LIVING LAB

Chee Keen Liang, Dr. Wenjun Zhu, Dr. Shinichi Kamiya, Dr. Ciyu Nie
Insurance Risk and Finance Research Centre, Nanyang Technological University

10 March 2026

Climate-Adjusted Mortality Modelling In Asia

Acknowledgement

The paper has greatly benefited from the insightful comments and suggestions provided by GAIP Partners. The authors express sincere gratitude for all their contributions.

Suggested Citation:

Global Asia Insurance Partnership. (2026). Climate-Adjusted Mortality Modelling in Asia. https://www.gaip.global/publications/climate-adjusted-mortality-modelling-in-asia/

Global Asia
Insurance Partnership

Executive Summary

Climate change is reshaping mortality patterns worldwide, and Asia—home to more than half of the global population—is among the most exposed regions. Rising temperatures, intensifying heatwaves, persistent cold events in temperate zones, and elevated air pollution levels present mounting risks to life and health. For insurers and governments, understanding how these hazards translate into mortality outcomes is critical for pricing, reserving, and long-term planning.

This study develops a new actuarial framework to quantify and project climate-attributable mortality across East and Southeast Asia. The framework separates climate-related mortality drivers—extreme heat, extreme cold, and PM2.5 air pollution—from other mortality causes to estimate the specific contribution of environmental risks to total mortality trends. Using historical data (1990–2019) from the Global Burden of Disease Study and climate scenarios from CMIP6, we assess mortality impacts across ten Asian markets: China, Japan, South Korea, Indonesia, Malaysia, Singapore, Thailand, Laos, Myanmar and Philippines.

A core contribution of this work is the introduction of a Climate Risk Adjustment Factor (CRAF)—an actuarial measure that quantifies the incremental mortality load arising from climate change under alternative IPCC climate scenarios (SSP1-2.6 to SSP5-8.5). CRAF can be applied to base mortality tables, providing insurers with a practical stress-testing tool to evaluate future climate risk exposure and incorporate climate-aware assumptions into underwriting, pricing, and capital modelling.

Key Findings:

- Climate-attributable mortality is non-negligible across Asia and exhibits substantial heterogeneity by geography and age groups, with higher burdens observed in aging populations and urbanised regions.
- Heat-related mortality shows an increasing trend, particularly in warmer Southeast Asian countries and among older adults, consistent with accelerated warming in the region.

- Cold-related mortality remains significant in East Asia, especially in countries with strong seasonal variation, and is projected to gradually decline as winters become milder under future climate pathways.
- Air pollution continues to be the dominant climate-linked mortality burden in Asia. However, future trajectories differ by country, reflecting variation in industrialisation, energy transition pathways, and air-quality policy effectiveness.
- Our ensemble modelling approach combining linear and generalised-linear structures provides consistent and robust performance across countries and climate variables, supporting the credibility of the proposed Climate Risk Adjustment Factor (CRAF) framework for mortality stress testing.

Implications for Insurers:

- Climate change introduces systematic and non-diversifiable mortality risk, particularly for life and health portfolios concentrated in Asia.
- Traditional mortality improvement models may understate long-term risks by not explicitly isolating climate effects.
- CRAF provides a transparent, scalable, and implementable actuarial tool for climate-adjusted mortality projections and capital adequacy assessments.
- The framework supports regulatory climate stress-testing expectations, aligning with emerging standards such as those from MAS, EIOPA, and the NAIC.

This report advances climate-mortality analytics by providing a data-driven, actuarially grounded method to quantify the mortality effects of climate change in Asia. The proposed Climate Risk Adjustment Factor (CRAF) bridges scientific research and insurance practice, offering the industry a practical tool to incorporate environmental risk into mortality projections, capital planning, and product development. As climate risk accelerates, life insurers, policymakers, and investors must prepare. This framework enables a proactive approach to safeguarding financial resilience and public health in one of the world's most climate-vulnerable regions.

Contents

1 Introduction

1.1 Why study multiple hazards of climate-induced deaths?

Studying the health impacts of multiple climate risk factors—such as heat, cold, and air pollution—is essential to understanding and mitigating the consequences of climate change on mortality. Climate change is not only an environmental concern but also a major public health crisis, with the World Health Organization (WHO) projecting an additional 250,000 deaths annually between 2030 and 2050 due to climate-related causes. These include both acute events like tropical storms and heatwaves, and chronic effects like deteriorating living conditions. Importantly, the health effects of these climate risks are not isolated; their interplay can significantly amplify mortality risk, especially in regions experiencing rapid urbanisation and infrastructure stress.

In Asia—particularly Southeast and East Asia—the effects of air pollution and non-optimal temperature are especially pronounced. While air pollution has long been recognized as a significant mortality driver, there has been a recent spike in related deaths after decades of decline, potentially reflecting a shift linked to continued industrialisation (Figure 1). Fine particulate matter (PM2.5) in particular poses severe risks, penetrating deep into the lungs and bloodstream to trigger cardiovascular, cerebrovascular, and respiratory diseases.

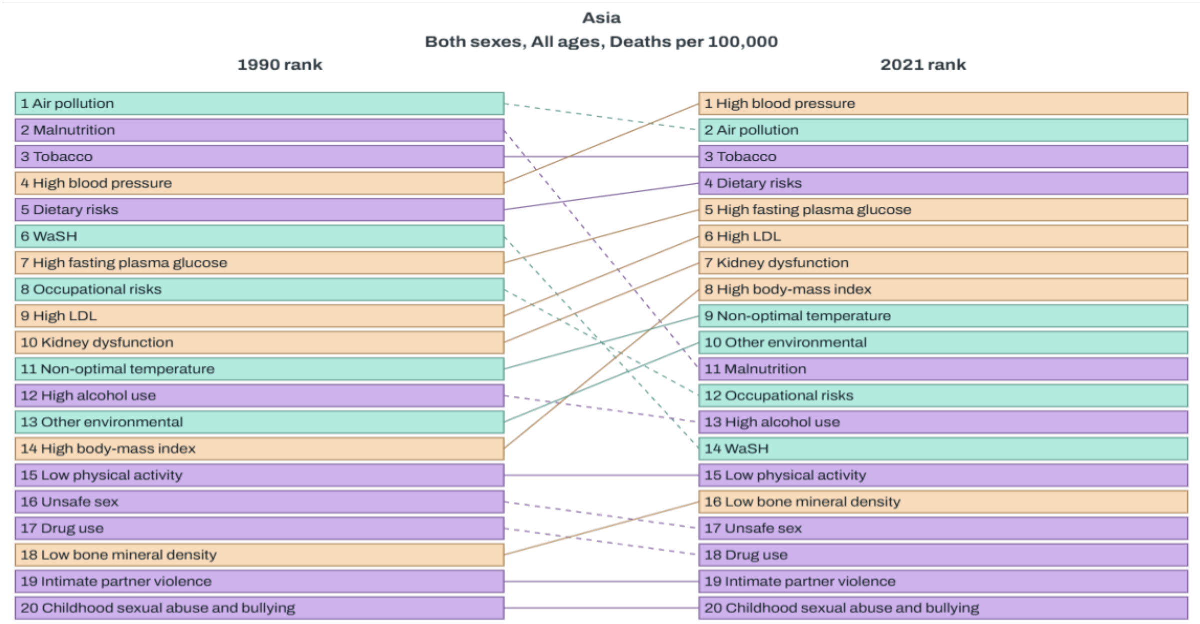


Figure 1: Most significant mortality factors in Asia,
Source: Global Burden of Disease Study 2021 (GBD 2021) Compare.

On the other hand, non-optimal temperature, though historically a less significant risk in Southeast Asia due to its stable tropical climate, shows a marginally increasing mortality trend (Figure 2). East Asia, with its wider seasonal variability, suffers higher death rates from both heat and cold exposures, reflecting the region's vulnerability to temperature extremes. While cold exposure tends to result in a greater number of deaths due to its frequency, extreme heat events are becoming more intense and prolonged due to global warming, with both ends of the temperature spectrum contributing to cardiovascular and respiratory strain. When combined with pollution, these effects may be exacerbated, as hot conditions intensify ozone formation and heighten susceptibility to airborne pollutants.

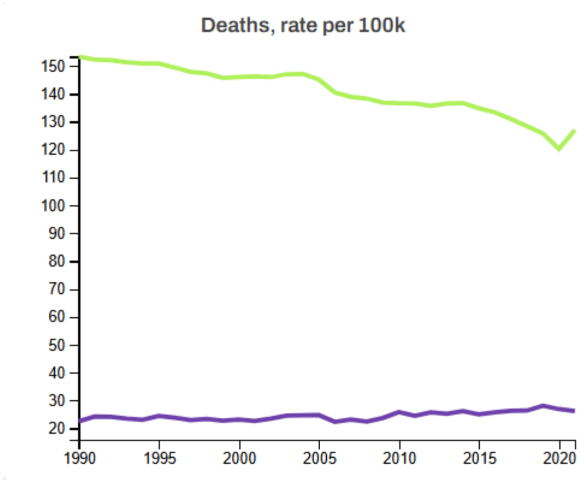


Figure 2: Historical death rate for air pollution (green) and non-optimal temperature (purple)
Source: Global Burden of Disease Study 2021 (GBD 2021) Results.

A multi-hazard approach is therefore critical for policy relevance. Mortality risk is shaped by the interaction of environmental, demographic, and infrastructural factors, and this interplay varies by country and region. By analyzing climate risks comprehensively—particularly in high-risk zones like East Asia—we can better identify emerging threats, monitor deviations in mortality trends, and develop targeted health and environmental policies. This also enables governments to differentiate between short-term disruptions and long-term shifts in climate vulnerability, making it possible to allocate resources efficiently and protect vulnerable populations.

1.2 Focus of this study

In this paper, we propose a general framework for estimating the impact of climate risks on mortality rates. This new method introduces a clear way to separate observed mortality into two parts: one caused by climate-related factors—such as air pollution, extreme heat, and extreme cold—and another caused by all other, non-climate-related factors. By isolating the impact of environmental risks, this approach offers a more accurate understanding of how climate change contributes to mortality, both historically and in future projections.

To estimate these components, we apply well-established forecasting techniques for overall and non-climate death rates. For the climate-related portion, we develop separate models for each risk factor using environmental data and air pollution data. These models explain how each climate condition relates to changes in death rates across different countries and age groups. To improve accuracy and reliability, we average the results from multiple model types, a ensemble technique widely used in predictive analytics and insurance risk modelling.

A key feature of this framework is the introduction of the *Climate Risk Adjustment Factor* (CRAF), which shows how much adjustment to future death rate is needed (under different climate scenarios), when modelling climate-related mortality separately from other-factor-caused mortality rates. This study focuses on two specific climate risks—non-optimal temperature and air pollution—but the proposed framework is general and flexible, allowing for the inclusion of other risk types as well. This provides a straightforward way to quantify the influence of each climate factor on mortality, making it highly relevant for insurance risk assessment and pricing.

What sets this method apart is its flexibility and ease of integration into insurance practice. Because it uses familiar modelling techniques and produces interpretable outputs like adjustment factors, it can be readily adopted by actuaries and underwriters to refine mortality projections, assess portfolio exposure to climate risk, and develop more climate-resilient products. This framework not only advances academic understanding of climate-related mortality but also provides insurers with practical tools to address emerging environmental risks.

This study focuses on Asia because the region faces some of the high mortality risks from climate-related factors, particularly temperature extremes and air pollution. Rapid urbanisation and industrialisation have led to worsening environmental conditions in many Asian countries, with Southeast Asia and East Asia showing especially high and rising death rates linked to air pollution. While deaths due to non-optimal temperatures are currently lower in Southeast Asia, East Asia ranks among the highest globally due to greater seasonal temperature variation. Despite this, research on temperature-related mortality in Asia—especially in Southeast Asia—remains limited. By focusing on Asia, this study addresses a critical research gap and provides insights that are directly relevant to the region’s evolving public health and environmental challenges.

2 *Literature review*

2.1 Non-optimal temperature

Non-optimal temperature includes exposure to both extreme heat and cold. Before discussing non-optimal temperature, we first understand the definition of optimal temperature. Then anything that is not in the range of optimal temperature will be non-optimal temperature.

2.1.1 Optimal temperature

Every population adapts over time to a range of local temperatures that minimizes adverse health outcomes. This range is often anchored by the Minimum Mortality Temperature (MMT)—the ambient temperature at which the lowest mortality rate is observed (e.g., Gasparrini et al, 2015). The MMT serves as a proxy for a population's thermal comfort zone, reflecting the region's climate, infrastructure, health system resilience, and population characteristics. For instance, Tobías et al. (2021) report that the country pooled MMT for Southeast Asia lies between 27°C and 29°C, while that for East Asia is lower, between 25.5°C and 26.5°C, both with 95% confidence intervals.

2.1.2 Non-optimal temperature

Non-optimal temperature refers to any ambient temperature that deviates from this MMT—either hotter (heat exposure) or colder (cold exposure). Both extremes are associated with increased mortality risks, though the mechanisms and prevalence differ.

High temperatures can cause physiological stress leading to heatstroke, cardiovascular overload, and respiratory complications, particularly during heatwaves. Heat also elevates ozone and air pollutant levels, worsening respiratory diseases, and increases the likelihood of wildfires, which contribute to toxic smoke exposure.

Low temperatures, on the other hand, elevate the risk of cardiovascular events, respiratory infections, and influenza-related complications, especially among vulnerable populations. Cold weather also tends to have a more sustained and widespread impact compared to short-term heat spikes. This is consistent with the finding that, in many temperate and subtropical regions, cold temperatures contribute to a larger share of temperature-related deaths, even if heat tends to attract more public attention due to its acute, visible impacts.

Beyond direct physiological effects, non-optimal temperatures also have indirect consequences on health and mortality (see, e.g., IPCC 2021). These include:

- **Increased vector-borne disease transmission** due to shifting climate patterns,
- **Compromised food and water safety** from temperature-sensitive contamination pathways, and
- **Population displacement and sanitation-related diseases** stemming from natural disasters, such as floods or saltwater intrusion caused by rising sea levels.

Using daily all-cause death counts and daily temperature data, Gasparrini et al. (2017) reports that in East Asia—which includes countries like China, Japan, and South Korea—cold temperatures during the period of 2010-2019 contribute significantly to excess mortality, accounting for around 7.4 to 8.7 percent of deaths. Heat-related deaths in this region are relatively low at present, about 0.3 to 0.5 percent. By the end of the century, under a high-emissions scenario (RCP8.5), cold-related deaths are expected to decline to 3.7 to 5.9 percent due to warming winters, while heat-related mortality will rise moderately to about 2.5 to 3.2 percent. The net effect in East Asia remains minimal, with a projected change in total temperature-related mortality of roughly –0.1 percent, indicating a balance between decreasing cold-related deaths and increasing heat-related ones.

In contrast, Southeast Asia—covering countries such as Thailand, Vietnam and the Philippines—faces a much more severe impact. Already experiencing warmer climates, this region during the period of 2010-2019 has a higher proportion of heat-related mortality, ranging from 0.6 to 1.7 percent. Cold-related mortality is already low and is expected to decline even further. By 2090–2099 under RCP8.5, the study forecasts a steep rise in heat-related deaths, reaching up to 16.7 percent of total mortality, while cold-related deaths would drop to around 0.7 percent. The overall net increase in temperature-related excess mortality in Southeast Asia could reach 12.7 percent, making it one of the most vulnerable regions to warming.

The methodology used in healthcare studies such as Gasparrini et al. (2015, 2017) offers a significant advantage in its ability to capture the high-resolution, short-term sensitivity between daily temperature fluctuations and daily mortality counts. By employing distributed lag non-linear models, these studies effectively estimate how both the magnitude and timing of temperature deviations—whether hot or cold—affect mortality risks over a span of days. This approach quantifies the relative risk of death at different temperature levels. As a result, it is particularly well-suited for informing short-term public health interventions, such as heatwave warnings or cold weather protection policies.

However, while this methodology excels in measuring immediate and localised health responses to temperature, it is less informative about how climate factors influence long-term changes in overall mortality rates at the population level. These models are designed to attribute mortality on a day-by-day basis relative to specific temperature exposures, assuming a stable baseline mortality rate and no adaptation change. On the other hand, our proposed approach explicitly models long-run mortality improvement trends and climate-driven deviations, which is more aligned with risk-management needs in insurance applications.

2.2 Ambient (outdoor) air pollution

Air pollution and climate change are closely interconnected through the emission of greenhouse gases and aerosols. Pollutants like carbon dioxide (CO_2) and methane contribute directly to global warming by trapping heat in the atmosphere, thereby increasing average global temperatures. Other air pollutants also absorb sunlight and heat the atmosphere, accelerating the melting of ice and snow (see, e.g., IPCC 2021).

There are several categorisations for air pollution in GBD, but we only focus on particulate matter (PM) pollution, specifically ambient particulate matter pollution. As the name suggests, PM is a common proxy indicator for the severity of this pollution. PM is further split into two categories: PM10 and PM2.5.

PM10 measures the presence of particles larger than micrometres in diameter in the air. Usually, these particles are deposited in our nose or throat, as they are large enough to be filtered by our nose hair. Short-term exposures are typically associated with worsening of respiratory diseases.

While for PM2.5, it measures the presence of much finer particles in the air, specifically those that are 2.5 micrometres or less in diameter. These particles are much finer and cannot be filtered by our nose and throat. The main impacts of PM2.5 on human health can be severe. They can penetrate our lung barrier, leading to respiratory disease and cancers. Respiratory disease deaths vary by age, sex, and country of residence. In general, the highest rates of respiratory disease deaths occur in people 60 years and older. Since PM2.5 is also capable of penetrating into the bloodstream, it can lead to cerebrovascular and cardiovascular deaths (see Table 1 for the definitions of each death).

Table 1: Summary of deaths caused by PM2.5

Exposure	Definition	Impact on human health
Cerebrovascular deaths	A general term for a variety of conditions that affect the brain's blood vessels and circulation.	Stroke and brain bleed
Cardiovascular deaths	Any disease involving the heart or blood vessels.	Heart attacks and strokes
Respiratory deaths	Conditions that affect the lungs and other parts of the respiratory system.	Asthma and lung cancer

Pozzer et al. (2022) reviews the literature of estimates of mortality from ambient air pollution, focusing on PM2.5 and ozone. The methodology commonly adopted by the literature is to combine pollutant concentration data with population density and mortality rates, which feed into exposure–response functions. Regardless of similarity between the methodology adopted by the air pollution studies and that for temperature-mortality studies, the air pollution studies use annual data to reflect the health effect of long-term exposure to air pollution.

However, it relies on stable baseline mortality data that may be imprecise in some regions. Thus, it is less informative about how climate factors influence long-term changes in overall mortality rates at the population level.

2.3 Review of modelling methodologies

Several statistical approaches have been proposed to model climate related mortality, including splines, relative risk models, distributed lag non-linear models (DLNMs), time series models and machine learning models.

Splines are the pioneer and foundation for most climate mortality modelling approaches. These are flexible regression tools that can capture complex non-linear relationships between mortality and exposure (temperature or air pollution). Common implementations include natural cubic splines, B-splines and P-splines. Armstrong (2006) Chas demonstrated that splines can be used to model the association between temperature and mortality.

DLNM extends the spline-based approach by allowing for lag effects. This approach is particularly suited to assess the delayed impact of environmental exposures on mortality. Since its introduction by Gasparrini in 2010, this model has gained much popularity and has been widely used in temperature-mortality studies in several regions such as UK (Lo et al., 2022) and China (Yang et al., 2012). Although DLNM utilises splines for modelling, it has the characteristics of time series models by allowing for lag effects. Despite its flexibility, DLNM is only suited to model daily or at most weekly deaths due to its lag characteristic. It is unusual for heatwaves or cold spells to have an impact on mortality after a year.

Relative risk (RR) models is one of the other main approaches used in environmental health studies, which quantifies the association between exposure and mortality risk compared to a baseline. These models estimate the multiplicative increase in mortality risk associated with the deviation of the exposure from an optimal condition. RR models often employ Poisson or quasi-Poisson regression frameworks to account for overdispersion in mortality data. The authors used this methodology to quantify the MMT in Section 2.0.2. A GBD study done by Burkart et al. (2021) employed this approach with Bayesian meta-regression frameworks to model cause-specific mortality of 176 causes across 23 temperature zones. This model provides an intuitive presentation on how mortality changes with exposure by providing the excess mortality per unit increase in exposure. However, they can only provide a general overview of the impact and is unable to model in much more granularity such as handling delayed effects of exposures.

Recently, machine learning models such as random forests has been proposed. Kim and Kim (2022) proposed to use random forests combined with spatial modelling to model heat-related mortality in South Korea. However, to date, most of the research deals with short-term mortality impacts without considering adaptation measures and mortality improvement over time. We aim to bridge this gap by adopting actuarial techniques and models to quantify the impact of climate change in the long-term. Our approach allows for mortality improvement and investigate different mortality trends under different climate scenarios.

3 Data exploration

3.1 Climate related mortality data

3.1.1 Data source

In this study, we consider three risk factors to study: Air pollution, high temperature (extreme heat exposure) and low temperature (extreme cold exposure). From the Global Burden of Disease (GBD) Study 2021, we obtained death counts per 100,000 exposures attributable to these risk factors respectively. We acknowledge the fact that these deaths are model estimates by GBD, and there may be uncertainty in these estimates.

Death data obtained should be interpreted with care. According to GBD, the risk factor is defined by: An attribute, behavior, exposure, or other factor which is causally associated with an increased (or decreased) probability of a disease or injury. If the probability decreases, the risk is a protective factor. In simple words, the deaths data represents how exposure to a risk factor will increase/decrease death counts.

The data includes annual death counts from 1990-2021 for 18 age groups. 5 ages are aggregated into one age group, starting from 0-5 ages as the first age group. Ages above 85 years are aggregated into one group. We obtained death data from selected regions in Asia. We focused on East Asia (EA) and SEA countries and performed a country-level analysis based on data availability.

We are unable to obtain climate data for Cambodia; thus it is excluded in subsequent research. All other countries in SEA (Indonesia, Malaysia, Singapore, Thailand, Laos, Myanmar and Philippines) and EA (China, Japan and South Korea) are studied.

3.1.2 Climate mortality trend of different ages

In this section, we seek to understand mortality trends of different ages in both regions. We show the death counts per 100,000 exposures for each age group in both regions and observe any regional differences.

3.1.2.1 Heat exposure

In general, heat exposure is associated with increased mortality across all age groups, though the magnitude and sensitivity vary significantly by age. Analysis of data from the Global Burden of Disease (GBD) 2021 for both East Asia and Southeast Asia (SEA) reveals consistent patterns that highlight the vulnerability of specific age groups to extreme heat.

Across all age groups, heat-related mortality risk is present, but the relationship between age and mortality exhibits a U-shaped curve (Figure 3). This shape reflects elevated risk at the extremes of the age spectrum, with a trough in middle age, where individuals tend to be more physiologically resilient and have fewer chronic health conditions.

Older adults (>60 years): This group consistently shows the highest levels of heat-related mortality. Several physiological and social factors contribute to this vulnerability (see e.g., Millyard et al., 2020):

- **Reduced thermoregulation:** Aging bodies are less efficient at dissipating heat due to impaired sweating and diminished cardiovascular responsiveness.
- **Prevalence of chronic diseases:** Conditions such as cardiovascular disease, diabetes, and respiratory illnesses—common in older populations—are aggravated by heat.
- **Medication use:** Some medications impair the body's ability to cope with heat stress.
- **Social isolation and mobility issues:** Older adults may live alone or lack access to cooling environments and hydration.

Young children (<5 years): Although the increase in mortality is less dramatic than in older adults, children under five also display notable sensitivity to heat exposure. Their immature thermoregulatory systems, higher metabolic rates, and dependency on caregivers for hydration and shelter make them particularly susceptible to heat exhaustion, dehydration and infectious diseases.

Middle-aged adults (15–59 years): Mortality rates due to heat are generally lower in this group, which forms the most physiologically robust segment of the population.

Nevertheless, individuals with underlying health conditions, those working in high-heat occupational settings (e.g., construction, agriculture), or experiencing poor housing conditions remain at risk.

Figure 3 clearly illustrate these patterns for East Asia and Southeast Asia, respectively:

- Both regions show a **sharp increase** in mortality among the elderly, with the steepest rise observed in individuals aged 70 and above.
- A modest **increase** in deaths is also observed among infants and toddlers, reaffirming the double vulnerability at the start and end of the life course.

These trends are consistent across regions, though absolute mortality levels may differ depending on healthcare access, climate adaptation, and infrastructure.

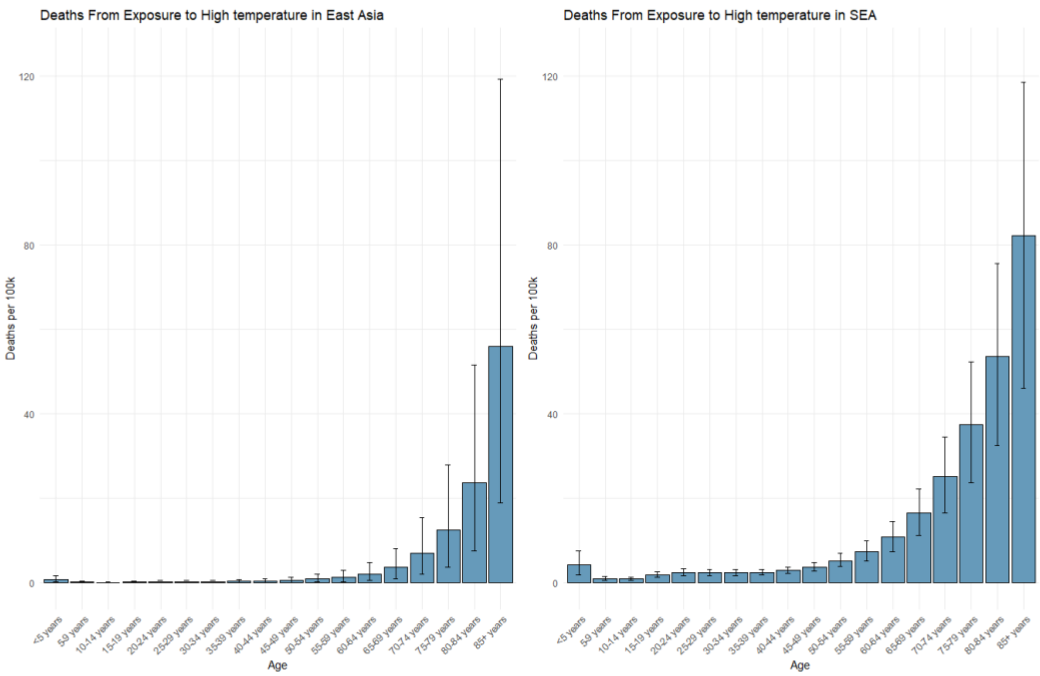


Figure 3: Deaths by age group due to heat exposure in East Asia and SEA
Data source: GBD (2021).

3.1.2.2 Cold exposure

Cold exposure remains a significant environmental risk factor contributing to mortality, particularly in regions with seasonal temperature variability such as East Asia and Southeast Asia. However, the effects vary markedly across age groups.

Data from the Global Burden of Disease (GBD) 2021 show that cold exposure exhibits an age-related gradient in mortality risk, similar to heat exposure, but with some important distinctions.

Older adults (>60 years) are once again the most vulnerable group. The mortality risk increases steeply with age, with particularly high excess deaths in the 70+ age group (e.g., Li, et al. 2022; Achebak, et al. 2024). This is attributed to:

- **Impaired thermoregulation in the elderly**, making them less able to maintain core body temperature.
- **Exacerbation of cardiovascular conditions** due to vasoconstriction and elevated blood pressure.
- **Respiratory complications**, including infections like pneumonia, which are more prevalent and severe in colder temperatures.
- **Reduced mobility, social isolation, and insufficient heating in homes**.

Middle-aged adults (roughly 30–60 years), however, display an interesting anomaly: the data indicate marginally negative excess deaths due to cold exposure—i.e., a small protective effect in this age group. This phenomenon may arise for several reasons such as better health, with stronger cardiovascular and immune function, making them more resilient to moderate cold stress. This group is also more economically active, with better access to heating, clothing, and healthcare, which mitigates risk.

Young children (<5 years) experience some elevated risk, though not as sharply as the elderly. Infants are less capable of generating body heat and rely on caregivers for warmth, but with adequate care, their vulnerability can often be managed.

This nonlinear pattern, as shown in Figure 4, underscores the U-shaped distribution of cold-related mortality. The elderly consistently show high excess mortality, but the middle-aged group experiences either neutral or slightly negative impacts, suggesting that cold exposure is not universally harmful across all demographics.

Moreover, global warming may lead to a reduction in cold-related mortality, particularly among the elderly—offsetting some of the increased deaths from heat exposure.

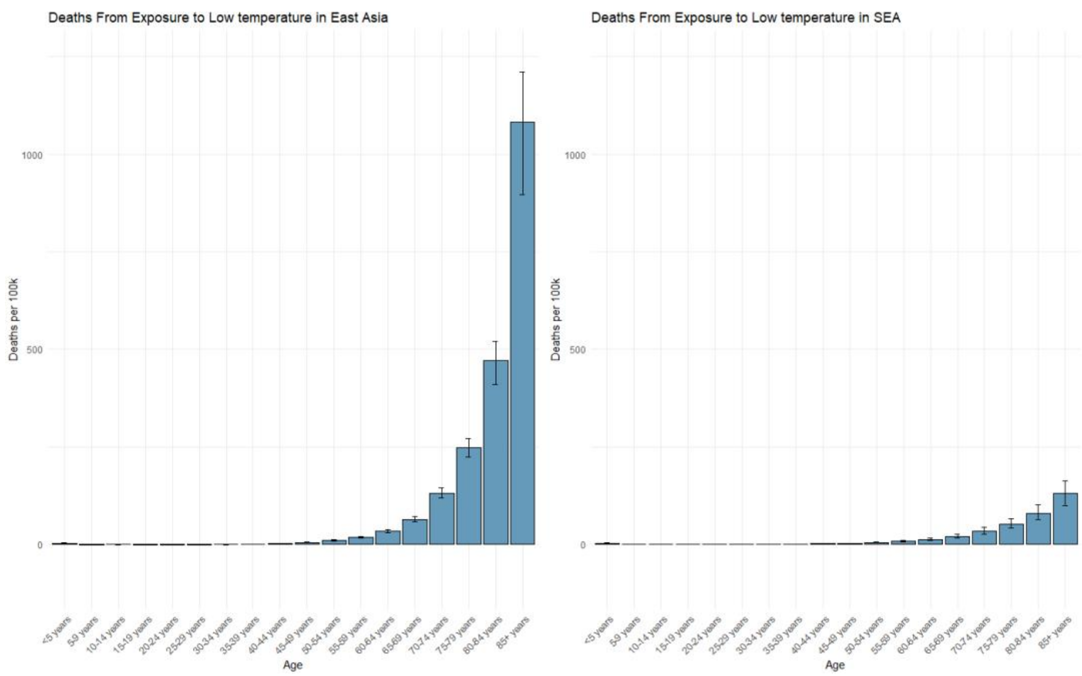


Figure 4: Deaths by age group due to cold exposure in East Asia and SEA
Data source: GBD (2021).

3.1.2.3 Air pollution

Air pollution—particularly fine particulate matter such as PM2.5—is a major global health risk and a significant contributor to premature mortality. Its effects vary by age and region, reflecting differences in physiological vulnerability, environmental exposure, and healthcare access. Data from GBD (2021) indicate distinct patterns in East Asia and Southeast Asia (SEA) in terms of age-specific mortality due to air pollution.

In East Asia, the age-mortality profile due to air pollution is strongly upward-sloping, showing a monotonically increasing curve (Figure 5). This means that as age increases, mortality attributable to air pollution also increases, with the most pronounced burden observed in individuals aged 60 and above.

In Southeast Asia, a slight U-shaped mortality curve is observed, suggesting that both the very young and the elderly are vulnerable. The differences in mortality curves between East Asia and SEA may also reflect regional variations in pollution sources, healthcare infrastructure, and climate conditions. For instance:
East Asian countries often experience high levels of PM2.5 from industrial emissions, coal burning, and vehicular exhaust, compounded by dense urban populations and cold-season smog events.

SEA countries may face more episodic pollution events such as transboundary haze from forest fires, in addition to urban air pollution, affecting broader age ranges, particularly the very young.

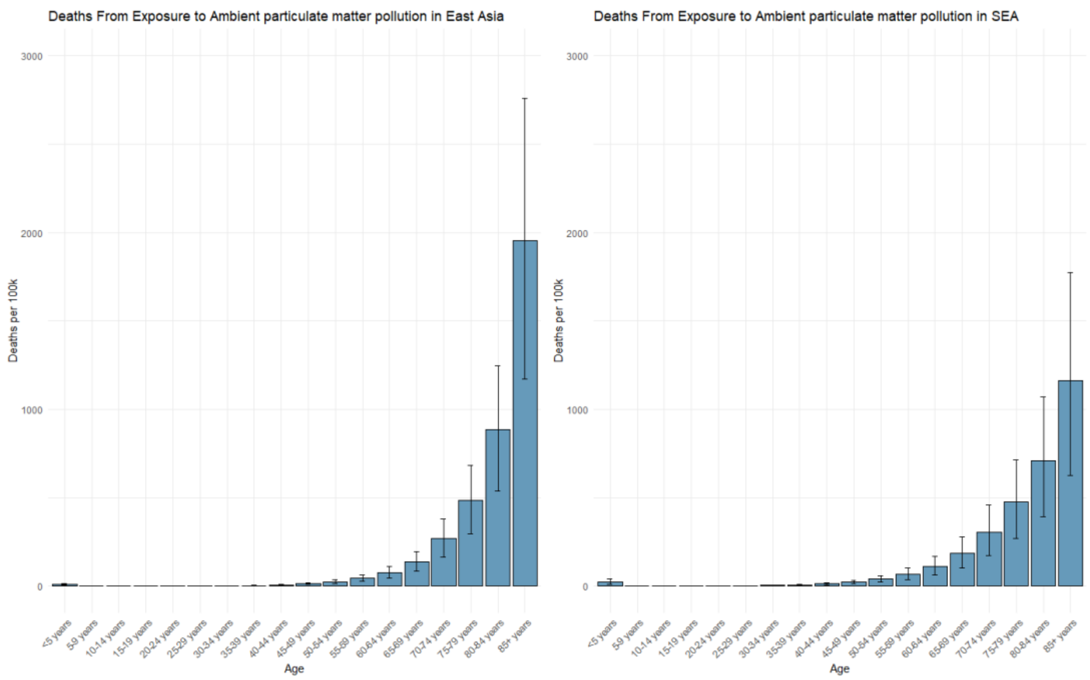


Figure 5: Deaths by age group due to air pollution in East Asia and SEA
Data source: GBD (2021).

3.1.3 Climate mortality trend of different countries

In this section, we seek to understand mortality trends of specific countries in both regions. We show the death counts per 100,000 exposures for each country and compare their differences. The countries are displayed geographically, starting with SEA countries, with EA countries at the right side of the plot.

3.1.3.1 Heat exposure

Figure 6 shows that Myanmar has the highest mortality rate from heat exposure, followed by Vietnam. These countries are in SEA and corresponds to the high temperature climate characteristic in SEA, which possibly explains the high mortality rate. However, some SEA countries have lower mortality rates such as Malaysia and Indonesia, possibly indicating the adaptation to high temperatures in these tropical countries. Japan and South Korea record significantly lower death rates due to less heat exposure compared with SEA countries.

The data reveal notable variation in heat-related mortality, which can be interpreted through a combination of climatic exposure, adaptive capacity, and socioeconomic development. Several factors likely contribute to these high mortality rates:

- **Chronic heat exposure without sufficient adaptive infrastructure** (e.g., limited access to cooling, inadequate housing insulation).
- **High proportion of outdoor workers** in agriculture and construction, who are more exposed to extreme heat.
- **Health system limitations**, which may reduce access to emergency care during heatwaves.
- **Demographic vulnerability**, including large rural populations and aging demographics in some regions.

Heat-related mortality rates are highest in countries classified as tropical monsoon climates, such as Myanmar, Vietnam and Thailand. Countries in the tropical rainforest zone—such as Indonesia, Malaysia, and Singapore—show lower heat-related mortality rates, despite similar or even higher temperature exposure. This suggests that climatic adaptation plays a crucial role in mediating the health impact of heat. On the other hand, countries that are cooler such as Japan and South Korea have lower heat-related mortality due to their low exposure.

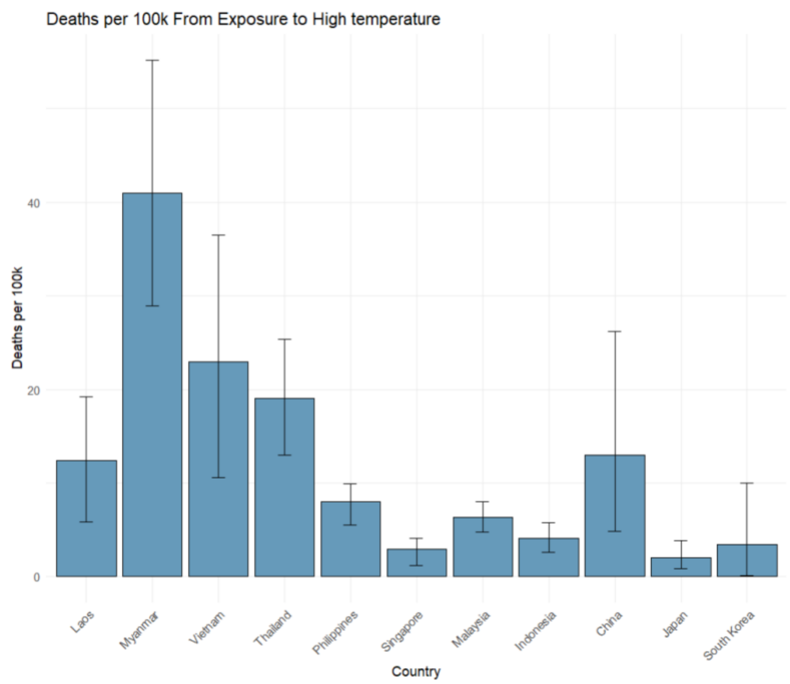


Figure 6: Mean death rate due to heat exposure
Data source: GBD (2021).

3.1.3.2 Cold exposure

Cold exposure remains a significant environmental risk factor for mortality, particularly in regions with seasonal climates. As shown in Figure 7, the mean death rate due to cold exposure varies substantially across countries in East and Southeast Asia, reflecting differences in climatic conditions, infrastructure, and population vulnerability.

Countries in East Asia, particularly China and South Korea, report the highest mortality rates from cold exposure in the region, despite economic development and growing infrastructure. Several factors explain this elevated burden:

- **Seasonal temperature variability:** These countries experience distinct winters with prolonged periods of cold temperatures, increasing population-level exposure.
- **Aging populations:** Elderly individuals are particularly vulnerable to cold-related complications such as cardiovascular strain, respiratory infections, and hypothermia.

- **Incomplete home insulation and heating access:** In many areas, especially rural China, homes may lack adequate heating or weatherproofing, exposing residents to indoor cold.
- **Air pollution interplay:** Cold temperatures often coincide with worsened air quality, especially during winter months due to coal burning and stagnant air, compounding respiratory health risks.

In contrast, countries in Southeast Asia—such as Thailand, Indonesia, Malaysia, and the Philippines—show very low or near-negligible mortality rates due to cold exposure. This is largely due to the tropical climate that dominates the region. These countries experience consistently warm or hot temperatures year-round, with virtually no exposure to temperatures below the human thermal comfort threshold.

This stark contrast between East Asia and Southeast Asia underscores the geographical specificity of climate-related health risks. Cold exposure is a region-specific hazard, posing a substantial threat in temperate and continental climates but virtually none in equatorial zones. It also suggests that cold-related deaths are preventable with proper housing, heating, and healthcare access—factors that remain unevenly distributed across East Asia. Furthermore, as global temperatures rise, some reduction in cold-related mortality may occur in East Asia, particularly if winters become milder.

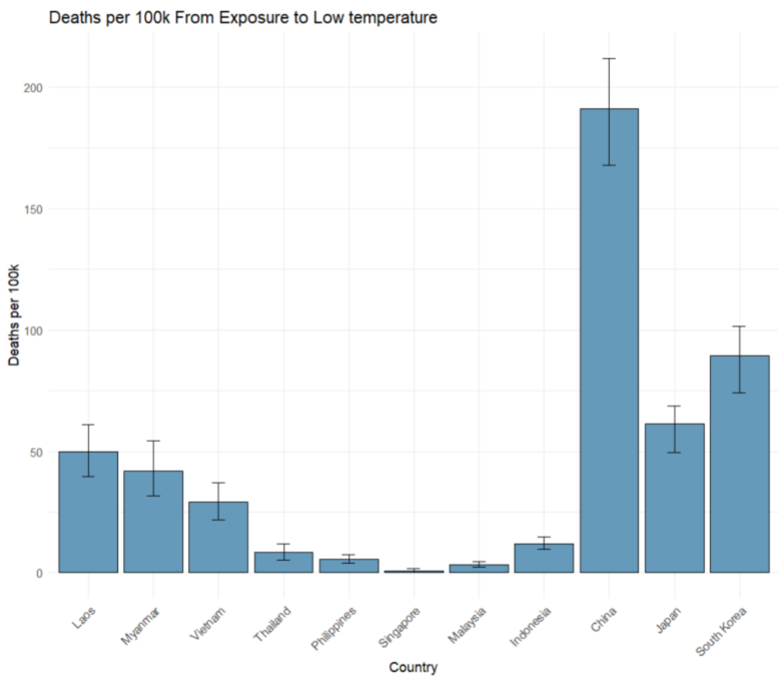


Figure 7: Mean death rate due to cold exposure

Data source: GBD (2021).

3.1.3.3 Air pollution

The impact of air pollution on mortality also varies substantially by country, shaped by differences in emission sources, population exposure, urbanisation, and mitigation efforts. Figure 8 from GBD (2021) shows the mean death rate attributable to air pollution, revealing several key patterns.

In East Asia, China records the highest mortality rate from air pollution and is the largest contributor to the overall air pollution-related death burden. Several factors explain this:

- China has a large industrial base with heavy reliance on coal, especially in northern provinces, leading to high concentrations of PM2.5, sulphur dioxide, and nitrogen oxides.
- Major cities such as Beijing and Tianjin experience sustained levels of air pollution that affect millions of people daily.
- Many parts of China have experienced decades of poor air quality, contributing to a chronic public health burden.

In Southeast Asia (SEA), Malaysia and Thailand stand out with notably higher death rates from air pollution compared to their neighbours. This categorises them as emerging high-risk countries in the region, for several reasons:

- Both countries are frequently affected by seasonal transboundary air pollution, primarily from biomass burning and forest fires in neighbouring countries, particularly Indonesia.
- Rapid urbanisation and high vehicle density in cities like Kuala Lumpur and Bangkok contribute to poor air quality, especially in areas with limited public transportation infrastructure.
- The growth of heavy industry and petrochemical facilities in parts of Thailand and Malaysia adds further to ambient air pollution levels.

Other SEA countries (such as Indonesia and the Philippines) also face pollution-related risks, though current data indicate comparatively lower death rates, likely due to a mix of lower population aging and differing exposure patterns.

The sharp contrast in air pollution mortality across countries illustrates that air pollution is both a transnational and local problem, suggesting that economic development alone does not shield populations from pollution-related harm. While emissions may originate in specific areas, their effects are regional in scope, requiring coordinated responses. In addition, mortality patterns are heavily influenced not just by pollutant levels, but also by population vulnerability, healthcare access, and chronic disease prevalence.

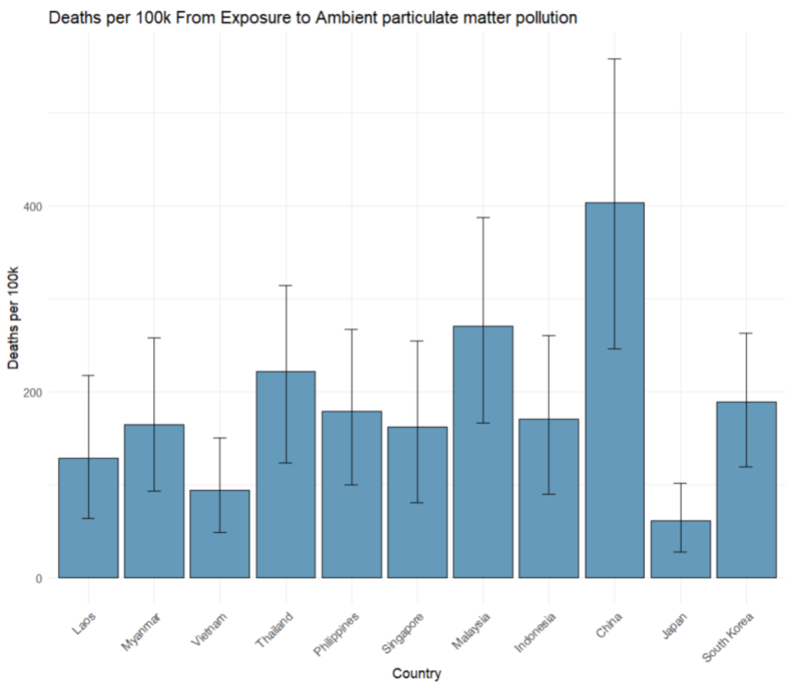


Figure 8: Mean death rate due to air pollution
Data source: GBD (2021).

3.2 Climate trend/scenario data

3.2.1 Data source

From the literature review above, we have identified the risk factors we wish to study and established a causal connection on how these risks affect death rates. Thus, we seek to explain these climate-related deaths by using related observable climate variables. We obtain the annual observations of climate data from Climate Change Knowledge Portal (CCKP), except for PM2.5 which is sourced from CMIP6. Below we identify some climate indicators which can be used to explain climate deaths.

Table 2: Climate risk studied, their indicators and naming

Climate risk	Indicators	Indicator name	Source
Extreme heat exposure	Cooling degree days	Cdd65	CCKP
Extreme cold exposure	Heating degree days	Hdd65	CCKP
Long-term temperature trend	Annual mean temperature	Tas	CCKP
Air pollution	PM2.5	PM2.5	CMIP6

We also obtained climate projections for four different climate scenarios, as defined by the Intergovernmental Panel on Climate Change (IPCC), namely SSP126, SSP245, SSP370 and SSP585. These scenarios represent different efforts in mitigating and adapting to climate change. Ideally, the best scenario is SSP126, which represents low challenges to both mitigation and adaptation. Below we show a summary of different representations of climate scenarios.

Table 3: Overview of different SSPs

	SSP126	SSP245	SSP370	SSP585
Carbon emission	High and immediate reduction	Moderate reduction	Minor reduction	Increasing
Energy sources	Renewables and biofuels	Renewables and fossil fuels	Fossil fuels	Increased reliance on fossil fuels
Global socio-economic trends	Prioritise sustainability and environment	Follow current trend	Slightly more emphasis on economic aspects	Prioritise economic benefits over environment

For the data obtained from CCKP, we obtain climate data from two models. For historical observations from 1990-2021, we used data from ERA5, while for future projections from 2022-2100, we used data from CMIP6. Although we would prefer to obtain data consistently from the same model, we note that CCKP does not provide future projections for ERA5.

For PM2.5, we use historical and projected data on PM2.5 concentrations, represented as the mass mixing ratio of PM2.5 in the atmosphere. The datasets are based on the CMIP6 model and cover various SSP (Shared Socioeconomic Pathways) scenarios that describe different future socioeconomic development paths. These datasets are provided by the NOAA-GFDL model and include monthly aerosol data, with a spatial resolution of approximately 100 km.

3.2.2 Climate scenario testing requirements

To assess the applicability of the scenarios defined by the IPCC to insurance practices, this section presents our understandings regarding whether life insurers are required to perform climate scenario testing on their liabilities as part of regulatory compliance.

To the best of our knowledge, out of the countries studied, only Singapore and Malaysia have relevant regulatory requirements. We note that the required scenarios set out by the regulators are different from our scenarios, and therefore the results might not be directly comparable. Recent climate scenarios recommended by regulators are centred around whether net zero is achieved by 2050 or not.

Singapore has three scenarios: Orderly Transition, Disorderly Transition and No Additional Policies. They respectively represent achieving net zero by 2050, achieving net zero after 2050 and no action to tackle climate change until 2050. Malaysia's scenarios are somewhat similar: Net Zero 2050, Divergent Net Zero 2050 and Nationally Determined Contributions. They respectively represent achieving net zero by 2050, accelerated achieving net zero before 2050 and policies are fully implemented but inadequate to facilitate an orderly transition. The scenarios are summarised in the table below:

Table 4: Scenario set out by Monetary Authority of Singapore (MAS)

Scenario	Orderly Transition	Disorderly Transition	No Additional Policies
Increase in temperature in 2050 relative to pre-industrial times	1.6°C	1.8°C	3.0°C

Source: (Monetary Authority of Singapore, 2022).

Table 5: Scenario set out by Bank Negara Malaysia

Scenario	Net Zero 2050	Divergent Net Zero 2050	Nationally Determined Contributions
Increase in temperature in 2100 relative to pre-industrial times	1.4°C	1.4°C	2.6°C
Transition risk	High	Moderate to high	Lower

Source: Bank Negara Malaysia (2024).

For comparability, we include the scenario definition for the different SSPs used in our analysis:

Table 6: SSP scenario set out by IPCC

Scenario	SSP126	SSP245	SSP370	SSP585
Increase in temperature in 2040-2060 relative to pre-industrial times	1.7°C	2.0°C	2.1°C	2.4°C

Source: (IPCC, 2021).

As seen from the comparison above, IPCC's climate scenarios do not necessarily align with the prescribed scenarios, from both timings and extent of temperature increase. However, the scenarios still present a certain degree of similarity, such as the orderly transition to net zero in 2050 scenario might align well with SSP126.

3.2.3 Climate trends

In this section, we seek to understand climate trends in the region, both historically and its future projections.

3.2.3.1 Extreme heat exposure: Cooling degree days (CDD65)

The CCKP defines Cooling Degree Days (CDD65) as the cumulative number of degrees by which the daily average temperature exceeds 65°F (approximately 18.33°C) over the course of a year. This metric is used to estimate the demand for energy needed for cooling buildings. An increasing trend in CDD65 is observable across all countries, indicating rising temperatures and a growing need for cooling—both in the historical record and in future climate projections. However, regional differences are apparent. In East Asian countries such as Japan, South Korea, and China, CDD65 values are generally lower because these countries experience cooler climates with more pronounced seasons. Temperatures exceed 65°F predominantly during the summer months, limiting the annual accumulation of cooling degree days. In contrast, countries in Southeast Asia typically record higher CDD65 values year-round due to consistently high temperatures. This regional disparity highlights how climate change and temperature increases will have uneven effects on cooling energy demand, with implications for infrastructure planning, energy consumption, and public health across different climates.

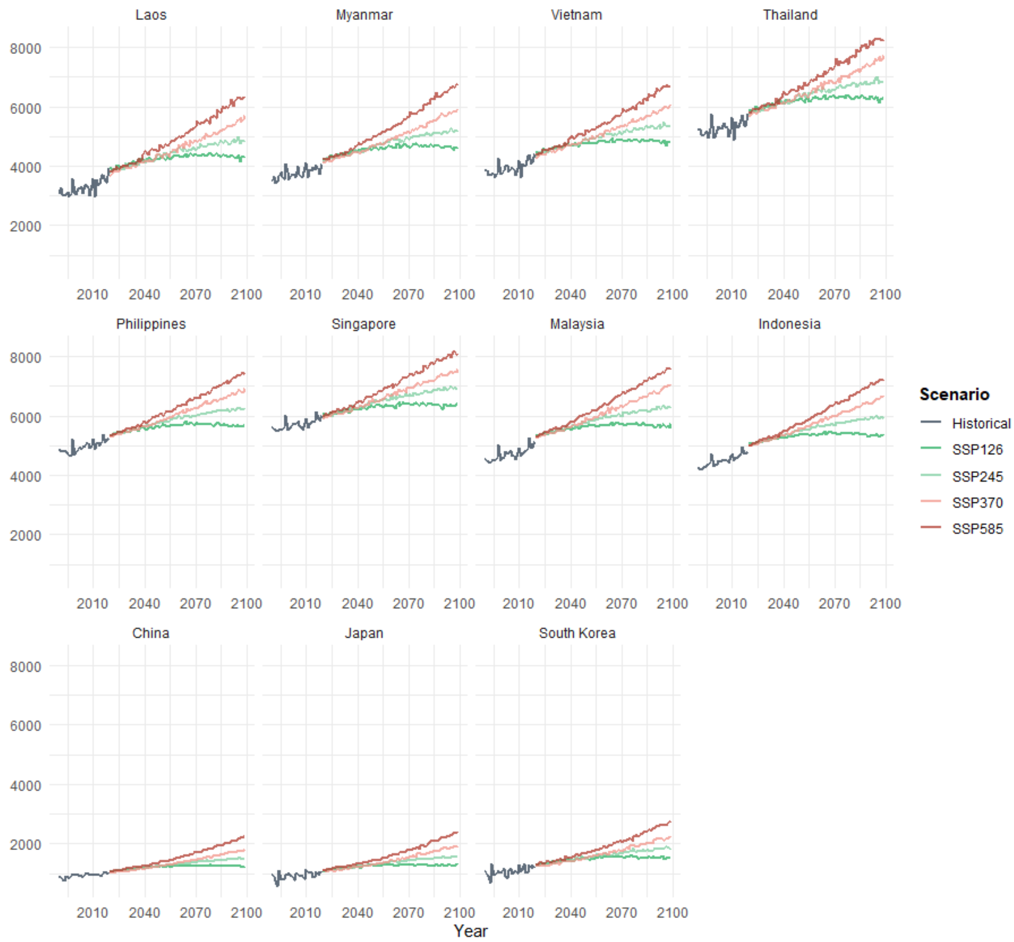


Figure 9: CDD65 of selected countries
Data source: CCKP (2021).

3.2.3.2 Extreme cold exposure: Heating degree days (HDD65)

In CCKP, heating degree days (HDD65) quantify the demand for energy needed to heat buildings by measuring how much, and for how long, the outside air temperature stays below a base threshold of 65°F (approximately 18.33°C) over the course of a year. A higher HDD65 value indicates colder climates where more heating is required, while a lower value suggests consistently warmer temperatures with little or no heating demand.

In Figure 10, we observe that Southeast Asian (SEA) countries exhibit extremely low HDD65 values—some approaching zero—reflecting their tropical climates where temperatures remain well above 18.33°C year-round. This sharply contrasts with East Asian countries like China, Japan, and South Korea, which have significantly higher HDD65 values due to their temperate climates and distinct winter seasons. During winter, average daily temperatures in East Asia frequently drop below the 65°F threshold, thereby increasing the cumulative HDD65. As such, the trend of HDD65 is the inverse of cooling degree days (CDD65), which measure the need for cooling in hot weather: while SEA countries score high on CDD65 due to consistently high temperatures, they show minimal HDD65, illustrating the stark climatic divide between tropical and temperate regions in Asia.

Figure 10: HDD65 of selected countries

Data source: CCKP (2021).

3.2.3.3 Long-term temperature trend: Annual mean temperature (Tas)

In CCKP, the annual mean temperature is calculated as the average of daily temperatures over a calendar year, expressed in degrees Celsius (°C). This metric is a key indicator of long-term climate trends and is commonly used to assess the impacts of global warming. Figure 11 shows that the annual mean temperature has been gradually rising across all regions, consistent with global climate change patterns driven by increasing greenhouse gas concentrations. However, significant regional variation exists. Southeast Asian (SEA) countries, such as Indonesia, Thailand, and the Philippines, typically record higher annual mean temperatures due to their equatorial or tropical climate zones, which experience warm conditions year-round. In contrast, East Asian countries like China, Japan, and South Korea exhibit lower mean temperatures, reflecting their more temperate climates with distinct seasonal variation and cooler winters. These regional differences underscore the importance of considering geographic and climatic context when analysing climate impacts and planning adaptation strategies.

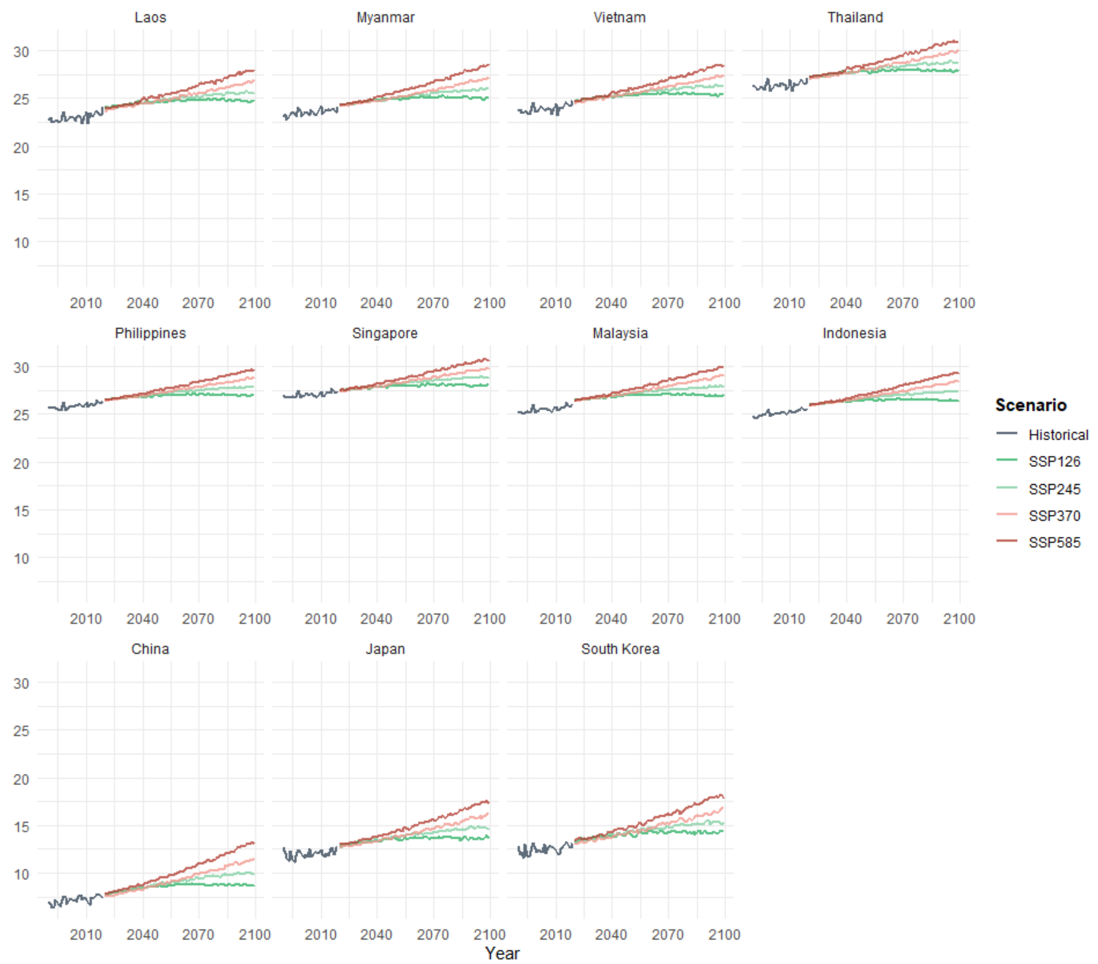


Figure 11: Annual mean temperature of selected countries
Data source: CCKP (2021).

3.2.3.4 Air pollution: PM2.5 (pm2.5)

PM2.5 levels, measured in micrograms per cubic meter (μg/m³) and averaged annually, have historically shown no consistent global trend, but regional patterns are evident. For instance, China has experienced a notable upward trend in PM2.5 concentrations in past decades, driven by rapid industrialisation and urbanisation. However, projections suggest a gradual decline in PM2.5 levels across many countries, indicating potential improvements in air quality due to stricter environmental regulations and shifts toward cleaner energy sources.

Interestingly, the projected trends for PM2.5 under the four Shared Socioeconomic Pathways (SSPs) differ markedly from those observed for temperature-related indicators. While temperature-related variables follow a more predictable sequence, PM2.5 projections display more irregular behavior. Notably, SSP370 often produces the most extreme or erratic PM2.5 outcomes, whereas SSP585 results appear surprisingly close to those under SSP126 or SSP245.

This study will not attempt to validate the projections but will adopt them as given. We also caution that forecasts of PM2.5-related mortality could be sensitive to this variability, and some volatility in the results should be expected.

Figure 12: PM2.5 of selected countries
Data source: CCKP (2021).

3.2.4 Relationship between climate variables

We study the interaction between climate variables, since it is also an important component of our study. The correlation is calculated using historical data. We focus on the correlation between PM2.5 with other variables, since they are temperature related. There is moderate correlation between PM2.5 and others, with a negative correlation with heat variables (CDD65 and mean temperature). This indicates that as temperature increase, PM2.5 will decrease. Conversely, a positive correlation with cold (HDD65) indicates that as temperature decreases, PM2.5 will increase.

We examine the interaction between climate variables as a key component of our study, recognizing that climate conditions often influence one another in complex ways. Specifically, we investigate the correlation between PM2.5 concentrations and various temperature-related indicators using historical data. PM2.5 is sensitive to changes in ambient temperature. Our analysis reveals a moderate correlation between PM2.5 and other climate variables. Notably, we observe a negative correlation between PM2.5 and heat-related variables such as cooling degree days (CDD65) and mean temperature. This suggests that higher temperatures are generally associated with lower PM2.5 levels. On the other hand, the positive correlation between PM2.5 and heating degree days (HDD65), a proxy for colder conditions, indicates that PM2.5 levels tend to rise as temperatures fall. This could be attributed to increased residential heating, reduced atmospheric mixing, and stagnant air conditions commonly observed during colder weather. These relationships underscore the importance of considering seasonal and temperature-related factors when assessing air pollution dynamics.

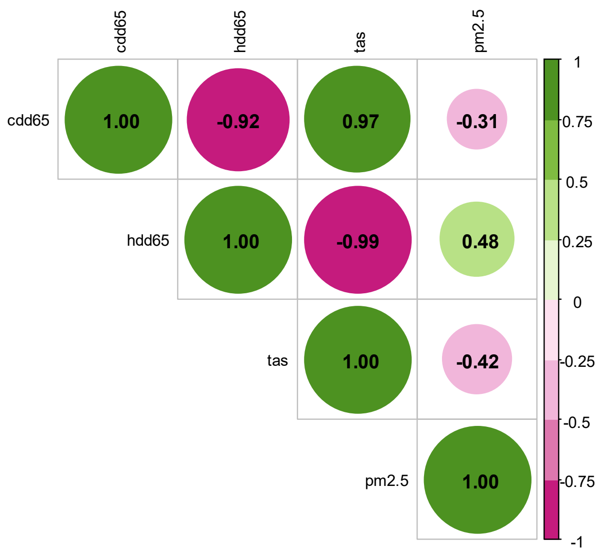


Figure 13: Correlation plot of climate variables

3.3 All-cause mortality data

3.3.1 Data source

To ensure consistency with climate data, we obtained all-cause death and population data from the Global Burden of Disease (GBD) Study 2021. Data obtained are already aggregated into age groups of 5 rather than integer ages, as it is the most granular scale available on the website. Thus, subsequent result presentation will be done in age groups as well. All-cause mortality, q, is then obtained by dividing all-cause death counts, D, by the population, E. A more formal definition of all-cause mortality is given:

$$q_{x,t,c} = \frac{D_{x,t,c}}{E_{x,t,c}}$$

Where the subscripts x, t, and c represent age group, calendar year, and country, respectively.

3.3.2 Mortality trends

In this section, we seek to understand mortality trends in East Asia and SEA region. As expected, the mortality trend is decreasing over time due to societal advancements such as improved healthcare. However, in recent years, there is a clear spike in mortality in the SEA region, most likely attributable to COVID-19. In future projection for mortality, this increase is treated as a one-off event as global epidemics such as these are uncommon and shall be modelled independent of the overall trend. Thus, moving forward, data up until 2019 will be used for model fitting, and projections will be done starting from 2020.

In general, mortality rates for young and middle age groups for both regions are quite similar but start to deviate as age increases. As age increases, mortality in East Asia is at a much lower rate than SEA. This is expected as East Asia countries have relatively advanced eldercare and medical infrastructure as compared to SEA.

Figure 14: Mortality Rates of East Asia and SEA
Data source: GBD (2021)

4 Methodology

4.1 Model structure and CRAF

We aim to separate climate related mortality trend from the overall mortality trend with the following formula:

$$q^E_{x,t,c} + q^C_{x,t,c} = q_{x,t,c},$$

where $q^C_{x,t,c}$ represents climate-related mortality, $q^E_{x,t,c}$ represents all-cause mortality excluding climate related mortality, and $q_{x,t,c}$ represents all-cause mortality.

We propose to use a standard Lee-Carter model (Lee and Carter, 1992) to fit $q^E_{x,t,c}$ and $q_{x,t,c}$. The climate-related mortality $q^C_{x,t,c}$ is an aggregation of mortalities resulted from hot temperature $q^{C(HT)}_{x,t,c}$, cold temperature $q^{C(CT)}_{x,t,c}$, and air pollution $q^{C(A)}_{x,t,c}$. In this project, we use Linear Regression (LM) and Generalised Linear Models (GLM) to model $q^{C(HT)}_{x,t,c}$, $q^{C(CT)}_{x,t,c}$ and $q^{C(A)}_{x,t,c}$ separately. Let $\hat{q}^E_{x,t,c}$, $\hat{q}_{x,t,c}$ and $\hat{q}^C_{x,t,c} = \hat{q}^{C(HT)}_{x,t,c} + \hat{q}^{C(CT)}_{x,t,c} + \hat{q}^{C(A)}_{x,t,c}$ be the model predicted mortality rates. The future projections for $\hat{q}^C_{x,t,c}$ are made for the four scenarios SSP126, SSP245, SSP370 and SSP585 according to their respective climate variables. To obtain ensemble predictions, we obtain final $\hat{q}^C_{x,t,c}$ projections by averaging the projections of the LM and GLM. The method to combine several individual models to produce more accurate predictions than a single model alone is widely used in machine learning context.

To evaluate the impacts of climate risk on overall mortality, we define the *climate risk adjustment factor* (*CRAF*) as following,

$$CRAF_{x,t,c} = \frac{\hat{q}^E_{x,t,c} + \hat{q}^{C(HT)}_{x,t,c} + \hat{q}^{C(CT)}_{x,t,c} + \hat{q}^{C(A)}_{x,t,c}}{\hat{q}_{x,t,c}} - 1 = \frac{\hat{q}^E_{x,t,c} + \hat{q}^C_{x,t,c}}{\hat{q}_{x,t,c}} - 1.$$

The interpretation of CRAF is as follows:

- Given an existing projected all-cause mortality rate $\hat{q}_{x,t,c}$, the climate-risk-adjusted mortality rate will be $\hat{q}_{x,t,c} * (1 + CRAF_{x,t,c})$;

- CRAF can be positive or negative values; positive/negative CRAF shows that the climate factor has worsening/improving impact on mortality rates;
- The larger the absolute value of CRAF, the larger the impact on mortality rates observed from climate factors.

The definition of CRAF is proposed with the aim to be useful in application. It can be used as a loading to adjust existing all-cause mortality tables for specified climate scenarios, which might be useful when performing climate stress testing. This allows insurers to better understand how climate change, especially in Asia, will impact their life business portfolio. A more detailed explanation on how to apply the CRAF will be included in Section 6.1.

The overall model structure is summarised and illustrated in Figure 15.

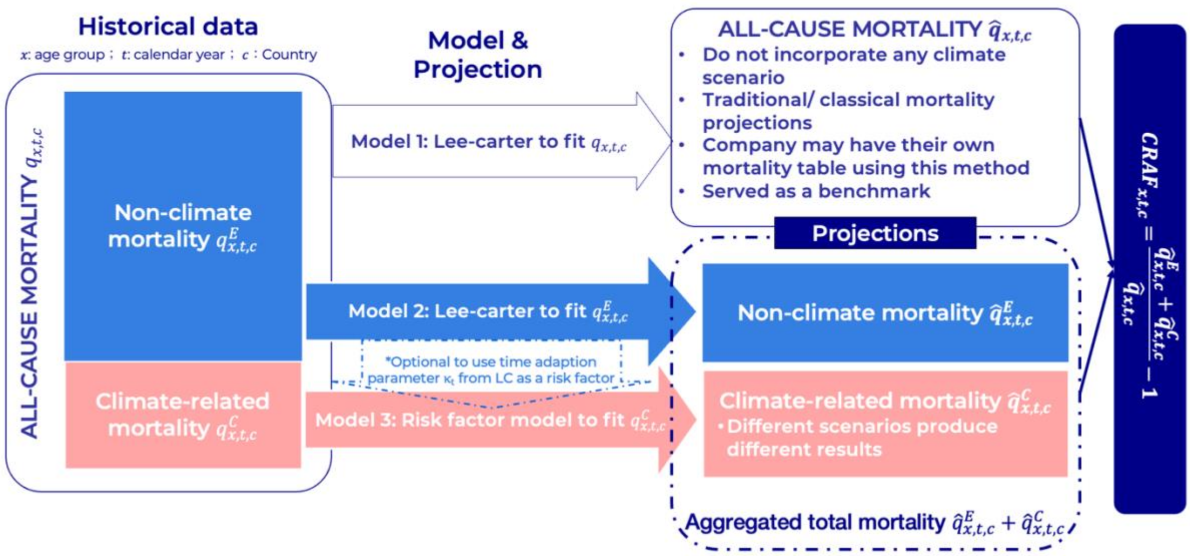


Figure 15: Model Structure

We now specify the models for $q^E_{x,t,c}$ and $q_{x,t,c}$ in Section 0, and the model description for $q^C_{x,t,c}$ will be specified in Section 4.3.

4.2 All-cause mortality modelling

We propose to adopt the Lee-Carter (LC) model, a well-known and widely used stochastic mortality model to fit $q_{x,t,c}$ and $q^E_{x,t,c}$. It provides an intuitive and accurate approach to modelling and projecting age-specific mortality rates over time. The model assumes that the logarithm of the force of mortality at age x, time t in country c can be decomposed into:

$$log(m_{x,t,c}) = \alpha_{x,c} + \beta_{x,c}\kappa_{t,c} + \varepsilon_{x,t,c} \ ,$$

where $\alpha_{x,c}$ and $\beta_{x,c}$ are age dependent parameters for country c, and $\kappa_{t,c}$ is a time dependent parameter, plus an error term with mean 0 and variance σ^2.

The key innovation of the Lee-Carter model is that it decomposes mortality data into age and time dependent parameters. By looking at age dependant parameters, we can understand the age specific trends of mortality. The time dependant parameter, $\kappa_{t,c}$, which captures the underlying mortality trend of the studied population over time. From empirical studies, this model is statistically robust, usually providing an adjusted R^2 of over 0.9. Besides the explainability advantage, parameters of this model are also relatively easy to estimate, thus making it a cost-effective model. The above advantages make the model a cornerstone in stochastic mortality modelling and widely used by demographers and actuaries. In subsequent research, our focus is to study changes in overall mortality under different climate scenarios. We do rely on the Lee-Carter model heavily for its predictions and using it to infer conclusions. However, we do not aim to refine the Lee-Carter model but merely using it as a benchmark for comparison purposes.

4.3 Climate mortality modelling

In this section, we describe the models used to analyse the effects of various risk factors on climate mortality.

4.3.1 Climate-related mortality model without population mortality trend

Our first approach is to model the climate-related mortality independently from other-caused mortality rates. Our aim is to model and forecast climate mortality using only climate variables. We construct separate models for air pollution, high temperature and cold temperature. The variable used are listed in the table below:

Risk factor	Variables used
Air pollution, $\boldsymbol{q_{x,t,c}^{C(A)}}$	$tas_{t,c}$, $pm2.5_{t,c}$
High temperature, $\boldsymbol{q_{x,t,c}^{C(HT)}}$	$tas_{t,c}$, $cdd65_{t,c}$
Cold temperature, $\boldsymbol{q_{x,t,c}^{C(CT)}}$	$tas_{t,c}$, $hdd65_{t,c}$

Table 7: Variables used for each climate risk factor

4.3.2 Climate-related mortality model with population mortality trend

Our second approach is to model the climate-related mortality concurrently with other-caused mortality, by incorporating the time dependant parameter $\kappa_{t,c}$ estimated from $q_{x,t,c}^{E}$ as an additional variable for modelling climate-related mortalities. The variable used are listed in the table below:

Risk factor	Variables used
Air pollution, $\boldsymbol{q_{x,t,c}^{C(A)}}$	$tas_{t,c}$, $pm2.5_{t,c}$, $\kappa_{t,c}$
High temperature, $\boldsymbol{q_{x,t,c}^{C(HT)}}$	$tas_{t,c}$, $cdd65_{t,c}$, $\kappa_{t,c}$
Cold temperature, $\boldsymbol{q_{x,t,c}^{C(CT)}}$	$tas_{t,c}$, $hdd65_{t,c}$, $\kappa_{t,c}$

Table 8: Variables used for each climate risk factor

Since the variables need to be used in LM and GLM later, we conducted a correlation analysis of $\kappa_{t,c}$ with all other climate variables once the LC model on $q_{x,t,c}^{E}$ is constructed. The results are shown in Figure 16 below. We note that statistically $\kappa_{t,c}$ is not highly correlated with our existing climate variables. It is slightly negatively correlated with high temperature exposure, while positively correlated with cold temperature. Its correlation with pm2.5 is close to 0, suggesting that the time-dependent mortality is less affected by the historical pm2.5 trend.

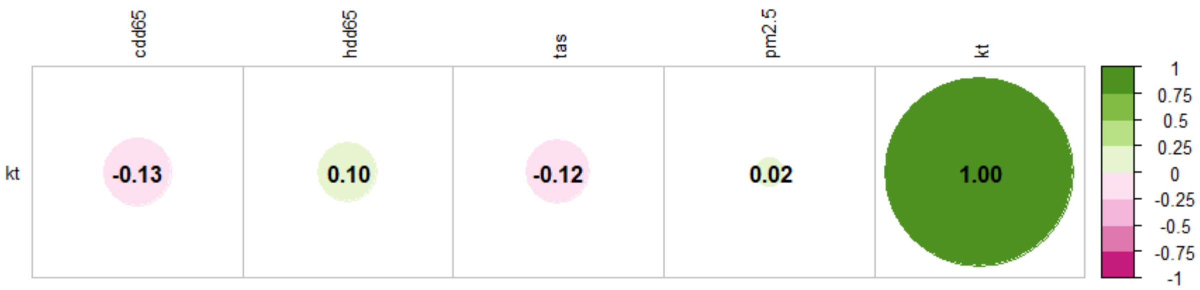


Figure 16: Correlation map

We now briefly describe the statistical models that has been used in this study.

4.3.3 Linear regression model (LM)

The first model is linear regression by assuming a linear relationship between climate mortality and climate-related variables. Taking air pollution mortality as an example, the model will be structured as:

- **Without** $\kappa_{t,c}$**:** $q_{x,t,c}^{C(A)} = \alpha_{x,c}^{C(A)} + \beta_{1,x,c}^{C(A)} tas_{t,c} + \beta_{2,x,c}^{C(A)} pm2.5_{t,c} + \varepsilon_{x,c,t}^{C(A)}$
- **With** $\kappa_{t,c}$**:** $q_{x,t,c}^{C(A)} = \alpha_{x,c}^{C(A)} + \beta_{1,x,c}^{C(A)} tas_{t,c} + \beta_{2,x,c}^{C(A)} pm2.5_{t,c} + \beta_{3,x,c}^{C(A)} e^{\kappa_{t,c}} + \varepsilon_{x,c,t}^{C(A)}$

Note that in the second equation above, the $\kappa_{t,c}$ is incorporated into the LM in the form of $e^{\kappa_{t,c}}$ as $\kappa_{t,c}$ is a parameter estimated for logarithm of the force of mortality.

4.3.4 Generalised linear models (GLM)

Generalised Linear Models (GLMs) extend linear regression by relaxing the linear relationship between Y and X_i. GLMs allow for Y to be non-linear to the extent that $g(Y)$, a non-linear transformation of Y, is linear with X_i. The only difference with linear regression is the link function $g(\cdot)$. The choice of $g(\cdot)$ depends on the distribution we assume Y to follow. In our case, we assume death counts follow a Poisson distribution, thus we use the log link function to transform Y. An example for modelling air pollution mortality can be:

- **Without** $\kappa_{t,c}$**:** $\log\left(q_{x,t,c}^{C(A)}\right) = \alpha_{x,c}^{C(A)} + \beta_{1,x,c}^{C(A)} tas_{t,c} + \beta_{2,x,c}^{C(A)} pm2.5_{t,c} + \varepsilon_{x,c,t}^{C(A)}$
- **With** $\kappa_{t,c}$**:** $\log\left(q_{x,t,c}^{C(A)}\right) = \alpha_{x,c}^{C(A)} + \beta_{1,x,c}^{C(A)} tas_{t,c} + \beta_{2,x,c}^{C(A)} pm2.5_{t,c} + \beta_{3,x,c}^{C(A)} \kappa_{t,c} + \varepsilon_{x,c,t}^{C(A)}.$

GLMs provide a more general framework for modelling various types of data. However, careful selection of the distribution family and link function are essential to ensure accurate results.

Technically the two approaches proposed in Section 0 and Section 4.3.2 differ only by one additional variable used ($\kappa_{t,c}$) in LM and GLM, which makes the two seemed to be very similar. However, the two have fundamental differences:

1. The first model (without kappa) assumes that climate-related mortality is only dependent on climate trends, whereas the second model (with kappa) assumes that climate-related mortality is also affected by the population mortality trend over time. The second model seemed to be more logically justified.
2. We are also interested in the model performances between the two and wish to test which one has better accuracy in projections. It turns out that the two models are quite similar in model performances measured by mean absolute percentage error (MAPE) and we could not determine whether one outperforms the other.

4.4 Performance evaluation

To perform a meaningful comparison of the models, we split the fitting dataset into training and test sets. The training set contains mortality rates from 1990-2014, while the test set contains mortality rates from 2015-2019. This allows us to compare both in and out of sample performances of both approaches. We exclude the COVID-19 period from our modelling process to avoid distortions driven by pandemic-related mortality shocks. Our objective is to isolate climate-related mortality patterns, and including pandemic-induced mortality spikes would bias estimates of long-term climate effects. This treatment of COVID-19 as an exogenous shock and exclusion from baseline mortality trend analysis is consistent with recent actuarial and demographic literature, where excess pandemic mortality is typically modelled separately to preserve structural mortality trends.

We evaluate the performance of our proposed approach and the LC model by comparing their mean absolute percentage error (MAPE). Specifically, we compare the MAPE of $\hat{q}^{E}_{x,t,c}$+ $\hat{q}^{C}_{x,t,c}$ with $\hat{q}_{x,t,c}$. The calculation of MAPE is as such:

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{x_i - \widehat{x_i}}{x_i}\right|$$

where x_i represents the actual values, $\widehat{x_i}$ represents the predicted values and N represents the total number of observations evaluated. This allows us to understand the absolute deviation of our fitted and forecasted values with the actual mortality rates. The interpretation of MAPE is such:

- **In-sample MAPE:** Measures the bias of the approach. This allows us to understand which approach can more accurately describe the dataset A lower MAPE represents a better fit to the historical mortality trend.
- **Out-of-sample MAPE:** Measures the variance of the approach. This allows us to understand which approach can generalise better with different datasets. A lower MAPE represents a more accurate forecast.

Generally, due to the bias-variance tradeoff, a model having a higher in-sample MAPE (bias) will have a lower out-of-sample MAPE (variance). When determining the best approach, we need to strike a balance between the magnitude of bias and variance. The MAPE only serves to provide insights of how well our approaches perform relative to the All-cause mortality Lee-Carter model. In our result presentation, all models are refitted using the 1990-2019 period to make full use of available data.

5 Key model results and analysis

5.1 Model Performance

5.1.1 Parameters significance analysis

For each risk factor, different countries and different age groups are found to have different parameter significance. We briefly present the parameter significance results in this section, as it may generate relevant inferences conclusions on how climate variables affect the relevant mortality rates.

For this section, we firstly selected China, Japan and Singapore to partially present the differences in model results on air-pollution affected deaths. From our analysis in Sections 3.1 and 3.2, we observed that the historical air-pollution mortalities between China and Japan were very different, and that the future climate scenarios projected for the two countries also differ a lot.

Table 9 and Table 10 shows the p-values for different parameters used in the $q_{x,t,c}^{C(A)}$ linear models for China and Japan respectively, where the cells highlighted in red are the ones with p-value less than 5%. We can observe that pm2.5 is almost always a significant variable when predicting air-pollution mortalities in China and Japan. For China, when $\kappa_{t,c}$ is included, tas becomes less significant than without $\kappa_{t,c}$. As for Japan, tas is almost never significant for every age group. The importance of the intercept for model without $\kappa_{t,c}$ was taken over by the importance of $\kappa_{t,c}$ when it is included in the LM.

Table 9: P-values for variables, China Air-pollution Mortality LM

	Model with $\kappa_{t,c}$				Model without $\kappa_{t,c}$		
AGE	(Intercept)	kt	pm2.5	tas	(Intercept)	pm2.5	tas
<5 years	0.3445	0.0612	0.0004	0.0458	0.1487	0.0000	0.0106
5-9 years	0.0739	0.0108	0.0000	0.0032	0.0213	0.0000	0.0006
10-14 years	0.1380	0.0275	0.0003	0.0049	0.0456	0.0000	0.0008
15-19 years	0.9505	0.0736	0.0000	0.0449	0.5707	0.0000	0.0107
20-24 years	0.0044	0.4276	0.0000	0.9477	0.0053	0.0000	0.8379
25-29 years	0.1004	0.5670	0.0003	0.2183	0.0600	0.0000	0.1327
30-34 years	0.0592	0.4787	0.0003	0.1580	0.0308	0.0000	0.0834
35-39 years	0.0002	0.1671	0.0000	0.0029	0.0000	0.0000	0.0006
40-44 years	0.0000	0.0365	0.0000	0.0015	0.0000	0.0000	0.0003
45-49 years	0.2607	0.2016	0.0000	0.6749	0.1325	0.0000	0.3844
50-54 years	0.0007	0.0711	0.0000	0.0774	0.0002	0.0000	0.0200
55-59 years	0.0088	0.3027	0.0000	0.2146	0.0031	0.0000	0.1006
60-64 years	0.0729	0.2685	0.0000	0.4881	0.0323	0.0000	0.2711
65-69 years	0.0883	0.0496	0.0000	0.6135	0.0295	0.0000	0.2502
70-74 years	0.0077	0.0075	0.0000	0.2196	0.0021	0.0000	0.0497
75-79 years	0.0332	0.0151	0.0000	0.3173	0.0093	0.0000	0.0855
80-84 years	0.0322	0.0200	0.0000	0.2280	0.0091	0.0000	0.0590
85+ years	0.0363	0.0042	0.0000	0.2017	0.0099	0.0000	0.0423

Table 10：P-values for variables, Japan Air-pollution Mortality LM

	Model with $\kappa_{t,c}$				Model without $\kappa_{t,c}$		
AGE	(Intercept)	kt	pm2.5	tas	(Intercept)	pm2.5	tas
<5 years	0.2553	0.0016	0.0003	0.0437	0.0139	0.0000	0.2359
5-9 years	0.0729	0.0942	0.0001	0.0663	0.0073	0.0000	0.1341
10-14 years	0.1873	0.1117	0.0006	0.0751	0.0288	0.0000	0.1431
15-19 years	0.2603	0.0117	0.0013	0.0687	0.0218	0.0000	0.2241
20-24 years	0.0577	0.0031	0.0001	0.0625	0.0022	0.0000	0.2682
25-29 years	0.0570	0.0215	0.0001	0.0706	0.0032	0.0000	0.2019
30-34 years	0.1404	0.0694	0.0016	0.0865	0.0157	0.0000	0.1831
35-39 years	0.1339	0.0518	0.0031	0.0972	0.0132	0.0000	0.2161
40-44 years	0.0624	0.0234	0.0007	0.0564	0.0037	0.0000	0.1660
45-49 years	0.0753	0.0108	0.0030	0.1531	0.0039	0.0000	0.4065
50-54 years	0.0788	0.0208	0.0026	0.1004	0.0049	0.0000	0.2670
55-59 years	0.1040	0.0000	0.0055	0.0625	0.0029	0.0000	0.4826
60-64 years	0.0566	0.0000	0.0004	0.0527	0.0015	0.0000	0.4756
65-69 years	0.1975	0.0009	0.0056	0.1031	0.0088	0.0000	0.4390
70-74 years	0.1741	0.0000	0.0037	0.1216	0.0054	0.0000	0.6457
75-79 years	0.1716	0.0000	0.0005	0.0439	0.0043	0.0000	0.5882
80-84 years	0.1989	0.0000	0.0011	0.0636	0.0053	0.0000	0.6062
85+ years	0.0777	0.0000	0.0008	0.0770	0.0020	0.0000	0.7033

Initially we had the impression that pm2.5 should always be a significant variable when modelling air-pollution mortalities, but when we examine the results for Singapore (Table 11), we saw that tas and $\kappa_{t,c}$ are statistically significant in both model versions, whereas pm2.5 never has been a statistically significant variable. According to the model results, Singapore's air-pollution related deaths are more correlated to population trend as well as the overall temperature trend, instead of pm2.5. Table 12 summarises the observed parameter significance[1].

[1] "Yes" indicates that not less than 50% of age-groups has p-values less than 0.05, showing statistical significance of the parameter in the model; "No" indicates that less than 50% of age-groups has p-values less than 0.05, showing statistical insignificance of the parameter in the model.

Table 11: P-values for variables, Singapore Air-pollution Mortality LM

	Model with $\kappa_{t,c}$				Model without $\kappa_{t,c}$		
AGE	(Intercept)	kt	pm2.5	tas	(Intercept)	pm2.5	tas
<5 years	0.0063	0.0000	0.8973	0.0331	0.0046	0.5462	0.0106
5-9 years	0.0001	0.0000	0.9034	0.0008	0.0003	0.5108	0.0011
10-14 years	0.0028	0.0000	0.7891	0.0107	0.0004	0.4914	0.0013
15-19 years	0.0046	0.0000	0.9224	0.0210	0.0008	0.6096	0.0030
20-24 years	0.0006	0.0000	0.7236	0.0039	0.0003	0.4496	0.0012
25-29 years	0.0007	0.0000	0.4583	0.0043	0.0005	0.3511	0.0018
30-34 years	0.0018	0.0000	0.7115	0.0077	0.0005	0.4446	0.0018
35-39 years	0.0003	0.0000	0.9133	0.0014	0.0001	0.6250	0.0005
40-44 years	0.0007	0.0000	0.8698	0.0047	0.0004	0.5063	0.0016
45-49 years	0.0005	0.0000	0.8286	0.0032	0.0001	0.6737	0.0007
50-54 years	0.0004	0.0000	0.8873	0.0033	0.0004	0.5935	0.0016
55-59 years	0.0011	0.0000	0.8949	0.0055	0.0006	0.5151	0.0018
60-64 years	0.0017	0.0000	0.9126	0.0069	0.0005	0.5293	0.0016
65-69 years	0.0008	0.0000	0.9950	0.0034	0.0002	0.5817	0.0008
70-74 years	0.0007	0.0000	0.9320	0.0035	0.0003	0.5411	0.0010
75-79 years	0.0005	0.0000	0.9845	0.0031	0.0002	0.5655	0.0009
80-84 years	0.0014	0.0000	0.7472	0.0086	0.0003	0.7186	0.0014
85+ years	0.0005	0.0000	0.7729	0.0080	0.0001	0.7261	0.0012

Table 12: Summary of parameter importance (Air-pollution Mortality LM)

	Model with $\kappa_{t,c}$				Model without $\kappa_{t,c}$		
Location	(Intercept)	kt	tas	pm2.5	(Intercept)	tas	pm2.5
China	YES	NO	NO	YES	YES	YES	YES
Indonesia	YES	YES	YES	YES	YES	YES	YES
Japan	NO	YES	NO	YES	YES	NO	YES
Laos	YES	NO	YES	NO	YES	YES	NO
Malaysia	YES	YES	NO	YES	YES	YES	YES
Myanmar	YES	NO	NO	NO	YES	NO	YES
Philippines	YES	YES	NO	NO	NO	NO	NO
Singapore	YES	YES	YES	NO	YES	YES	NO
South Korea	NO	YES	YES	YES	NO	YES	YES
Thailand	YES	YES	NO	NO	YES	YES	NO
Vietnam	NO	NO	YES	YES	NO	YES	YES

Similarly, our analysis of parameter significance for heat temperature exposure and cold temperature exposure models indicates that variable effects differ by age group and country, without a consistent pattern of significance across all variables. For clarity and conciseness, summary tables (Table 12 and Table 14) are provided to show parameter importance for each country.

Table 13: Summary of parameter importance (Heat Temperature Mortality LM)

	Model with $\kappa_{t,c}$				Model without $\kappa_{t,c}$		
Location	(Intercept)	kt	tas	cdd65	(Intercept)	tas	cdd65
China	NO	YES	NO	NO	NO	NO	NO
Indonesia	YES	NO	YES	YES	YES	YES	YES
Japan	YES	YES	YES	YES	YES	NO	YES
Laos	NO	YES	NO	NO	NO	NO	NO
Malaysia	NO	YES	NO	NO	NO	NO	NO
Myanmar	NO	YES	NO	NO	YES	NO	YES
Philippines	NO	YES	NO	NO	NO	NO	NO
Singapore	NO	YES	NO	NO	NO	NO	NO
South Korea	NO	YES	NO	NO	NO	NO	NO
Thailand	NO	YES	NO	NO	NO	NO	NO
Vietnam	YES	YES	YES	YES	YES	NO	YES

Table 14: Summary of parameter importance (Cold Temperature Mortality LM)

	Model with $\kappa_{t,c}$				Model without $\kappa_{t,c}$		
Location	(Intercept)	kt	tas	hdd65	(Intercept)	tas	hdd65
China	YES	YES	YES	NO	YES	YES	YES
Indonesia	NO	NO	YES	NO	NO	YES	NO
Japan	YES	YES	NO	NO	YES	YES	NO
Laos	YES	YES	YES	NO	YES	YES	NO
Malaysia	NO	YES	YES	NO	NO	YES	NO
Myanmar	YES	YES	NO	YES	YES	NO	YES
Philippines	YES	YES	YES	YES	YES	YES	YES
Singapore	YES	YES	YES	--	YES	YES	--
South Korea	YES	YES	YES	NO	YES	YES	NO
Thailand	YES	NO	YES	YES	YES	YES	YES
Vietnam	YES	YES	YES	YES	YES	YES	YES

5.1.2 MAPE results

In this section, we present model performance results based on MAPE for both in-sample and out-of-sample performances. Table 15 and Table 16 summarised the MAPE results by country and age-group respectively. A full breakdown of MAPE by country and age group will be included in the Appendix.

Statistically we are unable to draw a unified conclusion on the best-performing model out of the three (benchmark LC model, separate climate model with $\kappa_{t,c}$ and separate climate model without $\kappa_{t,c}$) across all countries, but we can observe that the our approach to separately model climate related mortalities generally has better out-of-sample MAPE, especially if we look at the results for age-groups. The average out-of-sample MAPE for our models are 17.64% (with $\kappa_{t,c}$) and 17.73% (without $\kappa_{t,c}$), out-performing our benchmark LC model (20.23%). The climate mortality model with $\kappa_{t,c}$ marginally out-performs the one without $\kappa_{t,c}$ on average (both in-sample and out-of-sample).

Table 15: MAPE by Country

	In-sample (1990-2014) MAPE			Out-of-sample (2015-2019) MAPE		
Country	With $\kappa_{t,c}$	Benchmark	Without $\kappa_{t,c}$	With $\kappa_{t,c}$	Benchmark	Without $\kappa_{t,c}$
China	3.64	3.86	3.66	46.20	53.17	46.24
Indonesia	2.38	2.38	2.37	2.69	2.31	2.67
Japan	3.56	3.55	3.61	10.96	11.02	10.94
Laos	0.98	0.99	0.97	29.04	30.08	29.10
Malaysia	4.22	4.52	4.22	11.10	15.69	11.72
Myanmar	3.05	3.05	3.03	6.26	6.62	6.24
Philippines	2.25	2.34	2.30	3.31	3.51	3.29
Singapore	6.05	5.69	6.51	23.55	27.33	24.63
South Korea	5.62	5.61	5.77	22.60	26.37	22.02
Thailand	7.47	7.76	7.62	27.32	35.78	27.15
Vietnam	2.45	2.54	2.49	10.97	10.68	10.99
Overall	3.79	3.84	3.87	17.64	20.23	17.73

From Table 15, the in-sample MAPE shows an average of approximately 3.8% fitting errors, with most of countries resulting with 3-4% MAPE. The out-of-sample MAPE, however, is drastically different across different countries, ranging from approx. 2% (Indonesia) to close to 46% (China). The models do not perform universally well for each country. This may be caused by significant differences between each country on their demographical, geographical and climate conditions; their existing infrastructure to mitigate climate risks (e.g. air-conditioner or heating systems in-place), as well as their healthcare systems.

In addition, the prediction accuracy relies heavily on whether the underlying mortality trend changed significantly during the out-of-sample period. For China, the notable deterioration in performance from in-sample MAPE of approximately 4% to out-of-sample MAPE at close to 46%, hinting that the mortality trend changed significantly during 2015-2019 as compared to 1990-2014. If future mortality trends change significantly from the fitting period, predictions all three models can be rather inaccurate.

From Table 16 the out-of-sample MAPE are worse for younger age groups (higher than 20% for ages from 0-19) and are all below 20% for older age groups. The model performances are rather stable across different age groups and did not present with high volatilities as compared to country-wise results in Table 15.

Table 16: MAPE by Age-group

	In-SAMPLE (1990-2014) **MAPE**			**OUT-OF-SAMPLE** (2015-2019) **MAPE**		
Age Group	**With $\kappa_{t,c}$**	**Benchmark**	**Without $\kappa_{t,c}$**	**With $\kappa_{t,c}$**	**Benchmark**	**Without $\kappa_{t,c}$**
<5 years	5.28	5.72	5.53	29.24	33.67	29.60
5-9 years	6.13	6.10	6.19	28.49	30.26	28.73
10-14 years	6.27	6.27	6.31	24.18	25.30	24.24
15-19 years	5.15	5.18	5.22	23.55	24.47	23.62
20-24 years	4.05	4.09	4.11	18.05	19.61	18.11
25-29 years	5.32	5.19	5.40	19.82	21.39	19.90
30-34 years	4.96	4.82	5.02	19.25	21.06	19.37
35-39 years	3.16	3.19	3.15	15.24	16.99	15.38
40-44 years	2.61	2.64	2.71	13.83	15.49	13.95
45-49 years	2.62	2.59	2.62	10.84	12.44	10.93
50-54 years	2.75	2.88	2.95	14.30	17.15	14.42
55-59 years	2.61	2.64	2.87	16.04	19.41	16.21
60-64 years	2.84	2.87	2.96	16.45	20.22	16.61
65-69 years	3.07	3.08	3.07	15.23	19.72	15.31
70-74 years	2.58	2.62	2.65	12.94	17.20	12.80
75-79 years	2.45	2.37	2.54	11.46	15.66	11.42
80-84 years	2.71	2.73	2.71	12.90	15.59	12.81
85+ years	3.64	4.23	3.61	15.68	18.58	15.68
Overall	**3.79**	3.84	3.87	**17.64**	20.23	17.73

We are aware that our approaches incorporate more parameters and MAPE performance measure did not incorporate enough penalties for model complexity. This may potentially cause overfitting issues in our model. A more holistic generalisation method (for example LASSO) may be used to generate better fittings to our data. However, the aim of this study is not to propose a model that predicts mortality with better accuracy, but to provide better understandings of climate related mortalities and to allow for mortality projections under different climate scenarios, which the LC model is unable to do. Our approach provides much granular information while not sacrificing much model performance. This would be valuable for practitioners seeking to perform scenario testing to understand the impact of climate change on mortality, while still able to do so knowing that the results are still reliable.

5.2 Country-specific results

In the following sections, we will present our model results for each country in alphabetical order. For brevity, we present the with-$\kappa_{t,c}$ model results for all countries, given that it has the lowest MAPE on average. We selectively present the projected mortality rates and CRAF for 2030 and 2050, respectively, to provide insights on how the countries will be impacted in the shorter-term (2030) and longer-term (2050). We also present the life expectancy at birth (by period) results for each country from 2020-2060 to show the overall trends in the future. We have summarised some of our key observations from the result in Table 17 for easy references.

Table 17: Result summary of Climate impact and Life expectancy by country

Country	Most affected age-groups	Lowest Life expectancy scenario (2060)	Highest Life expectancy scenario (2060)	Life Expectancy range from 2020-2060
China	Young and old age	SSP370	SSP126	77-84
Indonesia	Young and mid age	SSP585	SSP126	71-75
Japan	Old age	SSP370	SSP126	82-87
Laos	Mid to old age	SSP585	SSP126	70-79
Malaysia	Mid to old age	SSP126	SSP370	73-77
Myanmar	Mid to old age	SSP370	SSP126	70-79
Philippines	Young and old age	SSP126	SSP585	71-72
Singapore	Mid to old age	SSP126	SSP585	82-89
South Korea	Mid to old age	SSP126	SSP370	82-89
Thailand	Young and old age	SSP126	SSP370	75-81
Vietnam	Old age	SSP370	SSP126	74-78

As we present and comment on the model results, we wish to sideline our comments with the degree of prediction accuracy indicated by MAPE results in Section 5.1.2.

5.2.1 China

Figure 17 shows mortality-rates and CRAF projections for China in year 2030 and 2050. We note that majority of CRAF are positive for all four climate scenarios, showing that without separate models for climate related mortality, we may tend to underestimate the overall mortality rates.

In the short term, the impact of climate change is minimal. The solid line ("No Climate") represents Lee-Carter's model projections for all-cause mortality, served as our benchmark scenario. Our projections under different climate scenarios do not differ too much from the benchmark. We do notice a slightly higher mortality rate under SSP370, and the reason is because high air pollution mortality rates in China coupled with slow PM2.5 improvement in the short term. The CRAF is generally higher at younger ages, which is because of smaller mortality rates which causes large % change when its absolute value increases slightly. For middle and old ages, the CRAF is more stable around 5-10%, and as expected the CRAF under SSP370 is the largest due to high air pollution mortality rates.

In the long term for 2050 projections, the trends are similar to those in 2030 but with magnified impacts. Mortality rates under SSP370 become significantly higher and deviate from the benchmark scenario. This provides insights that air pollution will be a significant health and mortality hazard in the future if the climate develops in line with SSP370. The CRAF shows a similar pattern, with CRAF under SSP370 being significantly higher than the other scenarios.

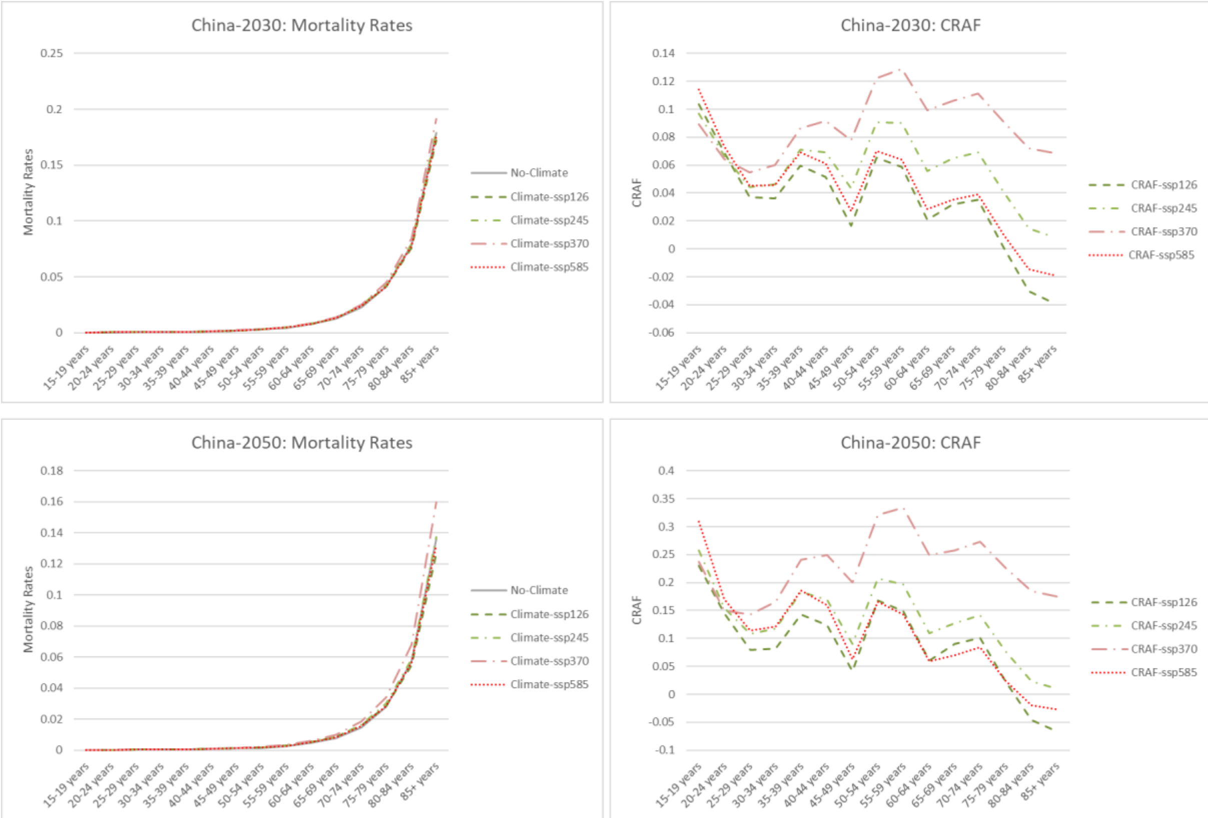


Figure 17: Projected mortality and CRAF in 2030 & 2050, China

Figure 18 shows the projected life expectancy for four scenarios against our benchmark scenario. Compared to the benchmark, China shows lower life expectancy under all climate scenarios. SSP126, SSP245 and SSP585 remains very similar, trailing only slightly below the benchmark. SSP370 consistently projects the lowest outcomes, about one to two years below the benchmark, reflecting slower health and social progress.

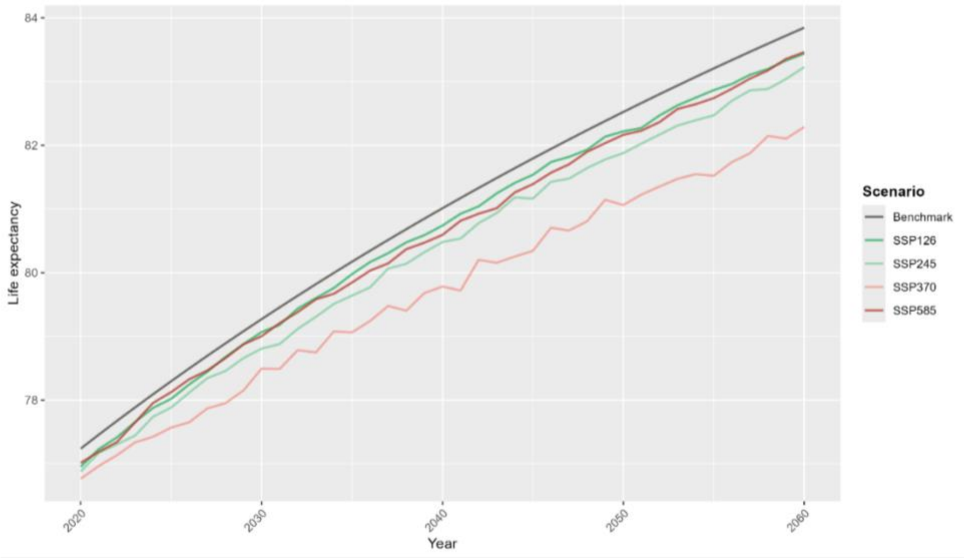


Figure 18: Projected life expectancy of China

5.2.2 Indonesia

In shorter-term, mortality rates for Indonesia are nearly identical across all climate scenarios, showing minimal divergence across age groups. This indicates that climate impacts on overall mortality remain small in the short term. The CRAF values, however, show slight variation by age: younger and middle-aged groups experience small positive adjustments, while older age groups see slightly negative or near-zero values. Among the scenarios, SSP126 exhibits the most negative CRAF values, implying a modest protective effect, while SSP585 and SSP370 shows higher positive adjustments, suggesting relatively greater vulnerability to climate impacts.

In longer-term, small separations between climate and no-climate scenarios begin to appear—especially in older age groups—hinting at growing climate-related influences over time. The CRAF values also rise across most ages compared to shorter-term. The differences between scenarios become clearer: SSP585 and SSP370 yield the highest CRAFs (larger adverse climate effects), while SSP126 remains the most negative or least affected, indicating greater resilience under sustainable pathways.

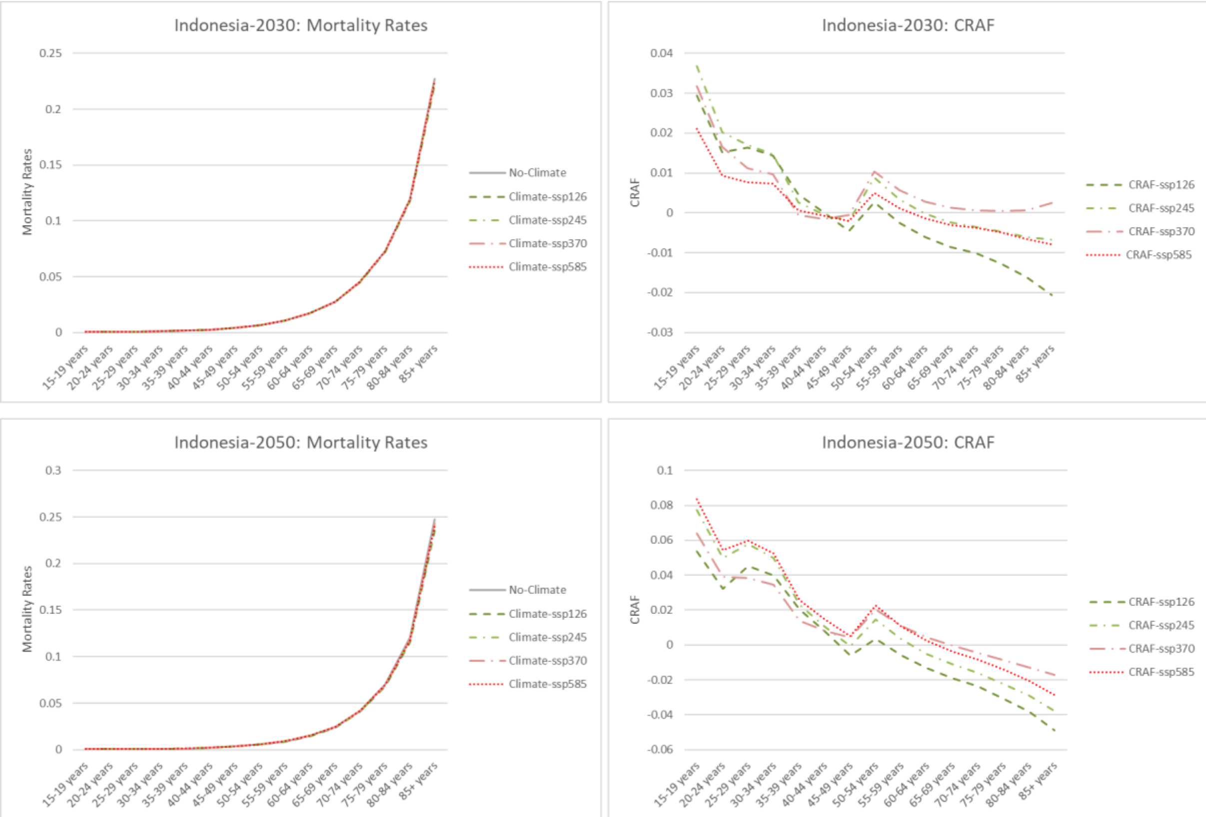


Figure 19: Projected mortality and CRAF in 2030 & 2050, Indonesia

Compared to the benchmark, Indonesia's life expectancy under SSP126 and SSP245 stays slightly above or close to it across most years, indicating stronger health and development outcomes. SSP370 and SSP585, however, remain consistently below the benchmark, with SSP585 showing the lowest trajectory by 2060. The benchmark represents a mid-range path, sitting between the higher sustainability scenarios (SSP126/245) and the lower-performing ones (SSP370/585).

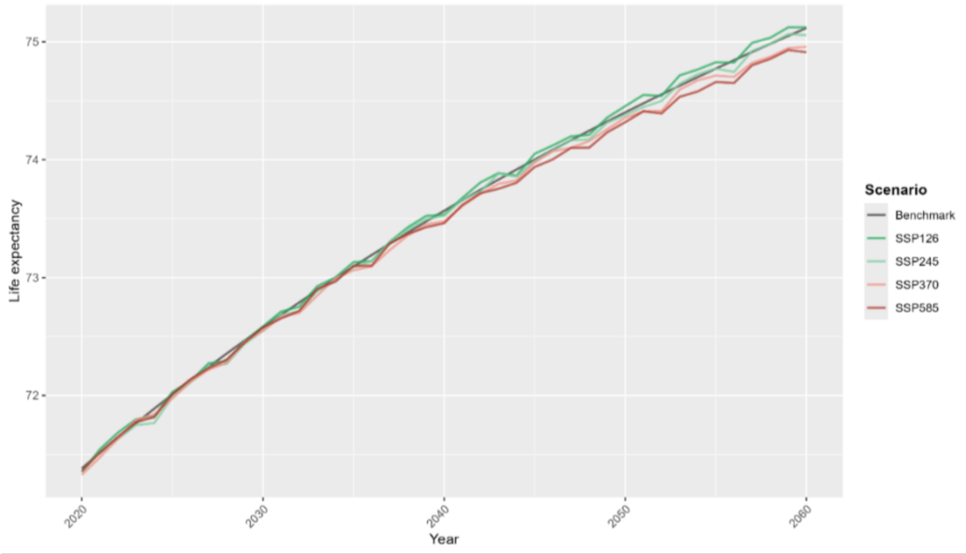


Figure 20: Projected life expectancy of Indonesia

5.2.3 Japan

Similar to China, in the short term, there is no visible and significant deviation in mortality rates under different SSP scenarios with the benchmark scenario. However, we note a diverging trend in CRAF for older ages, which might indicate a higher sensitivity to climate risks in the older age group. Also for young to mid-aged populations, the CRAF for SSP126, SSP245 and SSP585 tend to be negative, while SSP370 is positive for all ages above 30.

Over the long term, the results are similar. Higher sensitivity in older ages, and no large and visible deviations from the benchmark scenario. This might imply that climate risk is not a significant risk factor for mortality in Japan.

Japan's life expectancy steadily increases across all scenarios with only minor differences among them. SSP126, SSP245 and SSP585 closely follow the benchmark, while SSP370 remains slightly lower throughout. Overall, all scenarios project continued longevity gains.

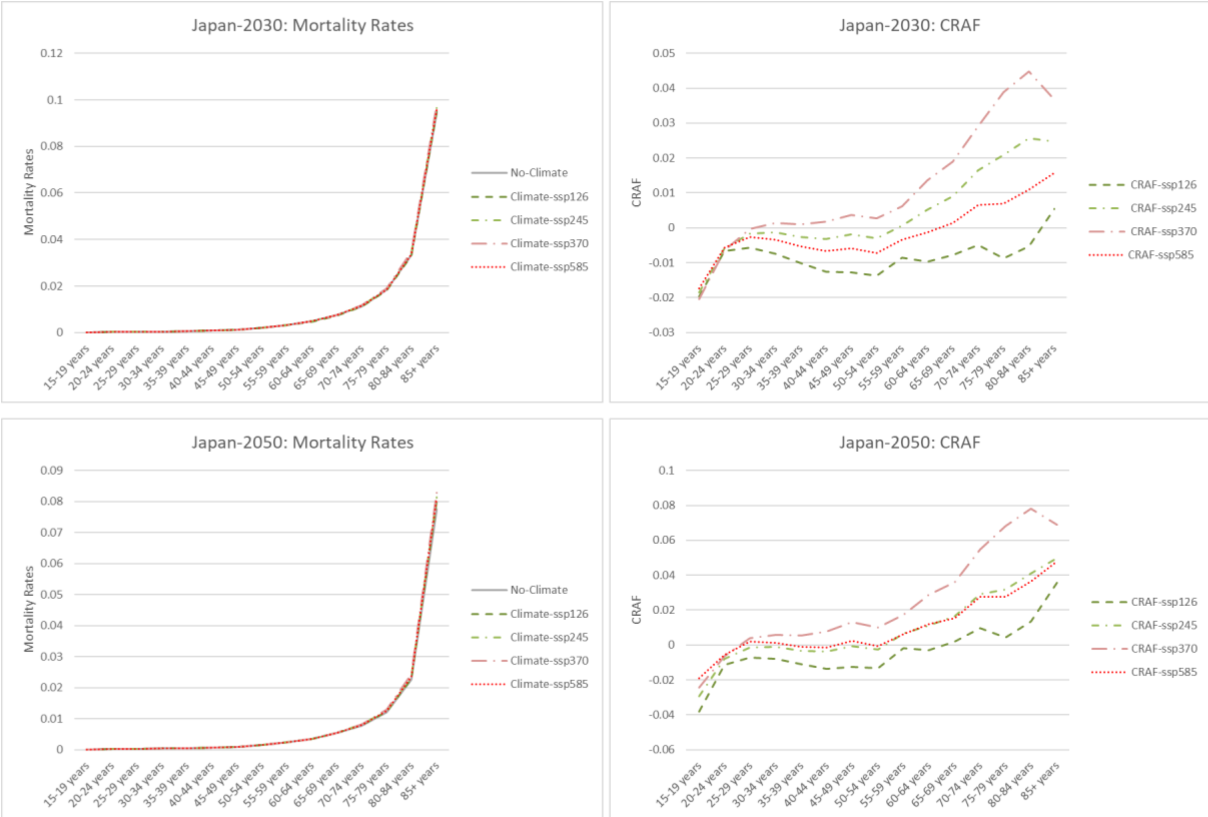


Figure 21: Projected mortality and CRAF in 2030 & 2050, Japan

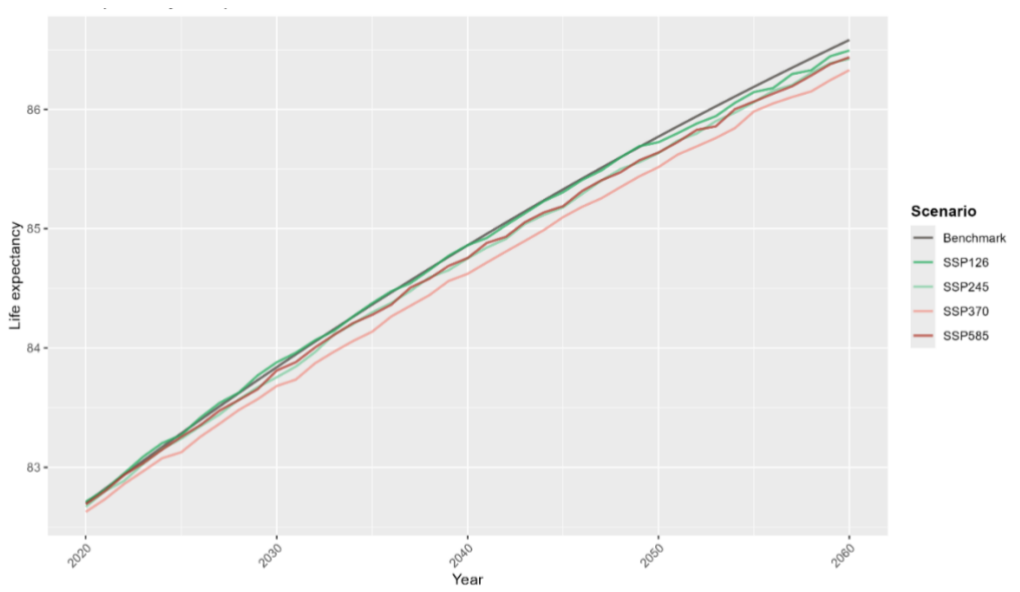


Figure 22: Projected life expectancy of Japan

5.2.4 Laos

In shorter-term, mortality rates in Laos are nearly identical across all climate scenarios. The CRAF values are negative across all age groups, indicating slight reductions in mortality under climate scenarios relative to the baseline. However, the differences among scenarios are small—SSP126 and SSP245 show the most negative CRAFs (minor benefits), while SSP370 and SSP585 trend closer to zero, suggesting a weaker or neutral climate impact on mortality in the short run.

In longer-term, mortality rates remain closely aligned across all scenarios but begin to show slight divergence among older age groups. The CRAF values becoming more negative overall. The differences between scenarios widen slightly, with SSP126 and SSP245 continuing to show the lowest (most negative) CRAFs, reflecting more favourable health conditions under sustainable pathways. In contrast, SSP370 and SSP585 exhibit higher (less negative) CRAFs, suggesting relatively greater climate-related stress.

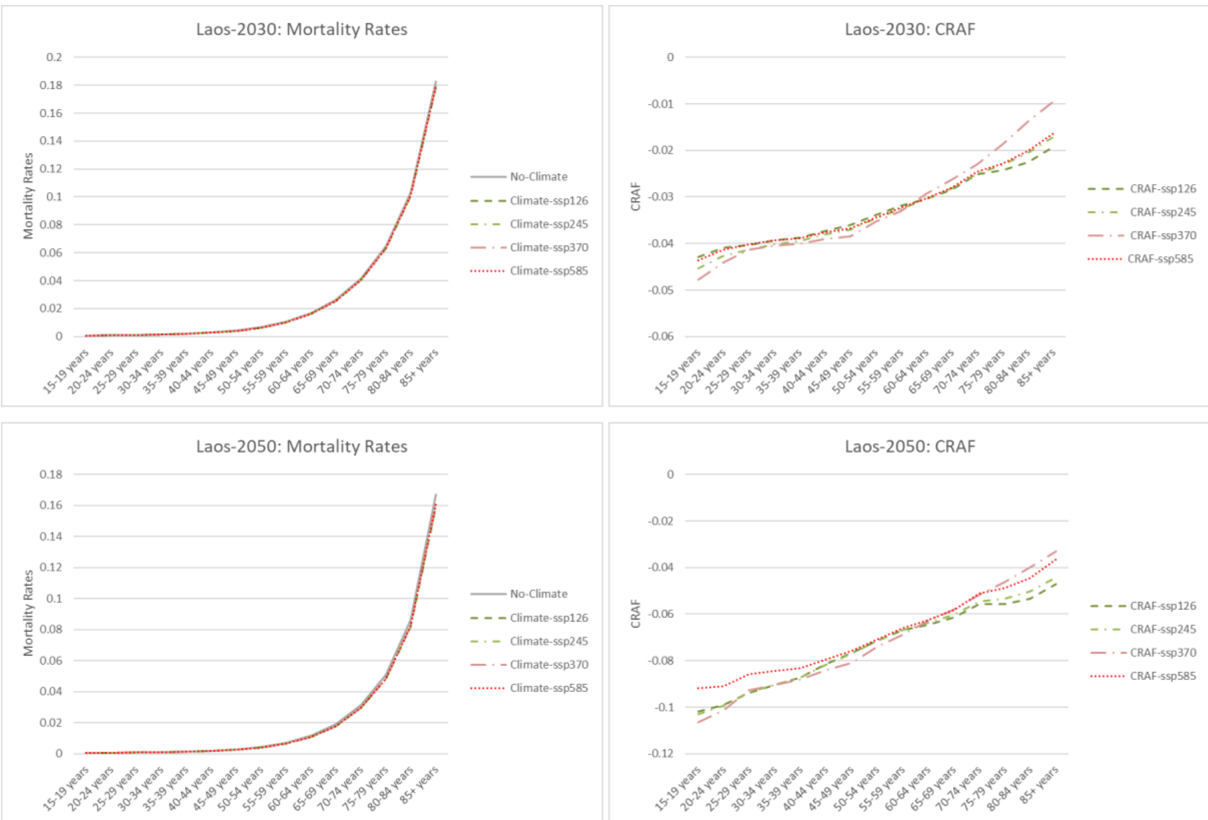


Figure 23: Projected mortality and CRAF in 2030 & 2050, Laos

Laos's life expectancy rises steadily across all scenarios. All climate scenarios show almost identical results in life expectancy, with SSP126 slightly above others and SSP585 slightly below the others. All climate scenarios remain above the benchmark. This suggests that, unlike in many other countries, all climate–socioeconomic scenarios project better outcomes for Laos than the baseline, with sustainable pathways (SSP126/245) offering the most pronounced gains.

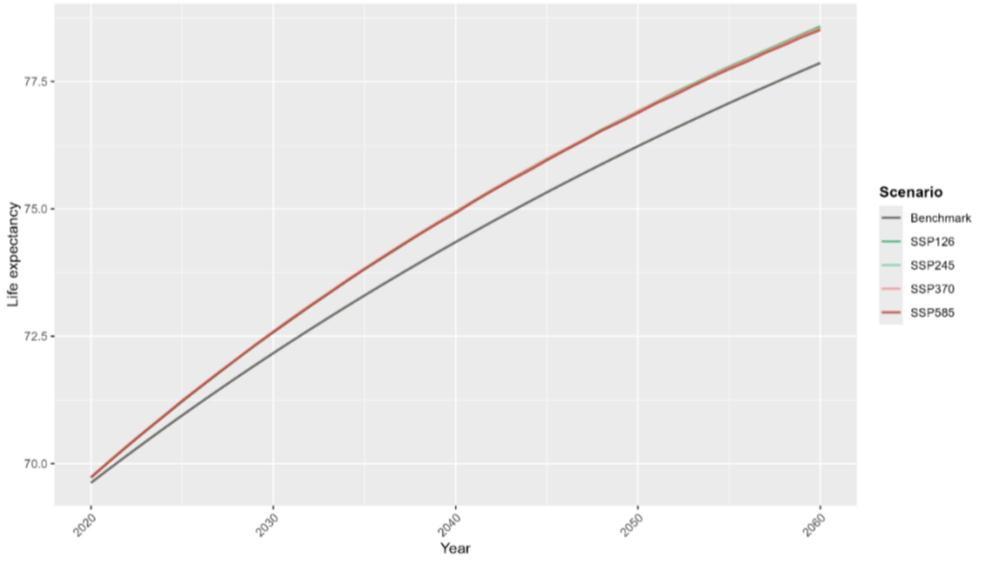


Figure 24: Projected life expectancy of Laos

5.2.5 Malaysia

In the short term, we already see a decrease in mortality rates from the benchmark scenario. Taking a closer look at the CRAF, all SSP scenarios suggest an increase in mortality from age 50 onwards, and a sharp decrease after age 80. We are unsure whether this sharp decrease is caused by a smaller population in the older ages, resulting in not so credible estimates, or simply because the older population is relatively insensitive to climate risks.

Over the long term, the SSP predictions deviate more from the benchmark scenario, especially for ages 85 and above. For other ages, they remain in line with the benchmark scenario. For younger ages, the CRAF shows to be high due to close to zero mortality values at these ages. For older ages above 75, the mortality rates under climate scenarios are visually lower than the benchmark, and CRAFs are negative for all scenarios.

Malaysia's life expectancy increases gradually from 2020 to 2060 under all scenarios, but the benchmark projects a much higher and smoother rise compared to all SSP pathways. When we examine the projected mortality rates of Malaysia, we observe that the benchmark all-cause mortality model consistently predicts lower mortality rates for ages 40-80, and much higher mortality rates for ages 80 and above, in comparison to our climate model approaches. LC model results for $\kappa_{t,c}$ in both $q_{x,t,c}$ and $q^{E}_{x,t,c}$ shows higher uncertainties in comparison to other countries. Among the scenarios, SSP370 shows the highest life expectancy, followed by SSP585, while SSP126 and SSP245 remain consistently lower. All modelled climate scenarios anticipate slower improvements in longevity.

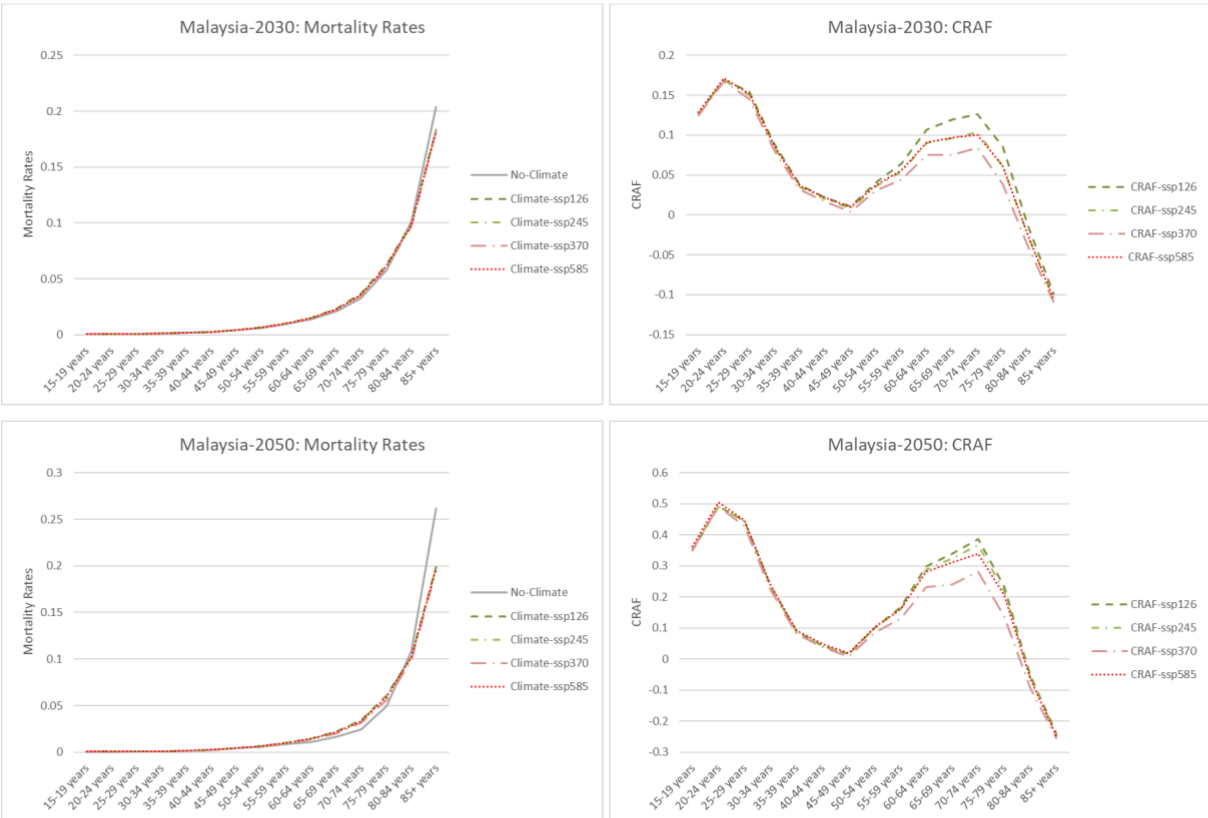


Figure 25: Projected mortality and CRAF in 2030 & 2050, Malaysia

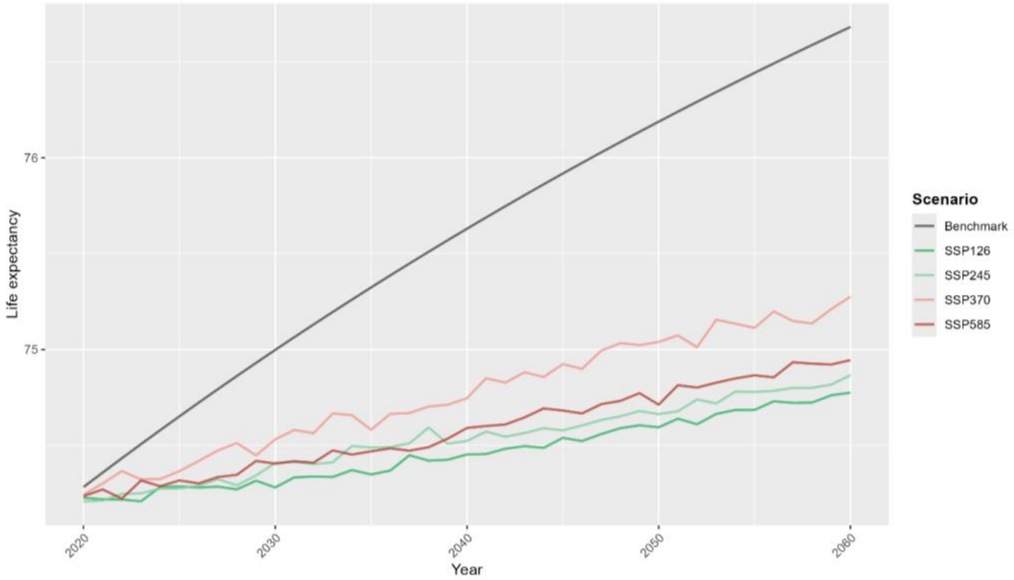


Figure 26: Projected life expectancy of Malaysia

5.2.6 Myanmar

In short-term, mortality rates in Myanmar are nearly identical across all climate scenarios and the No-Climate baseline, indicating minimal short-term climate influence on overall mortality levels. The CRAF, however, shows clear age-specific variations: positive adjustments for middle-aged to older adults (around 40–70 years) and negative values for the youngest and oldest groups. Among scenarios, SSP370 exhibits the highest positive CRAF peak—suggesting the strongest climate-related mortality effects—followed by SSP245, while SSP585 and SSP126 remain slightly lower, reflecting milder impacts under more sustainable pathways.

In longer-term, mortality rates still display little overall divergence among scenarios, though minor gaps begin appearing at older ages. The CRAF with positive adjustments becoming more pronounced across most adult age groups, particularly between ages 45 and 70. SSP585 shows the highest CRAFs, implying greater climate-driven mortality pressure under high-emission conditions, followed by SSP370. In contrast, SSP126 and SSP245 show lower CRAFs, suggesting relatively better adaptation and reduced health impacts in sustainable development pathways.

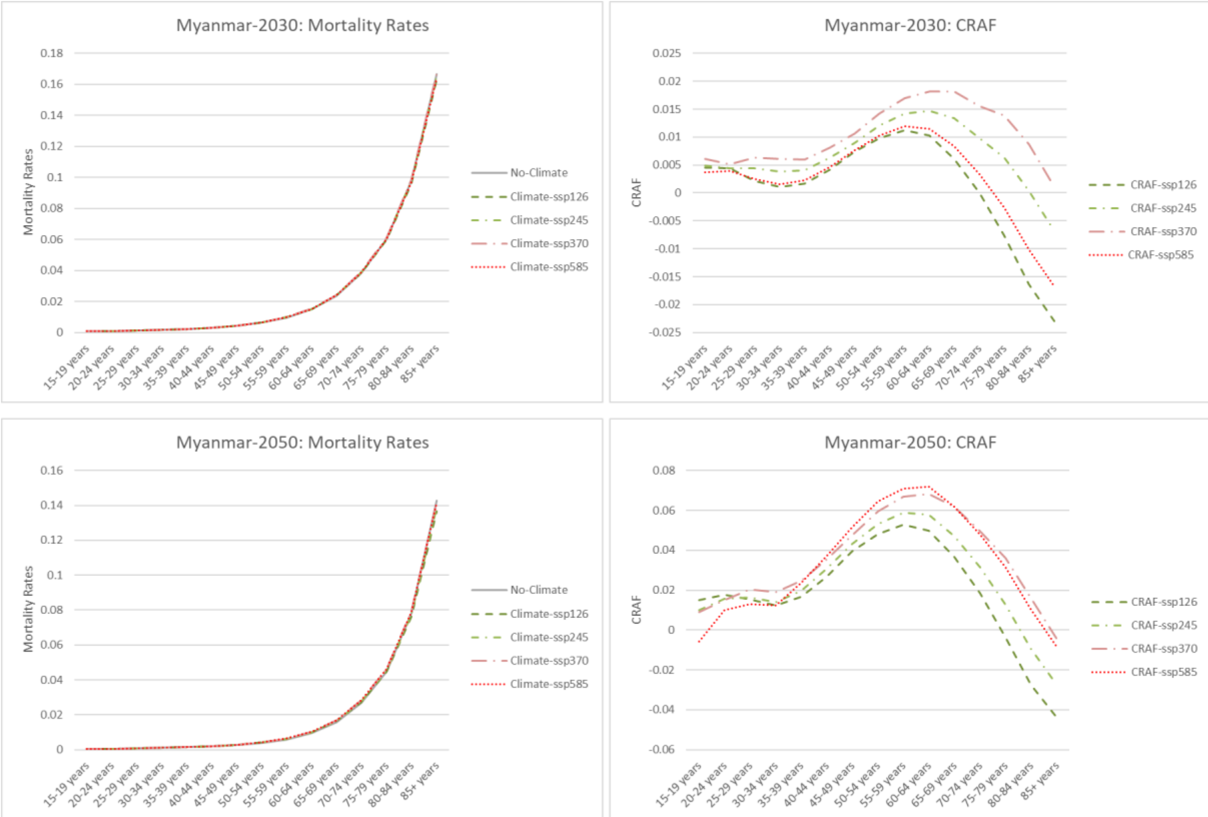


Figure 27: Projected mortality and CRAF in 2030 & 2050, Myanmar

Myanmar's life expectancy increases steadily across all scenarios, though the benchmark projects consistently higher values throughout. Among the SSP scenarios, SSP126 and SSP245 perform best, staying closest to the benchmark, while SSP370 and SSP585 remain lower across the projection period. This pattern indicates that sustainable development pathways support stronger health and longevity gains, whereas higher-emission or less adaptive scenarios lead to slower improvements in life expectancy.

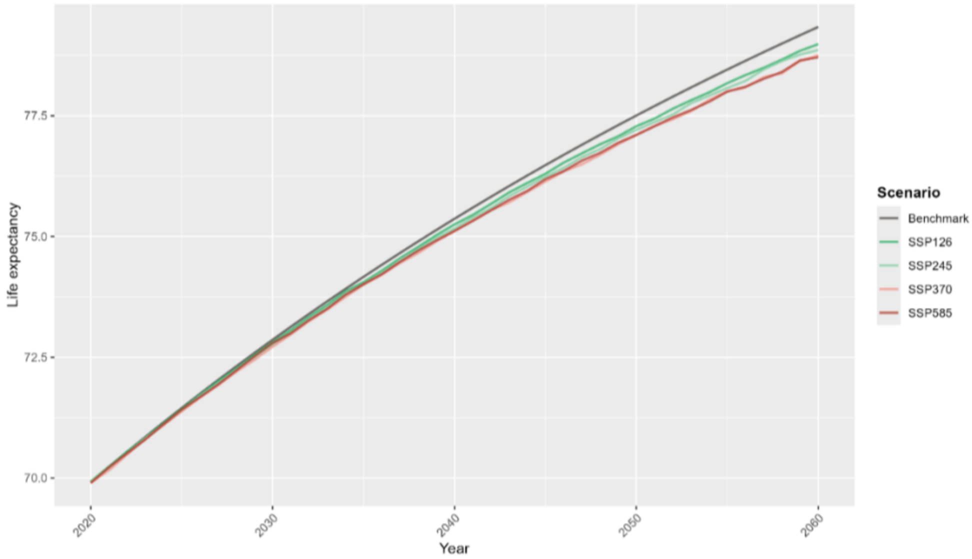


Figure 28: Projected life expectancy of Myanmar

5.2.7 Philippines

The CRAF for Philippines reveal minor age-specific differences, despite almost identical mortality rate projected under all scenarios in short term. We see slightly positive adjustments for younger adults (15–40 years), turning negative for middle-aged and older groups before slightly rebounding at the oldest ages. Among the scenarios, SSP585 shows the highest positive CRAFs for younger ages, while SSP126 shows the highest CRAFs for old age groups beyond 70.

By 2050, mortality rates remain broadly consistent across scenarios. The CRAF patterns strengthen modestly compared to 2030, with positive values persisting for younger to mid-aged adults and negative adjustments for older groups. The high-emission scenario SSP585 exhibits the largest positive CRAFs, implying the strongest adverse climate-related effects on mortality, while SSP370 continues to show the lowest levels.

The Philippines' life expectancy shows a modest rise from 2020 to 2060. All SSP scenarios project higher life expectancy than the benchmark. Among the scenarios, SSP370 records the highest life expectancy, followed by SSP126 and SSP245, while SSP585 seems to have the lowest life expectancy projections among the SSP pathways, though still above the benchmark. This indicates that sustainable and moderate-emission pathways yield more favourable long-term health outcomes compared to high-emission futures.

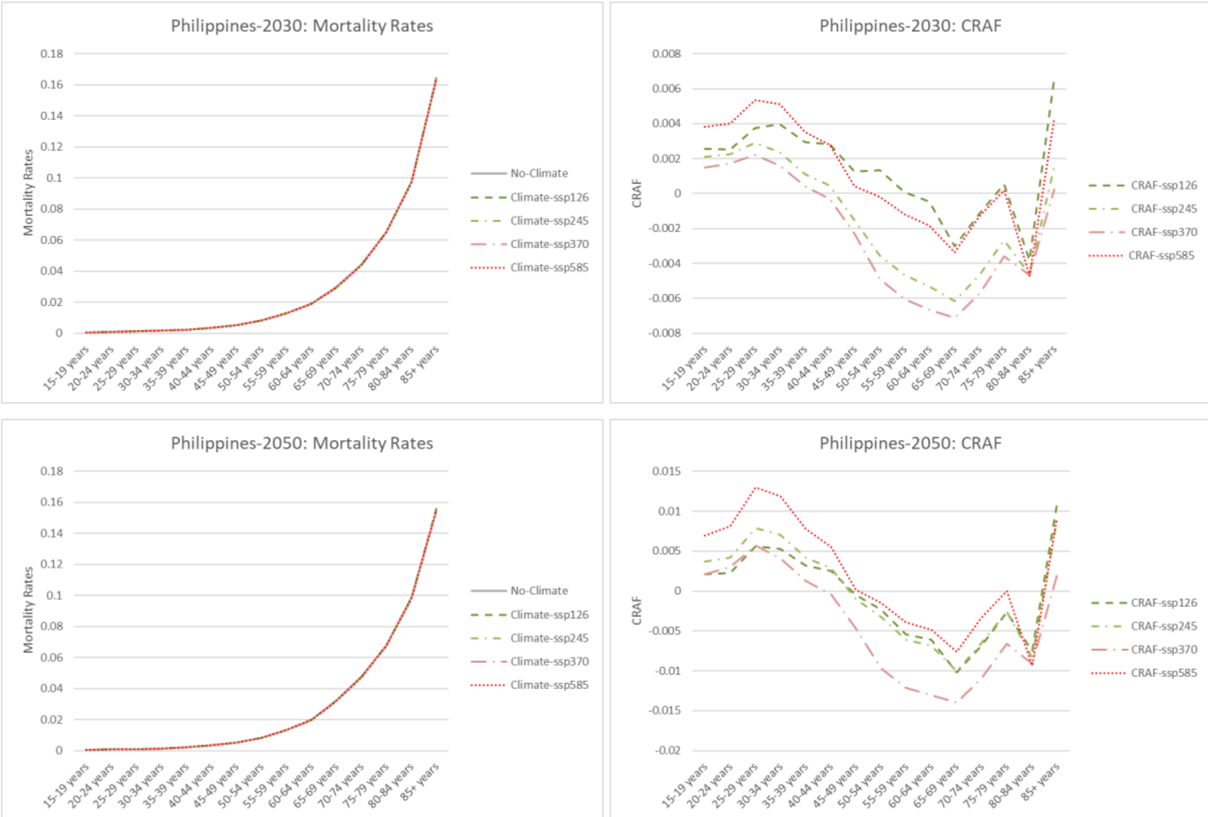


Figure 29: Projected mortality and CRAF in 2030 & 2050, Philippines

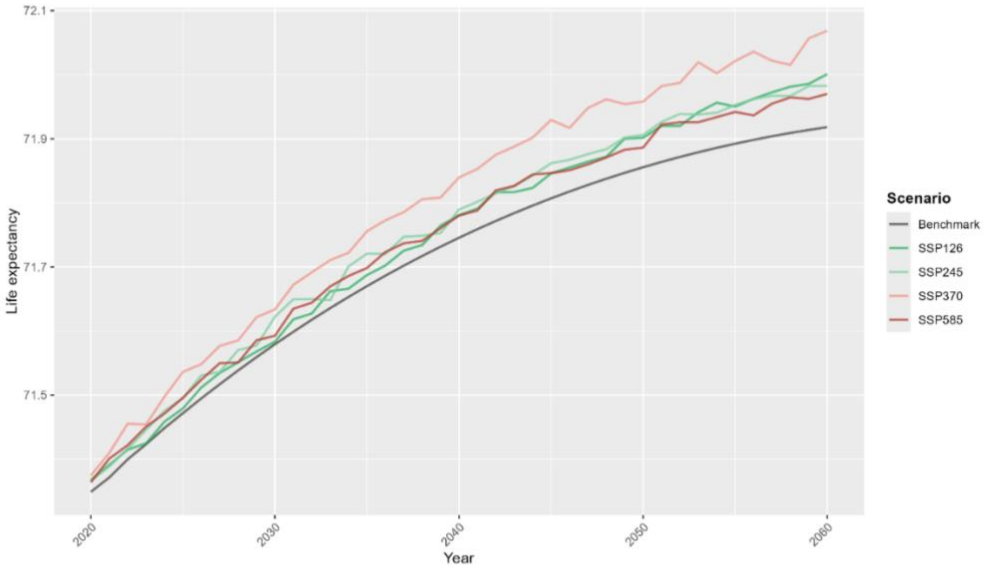


Figure 30: Projected life expectancy of Philippines

5.2.8 Singapore

In the short term, there is no significant difference between projected SSP rates and benchmark scenario rates. The CRAF is larger for older age groups, but the higher values are only ranging between 4-7%. This suggests that climate risk may not be a significant risk factor for mortality in the short term for Singapore.

In the long term, the mortality rates for each climate scenarios are still close to the benchmark, but the CRAF shows wider ranges across different SSP scenarios. The larger CRAF may be partially caused by the overall low mortality rates in Singapore, such that the small absolute deviations in mortality can cause large relative deviations (and therefore large CRAF values). Our current results suggest that climate impacts on mortality rates are not significant for Singapore overall.

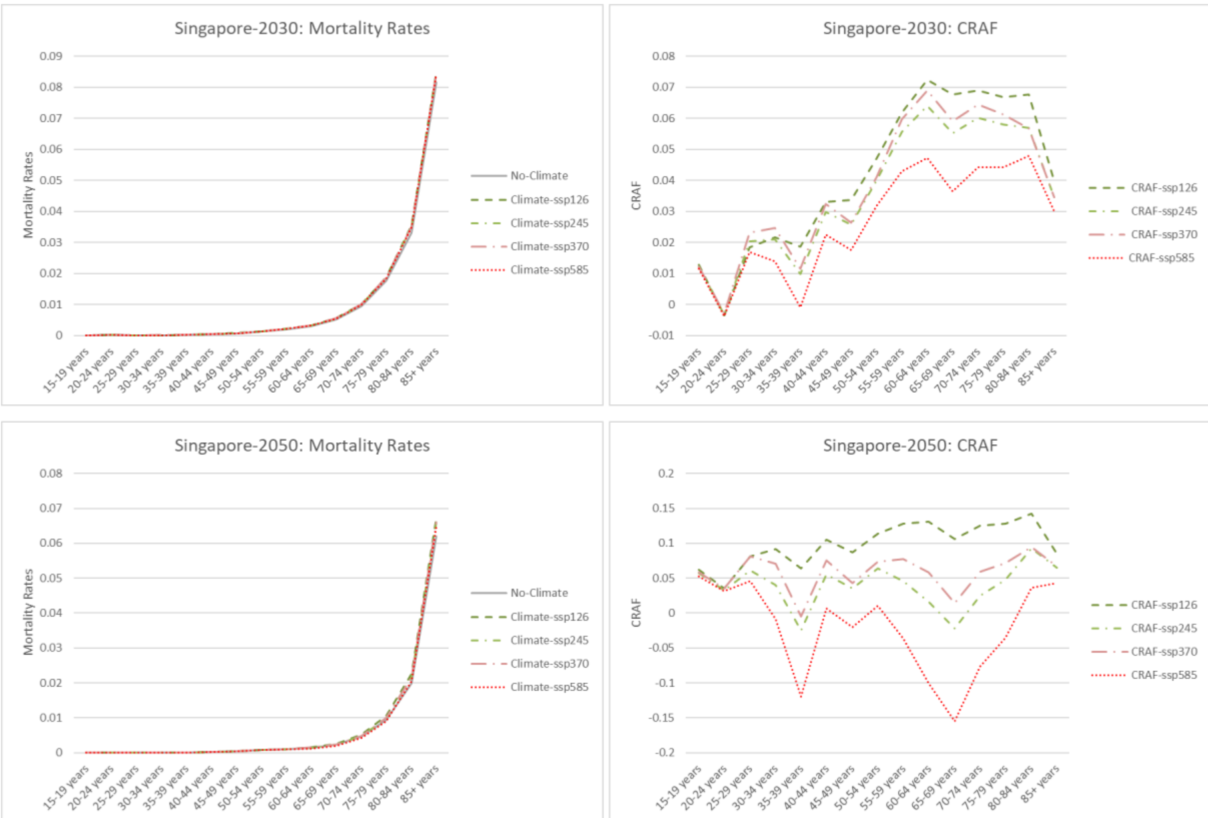


Figure 31: Projected mortality and CRAF in 2030 & 2050, Singapore

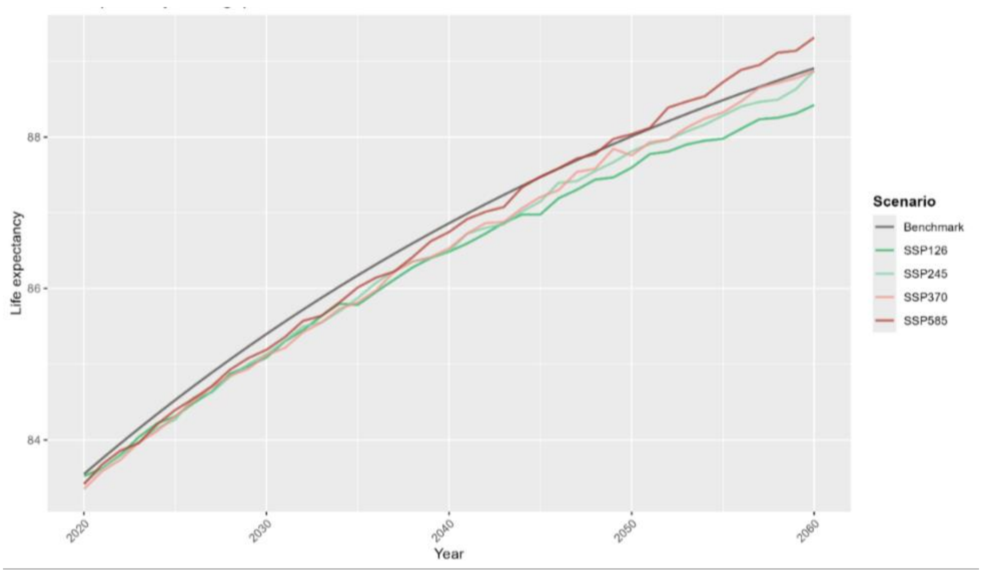


Figure 32: Projected life expectancy of Singapore

Singapore's life expectancy rises steadily across all scenarios from 2020 to 2060, though the rate of increase varies by pathway. SSP370 and SSP585 project the highest life expectancies by 2060, with SSP585 exceeding the benchmark by 2050. SSP126 and SSP245 remain below the benchmark, indicating relatively slower gains under more sustainable development paths. Overall, while all scenarios show continued improvements in longevity, higher-emission pathways (SSP370/585) yield the largest projected increases by 2060.

5.2.9 South Korea

For South Korea in short term, middle-aged and elderly populations experience the highest positive adjustments, peaking around 65–80 years. Among scenarios, SSP126 shows the largest positive CRAFs—suggesting the strongest climate-related mortality increases—followed by SSP245 and SSP585, while SSP370 remains close to zero or slightly negative, indicating weaker effects.

For longer-term, the CRAF values amplify considerably, suggesting stronger climate-related impacts over time. Positive adjustments become more pronounced for older adults, again peaking between 60 and 80 years. SSP126 exhibits the highest CRAFs, implying elevated sensitivity or overcompensation under its assumptions, while SSP585 and SSP245 show moderate effects. SSP370 remains the least affected, with near-zero or negative CRAFs across most ages, indicating the weakest climate influence on mortality.

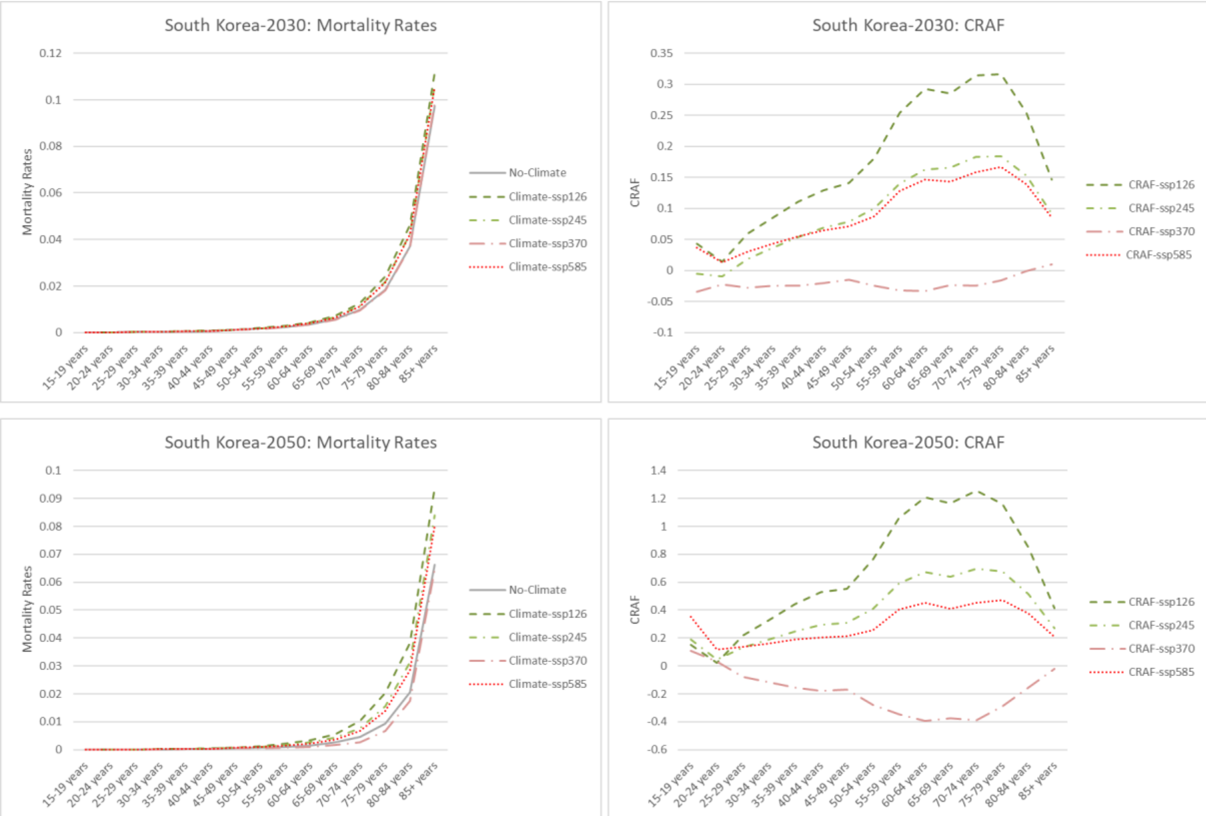


Figure 33: Projected mortality and CRAF in 2030 & 2050, South Korea

South Korea's life expectancy rises steadily across all scenarios. Among the scenarios, SSP370 tracks close to but slightly higher than the benchmark. SSP585 projections sits below the benchmark, while SSP245 and SSP126 remain further below.

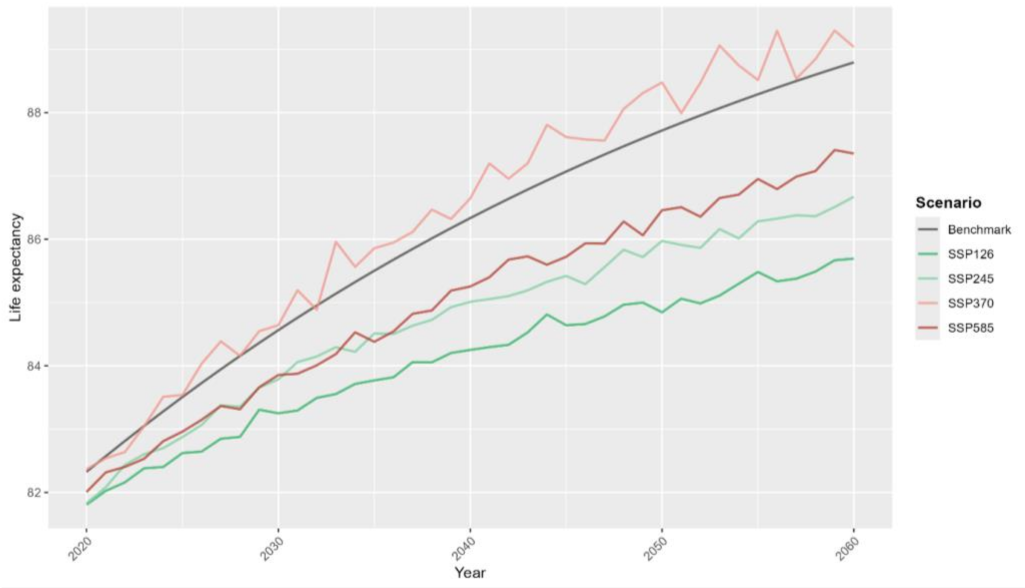


Figure 34: Projected life expectancy of South Korea

5.2.10 Thailand

In 2030, mortality rates in Thailand are nearly identical across all climate scenarios. The CRAF show small but variable age-specific impacts—positive for middle-aged groups and slightly negative for younger and older ages. SSP126 exhibits the highest positive CRAFs, indicating slightly stronger climate-related mortality adjustments, while SSP370 tends to show negative CRAFs, suggesting minor reductions in mortality under the scenario.

By 2050, mortality rates remain very similar across scenarios but diverge slightly at older ages. The CRAF showing a clearer positive adjustment for middle-aged to early elderly groups (around 45–70 years). SSP126 and SSP245 show the highest positive CRAFs, implying stronger climate-related effects, whereas SSP370 continues to record the lowest or negative CRAFs, reflecting relatively smaller or offsetting climate impacts.

Thailand's life expectancy rises steadily across all scenarios though differences emerge over time. The benchmark projects the highest and smoothest growth, reaching about age 81 by 2060. Among the SSPs, SSP370 and SSP585 stay close to the benchmark but outperform SSP126 and SSP245. Overall, while all scenarios indicate continued longevity improvements, higher-emission pathways

(SSP370/585) are associated with somewhat stronger gains than the more sustainable ones (SSP126/245).

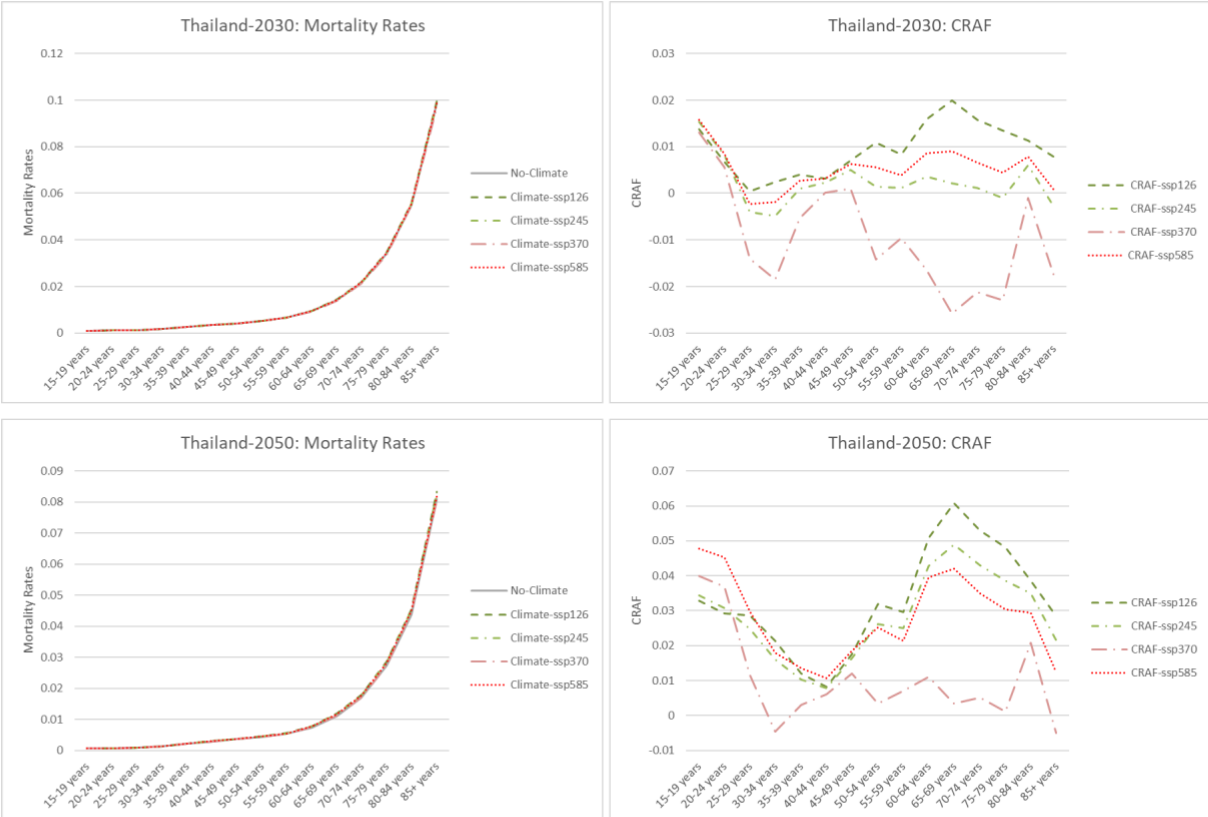


Figure 35: Projected mortality and CRAF in 2030 & 2050, Thailand

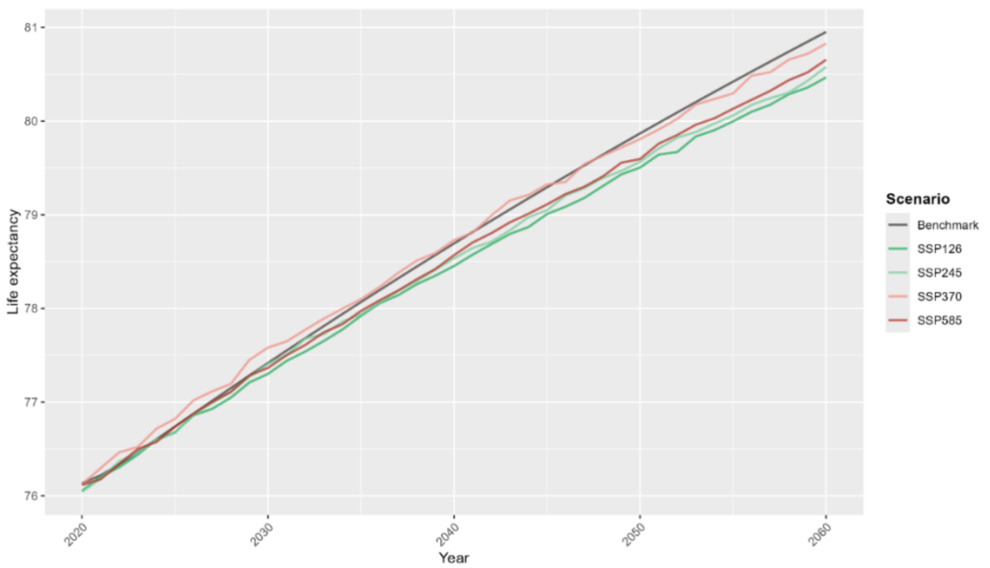


Figure 36: Projected life expectancy of Thailand

5.2.11 Vietnam

For Vietnam, The CRAF shows uniformly negative values across most age groups, suggesting a slight reduction in mortality under climate-influenced scenarios. Among pathways, SSP126 and SSP245 exhibit the most negative CRAFs—implying small health benefits or better resilience—while SSP370 and SSP585 remain closer to zero, indicating weaker improvements or neutral effects.

By 2050, mortality rates remain very similar across scenarios but start diverging slightly among older populations. The CRAF values deepen further, especially for SSP126 and SSP245, showing stronger negative adjustments that point to continued improvements in mortality outcomes under sustainable development. SSP370 stays nearly flat with minimal change, while SSP585 becomes more negative but remains less pronounced than the sustainable pathways. Overall, Vietnam's mortality trends suggest that long-term climate impacts may modestly benefit health outcomes under low-emission, sustainable scenarios.

Vietnam's life expectancy increases consistently across all scenarios from 2020 to 2060, with clear separation between pathways. SSP126 and SSP245 project the highest life expectancies, both well above the benchmark, reflecting stronger health and socioeconomic progress under sustainable development. In contrast, SSP370 and SSP585 remain lower, though still outperforming the benchmark. Overall, the results suggest that Vietnam's longevity improves under all futures, but the gains are greatest in low-emission, sustainability-focused pathways.

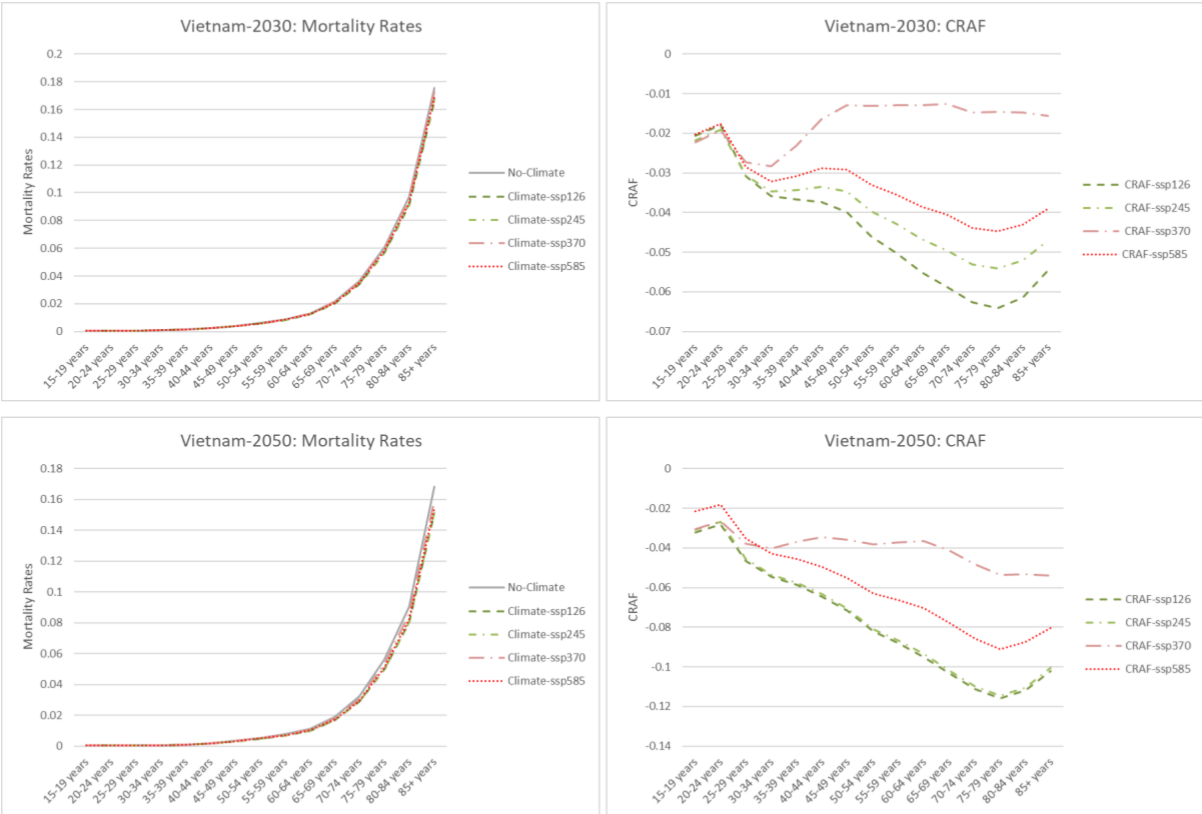


Figure 37: Projected mortality and CRAF in 2030 & 2050, Vietnam

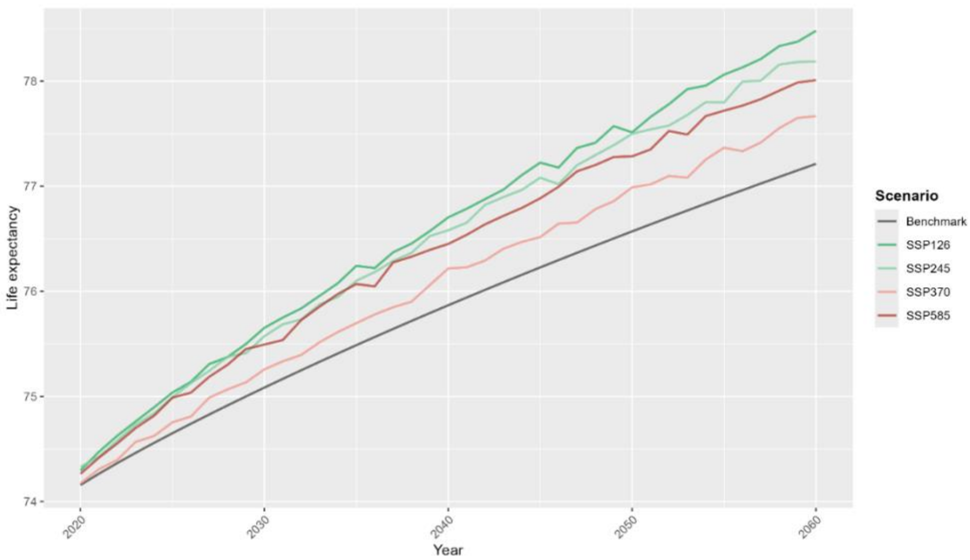


Figure 38: Projected life expectancy of Vietnam

5.2.12 Result Summary

We briefly summarise the CRAF results described in sections above in this section by plotting the CRAFs of all countries together, in the four climate scenarios respectively, for year 2030 and 2050.

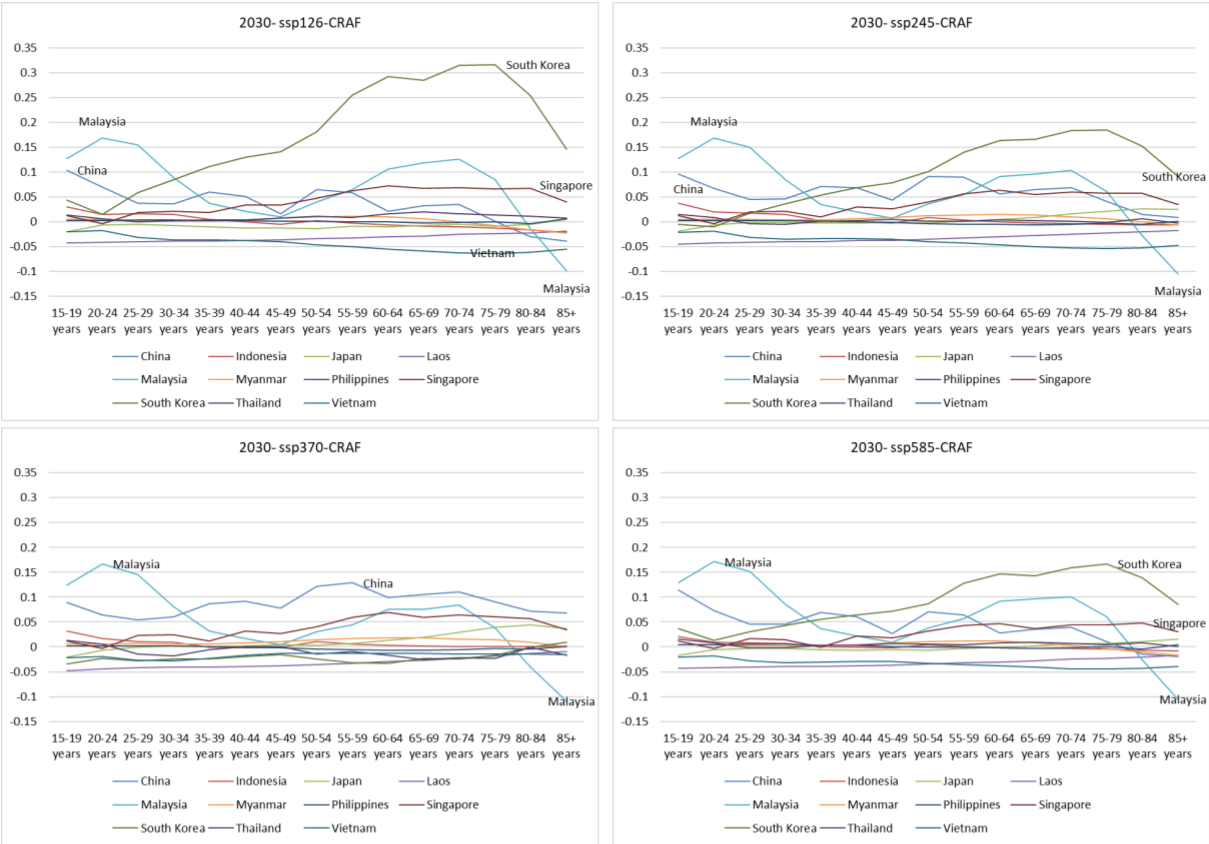


Figure 39: CRAF for SSP scenarios by country (2030)

Across the four 2030 climate scenarios (SSP126, SSP245, SSP370, and SSP585), the CRAF curves reveal largely stable age-related patterns for most countries. Typical ranges of CRAFs across all scenarios are between -0.05 to 0.1, with only a few displaying notable higher values. South Korea stands out with the strongest positive ridge except for scenario SSP370, rising across middle to older ages before tapering at the 85+ group. Malaysia also shows comparatively wider range of CRAF values, with usually higher CRAFs for younger ages and negative CRAFs for older ages. China displays the highest CRAFs in scenario SSP370, showing a high mortality risk in this scenario in comparison to other three. In contrast, several countries—including Vietnam, Myanmar, Laos, Thailand, and at times the Philippines and Indonesia—feature consistently negative CRAFs across wide sections of the age distribution. These negative values indicate scenarios where climate-adjusted mortality risk in 2030 falls below the baseline, particularly at older ages for Vietnam and at younger ages for Malaysia under some pathways. As scenarios intensify from SSP126 to SSP585, the overall shape of country trajectories remains intact, but both positive and negative deviations become slightly more pronounced. Overall, the charts portray a region where most countries maintain modest climate-mortality adjustments, but with clear pockets of both elevated and reduced relative risk depending on country and age group.

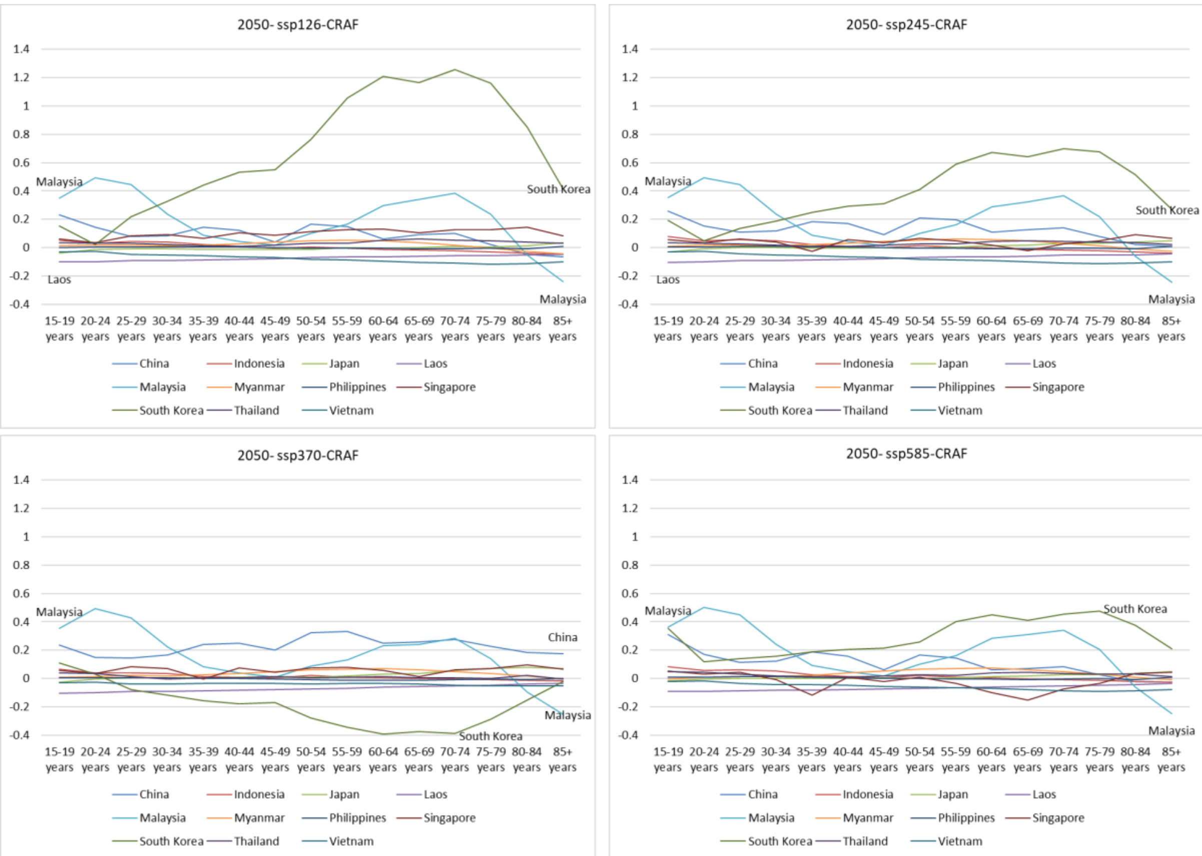


Figure 40: CRAF for SSP scenarios by country (2050)

For 2025 results, the CRAF profiles reveal a more accentuated pattern of climate-adjusted mortality changes compared with 2030. Typical range of CRAFs is now between -0.1 to 0.2, with sharper peaks and deeper troughs emerging for specific countries. South Korea continues to dominate the landscape with the highest and most pronounced positive CRAF values, rising steadily from mid-adulthood and forming a broad crest between ages 50 and 79 across all scenarios. Malaysia also displays elevated CRAFs at younger and middle age groups, often followed by a steep decline into negative territory among the oldest groups. China continues to show highest mortality risk under SSP370. Singapore, Indonesia, Thailand, Myanmar, Japan, the Philippines, and Vietnam generally maintain near-zero curves with low variability, reflecting relatively muted climate-related mortality adjustments in 2050. Negative CRAFs are more visible in 2050 than in 2030. Laos shows persistent negative values across much of the age range. As climate scenarios intensify from SSP126 to SSP585, the overall shape of each country's trajectory remains consistent.

Table 18 summarises key observations of CRAF results, including the most affected age groups, highest mortality risk scenario in year 2050 and their corresponding CRAF ranges.

Table 18: Summary of CRAF observations by country

Country	Most affected age-groups	Highest mortality risk scenario (2050)	CRAF ranges under highest mortality risk in 2050
China	Young and old age	SSP370	0.14 to 0.33
Indonesia	Young and mid age	SSP585	-0.03 to 0.08
Japan	Old age	SSP370	-0.02 to 0.08
Laos	Mid to old age	SSP585	-0.09 to -0.03
Malaysia	Mid to old age	SSP126	-0.24 to 0.49
Myanmar	Mid to old age	SSP370	-0.01 to 0.06
Philippines	Young and old age	SSP126	-0.01 to 0.01
Singapore	Mid to old age	SSP126	0.03 to 0.14
South Korea	Mid to old age	SSP126	0.02 to 1.25
Thailand	Young and old age	SSP126	0.01 to 0.06
Vietnam	Old age	SSP370	-0.05 to -0.02

6 Conclusion

We studied climate-related deaths in East Asia and SEA, focusing on air pollution, extreme heat and extreme cold deaths. Projections for climate-related deaths are then performed, and significance of climate risk in the future is accessed by comparing the impact of climate risk mortality with all-cause mortality.

The main focus of this study is to access the significance of climate risk in each region and country, by trying to disentangle climate effects from the overall mortality trend. If the difference between all-cause mortality and mortality without climate risk, i.e. CRAF is large, then we say the impact is significant. The larger/smaller the CRAF, more severe/favourable the impact is, depending on an increase/decrease in the mortality rates after including climate related deaths.

Our main contribution lies in providing a ratio to adjust for climate risks in life tables. This allows insurers who wish to incorporate climate risks in their life portfolios to have a benchmark or approximation to adjust their mortality experiences. The flexibility of having several climate scenarios to project mortality allows for scenario testing and understand how mortality experience will develop under different scenarios.

6.1 Recommendations

6.1.1 Adjusting mortality tables using CRAF

One of the most possible use cases of the CRAFs is when climate related scenario analysis or stress testing is to be conducted. If all relevant data are available at company level, one may wish to fit his/her own data using our proposed model to obtain their own climate-scenario adjusted mortality rates. However, we expect such data at company level to be scarce, especially the data related to climate-caused deaths. An alternative approach is to apply our CRAF results to an existing all-cause mortality table to obtain a climate-scenario-adjusted mortality table for further analysis. We hereby briefly explain how it can be done conveniently. Please note that the full tables of mortality rates, CRAFs, MAPE across all age groups from age 15 to 85+ will be made available to GAIP partners[2].

Suppose a particular insurance company already had an existing mortality table that is being used in product development and evaluation, and that the company wishes to assess the possible impacts of different climate scenario on their portfolio. The steps taken to adjust the mortality table is described below:

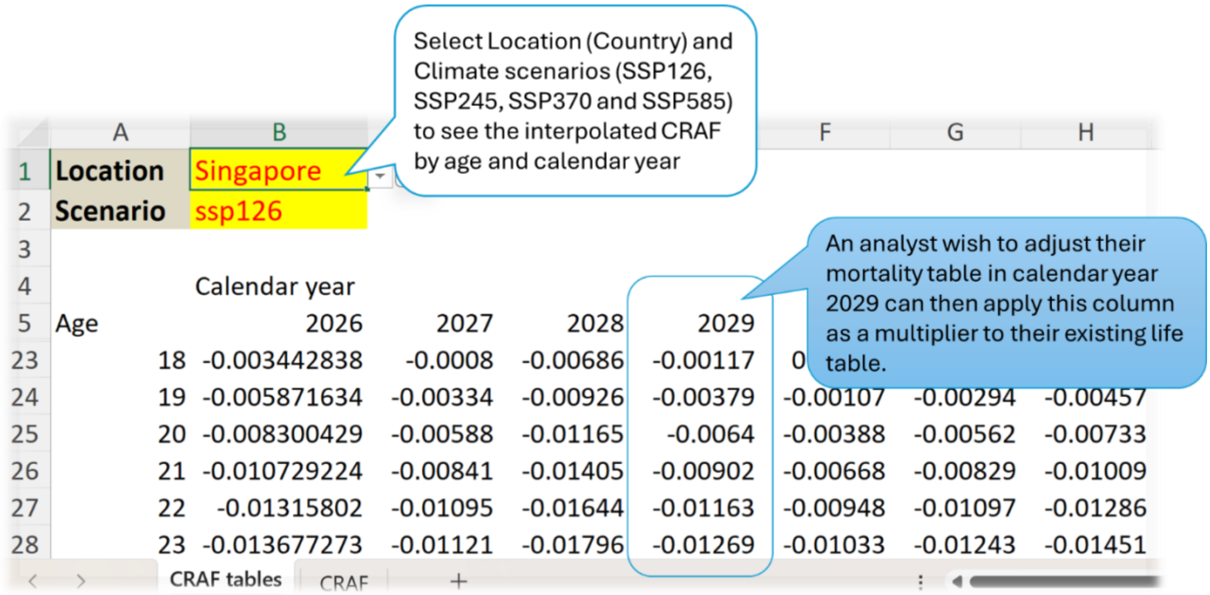
1. Suppose Figure 41 is a snapshot of an all-cause mortality table for Singapore in calendar year 2029 that is currently used (hypothetical numbers, $q_{x,2029,Singapore}$);

	A	B
1	**location_name**	**Singapore**
2		
3	**Mortality rates**	**Year**
4	**ages**	**2029**
5	18	0.000128078
6	19	0.000142695
7	20	0.000155784
8	21	0.000165881
9	22	0.000171522
10	23	0.000171783
11	24	0.000167891

Figure 41: Mortality table snapshot

2. Using the CRAF table provided by GAIP, one can choose "Singapore" and scenario to be considered (e.g. SSP126) and see all the CRAFs for all ages and all calendar years. To adjust for calendar year 2029 mortality rates, we find the column "2029" ($CRAF_{x,2029,Singapore}$) as indicated in Figure 42.

[2] The tables will be made available on the login section of the GAIP website at www.gaip.global.



	A	B	C	D	E	F	G	H
1	Location	Singapore						
2	Scenario	ssp126						
3								
4		Calendar year						
5	Age	2026	2027	2028	2029			
23	18	-0.003442838	-0.0008	-0.00686	-0.00117	0		
24	19	-0.005871634	-0.00334	-0.00926	-0.00379	-0.00107	-0.00294	-0.00457
25	20	-0.008300429	-0.00588	-0.01165	-0.0064	-0.00388	-0.00562	-0.00733
26	21	-0.010729224	-0.00841	-0.01405	-0.00902	-0.00668	-0.00829	-0.01009
27	22	-0.01315802	-0.01095	-0.01644	-0.01163	-0.00948	-0.01097	-0.01286
28	23	-0.013677273	-0.01121	-0.01796	-0.01269	-0.01033	-0.01243	-0.01451

Figure 42: CRAFs snapshot

3. The adjusted mortality table (Singapore year 2029) under scenario SSP126 is then $q_{x,2029,Singapore} * (1 + CRAF_{x,2029,Singapore})$ for all ages x.
4. The climate-adjusted mortality table can then be used in subsequent analysis.

6.1.2 Simulation results: EV adjustments

Our model projections for different climate scenarios have shown that the mortality trends can sometimes be quite different from our benchmark scenario. For in-force guaranteed level premium life insurance—especially competitively priced, mortality-sensitive products like term life—the impact of mortality can significantly reduce profitability. We use a simplified example of a term-20 life insurance portfolio to illustrate this point. Figure 43 shows the change in Embedded Value (EV) for the term life portfolio in each climate scenario in comparison to the EV calculated with benchmark LC-model projected mortality for four selected countries (Singapore, Malaysia, Japan and China). The embedded value (EV) calculation is based on standard term-life pricing assumptions at issue in 2020, age 45, a 20-year period. EV results incorporate projected premiums, claims, expenses, investment returns, and taxes over the policy horizon under each mortality assumption. The assumptions for the EV calculation can be found in Appendix 7.2.

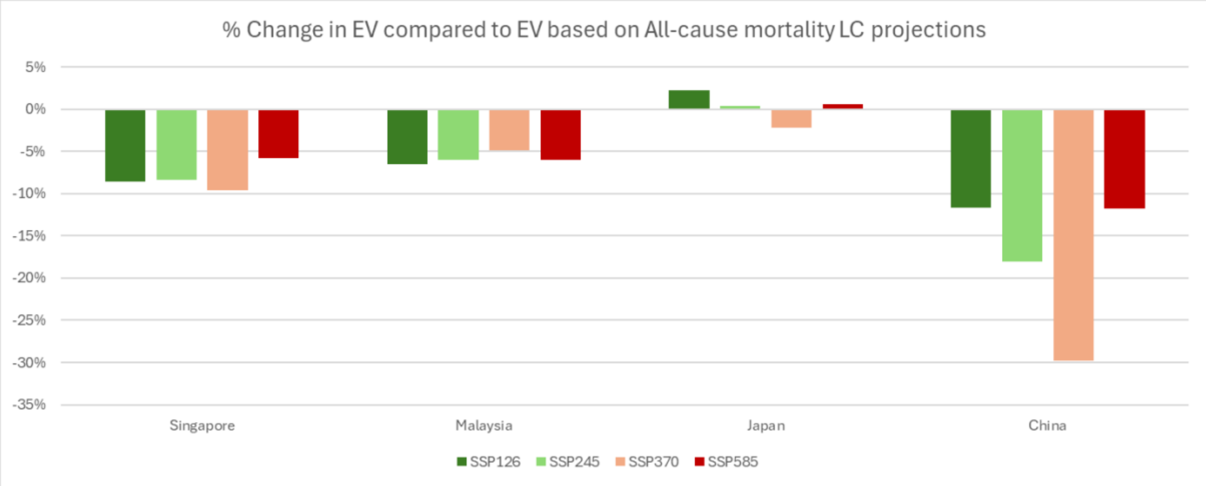


Figure 43: Percentage change in EV in each scenario compared to EV based on all-cause mortality LC model

The EV comparison shows that the financial impact can be quite significant under different climate scenarios. On the other hand, for in-force products with longevity risk such as annuities or pension schemes, we could expect some mortality gain. Because the climate-related mortality impact varies by country and by age group, companies should pay close attention to their product mix and business risk mix. For example, the EV calculation for Japan shows a small gain for most climate scenarios (except for SSP370) because Japan is predicted to have mortality improvements for ages below 60 in these three scenarios.

Given that our model predicts different impact of climate on population mortality rates under different scenarios, we strongly encourage life insurance companies to review the EV impact under different scenarios in their own portfolios, and to incorporate such mortality scenarios as part of their risk management practices. We are sharing a set of tools as electronic supplement material of this report with partners of Global Asia Insurance Partnership via the members-only section of their website at www.gaip.global. Life insurance practitioners can refer to these tools for climate scenario testing of their book of business. Appendix 7.3 provides more details about the electronic supplementary material.

6.2 Limitations

Our study assumes that climate risk factor is independent with other risk factors, such as occupational and dietary risks. In practice, these factors may interact, and climate change can influence socioeconomic and behavioural determinants of health. For example, climate change may impact crop growth and harvest, and in turn affect people's diet by introducing certain nutritional deficiencies. To incorporate such cross-factor interactions, future research will require more comprehensive data and advanced multivariate modelling approaches.

We analyse four SSP climate scenarios; however, we do not recommend a single benchmark pathway for practical implementation. Although comparison of mortality rates between benchmark LC model and different SSP scenarios can be done to have a feeling of which SSP scenario is more similar to the benchmark pathway, scenario choice should reflect country-specific development trajectories and regulatory guidance. Expert judgement is essential when selecting an appropriate climate scenario for stress testing or pricing applications.

Our estimations of CRAFs are preliminary and exhibit year-to-year variations. As such, CRAF values should not be applied mechanically. It is highly recommended that CRAF should be interpreted alongside projected mortality rates, as it provides a percentage adjustment to reflect climate-related mortality risk rather than a standalone mortality estimate.

The regression specification used to fit and estimate $\hat{q}^{C}_{x,t,c}$ may be subject to model misspecification, as our selection of explanatory variables is based on available data and literature guidance. Further empirical studies, more granular environmental data, and alternative modelling strategies could enhance accuracy and robustness.

Finally, the CRAF is designed as a forward-looking, scenario-based tool for stress testing climate-related mortality risks, rather than for adjusting central life table estimates or modifying baseline mortality assumptions. It offers an additional, transparent layer of adjustment to capture potential climate impacts, both explicit and implicit, while preserving the integrity of established mortality baselines. Users are encouraged to continue collecting relevant mortality and climate-related data over time and to monitor the application of the CRAF, so that its use can be refined and better informed by emerging evidence.

7 Appendix

7.1 Data preprocessing

7.1.1 Variable standardisation

Before model fitting, we employ standardization to ensure each climate variable has the same weight. The reason is to not let climate variables with larger scales incorrectly influence model parameters and interpretation of results. From the boxplot below, we can see that CDD65 and HDD65 have significantly larger scales than PM2.5 and mean temperature. If we do not standardize the scale of each variable, then CDD65 and HDD65 will have more weight in the model and undermine the importance of PM2.5 and mean temperature.

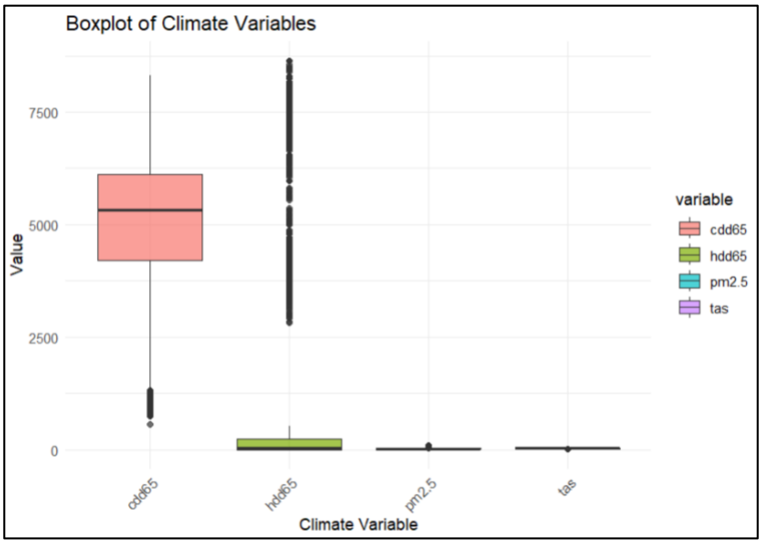


Figure 44: Boxplot of climate variables

The standardisation we employ is z-score standardisation. It is relatively simple, and is achieved with the following formula:

$$z = \frac{x - \mu}{\sigma}$$

where x is the original variable values, μ is the mean of the variable values, and σ is the standard deviation of the variable values. For consistency, we apply z-score standardisation to all four variables considered.

7.1.2 Mortality rate transformation

We note that some of the climate mortality rates can be negative, as described by the saved deaths property in Section 3.1. However, the lower bound for Poisson distribution, which is the main assumption for the distribution of death counts, is 0. To address the problem, we add 1 to all climate mortality rates to ensure they are all positive. When using the model to perform predictions, deduct 1 to all predicted mortality rates to recover the actual rates. This workaround will be used during GLM modelling, where the Poisson distribution is assumed for modelling death counts.

7.2 EV assumptions

Product description

	Description
Product	Term-20 life insurance
Issue age	45
Issue date	1/1/2018
Sum insured	1,000,000
Premium	Singapore: 3,000; Japan: 3,700; China: 5,200; Malaysia: 9,600
Sales commission	75% of first year premium

Assumption

	Pricing Assumption	Valuation Assumption	Solvency Assumption
Interest rate	4.5%	3.5%	3.0%
Inflation	3.0%	2.0%	2.0%
Acquisition expense	500	500	500
Maintenance expense	200	220	240
Lapse rate	2.5% in policy year 1-5; 5.0% thereafter	2.0 % in policy year 1-5; 4.0% thereafter	1.25% in policy year 1-5; 2.5% thereafter
Mortality rate	Simulated mortality rates in Scenario 1-6 in Section 5.2.2	Simulated mortality rates in Scenario 1-6 in Section 5.2.2 with 10% MfAD	Simulated mortality rates in Scenario 1-6 in Section 5.2.2 with 20% MfAD

- EV valuation date: December 31, 2022
- For simplicity, we assume no basis change in any scenario.
- Premiums are calculated based on pricing assumptions and an IRR of approximately 15% for all countries.

7.3 Mortality/CRAF projection tables (for Section 5.2) and MAPE by country

The tables below show the mortality rates and CRAFs for each in-scope country under the different climate scenarios for selected age groups. MAPE results by age-groups for each country are also included. Please note that the full tables of mortality rates, CRAFs, MAPE across all age groups from age 15 to 85+ will be made available to GAIP partners.

7.3.1 China

- **Mortality/CRAF projections**

location_name	China	China-2030: Mortality Rates
year	2030	

Age_groups	No-Climate	Climate-ssp126	Climate-ssp245	Climate-ssp370	Climate-ssp585
30-34 years	0.000652	0.000676	0.000682	0.000691	0.000682
60-64 years	0.007882	0.008048	0.008322	0.008666	0.008106
85+ years	0.179050	0.172109	0.180526	0.191336	0.175683

location_name	China	China-2050: Mortality Rates
year	2050	

Age_groups	No-Climate	Climate-ssp126	Climate-ssp245	Climate-ssp370	Climate-ssp585
30-34 years	0.000419	0.000453	0.000468	0.000488	0.000469
60-64 years	0.004959	0.005259	0.005504	0.006194	0.005250
85+ years	0.135833	0.126747	0.137211	0.159668	0.132173

location_name	China	China-2030: CRAF
year	2030	

Age_groups	CRAF-ssp126	CRAF-ssp245	CRAF-ssp370	CRAF-ssp585
30-34 years	0.03609	0.04638	0.06006	0.04555
60-64 years	0.02104	0.05584	0.09940	0.02842
85+ years	-0.03876	0.00824	0.06862	-0.01880

location_name	China	China-2050: CRAF
year	2050	

Age_groups	CRAF-ssp126	CRAF-ssp245	CRAF-ssp370	CRAF-ssp585
30-34 years	0.08242	0.11740	0.16503	0.12112
60-64 years	0.06058	0.10988	0.24910	0.05880
85+ years	-0.06689	0.01014	0.17547	-0.02695

- **MAPE Results**

	In-sample (1990-2014) MAPE			Out-of-sample (2015-2019) MAPE		
Age Group	With $\kappa_{t,c}$	Benchmark	Without $\kappa_{t,c}$	With $\kappa_{t,c}$	Benchmark	Without $\kappa_{t,c}$
30-34 years	3.29	3.20	3.29	48.89	53.40	48.86
60-64 years	1.95	2.46	1.95	37.26	45.13	37.42
85+ years	4.91	6.24	5.16	33.10	42.50	32.94

7.3.2 Indonesia

- **Mortality/CRAF projections**

location_name	Indonesia				
year	2030	Indonesia-2030: Mortality Rates			
Age_groups	**No-Climate**	**Climate-ssp126**	**Climate-ssp245**	**Climate-ssp370**	**Climate-ssp585**
30-34 years	0.001195	0.001212	0.001212	0.001206	0.001204
60-64 years	0.017300	0.017196	0.017296	0.017349	0.017276
85+ years	0.226924	0.222233	0.225396	0.227487	0.225144

location_name	Indonesia				
year	2050	Indonesia-2050: Mortality Rates			
Age_groups	**No-Climate**	**Climate-ssp126**	**Climate-ssp245**	**Climate-ssp370**	**Climate-ssp585**
30-34 years	0.000794	0.000826	0.000834	0.000822	0.000836
60-64 years	0.014908	0.014708	0.014831	0.014970	0.014943
85+ years	0.247218	0.235102	0.237924	0.242955	0.240200

location_name	Indonesia			
year	2030	Indonesia-2030: CRAF		
Age_groups	**CRAF-ssp126**	**CRAF-ssp245**	**CRAF-ssp370**	**CRAF-ssp585**
30-34 years	0.01441	0.01475	0.00974	0.00726
60-64 years	-0.00605	-0.00023	0.00283	-0.00138
85+ years	-0.02068	-0.00674	0.00248	-0.00785

location_name	Indonesia			
year	2050	Indonesia-2050: CRAF		
Age_groups	**CRAF-ssp126**	**CRAF-ssp245**	**CRAF-ssp370**	**CRAF-ssp585**
30-34 years	0.03981	0.04979	0.03444	0.05256
60-64 years	-0.01345	-0.00515	0.00412	0.00235
85+ years	-0.04901	-0.03760	-0.01724	-0.02839

- **MAPE Results**

	In-sample (1990-2014) MAPE			**Out-of-sample (2015-2019) MAPE**		
Age Group	With $\kappa_{t,c}$	Benchmark	Without $\kappa_{t,c}$	With $\kappa_{t,c}$	Benchmark	Without $\kappa_{t,c}$
30-34 years	1.86	1.74	1.89	2.44	1.84	2.52
60-64 years	2.77	2.92	2.79	3.04	2.89	2.84
85+ years	1.92	2.00	1.86	1.38	1.96	1.57

7.3.3 Japan

- **Mortality/CRAF projections**

location_name	Japan	Japan-2030: Mortality Rates
year	2030	

Age_groups	No-Climate	Climate-ssp126	Climate-ssp245	Climate-ssp370	Climate-ssp585
30-34 years	0.000453	0.000450	0.000453	0.000454	0.000452
60-64 years	0.004806	0.004760	0.004831	0.004872	0.004800
85+ years	0.094478	0.094987	0.096819	0.097951	0.095956

location_name	Japan	Japan-2050: Mortality Rates
year	2050	

Age_groups	No-Climate	Climate-ssp126	Climate-ssp245	Climate-ssp370	Climate-ssp585
30-34 years	0.000372	0.000369	0.000371	0.000374	0.000372
60-64 years	0.003411	0.003401	0.003449	0.003510	0.003451
85+ years	0.077457	0.080232	0.081326	0.082808	0.081160

location_name	Japan	Japan-2030: CRAF
year	2030	

Age_groups	CRAF-ssp126	CRAF-ssp245	CRAF-ssp370	CRAF-ssp585
30-34 years	-0.00743	-0.00137	0.00130	-0.00348
60-64 years	-0.00970	0.00515	0.01372	-0.00120
85+ years	0.00540	0.02478	0.03677	0.01565

location_name	Japan	Japan-2050: CRAF
year	2050	

Age_groups	CRAF-ssp126	CRAF-ssp245	CRAF-ssp370	CRAF-ssp585
30-34 years	-0.00788	-0.00116	0.00590	0.00122
60-64 years	-0.00276	0.01115	0.02892	0.01179
85+ years	0.03582	0.04995	0.06909	0.04780

- **MAPE Results**

	In-SAMPLE (1990-2014) **MAPE**			**OUT-OF-SAMPLE** (2015-2019) **MAPE**		
Age Group	With $\kappa_{t,c}$	Benchmark	Without $\kappa_{t,c}$	With $\kappa_{t,c}$	Benchmark	Without $\kappa_{t,c}$
30-34 years	3.29	3.19	3.20	17.90	17.34	18.15
60-64 years	2.98	2.81	3.14	4.40	4.86	4.09
85+ years	1.88	2.54	2.41	15.90	18.20	15.27

7.3.4 Laos

- **Mortality/CRAF projections**

location_name	Laos	Laos-2030: Mortality Rates
year	2030	

Age_groups	No-Climate	Climate-ssp126	Climate-ssp245	Climate-ssp370	Climate-ssp585
30-34 years	0.001539	0.001478	0.001477	0.001476	0.001478
60-64 years	0.016646	0.016140	0.016140	0.016158	0.016142
85+ years	0.182472	0.178961	0.179343	0.180744	0.179488

location_name	Laos	Laos-2050: Mortality Rates
year	2050	

Age_groups	No-Climate	Climate-ssp126	Climate-ssp245	Climate-ssp370	Climate-ssp585
30-34 years	0.000991	0.000902	0.000902	0.000902	0.000908
60-64 years	0.011606	0.010858	0.010867	0.010878	0.010881
85+ years	0.167184	0.159290	0.159806	0.161663	0.161098

location_name	Laos	Laos-2030: CRAF
year	2030	

Age_groups	CRAF-ssp126	CRAF-ssp245	CRAF-ssp370	CRAF-ssp585
30-34 years	-0.03936	-0.04023	-0.04049	-0.03934
60-64 years	-0.03041	-0.03037	-0.02930	-0.03028
85+ years	-0.01924	-0.01715	-0.00947	-0.01635

location_name	Laos	Laos-2050: CRAF
year	2050	

Age_groups	CRAF-ssp126	CRAF-ssp245	CRAF-ssp370	CRAF-ssp585
30-34 years	-0.09035	-0.09034	-0.09027	-0.08438
60-64 years	-0.06449	-0.06372	-0.06277	-0.06253
85+ years	-0.04722	-0.04413	-0.03303	-0.03640

- **MAPE Results**

	In-sample (1990-2014) MAPE			**Out-of-sample (2015-2019) MAPE**		
Age Group	With $\kappa_{t,c}$	Benchmark	Without $\kappa_{t,c}$	With $\kappa_{t,c}$	Benchmark	Without $\kappa_{t,c}$
30-34 years	1.06	1.11	1.05	28.97	29.76	28.99
60-64 years	1.07	1.18	1.02	29.82	31.39	29.90
85+ years	0.95	0.86	0.97	20.34	19.82	20.36

7.3.5 Malaysia

- **Mortality/CRAF projections**

location_name	Malaysia	Malaysia-2030: Mortality Rates
year	2030	

Age_groups	No-Climate	Climate-ssp126	Climate-ssp245	Climate-ssp370	Climate-ssp585
30-34 years	0.001125	0.001224	0.001220	0.001215	0.001222
60-64 years	0.013650	0.015105	0.014886	0.014675	0.014897
85+ years	0.203977	0.183824	0.182681	0.181695	0.182412

location_name	Malaysia	Malaysia-2050: Mortality Rates
year	2050	

Age_groups	No-Climate	Climate-ssp126	Climate-ssp245	Climate-ssp370	Climate-ssp585
30-34 years	0.000948	0.001172	0.001170	0.001159	0.001173
60-64 years	0.011109	0.014426	0.014311	0.013685	0.014241
85+ years	0.261611	0.198878	0.198134	0.194831	0.196983

location_name	Malaysia	Malaysia-2030: CRAF
year	2030	

Age_groups	CRAF-ssp126	CRAF-ssp245	CRAF-ssp370	CRAF-ssp585
30-34 years	0.08823	0.08460	0.08016	0.08594
60-64 years	0.10656	0.09054	0.07511	0.09138
85+ years	-0.09880	-0.10440	-0.10924	-0.10572

location_name	Malaysia	Malaysia-2050: CRAF
year	2050	

Age_groups	CRAF-ssp126	CRAF-ssp245	CRAF-ssp370	CRAF-ssp585
30-34 years	0.23632	0.23474	0.22253	0.23797
60-64 years	0.29861	0.28825	0.23186	0.28196
85+ years	-0.23979	-0.24264	-0.25526	-0.24704

- **MAPE Results**

	In-sample (1990-2014) MAPE			Out-of-sample (2015-2019) MAPE		
Age Group	With $\kappa_{t,c}$	Benchmark	Without $\kappa_{t,c}$	With $\kappa_{t,c}$	Benchmark	Without $\kappa_{t,c}$
30-34 years	4.10	3.77	3.88	0.75	5.62	1.02
60-64 years	3.07	3.00	3.06	14.03	20.76	15.55
85+ years	6.26	8.07	6.67	22.66	23.32	23.16

7.3.6 Myanmar

- **Mortality/CRAF projections**

location_name	Myanmar	Myanmar-2030: Mortality Rates
year	2030	

Age_groups	No-Climate	Climate-ssp126	Climate-ssp245	Climate-ssp370	Climate-ssp585
30-34 years	0.001721	0.001723	0.001728	0.001731	0.001724
60-64 years	0.015101	0.015255	0.015323	0.015375	0.015275
85+ years	0.166777	0.162958	0.165644	0.166966	0.163978

location_name	Myanmar	Myanmar-2050: Mortality Rates
year	2050	

Age_groups	No-Climate	Climate-ssp126	Climate-ssp245	Climate-ssp370	Climate-ssp585
30-34 years	0.001081	0.001095	0.001096	0.001102	0.001095
60-64 years	0.009620	0.010098	0.010176	0.010276	0.010313
85+ years	0.142754	0.136534	0.138888	0.142167	0.141594

location_name	Myanmar	Myanmar-2030: CRAF
year	2030	

Age_groups	CRAF-ssp126	CRAF-ssp245	CRAF-ssp370	CRAF-ssp585
30-34 years	0.00104	0.00385	0.00606	0.00153
60-64 years	0.01022	0.01471	0.01813	0.01152
85+ years	-0.02290	-0.00679	0.00113	-0.01679

location_name	Myanmar	Myanmar-2050: CRAF
year	2050	

Age_groups	CRAF-ssp126	CRAF-ssp245	CRAF-ssp370	CRAF-ssp585
30-34 years	0.01232	0.01412	0.01914	0.01238
60-64 years	0.04969	0.05779	0.06818	0.07199
85+ years	-0.04357	-0.02708	-0.00411	-0.00813

- **MAPE Results**

	In-sample (1990-2014) MAPE			**Out-of-sample (2015-2019) MAPE**		
Age Group	With $\kappa_{t,c}$	Benchmark	Without $\kappa_{t,c}$	With $\kappa_{t,c}$	Benchmark	Without $\kappa_{t,c}$
30-34 years	4.04	4.03	4.06	14.44	13.63	14.42
60-64 years	2.36	2.49	2.28	5.42	6.26	5.35
85+ years	1.70	1.60	1.70	12.09	11.74	12.07

7.3.7 Philippines

- **Mortality/CRAF projections**

location_name	Philippines	Philippines-2030: Mortality Rates
year	2030	

Age_groups	No-Climate	Climate-ssp126	Climate-ssp245	Climate-ssp370	Climate-ssp585
30-34 years	0.001738	0.001745	0.001742	0.001741	0.001747
60-64 years	0.018989	0.018980	0.018888	0.018862	0.018954
85+ years	0.163399	0.164472	0.163646	0.163436	0.164099

location_name	Philippines	Philippines-2050: Mortality Rates
year	2050	

Age_groups	No-Climate	Climate-ssp126	Climate-ssp245	Climate-ssp370	Climate-ssp585
30-34 years	0.001503	0.001511	0.001514	0.001509	0.001521
60-64 years	0.019872	0.019751	0.019736	0.019613	0.019776
85+ years	0.154072	0.155735	0.155440	0.154368	0.155472

location_name	Philippines	Philippines-2030: CRAF
year	2030	

Age_groups	CRAF-ssp126	CRAF-ssp245	CRAF-ssp370	CRAF-ssp585
30-34 years	0.00397	0.00236	0.00160	0.00511
60-64 years	-0.00045	-0.00532	-0.00667	-0.00183
85+ years	0.00656	0.00151	0.00023	0.00429

location_name	Philippines	Philippines-2050: CRAF
year	2050	

Age_groups	CRAF-ssp126	CRAF-ssp245	CRAF-ssp370	CRAF-ssp585
30-34 years	0.00527	0.00702	0.00408	0.01189
60-64 years	-0.00607	-0.00685	-0.01300	-0.00482
85+ years	0.01079	0.00888	0.00192	0.00908

- **MAPE Results**

	In-sample (1990-2014) MAPE			Out-of-sample (2015-2019) MAPE		
Age Group	With $\kappa_{t,c}$	Benchmark	Without $\kappa_{t,c}$	With $\kappa_{t,c}$	Benchmark	Without $\kappa_{t,c}$
30-34 years	1.77	1.86	1.80	3.04	3.17	3.07
60-64 years	2.14	2.27	2.29	1.81	1.40	1.97
85+ years	4.77	4.84	4.77	4.41	4.19	4.31

7.3.8 Singapore

- ### Mortality/CRAF projections

location_name	Singapore	Singapore-2030: Mortality Rates
year	2030	

Age_groups	No-Climate	Climate-ssp126	Climate-ssp245	Climate-ssp370	Climate-ssp585
30-34 years	0.000144	0.000147	0.000147	0.000147	0.000146
60-64 years	0.003132	0.003359	0.003332	0.003348	0.003280
85+ years	0.081638	0.084882	0.084462	0.084460	0.084084

location_name	Singapore	Singapore-2050: Mortality Rates
year	2050	

Age_groups	No-Climate	Climate-ssp126	Climate-ssp245	Climate-ssp370	Climate-ssp585
30-34 years	0.000056	0.000062	0.000059	0.000060	0.000056
60-64 years	0.001390	0.001572	0.001412	0.001471	0.001251
85+ years	0.061906	0.067171	0.065939	0.066022	0.064576

location_name	Singapore	Singapore-2030: CRAF
year	2030	

Age_groups	CRAF-ssp126	CRAF-ssp245	CRAF-ssp370	CRAF-ssp585
30-34 years	0.02173	0.02107	0.02461	0.01401
60-64 years	0.07252	0.06399	0.06902	0.04730
85+ years	0.03974	0.03460	0.03458	0.02996

location_name	Singapore	Singapore-2050: CRAF
year	2050	

Age_groups	CRAF-ssp126	CRAF-ssp245	CRAF-ssp370	CRAF-ssp585
30-34 years	0.09211	0.04000	0.07094	-0.00827
60-64 years	0.13094	0.01595	0.05814	-0.09996
85+ years	0.08504	0.06514	0.06648	0.04312

- ### MAPE Results

	In-sample (1990-2014) MAPE			Out-of-sample (2015-2019) MAPE		
Age Group	With $\kappa_{t,c}$	Benchmark	Without $\kappa_{t,c}$	With $\kappa_{t,c}$	Benchmark	Without $\kappa_{t,c}$
30-34 years	6.57	5.80	7.21	36.33	37.89	37.19
60-64 years	4.88	3.23	5.89	24.71	31.80	26.57
85+ years	4.55	4.99	3.40	11.66	16.21	12.29

7.3.9 South Korea

- **Mortality/CRAF projections**

location_name	South Korea	South Korea-2030: Mortality Rates
year	2030	

Age_groups	No-Climate	Climate-ssp126	Climate-ssp245	Climate-ssp370	Climate-ssp585
30-34 years	0.000325	0.000352	0.000337	0.000317	0.000339
60-64 years	0.003471	0.004485	0.004037	0.003355	0.003980
85+ years	0.097378	0.111592	0.106292	0.098327	0.105695

location_name	South Korea	South Korea-2050: Mortality Rates
year	2050	

Age_groups	No-Climate	Climate-ssp126	Climate-ssp245	Climate-ssp370	Climate-ssp585
30-34 years	0.000145	0.000193	0.000173	0.000128	0.000168
60-64 years	0.001554	0.003431	0.002597	0.000942	0.002256
85+ years	0.066172	0.093672	0.083940	0.064688	0.080083

location_name	South Korea	South Korea-2030: CRAF
year	2030	

Age_groups	CRAF-ssp126	CRAF-ssp245	CRAF-ssp370	CRAF-ssp585
30-34 years	0.08466	0.03679	-0.02454	0.04298
60-64 years	0.29227	0.16298	-0.03347	0.14675
85+ years	0.14597	0.09154	0.00975	0.08541

location_name	South Korea	South Korea-2050: CRAF
year	2050	

Age_groups	CRAF-ssp126	CRAF-ssp245	CRAF-ssp370	CRAF-ssp585
30-34 years	0.32910	0.18879	-0.11836	0.15857
60-64 years	1.20771	0.67125	-0.39396	0.45159
85+ years	0.41560	0.26852	-0.02242	0.21023

- **MAPE Results**

	In-sample (1990-2014) MAPE			Out-of-sample (2015-2019) MAPE		
Age Group	With $\kappa_{t,c}$	Benchmark	Without $\kappa_{t,c}$	With $\kappa_{t,c}$	Benchmark	Without $\kappa_{t,c}$
<5 years	5.48	5.54	6.03	23.25	27.09	22.11
30-34 years	5.68	6.01	5.80	23.56	24.43	23.32
60-64 years	4.28	4.05	3.97	12.34	20.68	11.22
85+ years	4.40	5.56	3.95	17.27	24.24	16.70

7.3.10 Thailand

• Mortality/CRAF projections

location_name	Thailand	Thailand-2030: Mortality Rates
year	2030	

Age_groups	No-Climate	Climate-ssp126	Climate-ssp245	Climate-ssp370	Climate-ssp585
30-34 years	0.001894	0.001898	0.001885	0.001859	0.001890
60-64 years	0.009402	0.009552	0.009435	0.009248	0.009483
85+ years	0.098672	0.099443	0.098408	0.096959	0.098757

location_name	Thailand	Thailand-2050: Mortality Rates
year	2050	

Age_groups	No-Climate	Climate-ssp126	Climate-ssp245	Climate-ssp370	Climate-ssp585
30-34 years	0.001325	0.001354	0.001346	0.001319	0.001349
60-64 years	0.007426	0.007804	0.007744	0.007508	0.007720
85+ years	0.080871	0.083179	0.082616	0.080465	0.081869

location_name	Thailand	Thailand-2030: CRAF
year	2030	

Age_groups	CRAF-ssp126	CRAF-ssp245	CRAF-ssp370	CRAF-ssp585
30-34 years	0.00246	-0.00486	-0.01850	-0.00181
60-64 years	0.01590	0.00354	-0.01644	0.00863
85+ years	0.00782	-0.00268	-0.01736	0.00086

location_name	Thailand	Thailand-2050: CRAF
year	2050	

Age_groups	CRAF-ssp126	CRAF-ssp245	CRAF-ssp370	CRAF-ssp585
30-34 years	0.02148	0.01608	-0.00452	0.01787
60-64 years	0.05084	0.04279	0.01106	0.03956
85+ years	0.02854	0.02158	-0.00502	0.01234

• MAPE Results

	In-sample (1990-2014) MAPE			Out-of-sample (2015-2019) MAPE		
Age Group	With $\kappa_{t,c}$	Benchmark	Without $\kappa_{t,c}$	With $\kappa_{t,c}$	Benchmark	Without $\kappa_{t,c}$
30-34 years	20.87	20.38	20.87	23.06	31.90	23.16
60-64 years	2.66	3.64	3.00	26.58	36.37	26.25
85+ years	5.76	6.78	5.89	23.35	33.94	23.45

7.3.11 Vietnam

- **Mortality/CRAF projections**

location_name	Vietnam	Vietnam-2030: Mortality Rates
year	2030	

Age_groups	No-Climate	Climate-ssp126	Climate-ssp245	Climate-ssp370	Climate-ssp585
30-34 years	0.000926	0.000893	0.000894	0.000900	0.000897
60-64 years	0.013115	0.012392	0.012501	0.012946	0.012610
85+ years	0.175493	0.165923	0.167246	0.172745	0.168641

location_name	Vietnam	Vietnam-2050: Mortality Rates
year	2050	

Age_groups	No-Climate	Climate-ssp126	Climate-ssp245	Climate-ssp370	Climate-ssp585
30-34 years	0.000675	0.000638	0.000639	0.000648	0.000646
60-64 years	0.011112	0.010057	0.010073	0.010707	0.010330
85+ years	0.168259	0.151102	0.151335	0.159195	0.154735

location_name	Vietnam	Vietnam-2030: CRAF
year	2030	

Age_groups	CRAF-ssp126	CRAF-ssp245	CRAF-ssp370	CRAF-ssp585
30-34 years	-0.03585	-0.03466	-0.02829	-0.03212
60-64 years	-0.05515	-0.04679	-0.01291	-0.03846
85+ years	-0.05453	-0.04700	-0.01566	-0.03905

location_name	Vietnam	Vietnam-2050: CRAF
year	2050	

Age_groups	CRAF-ssp126	CRAF-ssp245	CRAF-ssp370	CRAF-ssp585
30-34 years	-0.05451	-0.05365	-0.04032	-0.04297
60-64 years	-0.09497	-0.09351	-0.03647	-0.07037
85+ years	-0.10197	-0.10059	-0.05387	-0.08038

- **MAPE Results**

	In-sample (1990-2014) MAPE			**Out-of-sample (2015-2019) MAPE**		
Age Group	With $\kappa_{t,c}$	Benchmark	Without $\kappa_{t,c}$	With $\kappa_{t,c}$	Benchmark	Without $\kappa_{t,c}$
30-34 years	2.07	1.95	2.14	12.33	12.64	12.37
60-64 years	3.13	3.48	3.13	21.55	20.86	21.54
85+ years	2.96	3.02	2.98	10.35	8.25	10.32

A. References

Achebak, H., Rey, G., Lloyd, S. J., Quijal-Zamorano, M., Fernando Méndez-Turrubiates, R., & Ballester, J. (2023). Drivers of the time-varying heat-cold-mortality association in Spain: A longitudinal observational study. Environment International, 182, 108284. https://doi.org/10.1016/j.envint.2023.108284

Armstrong, B. (2006). Models for the Relationship Between Ambient Temperature and Daily Mortality. Epidemiology, 17(6), 624–631. https://doi.org/10.1097/01.ede.0000239732.50999.8f

Burkart, K. G., Brauer, M., Aravkin, A. Y., Godwin, W. W., Hay, S. I., He, J., Iannucci, V. C., Larson, S. L., Lim, S. S., Liu, J., Murray, C. J. L., Zheng, P., Zhou, M., & Stanaway, J. D. (2021). Estimating the cause-specific relative risks of non-optimal temperature on daily mortality: a two-part modelling approach applied to the Global Burden of Disease Study. The Lancet, 398(10301), 685–697. https://doi.org/10.1016/s0140-6736(21)01700-1

Bank Negara Malaysia. (2024). 2024 Climate Risk Stress Testing Exercise Methodology Paper. https://www.bnm.gov.my/documents/20124/938039/CRST_Methodolgy_paper_V3.0.pdf

Gasparrini, A., Armstrong, B., & Kenward, M. G. (2010). Distributed lag non-linear models. Statistics in Medicine, 29(21), 2224–2234. https://doi.org/10.1002/sim.3940

Gasparrini, A., Guo, Y., Hashizume, M., Lavigne, E., Zanobetti, A., Schwartz, J., Tobias, A., Tong, S., Rocklöv, J., Forsberg, B., Leone, M., De Sario, M., Bell, M. L., Guo, Y.-L. L., Wu, C., Kan, H., Yi, S.-M., de Sousa Zanotti Stagliorio Coelho, M., Saldiva, P. H. N., & Honda, Y. (2015). Mortality risk attributable to high and low ambient temperature: a multicountry observational study. *The Lancet*, *386*(9991), 369–375. https://doi.org/10.1016/s0140-6736(14)62114-0

Gasparrini, A., Guo, Y., Sera, F., Vicedo-Cabrera, A.M., Huber, V., Tong, S., Coelho, M.D.S.Z.S., Saldiva, P.H.N., Lavigne, E., Correa, P.M. and Ortega, N.V., (2017). Projections of temperature-related excess mortality under climate change scenarios. The Lancet Planetary Health, 1(9), pp.e360-e367.

GBD Compare. (2021). VizHub; Institute for Health Metrics and Evaluation. https://vizhub.healthdata.org/gbd-compare/

GBD Foresight Visualisation. (2024). Institute for Health Metrics and Evaluation. https://www.healthdata.org/data-tools-practices/interactive-visuals/gbd-foresight-visualisation

GBD Results. (2024). Www.healthdata.org. https://www.healthdata.org/data-tools-practices/interactive-visuals/gbd-results

IPCC. (2021). Climate Change 2021 Working Group I Contribution to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change. https://www.ipcc.ch/report/ar6/wg1/downloads/report/IPCC_AR6_WGI_SPM.pdf

Kim, Y., & Kim, Y. (2022). Explainable heat-related mortality with random forest and SHapley Additive exPlanations (SHAP) models. Sustainable Cities and Society, 79, 103677. https://doi.org/10.1016/j.scs.2022.103677

Lee, Ronald D. and Carter, Lawrence. (1992). Modelling and Forecasting the Time Series of U.S. Mortality. Journal of the American Statistical Association, 87(419), 659 – 671. https://doi.org/10.2307/2290201

Li, Tiankai, Wang, Qi and Cheng, Cheping. (2022). Effect of aging on cardiovascular responses to cold stress in humans. *Frigid Zone Medicine*, vol. 2, no. 3, pp. 149-157. https://doi.org/10.2478/fzm-2022-0022.

Lo, Y. T. E., Mitchell, D. M., Thompson, R., O'Connell, E., & Gasparrini, A. (2022). Estimating heat-related mortality in near real time for national heatwave plans. Environmental Research Letters, 17(2), 024017. https://doi.org/10.1088/1748-9326/ac4cf4

Monetary Authority of Singapore. (2022). Financial stability review (November 2022). https://www.mas.gov.sg/-/media/MAS-Media-Library/publications/financial-stability-review/2022/Financial-Stability-Review-2022.pdf

Millyard, A., Layden, J. D., Pyne, D. B., Edwards, A. M., & Bloxham, S. R. (2020). Impairments to thermoregulation in the elderly during heat exposure events. Gerontology and Geriatric Medicine, 6, 2333721420932432.

Pozzer, A., Anenberg, S. C., Dey, S., Haines, A., Lelieveld, J., & Chowdhury, S. (2023). Mortality attributable to ambient air pollution: A review of global estimates. GeoHealth, 7, e2022GH000711. https://doi.org/10.1029/2022GH000711

Tobías, A., Hashizume, M., Honda, Y., Sera, F., Fook, C., Kim, Y., Royé, D., Chung, Y., Trần Ngọc Đăng, Kim, H., Lee, W., Íñiguez, C., Ana Maria Vicedo-Cabrera, Abrutzky, R., Guo, Y., Tong, S., Micheline, Paulo, Lavigne, É., & Patricia Matus Correa. (2021). Geographical Variations of the Minimum Mortality Temperature at a Global Scale. *Environmental Epidemiology*, *5*(5), e169–e169. https://doi.org/10.1097/ee9.0000000000000169

Yang, J., Ou, C.-Q., Ding, Y., Zhou, Y.-X., & Chen, P.-Y. (2012). Daily temperature and mortality: a study of distributed lag non-linear effect and effect modification in Guangzhou. Environmental Health, 11(1). https://doi.org/10.1186/1476-069x-11-63