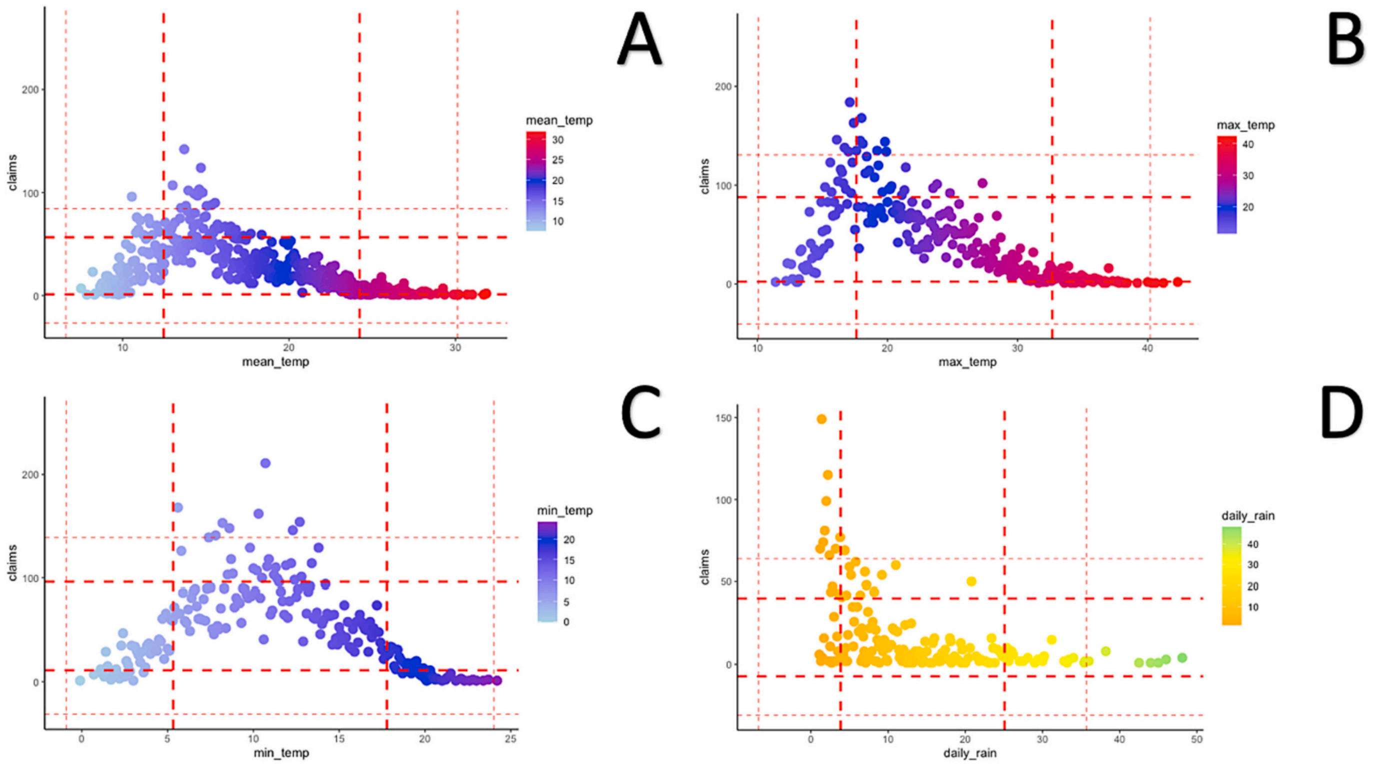

Fig. 5. Acute respiratory claims plotted against daily a) mean temperature, b) maximum temperature, c) minimum temperature and d) daily rainfall in Cape Town, South Africa. The thick red bars indicate one standard deviation from the mean and the thin red bars indicate two standard deviations from the mean.

between 0 and 5 °C, and it tapers off in very low temperatures unusual for Johannesburg or above 12 °C, common in warmer seasons (Fig. 6d). T_{mean} indicates a decrease in RR with rising temperatures, suggesting lower risk at warmer average temperatures (Fig. 6b). Rainfall RR exhibits high variability, with a possible increase around 60 mm daily rainfall (Fig. 6c).

For Gqeberha, the results of the DLNM provide a less clear indication of the key meteorological conditions associated with a heightened risk of acute upper respiratory disease. This may be as a result of the year-round rainfall conditions at the city, and the relatively moderate seasonal temperature range as a result of the proximity to the Indian Ocean and warm Agulhas current. There is no discernible change in the RR of acute respiratory diseases with increases (or decreases) in T_{max}, although notably there are rapidly increasing levels of the error margin of the model above and below 22 °C (Fig. 7a). For T_{min}, the DLNM suggests a heightened risk between temperatures of 16–18 °C, although importantly this is coupled with a considerable error margin. The error margin is lowest for a moderate level of risk from 3 to 12 °C. For $T_{mean,}$ the peak in RR is similarly associated with the greatest error margin; the lowest error margin is associated with a moderate level of risk at ~17 °C (Fig. 7b). As for temperature, the modelled peaks in risk for rainfall coincide with the greatest error margins. Overall, for Gqeberha, no definitive patterns in the risk of meteorological conditions can be determined using the DLNM, likely due to the suppressed seasonality in both temperature and rainfall for the city.

For Cape Town, a similar pattern in RR is modelled for T_{mean} as for Johannesburg: as T_{mean} increases, the RR of acute respiratory disease claims decreases (Fig. 8). For T_{max}, RR increases to a relatively stable level of moderate risk from 15 to 24 °C. As for Johannesburg, at >30 °C there is an increase in RR, but this is associated with a very large error margin, a function of the rarity of these extreme temperatures. For $T_{min,}$ the relative risk remains relatively constant, with a small increase between 5 and 10 °C, and similar to the hotter T_{max}, an increase in the margin of error from $T_{min} > 18$ °C (Fig. 8a). In the Johannesburg and Gqeberha regions, relative risk (RR) analysis for rainfall-related respiratory claims indicates increased uncertainty. However, there's a discernible uptick in claim risk at rainfall levels of 5-20 mm/day. The confidence in the model's predictions is higher for daily rainfall amounts of 0-5 mm and 25-32 mm, as reflected by the lower error margins in these ranges (Fig. 8c).

In this study, Distributed Lag Non-linear Models (DLNM) were applied to explore the associations between meteorological variables and the RR of acute respiratory diseases. Traditional correlation methods suggest a negative correlation between T_{max} and disease incidence. However, the DLNM analysis provides a more detailed depiction, revealing variations and complexities not captured by simple correlation coefficients. The DLNM approach unveils specific temperature and rainfall thresholds associated with changes in RR, emphasizing that a simplistic correlation may not adequately represent the relationships within extensive datasets (Gasparrini, 2011; Armstrong et al., 2014). Utilizing the DLNM for analysis facilitates a more comprehensive understanding of the data, allowing for more accurate public health interpretations and strategies based on the diverse environmental influences present in extensive meteorological and health datasets.

5. Discussion

5.1. Meteorological impact on acute respiratory diseases

Our analysis delves deeper into the associations between climate and respiratory illness across three distinct South African climatic zones. In Cape Town, the colder and wetter winter conditions appear to correlate with increased respiratory disease claims, a pattern consistent with global findings. Johannesburg's cold but drier winters suggest a different interaction between temperature and moisture in disease prevalence. Gqeberha presents a unique case with its year-round rainfall, which may dilute the pronounced seasonal effect seen in other regions.

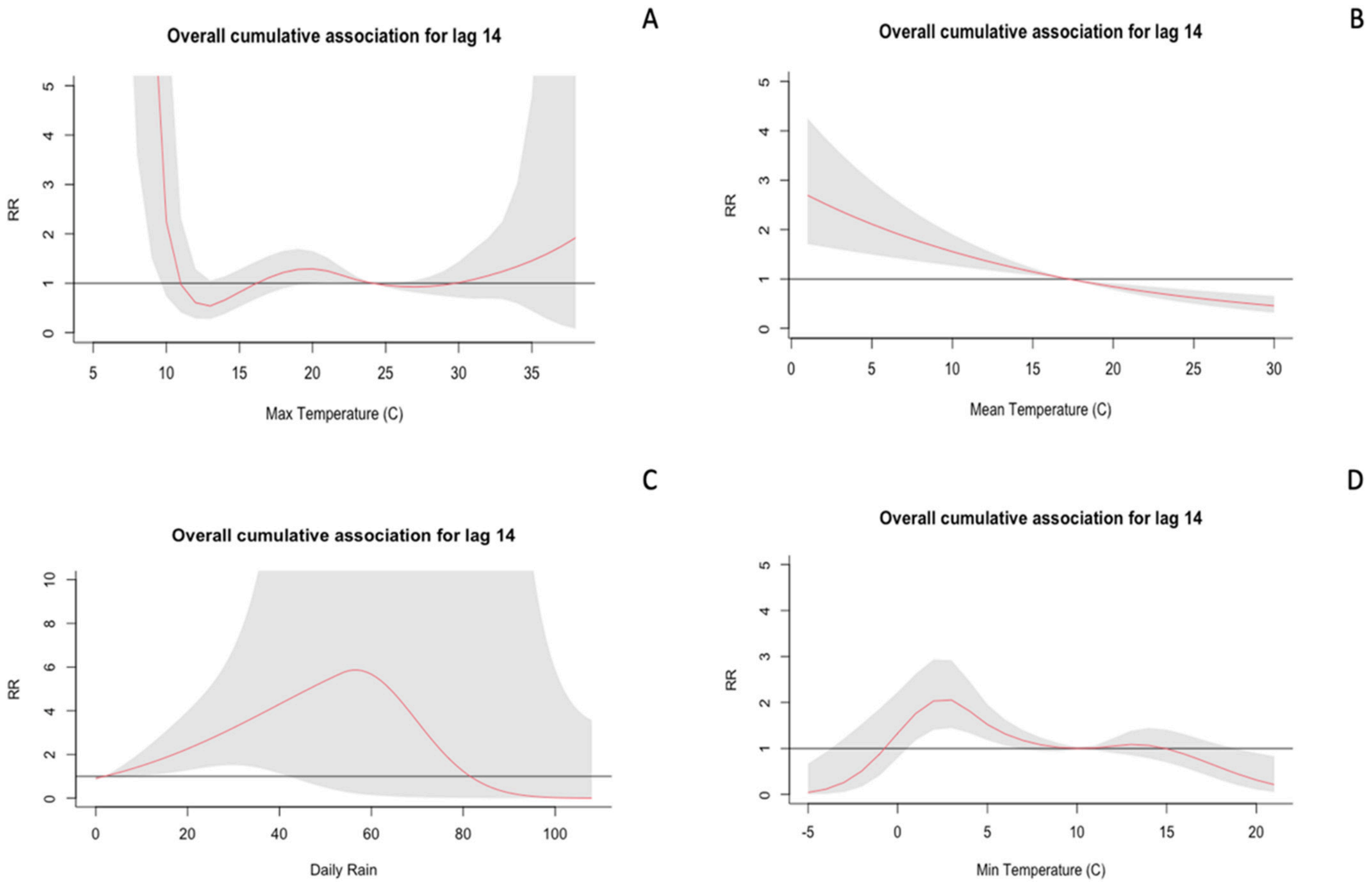

Fig. 6. Johannesburg relative risk for acute respiratory disease medical insurance claims at, a) maximum temperature, b) mean temperature, c) daily rain and d) minimum temperature over a 14-day lag.

The relatively consistent temperature across the zones contributes to subtler variations in disease prevalence than anticipated, underscoring the complex interplay of climate factors. The consistent temperature ranges across these zones, coupled with their distinct rainfall patterns, suggest that regional adaptations in public health strategies are necessary. Further examination of these complex relationships is warranted, considering local environmental and social factors that may modulate these associations.

Understanding the meteorological influences on acute respiratory diseases is essential for effective public health planning and interventions (D'Amato et al., 2015; Liu et al., 2020). Global research has demonstrated various temperature and rainfall ranges that influence the local risk of respiratory diseases (Takaro et al., 2013; Nsoesie et al., 2014; Zhang et al., 2020b, Ma et al., 2022). In winter rainfall zones, such as those studied in parts of Australia and the Mediterranean, a rise in respiratory diseases has been observed during colder and wetter conditions (Ebi and Forsberg, 2009; Rocklöv et al., 2014). This holds true for Cape Town, South Africa, where the distribution of climatic conditions and claims reveal that colder conditions and relatively wet conditions are associated with the heightened risk of acute upper respiratory disease claims (Thrastarson et al., 2017). In Johannesburg, a summer rainfall zone, cold temperatures and lower rainfall conditions are found to be associated with the highest risk of claims for respiratory diseases (Javanian et al., 2021; Kronfeld-Schor et al., 2021). For Gqeberha, a less distinct relative risk distribution is modelled, likely a function of the year-round rainfall, and less pronounced seasonal temperature differences. The subtleties in respiratory disease prevalence across South Africa's diverse climatic zones were less pronounced than expected, possibly due to the relatively consistent temperature ranges experienced across these regions that are distinguished primarily by their differences in rainfall seasonality (Philippon et al., 2012; Favre et al., 2016; Roffe et al., 2019). The analysis within our manuscript focuses on temperature and its correlation with respiratory disease prevalence. While rainfall was included in our evaluation, the data did not exhibit a strong correlation independent of temperature variations. We have not analyzed the impact of air pollutants due to the unavailability of consistent, region-wide data for the period of our study.

Our study provides a comprehensive analysis of the intricate relationship between various weather variables and the transmission dynamics of respiratory viruses, particularly influenza, in South Africa. The findings reveal that rather than extreme climatic conditions, it is the subtle interplay between temperature and humidity that significantly influences the prevalence and transmission patterns of these viruses (Pica and Bouvier, 2012). The virus appears to thrive during the weather conditions commonly experienced in winter, and during colder weeks in autumn and spring (Motlogeloa et al., 2023). This revelation is instrumental in redefining our approach towards influenza preparedness and response strategies, emphasizing the need for pre-emptive measures ahead of the identified high-risk periods (Fuhrmann, 2010).

5.2. Public health implications

A multifaceted public health approach, considering the various influences on respiratory disease prevalence (Shea et al., 2008), is supported by the findings of this study. A generalized seasonal strategy, rather than a focus on specific meteorological thresholds, appears more

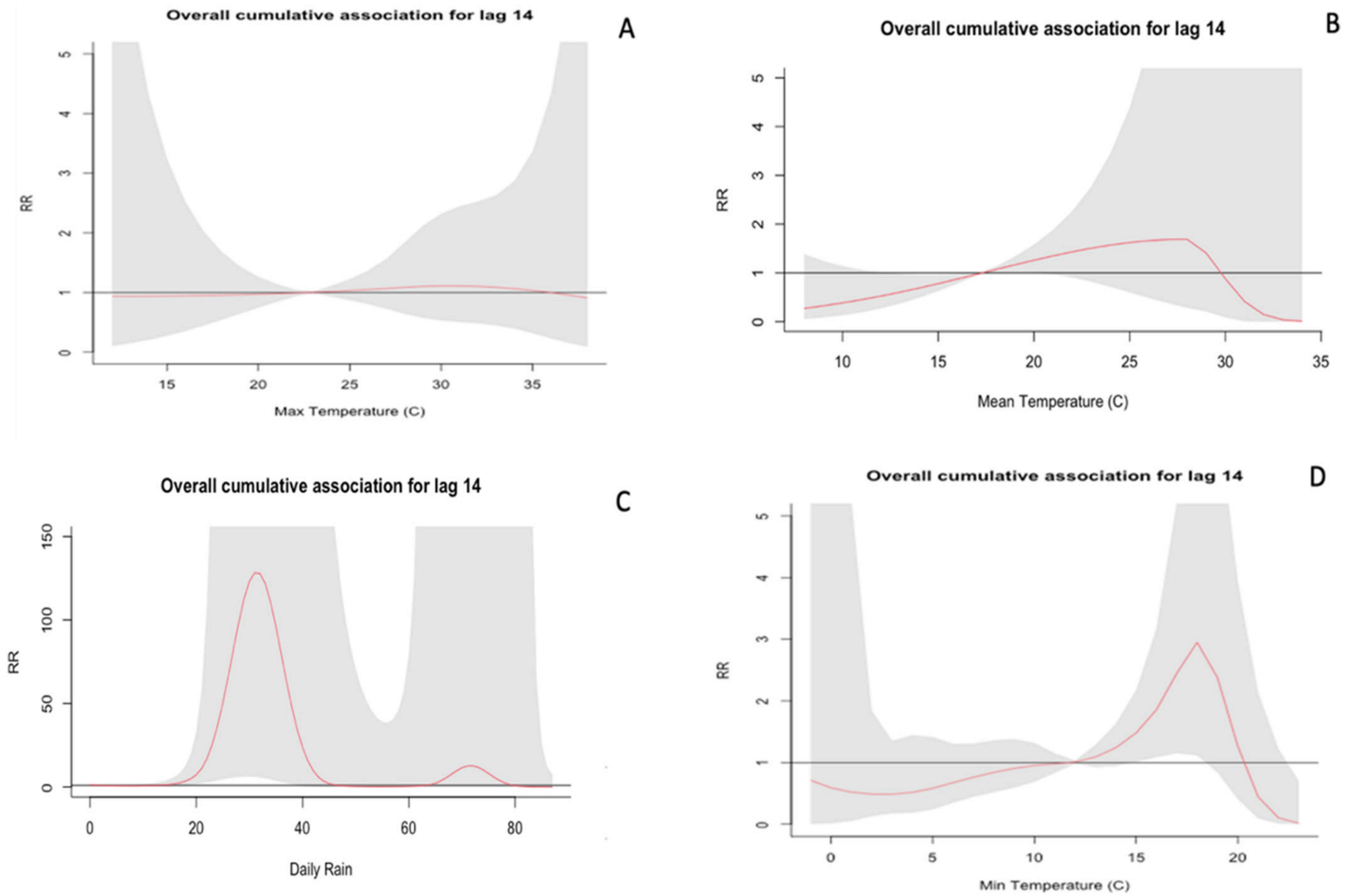

Fig. 7. Gqeberha relative risk for acute respiratory disease medical insurance claims at a) maximum temperature, b) mean temperature, c) daily rain and d) minimum temperature over a 14-day lag.

pragmatic due to the complex interplay between temperature, rainfall, humidity, and societal behaviours (Nsoesie et al., 2014; Jackson et al., 2021; Bi et al., 2007). The study underscores the significance of rainfall in influencing respiratory disease cases, suggesting a proactive public health stance during periods of increased rainfall (Motlogeloa et al., 2023; Treanor, 2016). Given the newfound understanding of the timing of influenza peaks, there is a pressing need to rethink and optimize vaccination strategies. The initiation of vaccination campaigns should be recalibrated to precede the early autumn period, which has been identified as a conducive environment for influenza transmission (Treanor, 2016). Such a proactive approach in administering vaccines could bolster community immunity, reduce susceptibility, and curtail the spread of the influenza virus (Tempia et al., 2017). Our findings underscore the imperative of developing adaptive public health strategies that resonate with the prevailing weather patterns conducive to the transmission of respiratory viruses (Watts et al., 2015). This involves a meticulous tailoring of various public health interventions, such as vaccination schedules, public health messaging, and the allocation of healthcare resources, to align with the nuanced weather patterns identified in the study (Shea et al., 2008). This study underscores the pivotal role of routine weather patterns in shaping the transmission dynamics of respiratory viruses in South Africa. It advocates for a re-evaluation and recalibration of existing public health strategies, particularly vaccination campaigns, to align more closely with the identified weather patterns. Such alignment could enhance the efficacy of preventive measures, fostering a more resilient community against the onslaught of respiratory viruses, including influenza. In light of the forecasting limitations, we propose a flexible vaccination strategy that incorporates short-term weather predictions, enabling rapid response to forecast cooler and wetter conditions, which are conducive to increased respiratory diseases. This insight necessitates a paradigm shift in our preparedness and response strategies, advocating for a more nuanced and weather-aligned approach to mitigate the impact of respiratory viruses, particularly influenza (Weaver et al., 2022).

6. Conclusion

In conclusion, this study clarifies the relationships between meteorological variables and the prevalence of claims for acute respiratory diseases in major South African cities. The findings are instrumental for enhancing public health planning and interventions, particularly in the unique context of a developing country like South Africa (Thrastarson et al., 2017). Our study reveals that temperature and rainfall variations in Johannesburg, Cape Town, and Gqeberha influence the patterns of respiratory disease claims, aligning with global research that indicates a correlation between meteorological variables and respiratory diseases (Javanian et al., 2021; Kronfeld-Schor et al., 2021). The insights derived from this study are pivotal for developing targeted communication strategies, early warning systems, and vaccination campaigns that are sensitive to the unique climatic and epidemiological profiles of each city (Motlogeloa et al., 2023; Nsoesie et al., 2014).

Strategic public health communication, based on the identified temperature and rainfall thresholds, can facilitate better preparedness and response to seasonal variations in respiratory diseases (Bi et al., 2007; Treanor, 2016). Tailoring these strategies to the specific needs and contexts of each city will enhance their effectiveness and relevance, ensuring a more resilient healthcare system and improved public health outcomes in the face of varying meteorological conditions (Jackson

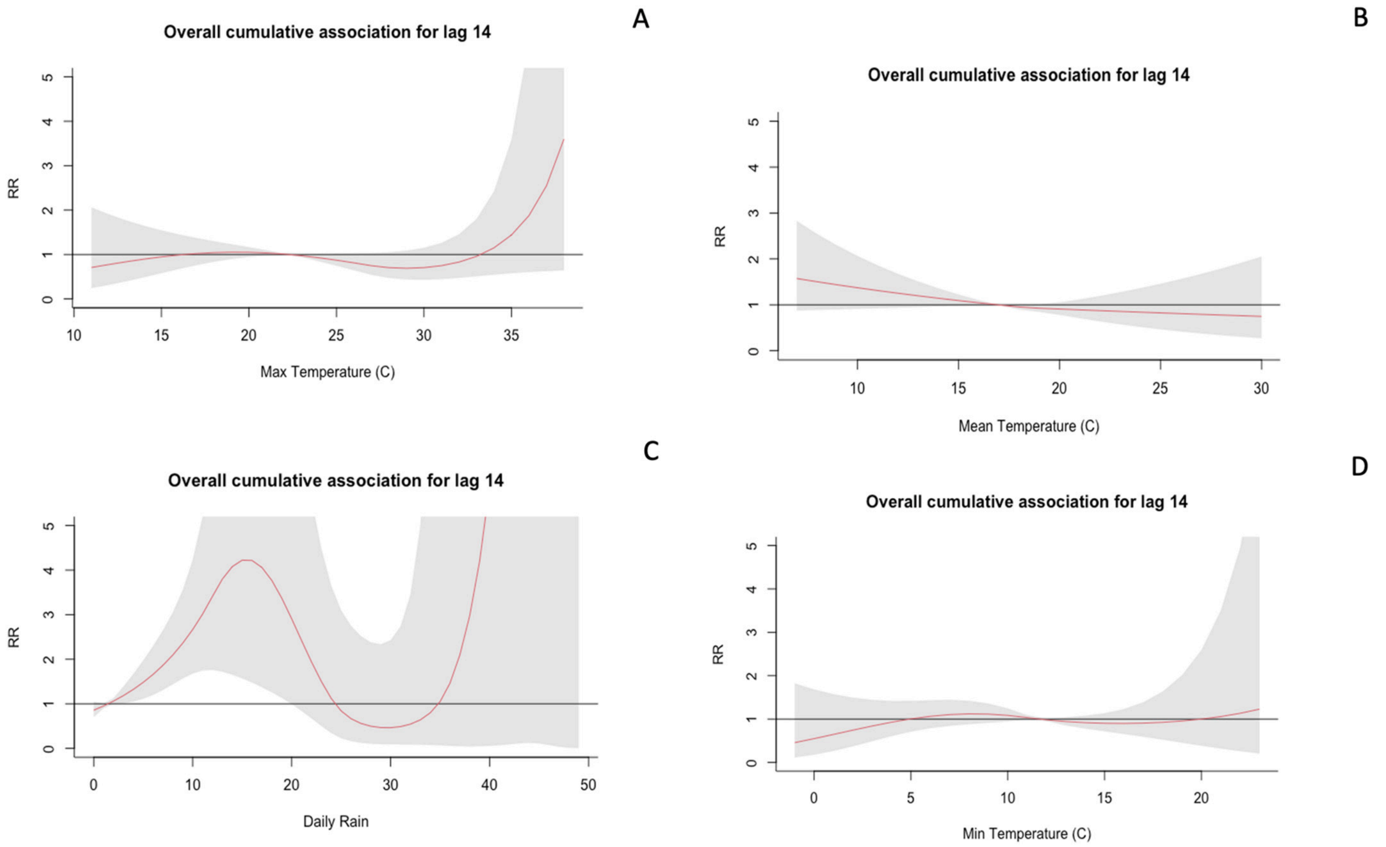

Fig. 8. Cape Town relative risk for acute respiratory disease medical insurance claims at a) maximum temperature, b) mean temperature, c) daily rain and d) minimum temperature over a 14-day lag.

et al., 2021). In light of these findings, it is essential to continue exploring and understanding the multifaceted impacts of meteorological variables on health, to inform more nuanced and effective public health strategies and interventions in various geographical and climatic contexts.

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Research ethics

Ethics clearance was obtained from the Witwatersrand Human Medical Research Ethics Committee, clearance number M210617. Authorization for data acquisition was obtained by DHMS. Data from Baragwanath Hospital were collected under the Respiratory and Meningeal Pathogens Research Unit's database compiled for the study "Surveillance on pathogen-specific causes of pneumonia and diarrhoea hospitalization in children" HREC reference no: 131109.

CRediT authorship contribution statement

Ogone Motlogeloa: Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis. **Jennifer M. Fitchett:** Writing – review & editing, Supervision, Methodology, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

We declare that the authors have no competing interests, financial or otherwise.

Data availability

The data that has been used is confidential.

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