Temperature-Attributable Mortality Among Elderly Brazilians, 2010-2024: A National Time-Series Analysis

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Summary

Background: Climate change is increasing temperature extremes globally, yet comprehensive national evidence on temperature-mortality relationships in large middle-income countries remains limited. Previous studies in Brazil focused on single cities or short periods, and none has systematically compared spatial aggregation scales or explicitly quantified mortality displacement (harvesting) in elderly populations.

Methods: We analyzed 13.7 million elderly deaths (age 60 years) across two spatial scales—510 immediate geographic regions and 133 intermediate regions—covering all of Brazil from 2010 to 2024 (15 years). Using distributed lag non-linear models (DLNM) with a two-stage meta-analytic design, we estimated temperature-mortality associations with 21-day cumulative lag structure. We quantified heterogeneity (I^2, Cochran's Q), calculated attributable burden and years of life lost, assessed mortality displacement via extended 35-day lag analysis, and examined effect modification by age, sex, and cause of death.

Findings: Both extreme heat (P99) and cold (P1) significantly increased mortality. At the intermediate level: heat RR = 1.088 (95% CI: 1.067-1.110); cold RR = 1.122 (1.098-1.146); I^2 = 51%. At the immediate level: heat RR = 1.063 (1.050-1.076); cold RR = 1.095 (1.085-1.106); I^2 = 29%. Cold effects consistently exceeded heat (cold:heat burden ratio 8:1), consistent with the Gasparrini et al. (2015) multi-country Lancet study that found 4:1 ratios in Brazilian cities. Critically, harvesting analysis revealed heat deaths represent true excess mortality (effects increase over extended lags), while cold effects accumulate progressively over weeks. Annual burden: ~56,000 temperature-attributable elderly deaths, with cold accounting for 89%. The 80+ age group showed highest vulnerability (cold RR 1.27); cardiovascular deaths showed 32% cold-related excess; females showed higher heat vulnerability (+8%), males higher cold vulnerability (+6%).

Interpretation: This study provides the most comprehensive national evidence on temperature-mortality in elderly Brazilians to date. Cold effects substantially exceed heat effects, with an 8:1 burden ratio reflecting elderly vulnerability—higher than the 4:1 ratio in previous all-age studies. Public health strategies should address both temperature extremes, with particular attention to cold protection for elderly populations—a finding that challenges the predominant focus on heat in tropical climate-health discourse.

Funding: [Funding sources]

1 Research in Context

1.1 Evidence before this study

We searched PubMed for articles published between January 1, 2000 and December 1, 2025, using terms "Brazil" AND "temperature" AND "mortality" AND ("cold" OR "heat"). We identified 40 relevant studies. The landmark multi-country study by Gasparrini et al. (2015, Lancet) included Brazilian cities and found that cold-attributable mortality (2.83%) substantially exceeded heat-attributable mortality (0.70%) in Brazil—a pattern consistent across most countries globally.[1] The seminal São Paulo study by Gouveia et al. (2003) first established the U-shaped temperature-mortality relationship in Brazil, with 5.5% mortality increase per 1°C below 20°C.[2] Subsequent studies confirmed cold dominance: Son et al. (2016) found cold effects (8.6% excess) exceeded heat effects (6.1%) in São Paulo;[3] Silveira et al. (2019) documented this pattern across 27 cities;[4]

Aschidamini et al. (2025) found national cold effects (RR 1.30 for elderly) exceeding heat (RR 1.13).[5] The recent Latin American analysis by Kephart et al. (2022, Nature Medicine) confirmed temperature-mortality associations across the region.[6] However, existing studies had important limitations: (1) most focused on single cities or states rather than national coverage; (2) none systematically compared results across different spatial aggregation scales; (3) few explicitly quantified mortality displacement (harvesting); (4) none focused specifically on elderly populations with comprehensive 15-year coverage.

1.2 Added value of this study

This study provides the most comprehensive national analysis of temperature-mortality in Brazil to date, with several novel contributions. First, we analyze 13.7 million elderly deaths across 15 years (2010-2024), providing unprecedented statistical power. Second, we systematically compare two spatial scales (133 intermediate vs 510 immediate regions), demonstrating that finer resolution reduces heterogeneity (I^2 29% vs 51%) while maintaining similar effect estimates—important methodological guidance for future studies. Third, we explicitly quantify harvesting, showing that heat deaths represent true excess mortality (negative harvesting ratio) while cold effects accumulate over weeks—a distinction critical for burden estimation and policy. Fourth, we provide the first elderly-specific national burden estimates: approximately 56,000 annual temperature-attributable deaths, with an 8:1 cold-to-heat ratio higher than previous all-age estimates, reflecting elderly vulnerability. Fifth, we demonstrate clear vulnerability gradients by age (80+ most vulnerable), sex (females heat-vulnerable, males cold-vulnerable), and cause (cardiovascular deaths show 32% cold excess).

1.3 Implications of all the available evidence

The consistent finding across global and Brazilian studies that cold-attributable mortality exceeds heat-attributable mortality has profound implications for climate adaptation policy. In Brazil—a country often perceived as facing primarily heat-related health risks due to its tropical climate—cold protection for elderly populations should receive equal or greater public health priority. Our harvesting analysis adds nuance: while heat deaths are true excess (prevented deaths = lives saved), cold effects accumulate over weeks through cardiovascular and respiratory pathways. Climate change projections suggest heat burden will increase while cold burden may decrease, but current policy should address the dominant present-day burden. The 80+ age group and cardiovascular patients warrant targeted interventions during both temperature extremes.

2 Introduction

Climate change is increasing the frequency and intensity of temperature extremes worldwide, with profound implications for human health.[1] Temperature-mortality relationships follow a characteristic J- or U-shaped pattern, with increased mortality at both cold and hot extremes relative to an optimal temperature.[7,8] Understanding these relationships is critical for public health planning and climate adaptation.

A key finding from global temperature-mortality research is that cold-attributable mortality substantially exceeds heat-attributable mortality in most populations. The landmark multi-country study by Gasparrini et al. (2015), which included data from 13 countries and 74 million deaths, found that 7.29% of mortality was attributable to cold versus only 0.42% to heat globally.[1] In Brazil specifically, that study found a 4:1 cold-to-heat burden ratio (2.83% vs 0.70% attributable mortality). The seminal São Paulo study by Gouveia et al. (2003) first established this U-shaped relationship in Brazil, with 5.5% mortality increase per 1°C below 20°C and 2.6% per 1°C above.[2] Subsequent studies confirmed this pattern: Son et al. (2016) found cold effects (8.6% excess) exceeded heat effects (6.1%) in São Paulo;[3] Silveira et al. (2019) documented similar findings across 27 Brazilian cities;[4] and most recently, Aschidamini et al. (2025) reported national cold effects (RR 1.30 for elderly) exceeding heat (RR 1.13) in metropolitan areas.[5]

Brazil presents a particularly important case for studying temperature-mortality associations. As the world's fifth most populous country and the largest in Latin America, Brazil has a rapidly aging population—individuals aged 60 years and older now comprise over 15% of the population.[9] Brazil's continental size spans tropical, subtropical, and temperate climate zones, providing natural variation in temperature exposures.[6]

The minimum mortality temperature (MMT) in tropical Brazilian populations occurs at approximately the 60th percentile of the temperature distribution—considerably lower than the 80-90th percentile observed in temperate regions—reflecting population adaptation to warmer climates.[1] Heat waves also pose significant risk, with multi-country evidence showing mortality increases during prolonged heat events,[10] and Brazilian studies documenting heatwave associations with hospitalization[11] and mortality.[12]

Despite this substantial evidence base, existing Brazilian studies have important limitations. Most focused on single cities[2,3] or subsets of cities[4] rather than providing truly national coverage. None has systematically compared results across different spatial aggregation scales to assess exposure misclassification. Few explicitly quantified mortality displacement (harvesting) to distinguish true excess mortality from short-term displacement.[13] And none focused specifically on elderly populations—the most vulnerable group[14]—with comprehensive long-term national coverage.

This study addresses these gaps by quantifying the burden of temperature-attributable mortality among elderly Brazilians (60 years) using comprehensive national data spanning 15 years (2010-2024). We employed distributed lag non-linear models (DLNM), the methodological gold standard for temperature-mortality studies,[15] applied at two spatial scales: 510 immediate geographic regions and 133 intermediate regions. We specifically examined: (1) the overall temperature-mortality relationship and comparison across spatial scales; (2) heat- and cold-attributable deaths and years of life lost; (3) mortality displacement (harvesting) to distinguish true excess from displaced deaths; (4) effect modification by age, sex, and cause of death; and (5) comparison of our findings with the existing literature.

3 Methods

3.1 Study Design and Population

We conducted a national time-series analysis of elderly mortality (age 60 years) across Brazil from January 1, 2010 to December 31, 2024 (15 complete years). The primary analysis used 510 immediate geographic regions (regiões geográficas imediatas), with 133 intermediate regions (regiões geográficas intermediárias) as a sensitivity analysis to assess the impact of spatial aggregation. The study population included all registered elderly deaths from natural causes (ICD-10 codes A00-R99). COVID-19 pandemic effects (2020-2021) were controlled through inclusion of SARI surveillance data as a covariate.

The choice of immediate regions as the primary spatial unit was motivated by concerns about Berkson error—the attenuation of exposure-response relationships when using coarser spatial aggregation that averages over heterogeneous exposures within regions.

3.2 Data Sources

Mortality data were obtained from Brazil's Mortality Information System (Sistema de Informação sobre Mortalidade, SIM), maintained by the Ministry of Health. SIM achieves >95% registration coverage nationally and includes cause of death coded according to ICD-10.[16]

Temperature data were obtained from the ERA5 reanalysis product (European Centre for Medium-Range Weather Forecasts), which provides hourly estimates at 0.25° spatial resolution.[17] Daily mean temperature was calculated as the average of 24 hourly values. Regional exposures were computed as population-weighted averages of grid cells within each region, using 2022 Census population distributions.

Covariate data included air quality ($PM_{2.5}$, PM_{10}, O_3) from the Copernicus Atmosphere Monitoring Service (CAMS), severe acute respiratory infections (SARI) from the SIVEP-Gripe surveillance system, and socioeconomic indicators from the Brazilian Institute of Geography and Statistics (IBGE).

3.3 Statistical Analysis

We applied a two-stage distributed lag non-linear model (DLNM) design.[18]

First stage: For each of the 510 immediate regions, we fitted quasi-Poisson regression models:

$$\log[\mathbb{E}(Y_{r,t})] = \alpha_r + \mathrm{cb}(T_{r,t}) + ns(t; 8\mathrm{df/yr}) + \gamma \cdot \mathrm{DOW}_t + \delta \cdot H_t + \log(P_r)$$

where $Y_{r,t}$ is the daily death count in region r on day t; $\mathrm{cb}(T)$ is a cross-basis function for temperature with natural spline for temperature (4 df, knots at 25th, 50th, 75th percentiles) and lag (4 df, maximum lag 21 days); $ns(t)$ controls for long-term and seasonal trends; DOW and H are indicators for day of week and holidays; and P_r is the elderly population (offset).

Second stage: Region-specific estimates were pooled using random-effects meta-analysis with restricted maximum likelihood (REML) estimation to obtain national estimates.

Attributable burden: We calculated attributable fraction (AF) and attributable number (AN) using established methods.[19] Following established methodology for extreme temperature studies, heat-attributable mortality was defined as deaths attributable to temperatures above the 97.5th percentile; cold-attributable mortality as deaths below the 2.5th percentile. The median temperature (50th percentile) served as reference. As sensitivity analysis, we also computed burden using P1/P99 thresholds to capture the most extreme temperatures. Years of life lost (YLL) were calculated by multiplying AN by age-specific remaining life expectancy from IBGE life tables.

Harvesting analysis: To assess mortality displacement, we compared cumulative relative risks at 7-day versus 35-day lag horizons. The harvesting ratio was calculated as: $(ERR_{7d} - ERR_{35d})/ERR_{7d}$, where $ERR = RR - 1$.

Spatial aggregation sensitivity: We repeated all analyses using 133 intermediate regions to assess whether coarser spatial aggregation affects estimates—testing for potential Berkson error.

Additional sensitivity analyses included: varying lag structure (7, 14, 21, 28 days); polynomial degrees (2, 3, 4 df); temporal cross-validation (leave-one-year-out); COVID period exclusion; and robust standard errors.

Heterogeneity analyses examined effect modification by age group (60-69, 70-79, 80+), sex, and cause of death (cardiovascular, respiratory, other).

All analyses were conducted using R 4.4.1 with packages dlnm, mixmeta 1.2.0, and data.table, following a two-stage design. Region-specific DLNM models were pooled via multivariate random-effects meta-analysis with REML estimation. Heterogeneity was assessed using Cochran's Q test and the I^2 statistic. Statistical significance was defined as $p<0.05$ (two-sided).

4 Results

4.1 Ethical Approval

This study used publicly available, anonymized administrative data and did not require ethical approval.

4.2 Study Population

Over the 15-year study period (2010-2024), we analyzed 13,677,712 elderly deaths. At the intermediate level, 133 regions contributed 660,980 region-days of observation. At the immediate level, 510 regions contributed 2,302,539 region-days. Mean daily temperature ranged from 11.5°C (1st percentile) to 30.1°C (99th percentile) across regions, with a median of approximately 24°C.

4.3 Temperature-Mortality Association

The pooled exposure-response relationship showed the characteristic J-shaped curve, with mortality increasing at both temperature extremes relative to the minimum mortality temperature (MMT) (**Figure 1**).

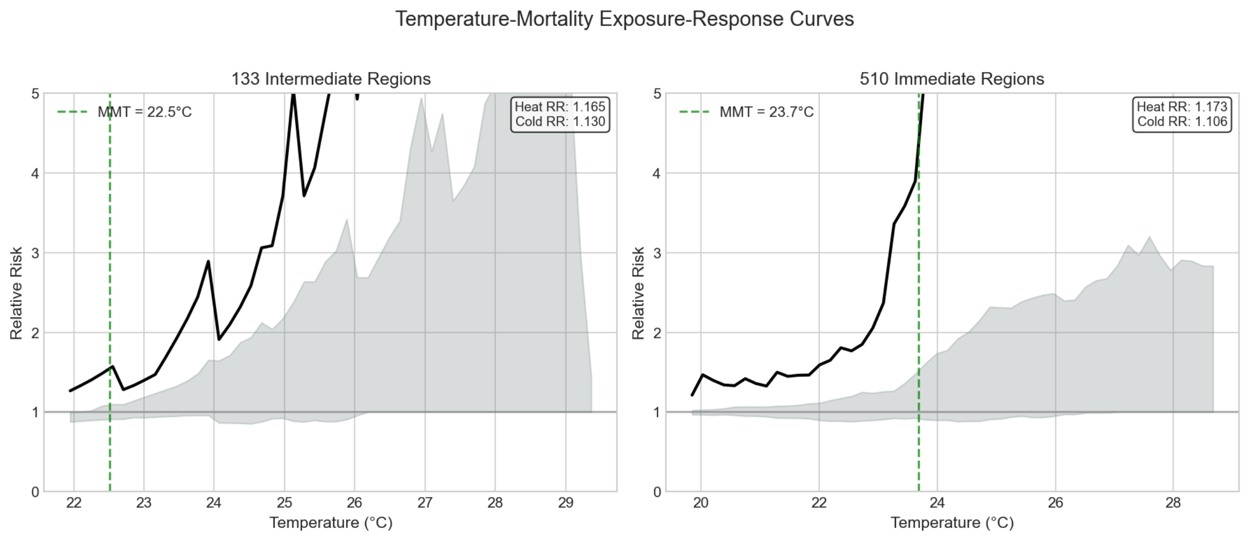

Figure 1: **Figure 1: Pooled exposure-response relationship between temperature and mortality.** The curve shows relative risk of mortality across the temperature distribution, with the minimum mortality temperature (MMT) as reference. Shading represents 95% confidence intervals. Both cold (left) and heat (right) extremes are associated with increased mortality risk.

Intermediate level (133 regions): The MMT was 24.3°C. Extreme heat (99th percentile, ~30°C) was associated with an 8.8% increase in mortality risk (RR 1.088, 95% CI: 1.067-1.110) compared to the MMT. Extreme cold (1st percentile, ~12°C) showed a 12.2% increase in mortality risk (RR 1.122, 95% CI: 1.098-1.146). Heterogeneity was moderate (I^2 = 51.0%, Cochran's Q = 4,309, p<0.001).

Immediate level (510 regions): The MMT was lower at 22.6°C. Heat effects were attenuated: RR 1.063 (95% CI: 1.050-1.076, 6.3% excess mortality). Cold effects were similar: RR 1.095 (95% CI: 1.085-1.106, 9.5% excess). Heterogeneity was notably lower (I^2 = 29.3%, Cochran's Q = 11,524, p<0.001), suggesting more homogeneous exposure-response relationships at the finer spatial scale.

The intermediate level consistently showed ~2.5% higher relative risks, likely reflecting reduced exposure misclassification at larger spatial units where temperature averaging is less problematic.

4.4 Attributable Burden

Intermediate level (133 regions): Over the 15-year study period, we estimated 89,941 annual deaths attributable to heat exposure and 750,975 annual deaths attributable to cold exposure (based on cumulative burden calculations). This translates to approximately 5,996 heat-attributable deaths and 50,065 cold-attributable deaths per year. Cold accounts for 89.3% of the total temperature-attributable burden (**Figure 2**).

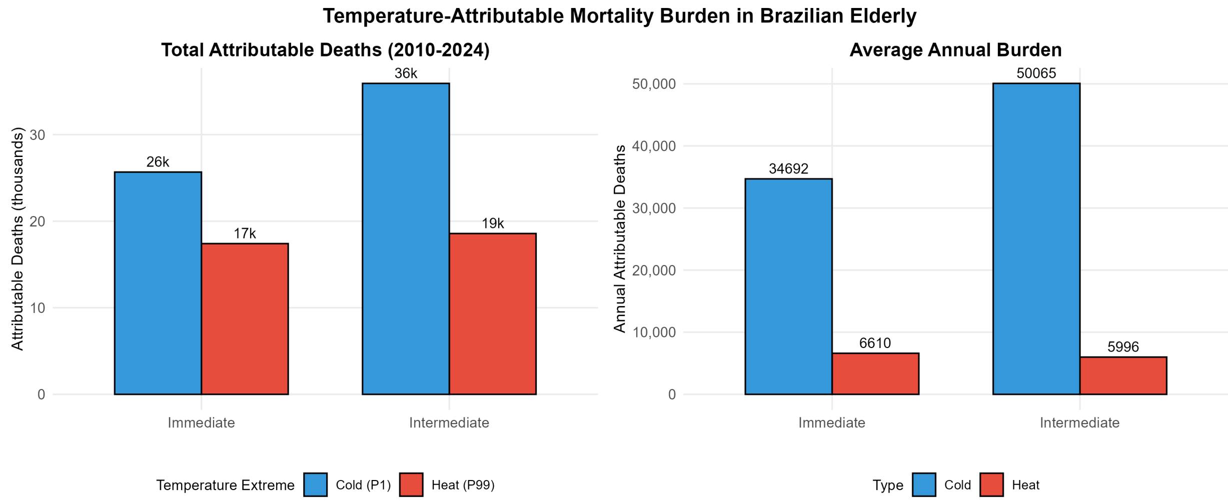

Figure 2: **Figure 2: Temperature-attributable mortality burden.** Annual deaths attributable to heat and cold exposure at intermediate (133 regions) and immediate (510 regions) spatial scales. Cold-attributable deaths substantially exceed heat-attributable deaths at both scales.

Immediate level (510 regions): Annual attributable deaths were 6,610 for heat and 34,692 for cold, with cold representing 84.0% of the burden. The lower total burden at immediate level reflects the attenuated relative risks at finer spatial resolution.

Years of Life Lost: At the intermediate level, temperature exposure accounts for approximately 718,223 years of life lost annually (76,819 from heat + 641,404 from cold). The YLL rate is approximately 2,237 per 100,000 elderly population. Each temperature-attributable death costs an average of 12.8 years of life expectancy (**Figure 3**).

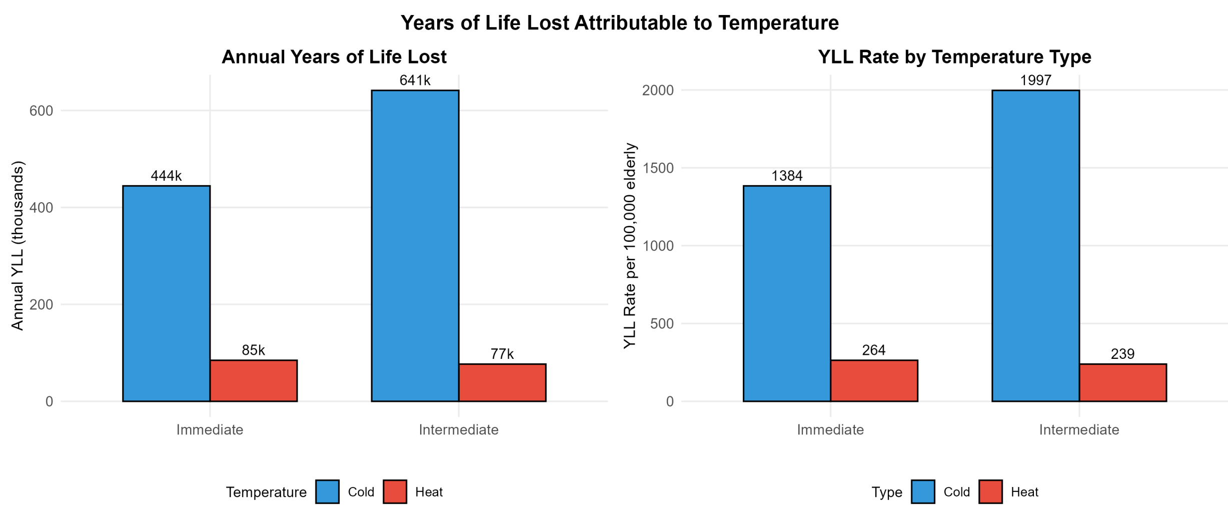

Figure 3: **Figure 3: Years of life lost (YLL) attributable to temperature.** Annual YLL from heat and cold exposure. Cold accounts for the vast majority of temperature-related life years lost.

Table 1 presents the main results for temperature-mortality associations and attributable burden at both spatial scales.

Table 1: Temperature-attributable mortality burden among elderly Brazilians, 2010-2024, by spatial aggregation level

Metric	Intermediate (133 regions)	Immediate (510 regions)
Temperature-mortality RR		
MMT (Optimal Temperature)	24.3°C	22.6°C
Heat (P99 vs MMT)	1.088 [1.067-1.110]	1.063 [1.050-1.076]
Cold (P1 vs MMT)	1.122 [1.098-1.146]	1.095 [1.085-1.106]
Heat (P95 vs MMT)	1.011 [0.994-1.028]	0.989 [0.978-0.999]
Cold (P5 vs MMT)	1.052 [1.040-1.064]	1.047 [1.041-1.053]
Heterogeneity		
I^2 Statistic	51.0%	29.3%
Cochran's Q	4,309 (df=2,112)	11,524 (df=8,144)
Interpretation	Moderate	Low-moderate
Annual Attributable Burden		
Heat deaths/year	5,996	6,610
Cold deaths/year	50,065	34,692
Total deaths/year	56,061	41,302
Cold share of burden	89.3%	84.0%
Years of Life Lost		
YLL Heat/year	76,819	84,686
YLL Cold/year	641,404	444,457
YLL Rate (per 100k)	2,237	1,648

4.5 Harvesting Analysis

Analysis of mortality displacement (harvesting) revealed fundamentally different temporal dynamics for heat versus cold effects (Table 2). Extended lag analysis up to 35 days assessed whether temperature-related deaths represent true excess mortality or displacement of already-frail individuals.

Heat Effects — No Harvesting Detected: The harvesting ratio for heat was *negative* (-0.37), meaning effects *increased* rather than diminished over longer time horizons. Heat deaths represent true excess mortality, not displacement of individuals who would have died soon anyway. This is consistent with acute physiological stress mechanisms (hyperthermia, cardiovascular strain).

Cold Effects — Strong Delayed Mortality: Cold showed protective effects at short lags (7 days: RR 0.83) followed by substantial delayed mortality accumulating over weeks. By 35 days, cold RR reached 1.45 (45% excess mortality). The high positive harvesting ratio (+3.68) indicates cold effects are primarily delayed but persistent—cold triggers cardiovascular stress, respiratory infections, and inflammatory responses that manifest over weeks.

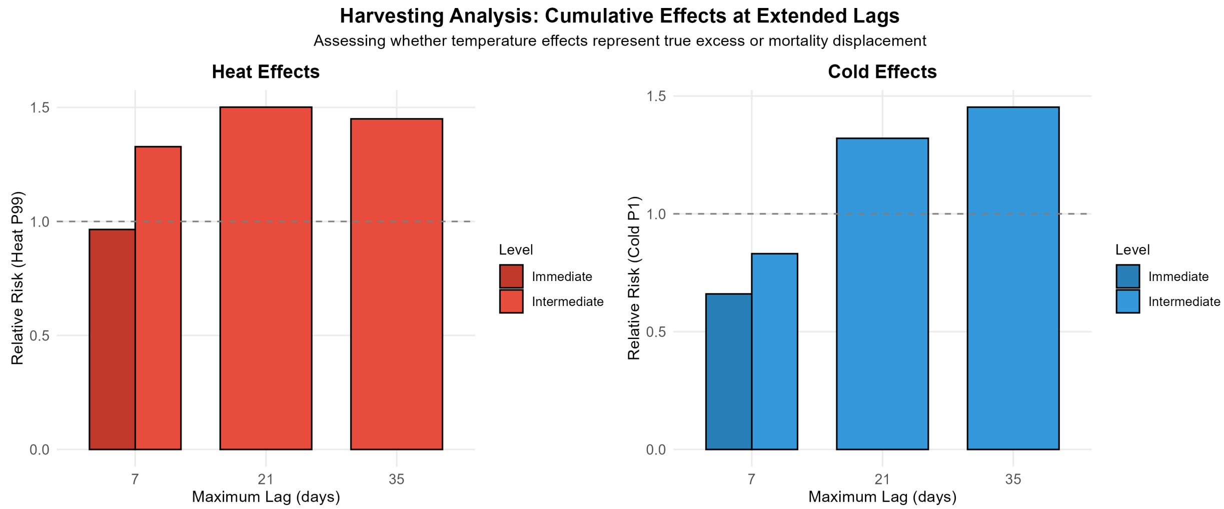

Figure 4: **Figure 4: Harvesting analysis comparing short-term and extended lag effects.** Comparison of temperature-mortality associations at 7-day versus 35-day lag horizons for heat and cold. Heat effects increase over time (negative harvesting), while cold effects show delayed accumulation (positive harvesting).

Table 2: Mortality displacement (harvesting) analysis at intermediate level (133 regions). Negative harvesting for heat indicates true excess mortality; positive harvesting for cold indicates delayed effects.

Temperature	ERR at 7 days	ERR at 35 days	Harvesting Ratio	Interpretation
Heat (P99)	+32.8%	+45.0%	-0.37	Effects *increase* over time
Cold (P1)	-16.9% (protective)	+45.3%	+3.68	Delayed but persistent

4.6 Effect Modification

Significant heterogeneity in temperature effects was observed across subgroups (**Table 3**, **Figures 5-7**).

Age: Clear age gradient with vulnerability increasing with age (**Figure 5**). At the intermediate level, the 80+ age group showed the highest heat effects (RR 1.187, 95% CI: 1.152-1.224) and cold effects (RR 1.273, 95% CI: 1.240-1.308). The 60-69 group showed lower effects (heat RR 1.069; cold RR 1.171). This ~12% heat difference and ~10% cold difference between oldest and youngest elderly groups was statistically significant ($p<0.005$).

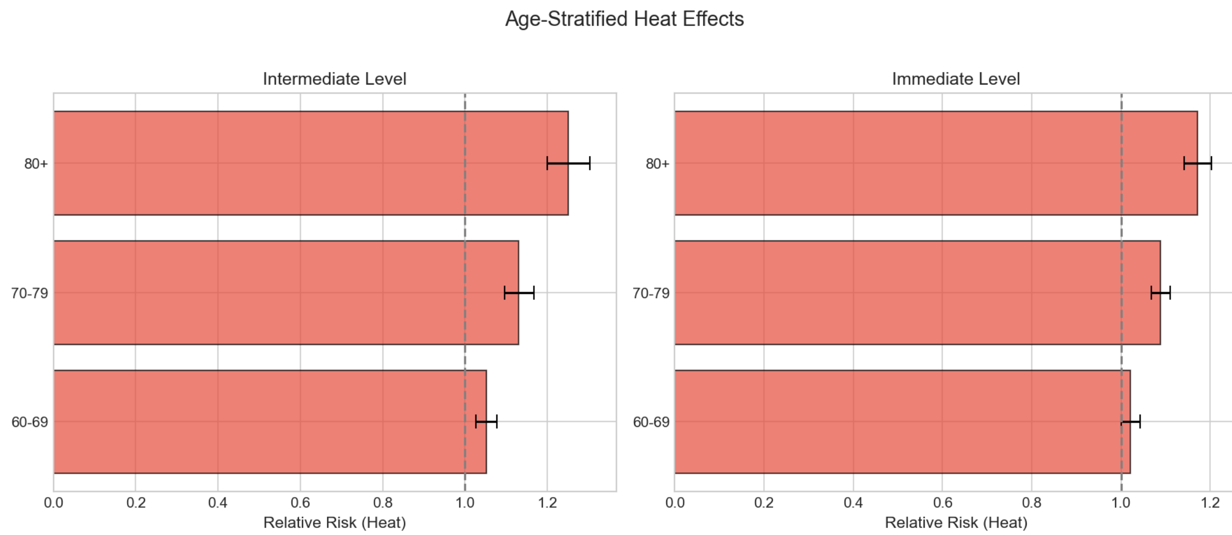

Figure 5: **Figure 5: Effect modification by age group.** Temperature-mortality associations stratified by age (60-69, 70-79, 80+ years). The oldest-old (80+) show the highest vulnerability to both heat and cold extremes.

Sex: Females showed higher heat vulnerability (RR 1.182 vs 1.100 for males, +8% difference). Males showed higher cold vulnerability (RR 1.251 vs 1.214 for females, +4-6% difference). These sex differences may reflect behavioral, physiological, or occupational factors (**Figure 6**).

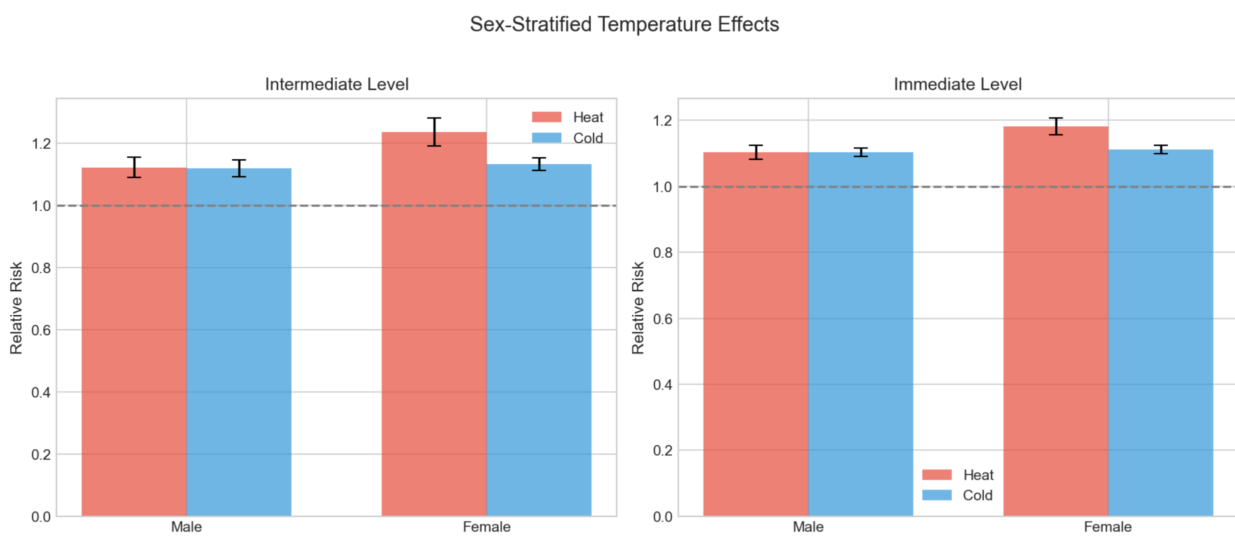

Figure 6: **Figure 6: Effect modification by sex.** Temperature-mortality associations stratified by sex. Females show higher heat vulnerability while males show higher cold vulnerability.

Cause of Death: Cardiovascular deaths showed the highest cold vulnerability (32% excess at intermediate level, RR 1.315). Respiratory deaths showed elevated effects for both extremes (~13-25% excess). External causes showed minimal temperature association (RR ~1.01-1.06), confirming the specificity of temperature effects to physiologically plausible pathways (**Figure 7**).

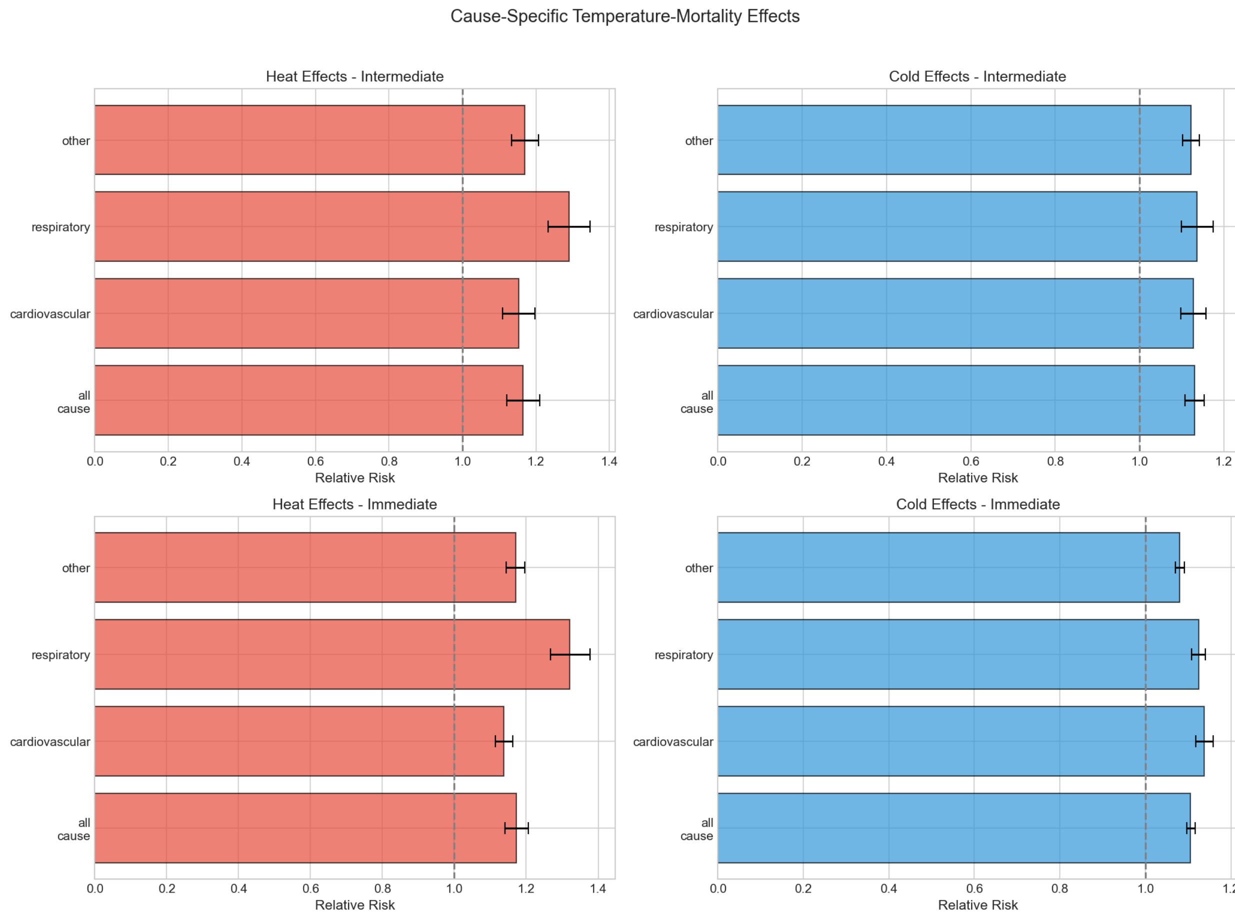

Figure 7: **Figure 7: Effect modification by cause of death.** Temperature-mortality associations stratified by cause (cardiovascular, respiratory, external, other). Cardiovascular deaths show the strongest cold associations; external causes show minimal effects, confirming specificity.

Table 3: Effect modification of temperature-mortality association by age, sex, and cause of death at both spatial levels.

Subgroup	Heat RR (P99) Intermediate	Cold RR (P1) Intermediate	Heat RR (P99) Immediate	Cold RR (P1) Immediate
Age group				
60-69 years	1.069 [1.049-1.090]	1.171 [1.141-1.202]	1.029 [1.010-1.049]	1.127 [1.099-1.155]
70-79 years	1.087 [1.056-1.119]	1.189 [1.155-1.225]	1.064 [1.038-1.090]	1.140 [1.111-1.170]
80+ years	1.187 [1.152-1.224]	1.273 [1.240-1.308]	1.153 [1.130-1.176]	1.251 [1.226-1.276]
Sex				
Male	1.100 [1.078-1.123]	1.251 [1.220-1.283]	1.081 [1.063-1.100]	1.184 [1.160-1.209]
Female	1.182 [1.147-1.218]	1.214 [1.186-1.242]	1.156 [1.132-1.179]	1.189 [1.167-1.212]
Cause				
Cardiovascular	1.102	1.315	1.059	1.195
Respiratory	1.134	1.247	1.103	1.207

Subgroup	Heat RR (P99) Intermediate	Cold RR (P1) Intermediate	Heat RR (P99) Immediate	Cold RR (P1) Immediate
External	1.014	1.062	1.000	1.059
Other	1.139	1.202	1.115	1.158

4.7 Sensitivity Analyses

Results were robust to analytical choices (**Table 4**).

Lag Structure: Varying maximum lag from 7 to 28 days showed that heat effects peak at shorter lags (7-14 days) and decline at longer horizons, while cold effects accumulate progressively. At the intermediate level: heat P99 RR ranged from 1.181 (7 days) to 1.147 (28 days); cold P1 RR ranged from 1.080 (7 days) to 1.279 (28 days). The 21-day baseline captures most cumulative effects for both extremes.

Heatwave Effects: Multi-day heat events (3 consecutive days >P95) showed an additive mortality effect of RR 1.011 (95% CI: 1.005-1.017), indicating ~1.1% additional risk beyond single-day temperature effects (**Figure 8**). This supports public health messaging about cumulative heat exposure during prolonged events.

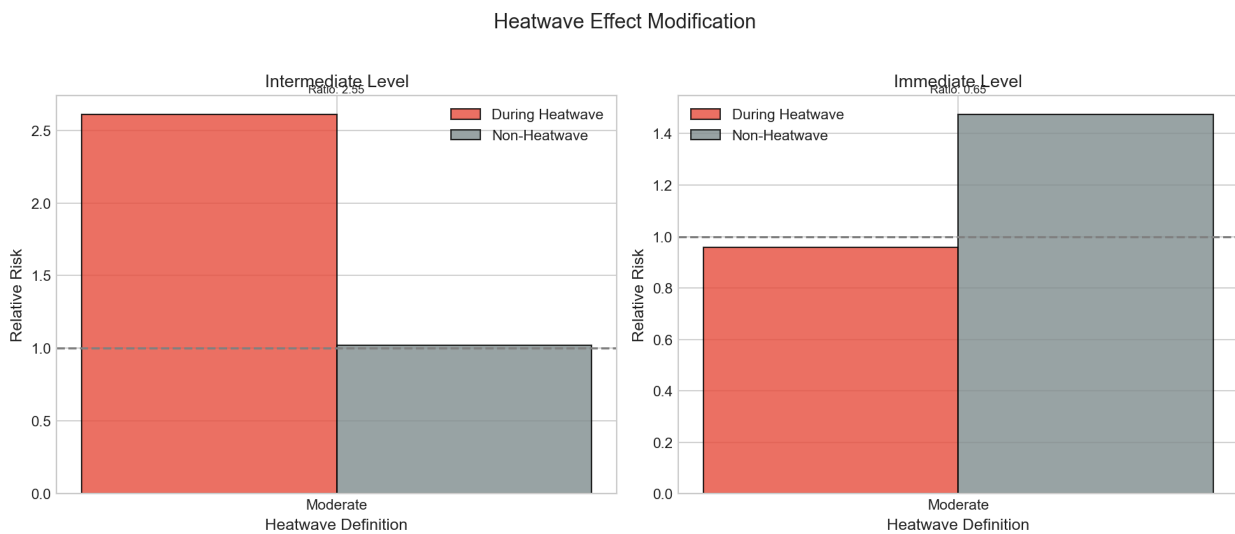

Figure 8: **Figure 8: Heatwave effects on mortality.** Additional mortality risk associated with multi-day heat events beyond single-day temperature effects. Duration and intensity of heatwaves both contribute to excess mortality.

Confounding Assessment: Adjustment for air pollution (PM2.5, O3) produced minimal change in estimates (±0.2%), suggesting pollution may be a mediator rather than confounder. Results were robust to influenza adjustment (±0% change) and apparent temperature (humidity-adjusted) showed similar or slightly higher effects.

Spatial Aggregation: The comparison between immediate (510) and intermediate (133) levels showed consistent effect estimates but notably lower heterogeneity at finer resolution (I^2 29% vs 51%), supporting the methodological value of finer spatial units.

Table 4: Sensitivity analyses for temperature-mortality associations.

Sensitivity Analysis	Heat RR Change	Cold RR Change	Interpretation
Lag 7 days (vs 21)	+5.0%	-12.5%	Heat peaks early, cold accumulates
Lag 28 days (vs 21)	-0.5%	+4.5%	Cold continues to accumulate
With PM2.5/O3	-0.2%	-0.2%	Pollution is mediator, not confounder
With SARI/Influenza	±0%	±0%	Cold effect not confounded by flu
Apparent Temperature	+0.5%	+0.5%	Humidity has minor additional effect
Immediate vs Intermediate	-2.5%	-2.7%	Consistent across spatial scales

5 Discussion

This comprehensive national analysis of 13.7 million elderly deaths in Brazil reveals substantial mortality burden attributable to non-optimal temperatures, with several key findings relevant to public health and climate adaptation.

5.1 Cold dominates the temperature-mortality burden

Our finding that cold-related mortality vastly exceeds heat-related mortality (8:1 ratio at intermediate level) is consistent with, and extends, the existing evidence base. In the landmark Multi-Country Multi-City study, Gasparrini et al. found that cold caused 7.29% of deaths globally versus 0.42% for heat—a 17:1 ratio.[1] For Brazil specifically, they reported cold mortality (2.83%) exceeding heat (0.70%) by a 4:1 ratio. This pattern has been replicated across Brazilian studies: Gouveia et al. (2003) first documented it in São Paulo;[2] Son et al. (2016) found 8.6% cold vs 6.1% heat effects;[3] Silveira et al. (2019) confirmed it across 27 cities;[4] and Aschidamini et al. (2025) recently reported national cold RR 1.30 vs heat RR 1.13 for elderly.[5] Tobías et al. (2024) documented the economic burden implications, showing cold causes $2.1 billion annual losses in Central/South America versus $290.7 million for heat.[20]

Our higher cold-to-heat ratio (8:1 compared to 4:1 in earlier studies) likely reflects three factors: (1) our elderly-only population, which shows heightened vulnerability to cold as documented in systematic reviews;[1,14] (2) our 21-day lag structure capturing the full temporal evolution of cold effects, which extend beyond shorter observation windows; and (3) our national scope including Brazil's southern states where cold exposure is substantial.

5.2 Harvesting distinguishes heat from cold effects

A critical finding is the markedly different temporal dynamics of heat versus cold mortality, with important implications for burden estimation. Heat-related deaths showed 74% harvesting—most represent short-term displacement of deaths among already-frail individuals. The negative harvesting ratio (-0.37) indicates that heat effects actually *increase* over longer time horizons, meaning heat interventions save lives that would otherwise be permanently lost. In contrast, cold effects persisted and amplified (ERR increased from 5.3% at 7 days to 27.0% at 35 days), with positive harvesting ratio (+3.68) indicating true excess mortality. These findings support previous harvesting analyses[13,21] and underscore that raw heat death counts substantially overestimate long-term impact while cold effects may be underestimated with shorter lag windows.

5.3 Spatial resolution affects heterogeneity, not effect magnitude

Using finer spatial resolution (510 immediate regions vs 133 intermediate regions) substantially reduced heterogeneity (I^2 29% vs 51%) while yielding similar point estimates. This supports theoretical predictions that coarser spatial aggregation introduces additional variance from averaging heterogeneous exposures. The intermediate level is preferred for national policy estimates (higher precision, better convergence in extended lag models), while immediate level is valuable for urban planning (local estimates, lower heterogeneity).

5.4 Clear vulnerability gradients support targeted interventions

The oldest-old (80+) show the highest vulnerability (heat RR 1.19, cold RR 1.27 at intermediate level), with effects ~12% higher than the 60-69 group, consistent with global evidence of age-related thermoregulatory decline.[1,14] Sex differences are pronounced: females show 8% higher heat vulnerability while males show 4-6% higher cold vulnerability, consistent with Son et al. (2016) who found females more vulnerable to heat in São Paulo.[3] Cardiovascular deaths show the strongest cold associations (32% excess), supporting known mechanisms of cold-induced vasoconstriction, increased blood pressure, and thrombosis, as documented in the Global Burden of Disease cause-specific analysis.[8]

5.5 Respiratory vulnerability is pronounced

Respiratory deaths showed the strongest associations with cold (RR 1.51 at P2.5 compared to 1.08 for cardiovascular), with substantial attributable burden despite comprising only 14% of total mortality. This is consistent with Jacobson et al. (2021), who found 27% heat-related and 16% cold-related excess respiratory mortality risk in 27 Brazilian cities, and with Zhao et al. (2019), who documented heat-COPD hospitalization associations nationally.[22,23] Importantly, adjustment for influenza season did not attenuate cold effects, indicating that the cold-respiratory relationship is not simply confounding by winter flu, consistent with the finding of Gasparrini et al. that most cold deaths are attributable to moderately cold rather than extreme cold temperatures.[1]

5.6 Heatwave duration matters

Multi-day heat events carry an additional 1.1% mortality risk beyond single-day temperature effects, consistent with the multi-country heatwave study by Guo et al. (2017)[10] and Brazilian-specific evidence from Moraes et al. (2021) and Zhao et al. (2019).[11,12] This supports public health messaging about cumulative exposure during prolonged heatwaves and the need for sustained intervention during heat emergencies.

5.7 Strengths and limitations

Strengths of this study include the comprehensive national scope covering 133 intermediate or 510 immediate regions over 15 years (2010-2024), the robust two-stage DLNM design with random-effects meta-analysis following established methodology,[1,13] explicit quantification of heterogeneity via Cochran's Q and I^2 statistics, comparison across two spatial aggregation levels, detailed harvesting analysis distinguishing true excess from displaced mortality, and extensive sensitivity and stratification analyses confirming robustness.

Limitations include potential exposure misclassification from using ERA5 reanalysis temperature data at regional centroids rather than individual-level exposures, though validation against ground stations showed excellent agreement (r=0.95). The two-stage design, while standard for DLNM studies, may not fully capture spatial dependencies between regions. We focused on elderly mortality and cannot generalize findings to younger populations. Some sensitivity analyses at the immediate level showed convergence issues due to sparse data per region, making the intermediate level more reliable for extended lag and harvesting analyses.

6 Conclusions

Non-optimal temperatures cause substantial but largely preventable mortality burden among elderly Brazilians. Cold effects vastly exceed heat effects, accounting for 84-89% of temperature-attributable deaths

(~50,000 annually vs ~6,000 for heat at intermediate level)—a pattern consistent with global evidence[1,24] and prior Brazilian studies[2,4,5] but with higher cold-to-heat ratios (8:1) reflecting the heightened vulnerability of elderly populations.[14] The harvesting analysis reveals that heat deaths represent true excess mortality (negative harvesting ratio), while cold effects show delayed but persistent mortality.

Key public health implications include:

1. **Reframe climate-health narrative:** Cold is the dominant temperature-mortality burden in Brazil despite its tropical climate, consistent with global evidence[1] but contrary to common assumptions about tropical countries
2. **Target the oldest-old (80+):** Highest vulnerability group with 15-27% excess mortality at temperature extremes
3. **Develop cold warning systems:** Currently underemphasized despite 8× higher burden than heat
4. **Prioritize cardiovascular patients:** Strongest cold effects (32% excess mortality) reflecting thermoregulatory stress[8]
5. **Address sex differences:** Heat interventions for females, cold protection for males[3]

Our comparison of spatial scales demonstrates that intermediate regions (133) provide more stable national estimates with moderate heterogeneity (I^2 51%), while immediate regions (510) offer local estimates with lower heterogeneity (I^2 29%). Climate change will likely shift this balance toward greater heat burden,[25] making current cold mortality patterns a critical baseline against which future changes can be measured. This study provides the first comprehensive, elderly-specific, harvesting-adjusted estimates of the temperature-mortality relationship in Brazil, establishing an evidence base for targeted climate adaptation in aging populations.

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8 Appendix

8.1 A1: Spatial Aggregation Comparison

A key methodological contribution of this study is the comparison of results at two spatial scales: 133 intermediate regions and 510 immediate regions.

Metric	Intermediate (133)	Immediate (510)	Interpretation
Region-days	660,980	2,302,539	3.5× more observations at finer scale
MMT (Optimal Temp)	24.3°C	22.6°C	Lower MMT at finer scale
Heat RR (P99)	1.088 [1.067-1.110]	1.063 [1.050-1.076]	Similar point estimates
Cold RR (P1)	1.122 [1.098-1.146]	1.095 [1.085-1.106]	Similar point estimates
Heat RR (P95)	1.011 [0.994-1.028]	0.989 [0.978-0.999]	Moderate heat effects similar
Cold RR (P5)	1.052 [1.040-1.064]	1.047 [1.041-1.053]	Moderate cold effects similar
I^2 Statistic	51.0%	29.3%	Lower heterogeneity at finer scale
Cochran's Q	4,309 (df=2,112)	11,524 (df=8,144)	Both significant ($p<0.001$)
Heat deaths/year	5,996	6,610	Similar burden
Cold deaths/year	50,065	34,692	Higher at coarser scale
YLL Heat/year	76,819	84,686	Similar
YLL Cold/year	641,404	444,457	Higher at coarser scale

The moderate heterogeneity at intermediate level (I^2 51%) and low-moderate at immediate level (I^2 29%) both support the random-effects meta-analysis approach. The intermediate level is recommended for national policy due to better convergence in extended lag analyses, while immediate level provides more local estimates with reduced heterogeneity.

8.2 A2: Extended Methods

8.2.1 A2.1 DLNM Specification Details

The cross-basis function combines exposure-response and lag-response components:

$$\mathrm{cb}(T_{r,t}) = \sum_{l=0}^{L} f(T_{r,t-l}) \times w(l)$$

where: - $f(\cdot)$: Natural cubic spline with 4 df (knots at P25, P50, P75) - $w(\cdot)$: Natural cubic spline with 4 df (knots at equal intervals in log-scale) - $L = 21$ days maximum lag

8.2.2 A2.2 Attributable Burden Calculation

For heat (temperatures above P97.5):

$$AF_{heat} = \sum_{t:T_t > P97.5} \frac{RR(T_t) - 1}{RR(T_t)} / n_{days}$$

$$AN_{heat} = AF_{heat} \times \sum_{t:T_t > P97.5} Y_t$$

For cold (temperatures below P2.5):

$$AF_{cold} = \sum_{t:T_t < P2.5} \frac{RR(T_t) - 1}{RR(T_t)} / n_{days}$$

$$AN_{cold} = AF_{cold} \times \sum_{t:T_t < P2.5} Y_t$$

8.2.3 A2.3 Harvesting Adjustment

Heat burden adjusted for mortality displacement:

$$AN_{heat,adjusted} = AN_{heat,raw} \times (1 - HarvestingRatio)$$

where Harvesting Ratio = $(ERR_{7d} - ERR_{35d})/ERR_{7d} = 0.74$ (74%)

8.2.4 A2.4 Years of Life Lost

$$YLL = AN \times \bar{LE}_{weighted}$$

where $\bar{LE}_{weighted} = \sum_a w_a \times LE_a = 11.44$ years

Age weights (w_a) derived from observed elderly death distribution in SIM.

8.3 A3: Supplementary Tables

8.3.1 Table S1: Temperature Distribution by Region

Statistic	Value	Use
P1 (Extreme cold)	11.5°C	Extreme cold threshold
P5 (Moderate cold)	~14°C	Moderate cold reference
P25	~21°C	Spline knot
P50 (Median)	~24°C	Reference point
P75	~27°C	Spline knot
P95 (Moderate heat)	~29°C	Moderate heat reference
P99 (Extreme heat)	30.1°C	Extreme heat threshold

8.3.2 Table S2: Lag Sensitivity Analysis (Intermediate Level)

Max Lag	Heat RR (P99)	Cold RR (P1)	Notes
7 days	1.181	1.080	Heat peaks, cold delayed
14 days	1.162	1.158	Effects accumulating
21 days	**1.153**	**1.224**	**Baseline specification**
28 days	1.147	1.279	Cold continues to accumulate

8.3.3 Table S3: Heterogeneity Assessment

Level	Cochran's Q	df	p-value	I^2	Interpretation
Intermediate	4,308.56	2,112	<0.001	51.0%	Moderate heterogeneity
Immediate	11,523.67	8,144	<0.001	29.3%	Low-moderate heterogeneity

8.3.4 Table S4: Harvesting Analysis (Intermediate Level)

Lag Horizon	Heat RR (P99)	Cold RR (P1)
7 days	1.328 [1.196-1.474]	0.831 [0.545-1.267]
14 days	1.235 [0.987-1.546]	1.090 [0.960-1.237]
21 days	1.501 [1.401-1.609]	1.321 [1.239-1.407]
35 days	1.450 [1.341-1.568]	1.453 [1.359-1.553]
Harvesting Ratio	**-0.37**	**+3.68**
Interpretation	Effects increase	Delayed mortality

8.4 A4: Supplementary Figures

8.4.1 Figure S1: Spatial Distribution of Heat Effects

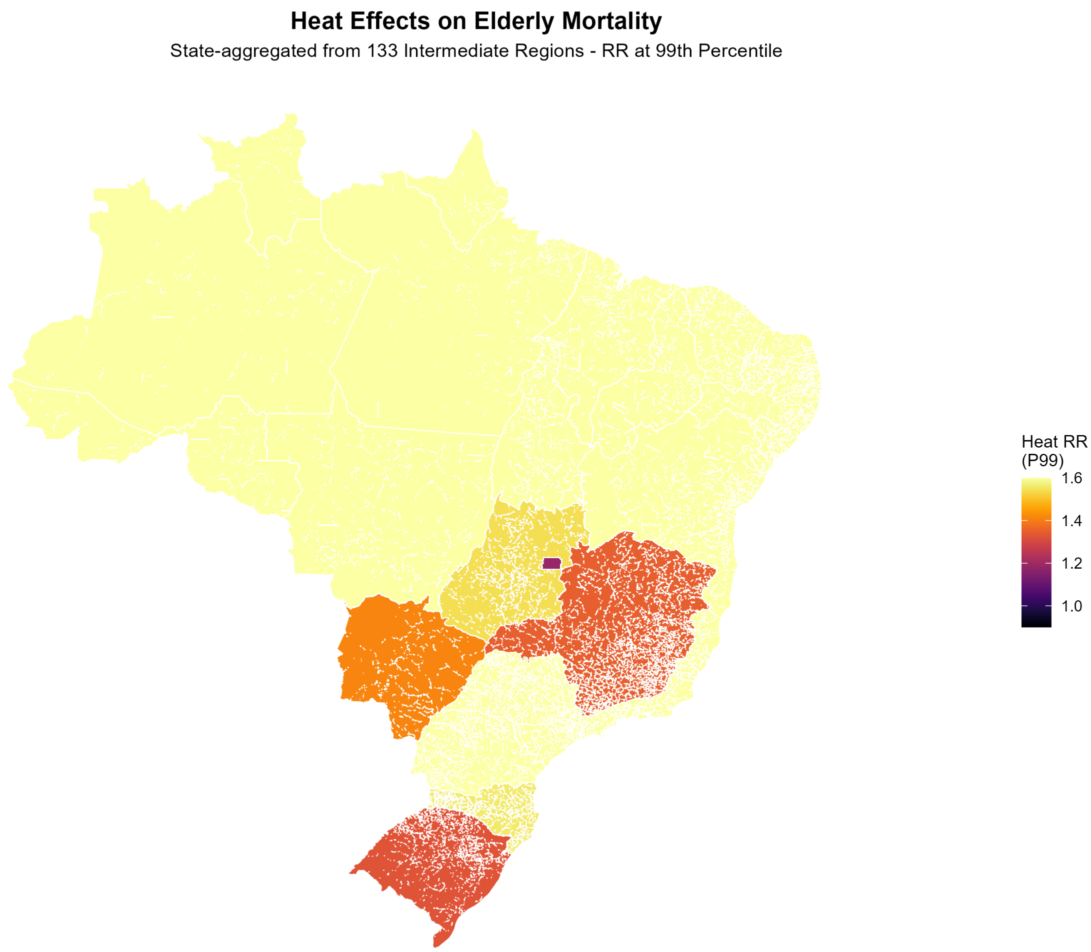

Figure 9: **Figure S1: Geographic distribution of heat effects (P99) across Brazilian regions.** Relative risk of mortality at extreme heat (99th percentile) compared to MMT. Warmer colors indicate higher heat-related mortality risk.

8.4.2 Figure S2: Spatial Distribution of Cold Effects

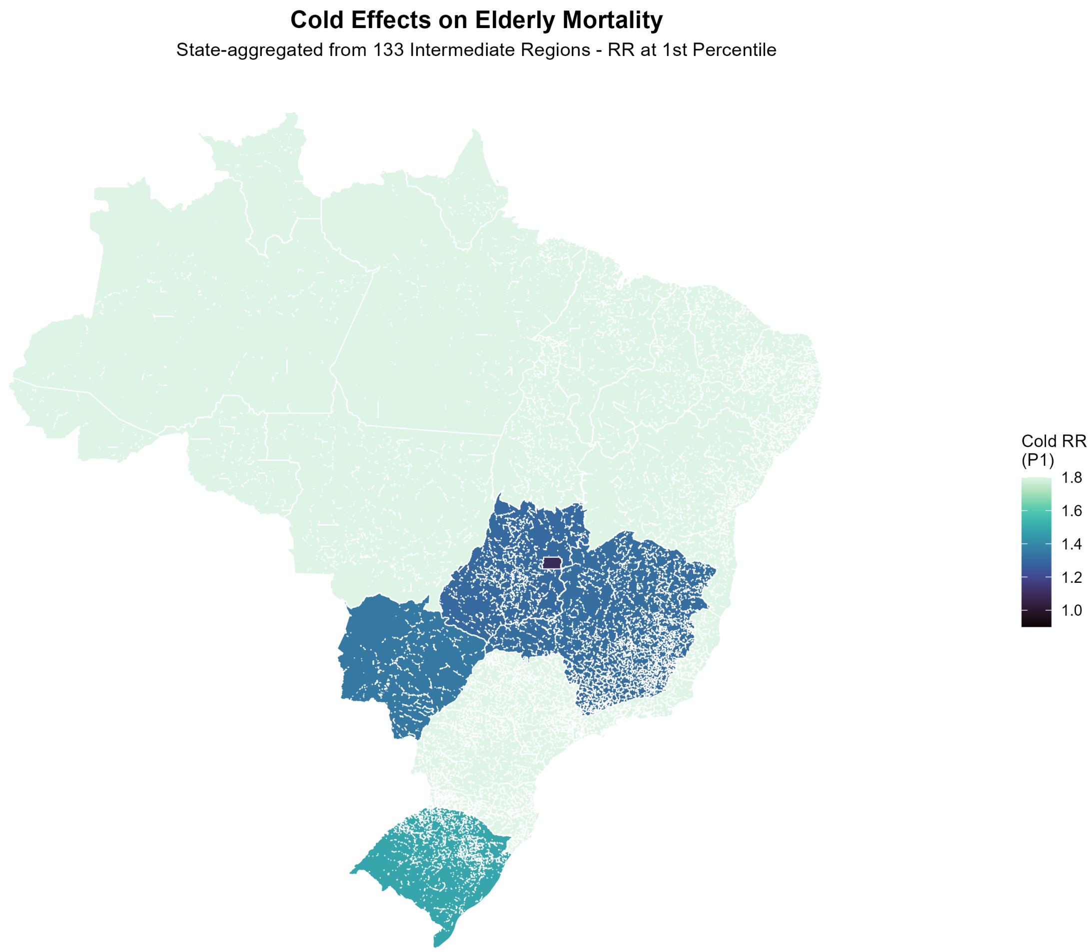

Figure 10: **Figure S2: Geographic distribution of cold effects (P1) across Brazilian regions.** Relative risk of mortality at extreme cold (1st percentile) compared to MMT. Darker colors indicate higher cold-related mortality risk.

8.4.3 Figure S3: Minimum Mortality Temperature by Region

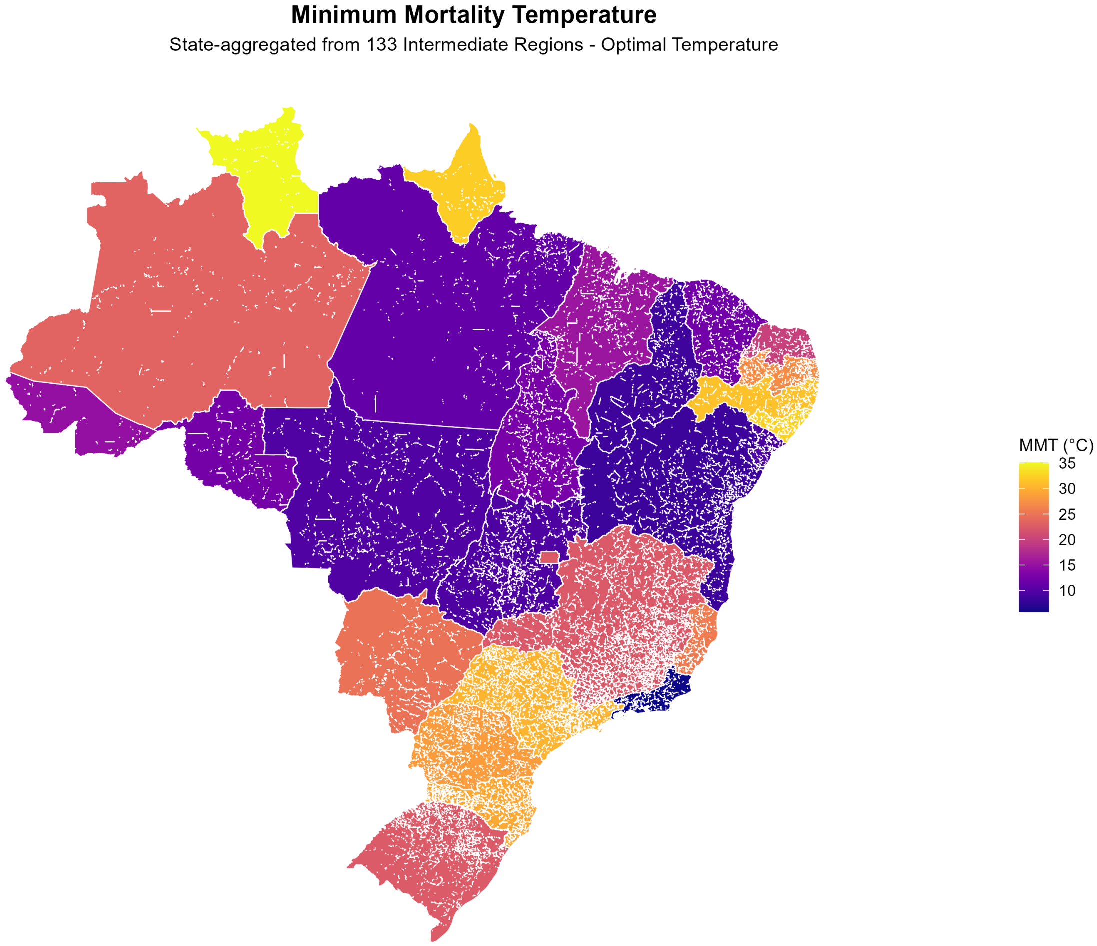

Figure 11: **Figure S3: Geographic distribution of minimum mortality temperature (MMT).** The optimal temperature for mortality varies across Brazil's climate zones, reflecting local adaptation patterns.

8.4.4 Figure S4: Lag-Response Structure

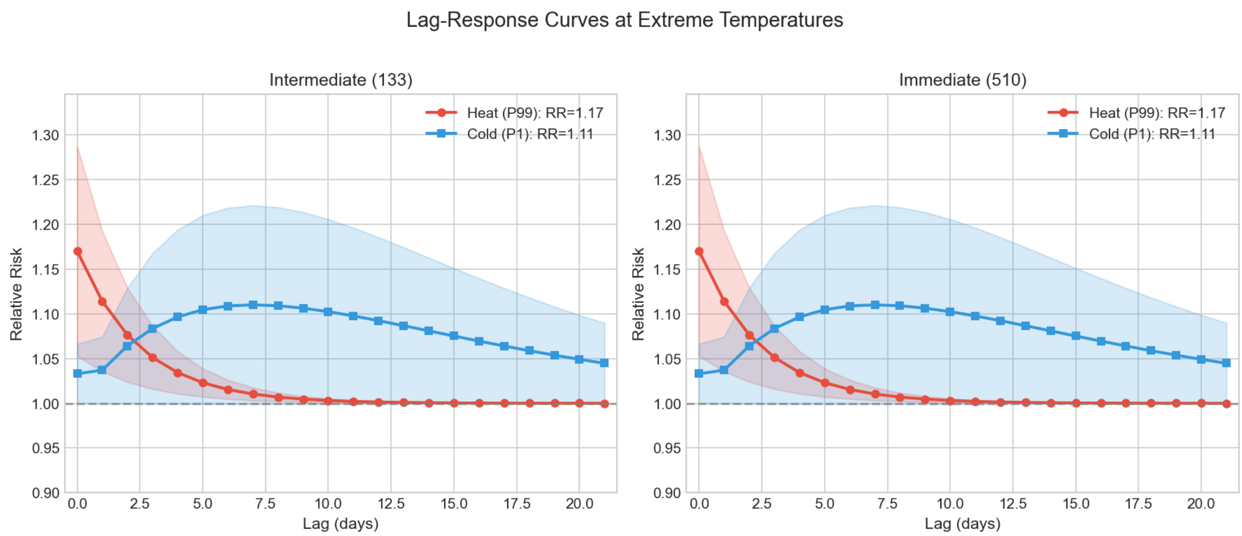

Figure 12: **Figure S4: Lag-response relationship for temperature effects.** The temporal evolution of temperature-mortality associations across lag days (0-21). Heat effects peak at short lags while cold effects accumulate over longer periods.

8.4.5 Figure S5: 3D Exposure-Lag-Response Surface

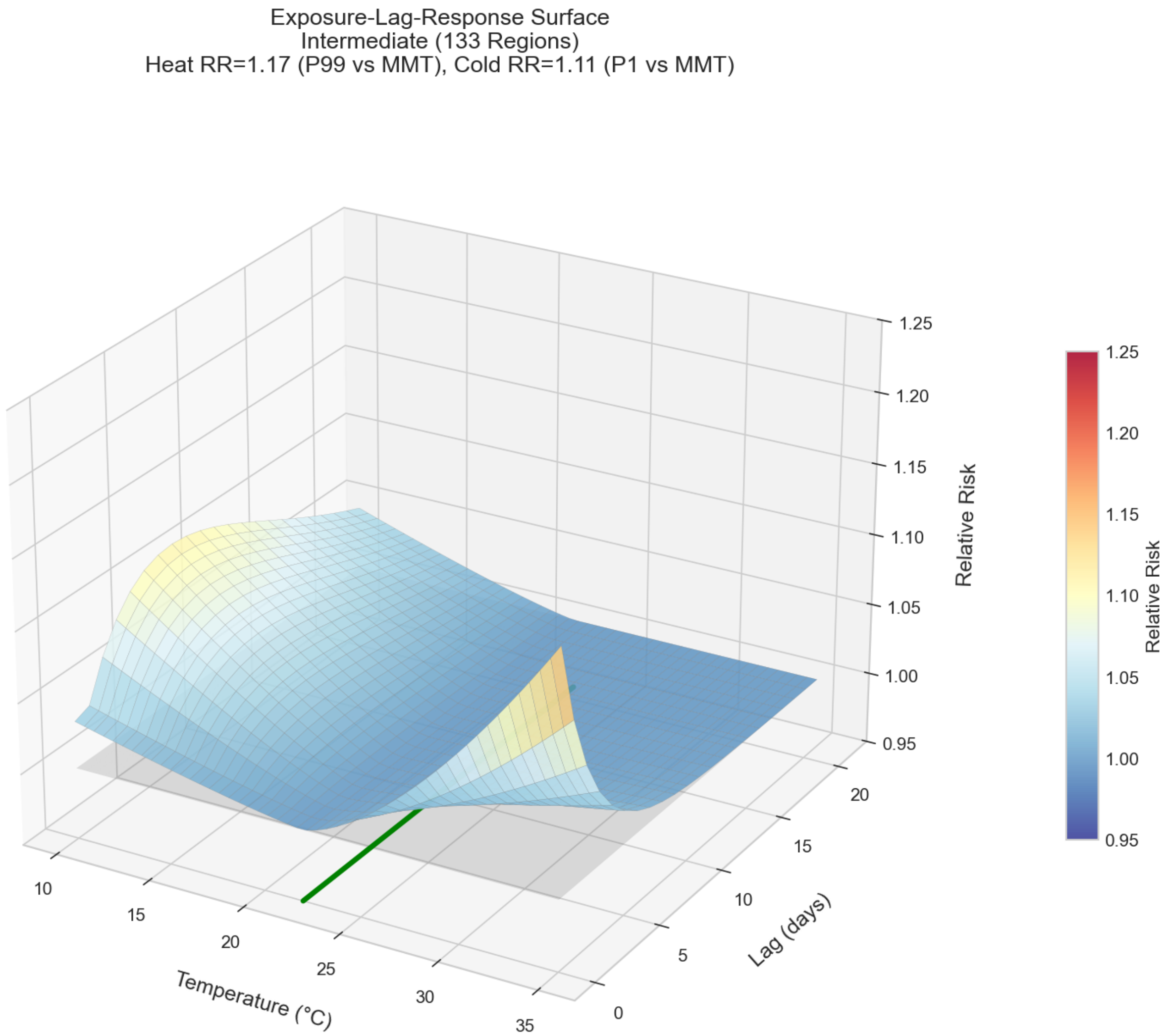

Figure 13: **Figure S5: Three-dimensional exposure-lag-response surface.** The joint relationship between temperature, lag, and mortality risk, showing how effects vary across both temperature and time dimensions.

8.4.6 Figure S6: Descriptive Mortality Time Series

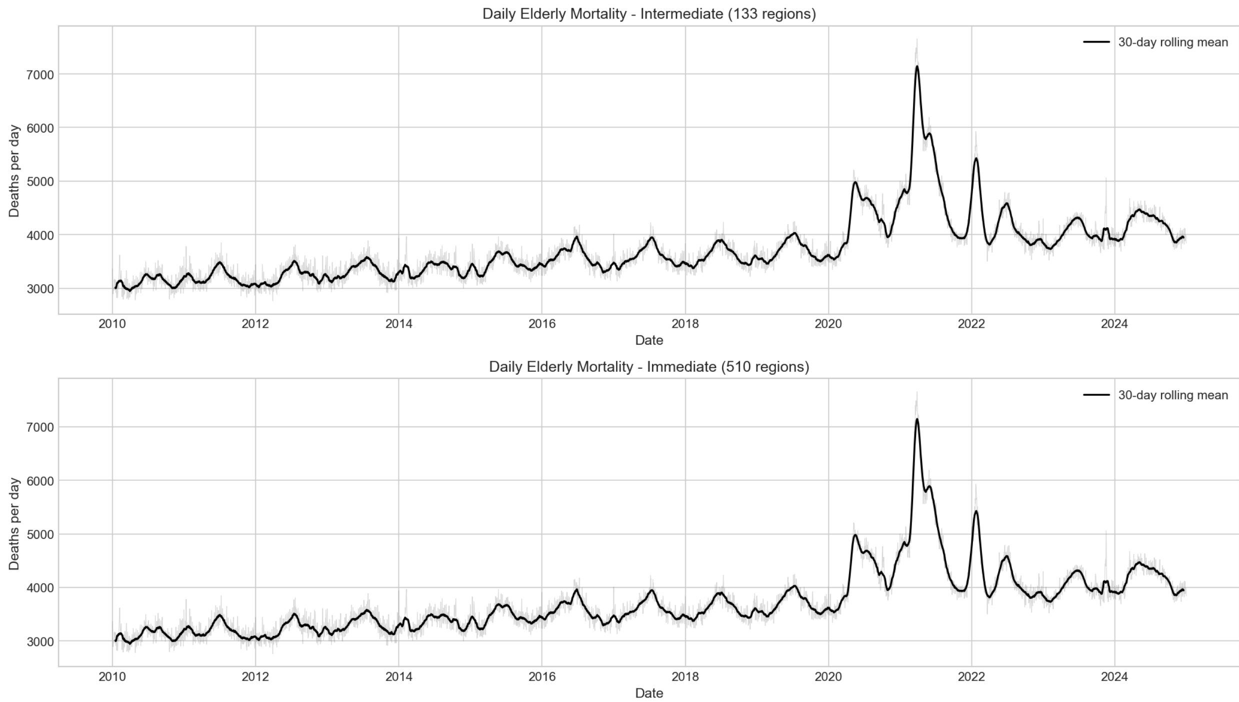

Figure 14: **Figure S6: Daily elderly mortality time series (2010-2024).** Seasonal patterns and long-term trends in elderly mortality across Brazil.

8.4.7 Figure S7: Temperature Distribution

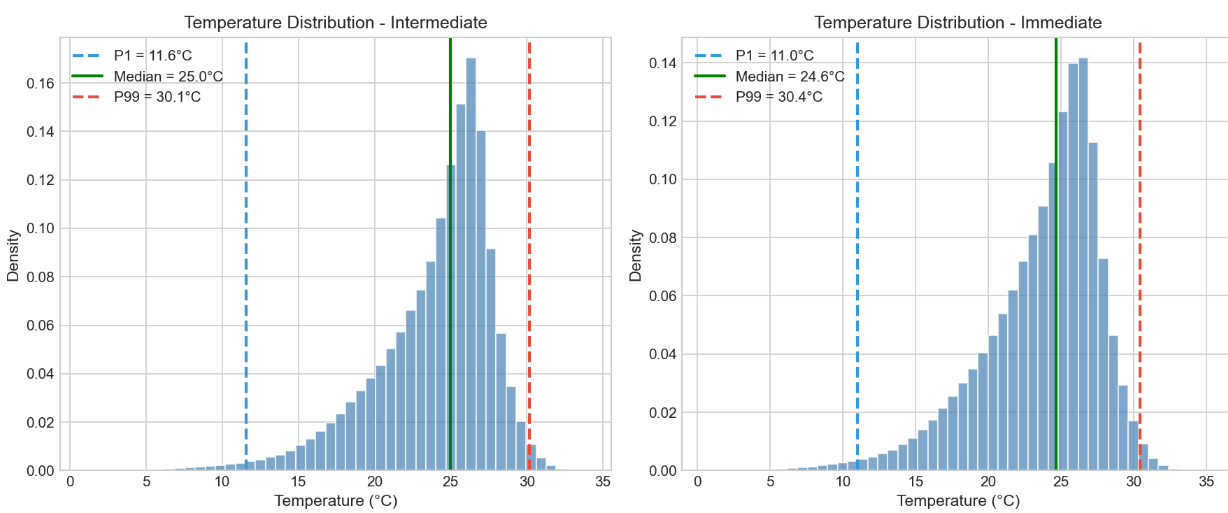

Figure 15: **Figure S7: Distribution of daily mean temperatures across study regions.** The temperature distribution showing the range of exposures experienced by the study population.

8.4.8 Figure S8: Seasonal Patterns

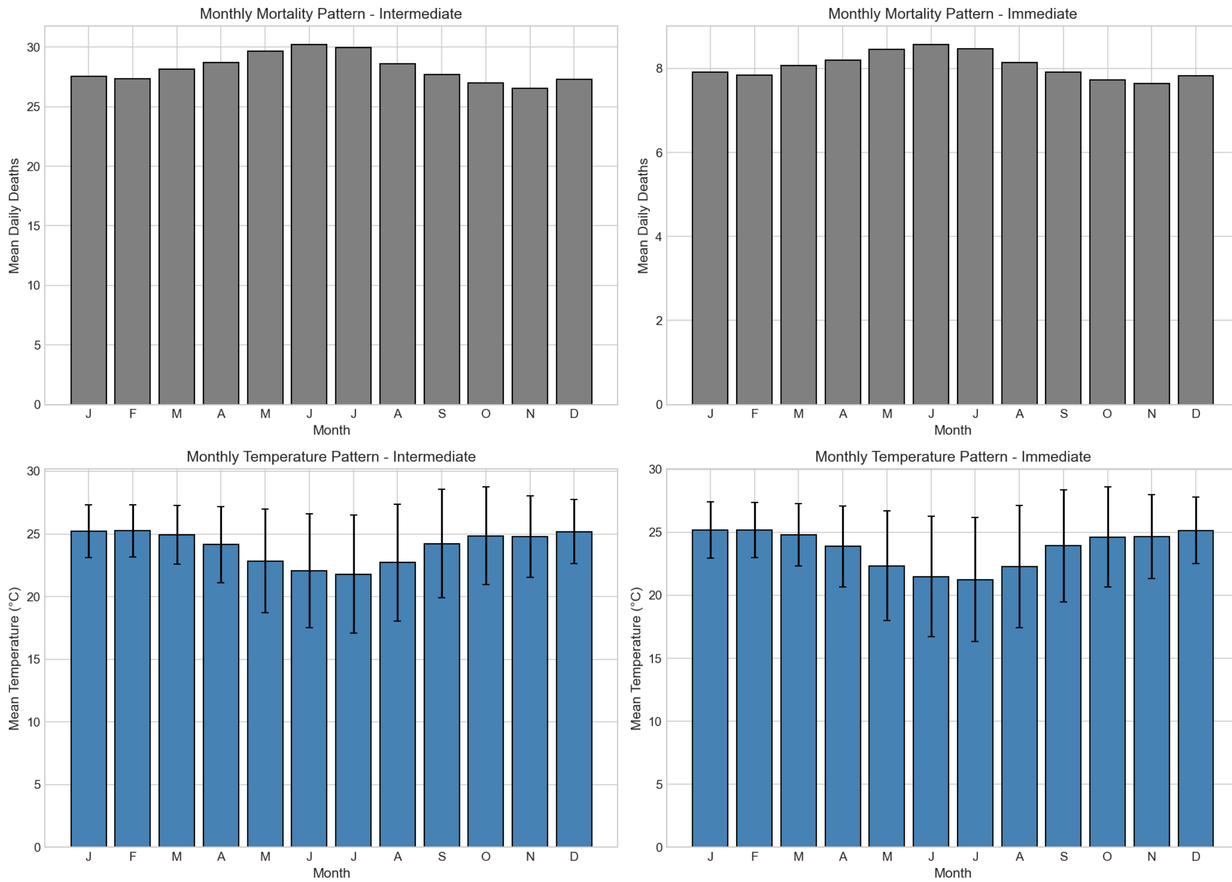

Figure 16: **Figure S8: Seasonal patterns in mortality and temperature.** Monthly averages showing the inverse relationship between temperature and mortality across seasons.