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From rising temperature to rising health concerns: A study of climate change effects in Paraguay ☆

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ABSTRACT

Projected temperature increases in Paraguay are expected to significantly impact public health. This study assesses the current health burden from adverse temperature conditions using mortality and morbidity data, and estimates future consequences under various climate models and emissions scenarios. According to the Global Burden of Disease, non-optimal temperatures caused approximately 640 deaths in Paraguay in 2019, 1.6% of total mortality. Cardiovascular diseases have the highest mortality rates, while infectious diseases are most impacted by heat exposure. Using panel data from 2015 to 2019, our econometric model suggests that non-optimal temperatures result in approximately 2,013 hospitalizations and 157,300 doctor visits annually within the public health system, representing 0.94% of hospitalizations and 1.97% of doctor visits. Our morbidity analysis reveals that seniors are more affected by higher-than-optimal temperatures, with hospitalizations among men and doctor visits for both genders increasing during high temperatures. To project future health burdens, we employ a comparative risk assessment for mortality estimation and applied our econometric model for morbidity evaluation. Comparing 2020 to 2050, we project an average increase in the mortality rate attributable to non-optimal temperatures between 1.5% and 21.6%, depending on the climate scenario. Hospitalizations are expected to double and doctor visits to triple during this period under the worst climate projections.

1. Introduction

Climate change is expected to significantly affect human health through various mechanisms, including rising temperatures and humidity, sea level rise, and extreme weather events. These changes interact with various other environmental risk factors. For instance, increased temperatures could promote the transmission of diseases such as malaria and dengue while creating a favorable environment for pathogen growth. Furthermore, water scarcity may compromise water quality and sanitation, thereby elevating the risk of diarrhea and other diseases. Changes in climate and in environmental conditions can also exacerbate respiratory diseases by interacting with local air pollution and the dispersion of allergens.

Scientific consensus, as reported by the IPCC, indicates that temperatures have surged by 1.1 °C since 1880, and it is widely recognized that limiting global warming to a maximum of 1.5 °C above pre-industrial levels by 2100 is imperative to mitigate the most severe consequences of climate change. However, current assessments based on the Paris Agreement commitments suggest that global warming is on track to reach between 2.4 and 2.6 °C by the end of the century (Zhongming et al., 2022). This underscores the critical importance of anticipating health consequences stemming from rising temperatures.

As emphasized in recent literature reviews concerning the intersection of health and climate (Ammann et al., 2021; Berrang-Ford

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et al., 2021), one of the extensively examined outcomes of climate change pertains to its impact on health. Abundant evidence shows the connection between non-optimal temperatures and excess mortality and morbidity. The Lancet Countdown on health and climate change has reported that extreme heat is linked to a wide range of health issues, including cardiovascular and respiratory diseases, suicides, injuries, and diabetes. Their estimate, as of 2019, suggests that 365,000 deaths globally can be attributed to extreme heat (Burkart et al., 2021). Furthermore, it is well-established that both excessively low and high temperatures can contribute to heightened mortality risks, as indicated by various studies (Burkart et al., 2021; Gao et al., 2019; Song et al., 2021; Zhao et al., 2021; Global Burden of Disease Collaborative Network, 2020; Vicedo-Cabrera et al., 2021). In a recent comprehensive meta-analysis comprising 62 studies, Faurie et al. (2022) reported a notable finding: a 1 °C increase in temperature is associated with a substantial 35 percent rise in heat-related mortality.

Extreme temperatures, whether excessively high or low, are also correlated to increased morbidity. In the above-mentioned study by (Faurie et al., 2022), each 1 °C rise in temperature is associated with an 18 percent increase in heat-related morbidity. Particularly, the most susceptible demographics encompass individuals over 65 years old, males, and those residing in temperate climate zones, who might have limited access to cooling facilities compared to hotter regions. The primary health outcomes associated with morbidity typically involve health services usage such as hospital admissions and doctor visits. On occasions, studies extend to other indicators, such as emergency ambulance calls. For instance,Li et al. (2021) reported that approximately 12 percent of ambulance calls in a sample of regions in China were attributed to heat-related issues.

However, it is worth noting that the majority of research concerning the health burden of climate change tends to be concentrated on developed economies, as highlighted in studies by Ammann et al. (2021), Faurie et al. (2022), and Rocque et al. (2021). According to Berrang-Ford et al. (2021), a significant lack of evidence is apparent for regions like Central Asia, North and Central Africa, and South America. This gap can be attributed, in part, to the tendency to predominantly review peer-reviewed literature and the presence of language barriers. Additionally, as pointed out by Green et al. (2019), there is a limited amount of research examining the connection between heat and health in Latin America. Recent papers have documented the detrimental effect of extreme temperature on mortality rates for a number of countries, including Mexico (CEPAL, 2014; Cohen and Dechezleprêtre, 2022), Colombia (Helo Sarmiento, 2023), and Argentina (García-Witulski et al., 2023).

Adding to the complexity of the issue, Alizadeh et al. (2022) reveal that over the past decade, the world's lowest-income quartile has experienced a 40 percent higher exposure to heatwaves compared to the highest quartile. This trend is expected to intensify in the future, making the examination of heat-related burdens in developing economies particularly pertinent.

Considering these circumstances, our research is specifically focused on Paraguay, a middle-income country situated in South America. Our aim is to provide insights into the unique challenges and repercussions of climate change-induced health-related risks within such contexts. Paraguay has faced a variety of environmental hazards that have resulted in significant loss of life. According to data from the Emergency Events Database (EM-DAT), the deadliest disasters in Paraguay between 1965 and 2021 have primarily been floods and epidemics. While the records from the DESINVENTAR database, aligned with the SENDAI Framework for Disaster Risk Reduction, also indicate that fires and epidemics have caused substantial casualties in specific regions. Furthermore, according to estimates from the Global Burden of Disease (GBD) Project, managed by the Global Burden of Disease Collaborative Network, air pollution emerges as the most significant health risk factor in Paraguay for the year 2019. This risk is closely linked to factors such as wildfires and the extensive use of biomass, among others. In contrast, GBD data indicates that deaths associated with water and sanitation have been on a declining trend, while those attributed to non-optimal temperatures have been on the rise. However, it is important to note that GBD primarily considers mortality and does not encompass morbidity indicators likely to be also affected by weather-related conditions.

In the case of Paraguay, there exists limited research addressing the influence of climate-related factors, such as vector-borne diseases (Martínez de Cuellar et al., 2014; Gómez Gómez et al., 2022) or wildfires (Irala et al., 2021). Additionally, only a handful of studies have focused on the prospective effects of climate change on health in Paraguay, and some of those that do exist are relatively dated. For example, a study carried out by the UN Economic Commission for Latin America and the Caribbean (CEPAL, 2014) examined the influence of two climate scenarios on diarrheal diseases, vector-borne diseases, and respiratory infections, using health data up to 2008. The study predicted a significant probability of elevated occurrences of diarrheal and infectious diseases by 2050. However, it does not foresee a comparable increase in respiratory infections. Another study, dating back to 2016, identified positive associations between climate change and the prevalence of diseases such as dengue and leishmaniasis (a parasitic disease), projecting their increase by the year 2030 (Nagy et al., 2016). Recent studies have further highlighted the potential impacts of climate change on Paraguay. Borchers-Arriagada et al. (2024) demonstrate that global warming could significantly escalate fire activity in Paraguay, leading to substantial health costs associated with air pollution. Conte Grand and Soria (2024) highlight that climate change would likely reduce workers' productivity, especially in the agricultural sector. This finding is corroborated by Benítez Rodriguez et al. (2024), who note that despite projected declines in crop productivity, Paraguay's wheat and soybean production and exports might increase. This is because the productivity declines in Paraguay are expected to be less severe compared to other regional producers. Consequently, this could result in higher national income, which may, in turn, facilitate better access to healthcare.

Given the expected substantial temperature rise in Paraguay, particularly in contrast to neighboring countries, as emphasized by Iturbide et al. (2022), it is essential to assess the mid-term and long-term consequences of this phenomenon to provide insight into the burden that climate change could impose on national authorities. Thus, this research makes a three-fold contribution. Firstly, it extends evidence of how climate change would impact health burdens in a middle-income country such as Paraguay. As mentioned above, literature reviews indicate a scarcity of studies focusing on developing countries, particularly in Latin America. This highlights the importance of our study in filling a critical research gap. Secondly, it assesses the effects of extreme temperatures on several health outcomes. Existing research for Paraguay is scarce and it only deals with its effect on morbidity without stratifying by age as we do. Thirdly, our study extends beyond historical evaluations by projecting potential impacts under various climate models and scenarios.

To address the objectives mentioned above, we employed a dual approach to assess the impact of climate change on health in Paraguay. For the mortality analysis, we adopted the GBD study methodology, which uses specific exposure-response functions for each cause of death related to non-optimal temperatures. This method allowed us to estimate the attributable fraction of deaths under various climate scenarios and models. To assess morbidity, we estimated a panel data econometric model covering the period from 2015 to 2019. This model enabled us to identify the relationship between monthly temperature distributions and hospitalization and doctor visit rates in the public health system, controlling for factors such as precipitation, relative humidity, and temporal and spatial fixed effects. By combining these approaches with climate projections and changes in the population structure over time, we estimated future health impacts for the years 2035, 2050, and 2100 under different emission scenarios.

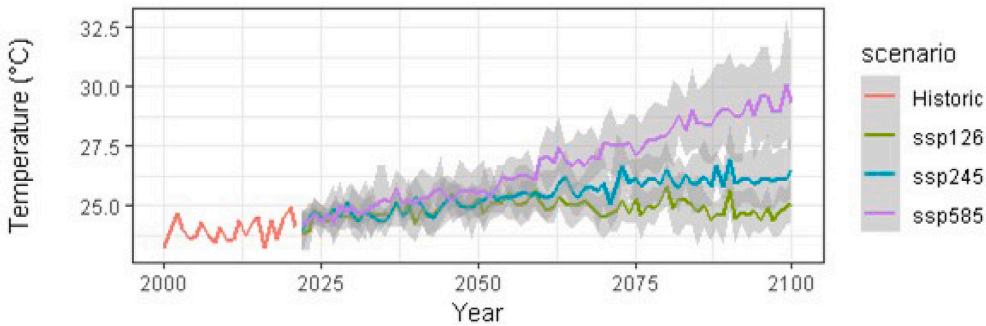


Fig. 1. Historic and projected mean annual temperature in Paraguay.
Notes: Own elaboration based on historical data from ERA5 and climate projections from CMIP-6 biased-adjusted (Noël et al., 2022; Climate Data Factory, 2022). The red solid line represent the historic average temperature. The other solid lines show the mean projected temperature across different climate models (GFDL-ESM4, IPSL-CM6A-LR, MPI-ESM1-2-HR, MRI-ESM2-0, and UKESM1-0-LLm) for each scenario: SSP126 (green), SSP245 (blue), SSP585 (purple). The gray area spans from percentile 10 to percentile 90.

The rest of the paper is structure as follows. Section 2 outlines observed current temperatures and their projected changes in Paraguay, forming the foundation for the assessments of mortality and morbidity. Section 3 details the empirical methodology and the data employed for these assessments. Section 4 provides the results, and Section 5 offers the conclusion.

2. Temperature and climate change prospects for paraguay

Paraguay is an inland country located in South America between Brazil, Bolivia and Argentina, with a population of approximately 7 million inhabitants (Instituto Nacional de Estadística, 2015) specially concentrated in the center-east of the country. Paraguay's climate is highly humid and warm year-round, with hot and rainy summers, and mild winters. There is low inter-annual variability across the country with annual mean temperatures ranging between 23 to 25 °C between the years 2000 and 2020, as indicated by the red line in Fig. 1.

Looking ahead, climate projections show a different picture that depends on the emissions' scenario. Specifically, the projections indicate that the annual mean temperature could rise to approximately 29.5 °C. For the rest of our study, given the limited availability of climate data from meteorological stations in Paraguay, we chose to use data derived from reanalysis of the global climate and weather. Atmospheric reanalysis is a scientific approach employed to construct comprehensive and consistent datasets, offering a complete view of past weather and climate conditions. This method entails the assimilation of historical observations gathered from diverse sources, including weather stations, satellites, and ocean buoys, into a numerical weather model.

Specifically, we use gridded daily mean temperatures projections from the Coupled Model Intercomparison Project Phase 6 (CMIP6) bias-adjusted with the ERA5-Land dataset (Noël et al., 2022) for alternative climate models and emission scenarios.[1] The CMIP6 is an initiative under the World Climate Research Program (WCRP). Like many other climate models, CMIP6 data is structured in a grid format with a spatial resolution of 0.1°, approximately 11 × 11 kilometers. This resolution implies that the Paraguayan territory is covered by approximately 3400 pixels (or cells). Finally, the climate projections encompass five different climate models and are based on three distinct emission scenarios typically used in climate modeling, as outlined in Table 1. We chose to incorporate multi-model climate projections to account for the inherent uncertainty in future climate modeling (see (Tebaldi et al., 2021).

Beyond 2020, the projected temperature in Fig. 1 differs between alternative emission scenarios, i.e., each solid line represents the mean

Table 1
Climate models and emission scenarios.

	Model/Scenario name	Description
Modeling center	GFDL-ESM4	NOAA-GFDL (National Oceanic and Atmospheric Administration, Geophysical Fluid Dynamics Laboratory)
	IPSL-CM6A-LR	IPSL (Institut Pierre-Simon Laplace)
	MPI-ESM1-2-LR	Max Planck Institute for Meteorology (MPI-M)
	MRI-ESM2–0	Meteorological Research Institute (MRI)
	UKESM1-0-LL	MOHC (Met Office Hadley Centre)
Emission scenario	Shared Socioeconomic Pathway 1-2.6 or SSP126	Scenario with mitigation policy aligned with a 2° pre-Paris agreement target
	Shared Socioeconomic Pathway 2-4.5 or SSP245	Scenario with intermediate mitigation policy, resulting in a warming of 2.1 to 3.5 °C
	Shared Socioeconomic Pathway 5-8.5 or SSP585	Extreme scenario with no mitigation policy, warming of 3.3–5.7 °C

Notes: This table describes the models and scenarios used in this study to estimate the effect of temperature changes on mortality and morbidity. Warming per scenario is based on Masson-Delmotte et al. (2021).

(biased-adjusted) value from six climate models: GFDL-ESM4, IPSL-CM6A-LR, MPI-ESM1-2-HR, MRI-ESM2-0, and UKESM1-0-LL. As expected, the farther we project into the future, the uncertainty grows, illustrated by the expanding range of the gray area, which encompasses the 10th to the 90th percentiles of mean daily temperature, considering all climate models.

By the end of this century, the mean adjusted temperature of the six models under emission scenario SSP585, anticipates a notable increase in the annual mean temperature. The increase in temperature will be more moderate under the SSP245 scenario. Nevertheless, it is worth noting that with the implementation of robust global mitigation policies aimed at addressing climate change, consistent with scenario SSP126, Paraguay could see annual temperatures at levels like those observed

[1] Bias-adjusted means that systematic errors from climate models have been corrected. The idea is to calibrate an empirical transfer function between the simulated and observed distribution to adjust the climate model output.

in the recent past. These policies hold the promise of curbing the significant temperature increases.[2]

We account for two primary sources of uncertainty in climate modeling: climate models and climate scenarios. Variations in model assumptions can lead to different outcomes even when starting with the same initial climate conditions, making it crucial to consider these differences. Additionally, models that forecast climate change rely on estimates of future greenhouse gas (GHG) concentrations from human activities, which are influenced by social and economic factors that drive GHG emissions. Projecting future GHG levels requires assumptions about potential changes in population, economic productivity, energy use, land use, and technology, among other factors. Given the inherent uncertainty in these assumptions, it is important to consider different scenarios. This approach is common in the literature (e.g., Tebaldi et al., 2021) and has been specifically applied to Paraguay (Haddad et al., 2021).

Our work examines four specific moments in time: 2020, 2035, 2050, and 2100, for each of the above-mentioned scenarios.[3] Fig. 2 shows the mean annual temperature for each moment in time (from left to right: 2020, 2035, 2050, and 2100), for all the pixels that overlay the country under three climate scenarios and one climate model (GFDL-ESM4) as an illustration. It depicts the spatial variability of temperatures, which are higher, and expected to increase more, in the northern part of the country. Moreover, in the higher emission scenarios, i.e. SSP245 and SSP585, it is expected that by the end of the century, the increase in temperature will be more pronounced. Annex A presents more details about temperature changes in Paraguay.

3. Methodology and data sources

This section is divided into two parts. The first subsection details the methodology and data used to estimate the relationship between temperature and mortality, whereas the second subsection describes the methodology and data used to estimate the impact of temperature on morbidity.

3.1. Mortality

According to GBD (2020), approximately 640 deaths in Paraguay in 2019 were attributed to exposure to non-optimal temperatures, with 42 percent of these deaths related to high temperatures and 58 percent to low temperatures. Fig. 3 illustrates the number of deaths attributable to non-optimal temperatures, disaggregated by cause of death. The total number of deaths corresponds to the sum of the values of all the bars presented in the graph. As illustrated in the figure, the number of deaths associated with specific causes, such as ischemic heart disease or strokes, increases during both extremely cold and hot days. However, for other causes of death, such as road injuries or drowning, the number of deaths decreases on days of extreme cold.

Regarding the health risks associated with high temperatures, Paraguay ranks higher than other countries in the Latin America and the Caribbean (LCN) region, and this risk appears to have significantly increased over time (see Fig. 4a). In 2019, the health risk from high temperatures in Paraguay reached a level comparable to the global average. Conversely, with respect to the health risks posed by low temperatures, Paraguay fares better than its regional counterparts (LCN) and the global average (see Fig. 4b).

To estimate the number of deaths attributable to temperature changes we followed the methodology of the GBD 2019 study (Global Burden of Disease Collaborative Network, 2020) and Burkart et al. (2021). The GDB study quantifies the impact of a broad range of health conditions (not only related to non-optimal temperatures), including non-communicable diseases (such as heart disease, cancer, and diabetes), infectious diseases, injuries, and risk factors like poor diet, tobacco use, and environmental factors. The GBD approach has been instrumental in shaping public health priorities and policies, helping governments and organizations allocate resources more effectively, and understanding the evolving health challenges that societies face (Murray, 2022).

Fig. 5 provides a schematic overview of our approach to evaluating the impact of temperatures on mortality. Our objective is to estimate the burden associated with non-optimal temperatures across various causes of death. To accomplish this, we adhered to the steps detailed below. In the figure, the steps where we performed calculations are highlighted in red, whereas the steps where we relied on inputs from other sources are indicated in black.

In Burkart et al. (2021), the first part of the study involves estimating a link between daily temperatures and mortality. In the second part of the study, the authors applied cause-specific relative risks from the first part to all locations globally. In this study, we rely on exposure-response curves or functions (ERF) for Paraguay from the Burkart et al. (2021) study. The ERF illustrates the connection between exposure to non-optimal temperatures and increased mortality risks. The ERFs are cause-specific and associated with the mean annual temperature and daily temperature for each pixel in the grids covering all Paraguay.[4] The causes of death linked to non-optimal temperatures in the GBD 2019 study are 17: chronic kidney disease; cardiomyopathy and myocarditis; hypertensive heart disease; ischemic heart disease; stroke; diabetes mellitus; animal contact; exposure to forces of nature; drowning; interpersonal violence; exposure to mechanical forces; other unintentional injuries; self-harm; other transport injuries; road injuries; lower respiratory infections; and chronic obstructive pulmonary disease.

Finally, population at different moments of time were obtained from population projections from the United Nations, distributed geographically (in a grid) according to gridded population projections from SSP scenarios.[5] Population projections are accessible at a resolution of 1×1 km. However, we consolidate this data to match the resolution of the temperature pixel, which is 11×11 km.

The first step to calculate the attributed mortality consists on retrieving the exposure-response function, denoted as $ERF(c, \overline{T_p}, T_{pd})$ where c stands for cause-of-death attributed to non-optimal temperatures, $\overline{T_p}$ represents the annual mean temperature in pixel p, and T_{pd} denotes the temperature in day d and pixel p.

The second step involves the computation of the relative risk, RR_{cpd}. The relative risk for each cause and pixel-day is the ERF in such pixel, relative to the ERF under a theoretical minimum exposure level, denoted TMREL (see Eq. (1)). The TMREL was estimated in Burkart et al. (2021) as the temperature that minimizes mortality, considering the

[2] Lovino et al. (2021) report similar trends for Paraguay using 19 climate models of CMIP6. Specifically, they report that, on average, the increases by 2100 are almost 1.7 °C in the sustainable development and low emissions scenario (SSP126), 3 °C in the middle-of-the-road development and medium emissions scenario (SSP245), and 5.5 °C in the fossil-fueled development and high emissions scenario (SSP585).

[3] For the mortality analysis, we calculate the health burden using each of the same ten-years period, or five-year period in the case of 2100. For the morbidity analysis, for each of these selected years, a ten-year average of climate data is used (including 5 years before and after the year of interest), except for 2100, where we use an average of the data covering that year and the previous four years. We do not expect this different procedure to have any substantial impact on the results obtained.

[4] Since we lack the data necessary to calculate the exposure-response function for mortality in Paraguay independently, we rely on the exposure-response function computed by Burkart et al. (2021) using the Global Burden of Disease methodology, which is also detailed in Fig. 5. If we had access to daily mortality data, we could apply the same approach as we did for morbidity to compute the exposure-response function directly.

[5] Standard projections, available in https://population.un.org/wpp/Download/Standard/MostUsed/.

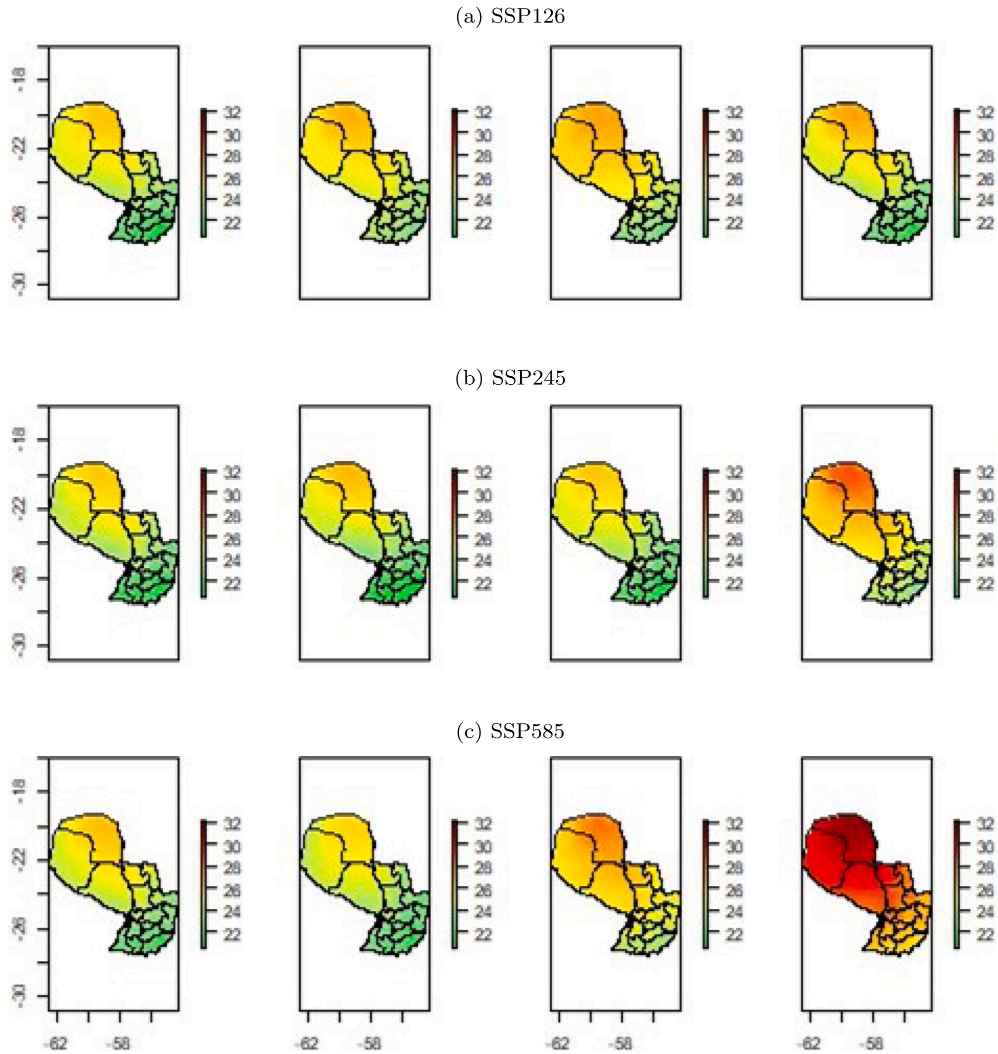


Fig. 2. Spatial distribution of mean annual temperature for model GFDL-ESM4.
Notes: Own elaboration based on historical data from ERA5 and climate projections from CMIP-6 biased-adjusted (Noël et al., 2022; Climate Data Factory, 2022). Time periods are represented from left to right: 2020, 2035, 2050, and 2100 Graph axes represent latitude and longitude. Lines within each map denote the division of 17 departmental councils (provinces) that exist in the country.

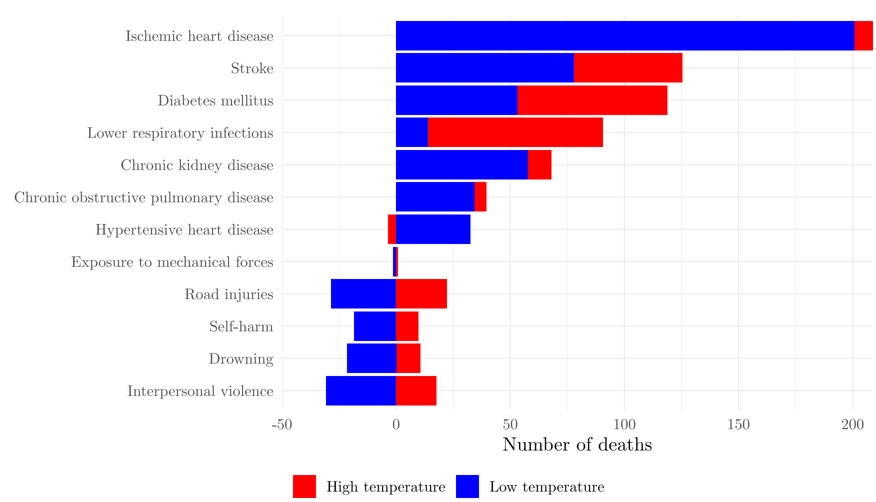


Fig. 3. Number of deaths by cause attributed to non-optimal temperatures in 2019.
Notes: Based on (Global Burden of Disease Collaborative Network, 2020). Zero represents average mortality under optimal temperature. Red indicates excess mortality attributable to high temperature and blue to low temperature. Both temperature extremes can increase or decrease mortality relative to optimal temperature.

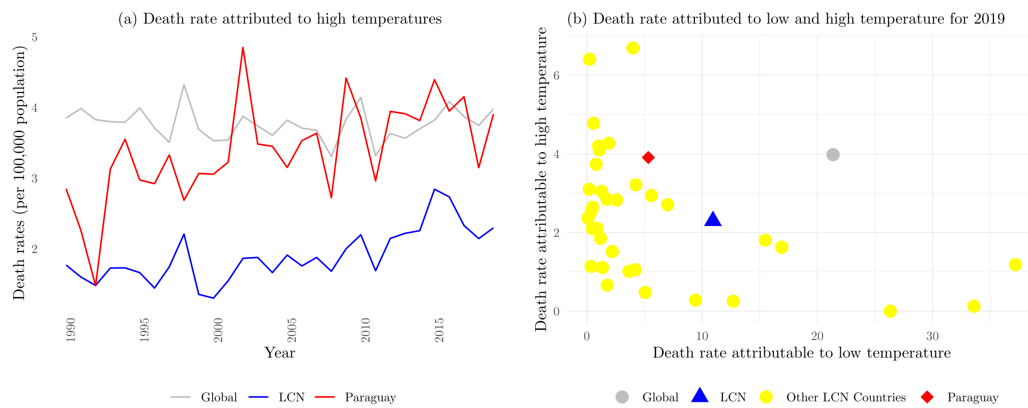


Fig. 4. Temperature risks benchmarking for Paraguay.
Notes: Based on Global Burden of Disease Collaborative Network (2020). LCN stands for average values in Latin America and the Caribbean countries.

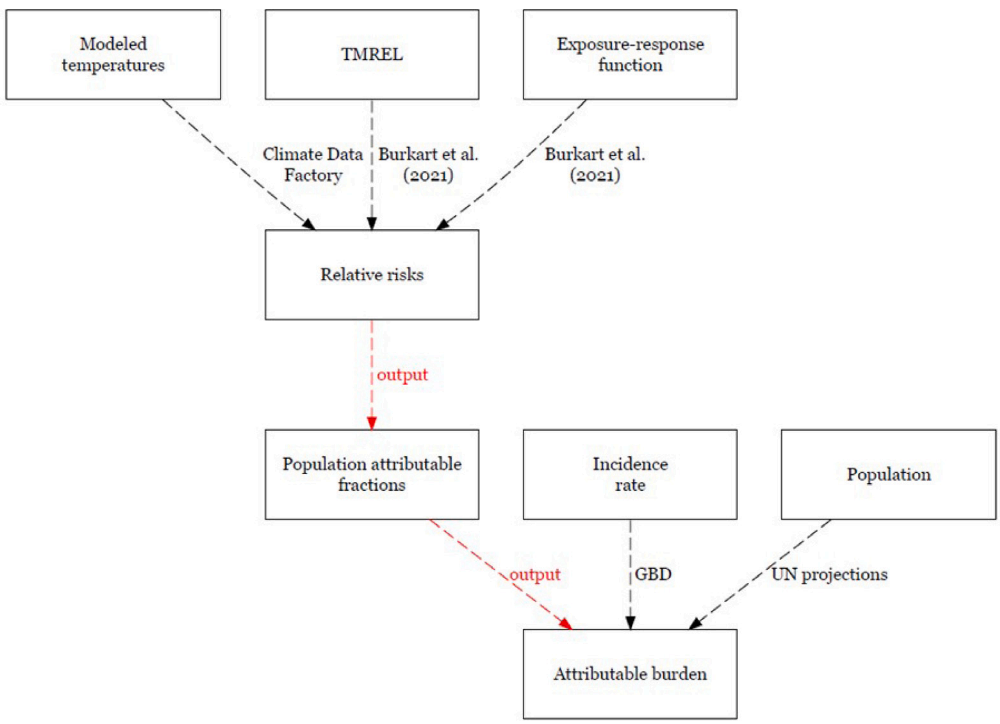


Fig. 5. Mortality methodology flow chart.
Notes: Black arrows represent data taken from a data source, and red arrows represent outcomes obtained based on our calculations. TMREL stands for Theoretical Minimum Risk Exposure Level.

number of deaths from all 17 causes combined. In turn, the $TMREL_p$ varies spatially since it depends on the annual mean temperature at each pixel p, and it changes along time and is location specific.[6] For instance, for Paraguay, for a pixel with annual mean temperature of 20 °C, the TMREL in 2020 was between 23.0 °C and 25.3 °C, with a mean value of 23.5 °C. This variability in TMREL is due to the fact that is not the same to have a day high temperature in a usually hot location or in a usually cold one.

$$RR_{cpd} = \frac{\exp(ERF(c, \overline{T_p}, T_{pd}))}{\exp(ERF(c, \overline{T_p}, TMREL_p))} \tag{1}$$

To retrieve the ERF values in Eq. (1), we first calculate the mean annual temperature for every pixel in Paraguay, $\overline{T_p}$. Then, for each pixel, we retrieve the optimal temperature, i.e., $TMREL_p$ based on Burkart et al. (2021).[7] For each pixel-day we define if T_{pd} was associated with health risks due to low or high temperatures using $TMREL_p$ as a cut-off. Thus, a "high temperature day" is when $T_{pd} > TMREL_p$. Otherwise, that day is defined as a "low temperature day".

Finally, for each pixel-day, we calculate the risk relative to the $TMREL_p$ based on the ERF for each cause of death c, RR_{cpd}, as indicated in Eq. (1). When $T_{pd} = TMREL_p$, the relative risk is equal to 1. Temperature effects can be either harmful or protective depending on whether the relative risk is above or below 1, respectively. Notice that the relative risk can be below 1 for certain causes, because the

[6] Paraguay's location ID is unique and is 136.

[7] After 2020, we use the 2020 value, as it is the latest year for which the TMREL is available.

TMREL was not calculated for each cause (in Burkart et al., 2021 but using the aggregate effects of all 17 temperature related causes.

The third step involves the calculation of population attributable fraction (PAF), i.e., the fraction of deaths that can be attributed to non-optimal temperatures. The PAF is a measure used in epidemiology to estimate the proportion of disease incidence in a population that can be attributed to a specific exposure or risk factor (Hanley, 2001). In other words, it quantifies the fraction of disease cases that could be prevented if the exposure to the risk factor were eliminated or reduced. The PAFs were computed by cause of death c, pixel p and day d as follows:

$$PAF_{cpd} = \begin{cases} \dfrac{RR_{cpd} - 1}{RR_{cpd}}, & \text{if } RR_{cpd} > 1 \\ RR_{cpd} - 1, & \text{if } RR_{cpd} > 1 \end{cases} \tag{2}$$

Then, we aggregate $PAFs$ from pixel-day, PAF_{cpd} to location (the country level in the case of Paraguay), and then we aggregate for each cause. $PAFs$ at the cause and day level, PAF_{cd}, are calculated as a population-weighted average of the daily pixel-level PAF for each cause, where population weights are the share of population in pixel p ($share\ Pop_p$):

$$PAF_{cd} = \sum_p (share\ Pop_p \times PAF_{cpd}) \tag{3}$$

The annual PAFs for each cause are calculated as the average among daily PAFs for each cause:

$$PAF_c = \frac{\sum_d PAF_{cd}}{number\ of\ days\ in\ the\ year} \tag{4}$$

The final step is the computation of the cause-specific deaths attributable to non-optimal temperatures, also called the attributable burden. In the GBD methodology, the attributable burden refers to the portion of the total burden of a specific health condition, injury, or risk factor that can be attributed to a particular cause or exposure. We multiply the PAFs by the total cause-specific deaths, which in turn are equal to an incidence rate multiplied by the population:

$$Attributable\ burden_c = population \times incidence\ rate_c \times PAF_c \tag{5}$$

where the incidence rate measures the number of cases every 10,000 people, attributed to a particular cause and was taken from GBD 2019 study (see Table B.1 in Annex B).

To calculate the attributable burden under the different climate scenarios, we use pixel-day temperature projections and gridded population projections, and apply the method described in Eq. (1) to Eq. (5).

3.2. Morbidity

As the GBD 2019 study exclusively centers on the influence of non-optimal temperatures on mortality, it is crucial to examine health outcomes associated with morbidity to gain a comprehensive understanding of the temperature-health relationship. To achieve this goal, we have applied a different empirical approach, characterized by three essential steps. Firstly, we estimate a model that establishes the relationship between monthly temperature distributions and the corresponding morbidity rates during 2015–2019. This approach allows us to estimate the exposure-response function of temperatures on morbidity. Secondly, we calculate the projected changes in temperature based on the five models and three climate scenarios described in Section 2. By incorporating these projections, we can anticipate the potential shifts in temperature patterns over time. Lastly, utilizing the estimated relationship between temperature and morbidity from the first step, we predict the morbidity attributable to non-optimal temperatures resulting from climate change.

By employing this comprehensive framework, we aim to provide a more complete understanding of the health impacts of climate change, specifically focusing on the morbidity implications related to non-optimal temperatures. We consider hospitalizations and visits to doctors in the public health system with monthly data at the department level[8] between 2015 and 2019 provided by the Paraguay Ministry of Health.[9]

Table 2
Morbidity rates by age-group.

Panel A. Hospital admissions rates	mean	sd	min	max
0–4 age-old	488.3	241.5	0	1,746
5-44 age-old	275.8	108.7	0	644.0
45–64 age-old	244.4	110.0	0	800.3
> 64 age-old	561.2	262.0	0	1,900
All ages	311.3	117.5	0	791.2
Panel B. Doctor visits rate	mean	sd	min	max
0–4 age-old	23,499	14,952	0	77,723
5-44 age-old	11,185	6,749	646.6	33,438
45–64 age-old	14,395	9,750	379.1	47,283
> 64 age-old	19,168	13,482	107.5	66,686
All ages	13,542	8,476	721.7	41,903

Notes: This table reports descriptive statistics of morbidity rates per 100,000 inhabitants at the province (*departamento*) level based on monthly data between 2015 and 2019 provided by the Ministry of Health. Number of observations is 1,080 (departments by month by year).

Table 2 presents statistics on morbidity rates for all causes, stratified into hospitalizations (Panel A) and doctor visits (Panel B), by age group and for all ages, measured per 100,000 inhabitants. In Panel A, the age group over 64 years has the highest average hospitalization rate, with 561.2 per 100,000 inhabitants, followed by the 0 to 4 years old group, with 488.3 per 100,000 inhabitants. In contrast, the age groups of 5 to 44 years and 45 to 64 years have lower average rates of 275.8 and 244.4 per 100,000 inhabitants, respectively, with less variability. For all ages combined, the average hospitalization rate is 311.3 per 100,000 inhabitants. In Panel B, children aged 0 to 4 years have the highest average rate of doctor visits, with 23,499 per 100,000 inhabitants and high variability. Adults over 64 years have an average rate of 19,168 visits per 100,000 inhabitants. The age groups of 45 to 64 years and 5 to 44 years have average rates of 14,395 and 11,185 per 100,000 inhabitants, respectively. For all ages combined, the average rate of doctor visits is 13,542 per 100,000 inhabitants. In summary, morbidity rates show higher hospitalizations and doctor visits among the youngest and oldest age groups.

The model used to estimate the exposure-response function can be describes as:

$$MR_{dmt} = \alpha + \sum_{j=1}^{5} \theta_j TEM_{dmtj} + \beta PRE_{dmt} + \gamma RH_{dmt} + \mu_{dt} + \rho_m + \epsilon_{dmt} \tag{6}$$

Where MR_{dmt} are the outcomes that correspond to the rates of hospitalizations or doctor visits per 100,000 inhabitants, in department d

[8] Paraguay is a unitary state with a leaning towards decentralization, as delineated by the constitution and legislation. For the purposes of the political and administrative structuring of the State, the national territory is divided, from greater to lesser degree, into departments, districts, or municipalities. Departments, within the limits of the constitution and laws, possess political, administrative, and regulatory autonomy in the pursuit of their interests. They also have independence in the collection and allocation of their resources.

[9] The Paraguayan health system is highly fragmented. The Ministry of Public Health and Social Welfare, or *Ministerio de Salud Publica y Bienestar Social* (MSPBS), has the mandate to provide free health services to the entire population, and in practice, covers 75 percent of the population. It operates its service delivery network independently from the second largest provider—the Social Security Institute or *Instituto de Previsión Social* (IPS)—which provides services to the formally employed, covering around 25 percent of the population (https://atlasgenero.ine.gov.py/detalle-indicador.php?id=48&year=2020). The information we use in our work corresponds to the MSPBS.

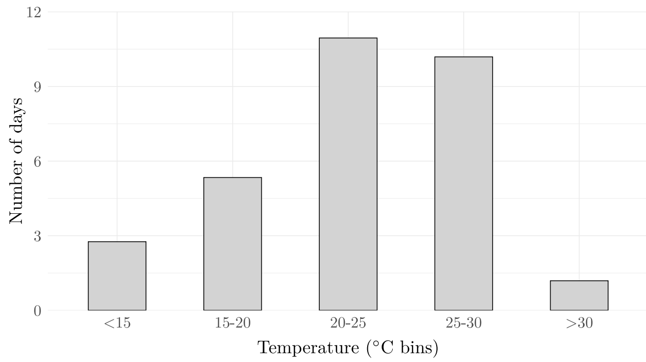


Fig. 6. Frequency distribution of monthly temperature in Paraguay (2015–2019).
Notes: Own calculations based on CMIP6-ERA5 dataset.

during month m in year t. Specifically, we conduct separate regressions of Eq. (6) for each age-group categorized as 0–4, 5–44, 45–64, and > 64 years old, and obtained an overall exposure-response function as the weighted average of the estimated coefficients from these four regressions, where population in each age-group are used as weights.

The exposure variables are captured through TEM_{dmtj}, which corresponds to the monthly mean temperature partitioned into temperature intervals known as bins. Each of the j bins captures the number of days falling in each temperature interval, for each department d, month m, and year t, respectively.[10] The other variables are controls for precipitation (PRE_{dmt}), relative humidity (RH_{dmt}), and fixed effects that control for factors that vary by department and year (μ_{dt}), and by month (ρ_m) to capture seasonality.

We include a total of five temperature bins in degrees Celsius: < 15; 15–20; 20–25; 25–30; > 30 °C. The temperature bin taken as the reference (the omitted bin in the regression) is 20–25 °C, corresponding to the mode of the frequency distribution of days in a month that fall into each bin (see Fig. 6), with the monthly mean temperature of 22.7 °C. The monthly average for precipitation is 134.16 mm, and 72.18% for relative humidity. The explanatory variables come from the same database as those for mortality, the CMIP6 ERA5 database.

Notice that we aggregate daily weather data into monthly summaries to mitigate what is known as the "harvesting effect". This phenomenon is a concept in epidemiological research that concerns the potential short-term consequences of environmental or health interventions on mortality or morbidity rates (Schwartz, 2001). The theory suggests that heat and cold waves may result in a temporary shift in the timing of deaths or health events rather than a genuine reduction in overall risk. In this context, we aim to avoid the situation where hospitalizations and doctor visits increased after a period with extreme temperatures but is followed by a period with below average hospitalizations or doctor visits. This pattern may occur because extreme temperatures could disproportionately affect individuals with pre-existing health vulnerabilities, who would likely have required hospitalization or doctor visits in the short term, regardless of the temperature. By aggregating data at the monthly level, we can more accurately assess the impact of temperature on morbidity, avoiding potential overestimation that might occur when looking at periods shorter than a month (Deschênes and Moretti, 2009).

[10] The primary benefit of employing bins, as opposed to alternative approaches for modeling non-linearity, lies in their adaptability. Bins permit the attribution of unique morbidity effects to each temperature category. This utilization of bins aligns with the predominant method found in contemporary economic research papers, simplifying comparisons and maintaining harmony with established literature (Deschênes and Greenstone, 2011; García-Witulski et al., 2023; Helo Sarmiento, 2023).

Our dataset comprises a total of 1080 observations, representing monthly morbidity rates in the 18 department councils over a span of five years, resulting in a balanced panel structure. To ensure the robustness of our model, we incorporate several checks, including utilizing the natural logarithm of the respective morbidity rate, introducing monthly lagged temperature bins, and considering gender and cause-specific morbidity.

Our parameters of interest are the θ_j for each age-group a. These parameters can be interpreted as the marginal change in the monthly age-group morbidity rate with respect to the rate in the reference (omitted) temperature bin, i.e., when the number of days in each of the other temperature bins varies by 1.

$$\Delta MR_{dmtaj} = \hat{\theta}_j \times \Delta TEM_{dmtj}, \text{ with } \Delta TEM_{dmtj} = 1 \tag{7}$$

Hence, $\Delta MR_{dmtaj} = \widehat{\theta_{aj}}$. Since the unit of analysis is a department (d) by month (m) by year (t), there will be a $\hat{\theta}$ for each age group (a) for each temperature bin (j), $\widehat{\theta_{aj}}$. Thus, ΔMR_{dmtaj} should be interpreted as the excess morbidity due to an additional day of non-optimal temperature.

The second step involves computing the projected number of days in each of the j temperature bin for each department d, month m in time period $t = \{2020, 2035, 2050, 2100\}$, i.e., TEM_{dmtj}, under the five climate models and the three scenarios described in Section 2. Due to space constraints, we report in Table C.1 in Annex C the monthly average number of days in each temperate bin for the whole country. For instance, in the year 2020 under climate model GFDL-ESM4 and scenario SSP126, there were on average 0.88 days with temperature under 15 °C, and 0.04 days with temperature above 30 °C. We then compute the change in the number of days in each bin in time $t = \{2035, 2050, 2100\}$ with respect to the baseline period (2020), i.e., ΔTEM_{dmtj}.

Then, for the last step, with the different values for $\widehat{\theta_{aj}}$ and ΔTEM_{dmtj} in hand, we calculate the change in the annual morbidity rates by age-group at the country level due to the change in the distribution of future temperatures as follows:

$$\Delta MR_{ta} = \sum_{d=1}^{18} \sum_{m=1}^{12} \sum_{j=1}^{4} \widehat{\theta_{aj}} \times \Delta TEM_{dmtj} \tag{8}$$

Thus ΔMR_{ta} should be interpreted as the change in the excess of morbidity between the baseline period of 2020 and a future period. Finally, we estimate the morbidity attributable to climate change as:

$$\Delta Cases_{ta} = \Delta MR_{ta} \times \frac{POP_{ta}}{100,000} \tag{9}$$

Where Pop_{ta} is the total population for each age group and is divided by 100,000 to convert the rate into cases. Eq. (9) is computed for each of the three scenarios.

4. Results

This section presents the results based on the methodological approaches outlined in the previous section. We first present the main results for mortality followed by the results for morbidity.

4.1. Mortality results

Temperature changes are projected to significantly increase the burden of mortality attributed to non-optimal temperatures in Paraguay. In absolute terms, the number of deaths is expected to rise from an estimated 660–690 in 2020, depending on the climate scenario, to 908–1042 by 2050 and 944–1666 by 2100. In relative terms, the mortality rates attributed to temperature changes are projected to increase by 1–22 percent by 2050 and by 5–94 percent by 2100 compared to 2020 levels, contingent on the climate scenario. Fig. 7 illustrates that the average mortality rate from all five models attributable to non-optimal temperatures is expected to rise across all three climate scenarios by

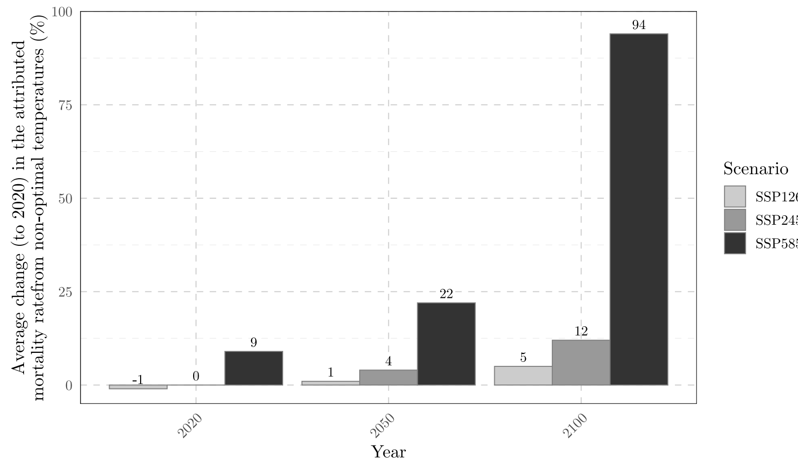


Fig. 7. Average change in the attributed mortality rate from non-optimal temperatures relative to 2020.
Notes: Own elaboration based on historical data from ERA5 and climate projections from CMIP-6 biased-adjusted (Noël et al., 2022; Climate Data Factory, 2022). See Table 1 for details on climate models and scenarios.

2050 and 2100 (see Table 1 for details). Under the worst-case scenario (SSP585), the mortality rate is projected to increase by 22 percent by 2050 and by 94 percent by 2100, potentially resulting in up to 380 additional deaths by 2050 and 1000 additional deaths by 2100.

Note that Paraguay's heat-related mortality burden due to climate change is one of the highest among the countries included in the global study by Vicedo-Cabrera et al. (2021).

Under various climate scenarios, significant changes in the frequency of low-temperature days are anticipated over time, as illustrated in Fig. A.1 in Annex A. Specifically, taking the SSP245 scenario as the reference scenario, the number of low-temperature days is expected to decrease while the number of high-temperature days will increase as time progresses. Notably, in the most severe climate scenario (SSP585), by the year 2100, the number of deaths attributed to low temperatures is projected to decrease significantly in absolute terms (see Fig. 8, Panel A, boxplot in blue).

Fig. 8 shows the attributed mortality for the selected years of interest under the three climate scenarios.[11] The total net (Fig. 8c) attributable burden considers both exposures to low (Fig. 8a) and high (Fig. 8b) temperatures. In the case of the health burden attributed to high temperatures exposure, it is expected to increase in time, especially from 2050 onwards, with an increase in all climate scenarios. Note that in some cases mortality is expected to be reduced, while in others, mortality is expected to increase.

4.2. Morbidity results

Fig. 9 illustrates the trends in the utilization of the public health system in Paraguay from 2015 to 2019. During this period, the annual average number of hospitalizations was approximately 215,000, while doctor visits averaged 8 million per year. Notably, both indicators of health service usage have shown an upward trend since 2016.

This upward trend could be attributed to several factors. Firstly, the population of Paraguay has been steadily increasing, leading to greater demand for healthcare services. Additionally, improvements in healthcare access and infrastructure may have facilitated more frequent use of public health facilities (Báscolo et al., 2018; Capurro and Harper, 2022). Socio-economic changes, such as rising income levels and increased health awareness, could also play a role in this trend.

[11] Detailed intermediary results (e.g., Population Attributable Fractions that are cause, time and location specific) are not reported due to length reasons. However, they are available upon request.

In this subsection, we present the results of the exposure-response function between temperature and morbidity. Specifically, we report the estimates of the θ_j parameters from Eq. (6) for each age-group a. These coefficients quantify the effect of an additional day in a month within temperature bin j on the monthly morbidity rate, compared to the optimal temperature range of 20-25 °C, which serves as the reference bin. Positive and statistically significant coefficients indicate an increase in morbidity during non-optimal temperature conditions. Moreover, it is expected that the magnitude of these coefficients will be larger for temperature bins that deviate further from the optimal range.

Table 3 presents the results for both morbidity outcomes: the hospitalization rate (Panel A) and the rate of doctor visits (Panel B). Due to space limitations, the table only displays the estimated θ_j parameters for each age group a. It should be noted that each regression (each row) incorporates the complete set of control variables as specified in Eq. (6). Also standard errors are clustered at that province (*departamento*) level. This approach is designed to account for the potential lack of independence of observations within administrative units. Morbidity rates often vary across space due to differences in climatic conditions, socioeconomic factors, infrastructure, and healthcare access that can create correlations among observations. By clustering the standard errors by province our model adjusts for this dependence, thereby enhancing the precision and reliability of our statistical inferences.

The findings indicate an increase in both hospitalization and doctor visit rates during periods with temperatures above the optimal range. Specifically, an additional hot day with an average daily temperature exceeding 30 °C raises the population-weighted monthly hospitalization rate by 1.19 per 100,000 inhabitants (last column of Specification 5 in Panel A). Similarly, an extra day of hot weather (>30 °C) results in an increase of 57.21 per 100,000 inhabitants in the population-weighted monthly doctor visit rate (last column of Specification 5 in Panel B). Both coefficients are statistically significant at the 10 percent confidence level. These effects correspond to a rise of 0.38% and 0.42%, respectively, compared to the monthly averages for hospitalization and doctor visit rates between 2015 and 2019. In contrast, an additional day of cold weather (below 15 °C) does not show statistical significance for either the hospitalization rate or the doctor visit rate.

Specifications 1 to 4 within each panel of Table 3 display the estimated coefficients but for different age-groups, $\widehat{\theta_{aj}}$. When considering hospitalizations, the most substantial impact is noticeable within the younger (Specification 1) and older populations (Specification 4). Specifically, an additional day of hot weather exceeding 30 °C leads to a monthly hospitalization rate increase of 3.05 and 3.82 per 100,000 inhabitants for each respective age group. These impacts translate to an

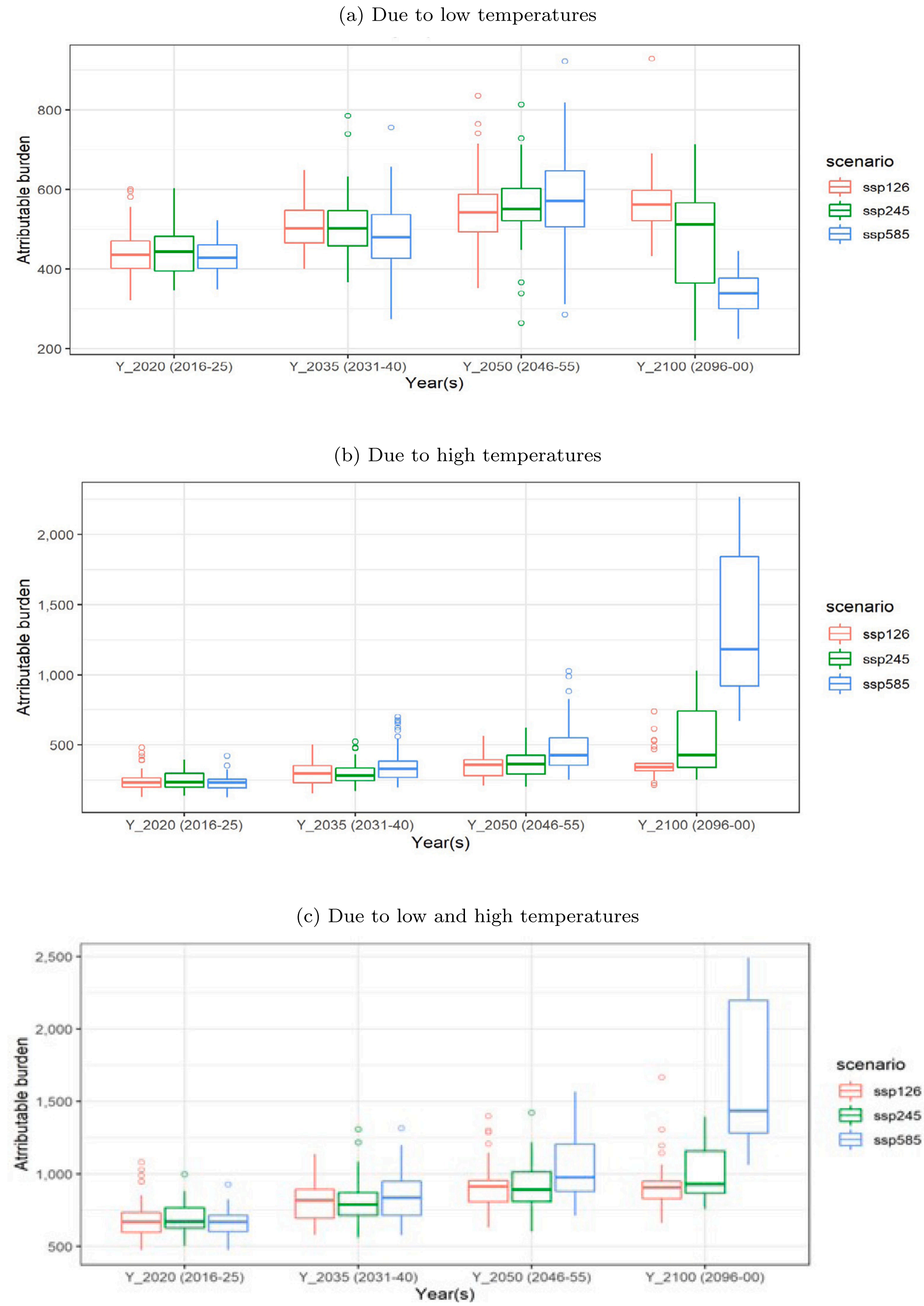


Fig. 8. Total attributable mortality burden from exposure (number of deaths).
Notes: Own elaboration. Box plot represents the median, two hinges, two whiskers, and all "outlying" points individually. The lower and upper hinges correspond to the first and third quartiles (the 25th and 75th percentiles). The upper whisker extends from the hinge to the largest value no further than 1.5*IQR from the hinge (where IQR is the inter-quartile range, or distance between the first and third quartiles). The lower whisker extends from the hinge to the smallest value at most 1.5*IQR of the hinge. Data beyond the end of the whiskers are called "outlying" points and are plotted individually.

increase of 0.62% and 0.68%, respectively, in relation to the monthly averages for the hospitalization rate and doctor visits rate between 2015 and 2019. Notably, in terms of hospital admissions among the adult population, it is primarily men who are significantly affected by heat (see Table D.1 in Annex D).

Doctor visits also increase on hot days across all age groups (Specifications 1–4 in Panel B). Elevated temperatures above the optimal range significantly impact visitation rates, particularly for older individuals. Conversely, colder temperatures do not significantly affect visitation rates. Additionally, both men and women experience an uptick in doctor visits during extremely high temperatures, with the increase being more pronounced for women than for men. For comprehensive results, please refer to Table D.1 in Annex D.

Table 4 presents the estimated coefficients $\widehat{\theta}_j$ by disease type for all age groups combined, for both hospitalizations (Panel A) and doctor visits (Panel B). Similar to the previous table, each regression is reported in a separate row and includes the same control variables as specified earlier. The results from Table 5 indicate that as temperatures

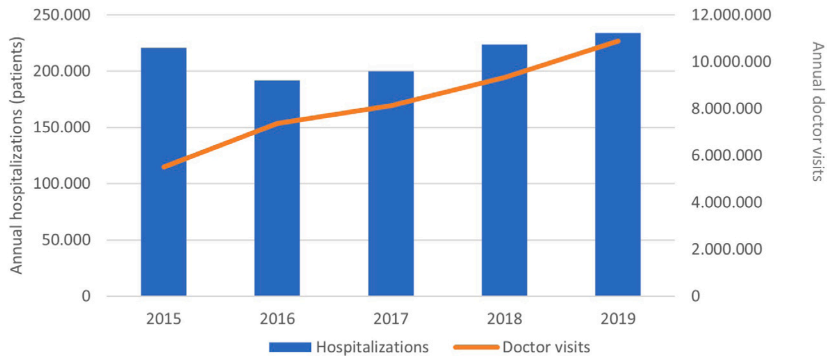


Fig. 9. Health care utilization in Paraguay.
Notes: Own elaboration based on data from the Ministry of Health. Blue bars show the annual number of hospitalization within the public health care system, while the solid orange line shows the annual number of doctor visits.

Table 3
Impact of an extra day of non-optimal temperature by age-group.

Panel A. Hospital admissions rate	< 15°	15–20°	25–30°	> 30°
1. 0–4 age-old	−1.80	−1.35	1.77***	3.05**
	(0.94)	(1.03)	(0.67)	(1.40)
2. 5-44 age-old	−0.60	−0.68	0.52**	0.72
	(0.27)	(0.44)	(0.26)	(0.59)
3. 45–64 age-old	−0.26	0.13	0.09	0.98*
	(0.51)	(0.50)	(0.27)	(0.54)
4. > 64 age-old	0.63	1.06	−0.32	3.82***
	(1.10)	(0.77)	(0.53)	(1.42)
5. Population weighted	−0.59	−0.51	0.52	1.19*
	(0.43)	(0.53)	(0.32)	(0.72)
Panel B. Doctor visits rate	< 15°	15–20°	25–30°	> 30°
1. 0–4 age-old	48.24*	−81.50	57.05**	85.35
	(27.65)	(54.04)	(26.13)	(81.31)
2. 5-44 age-old	15.68	−42.35	26.94***	48.08*
	(18.42)	(16.38)	(6.83)	(25.74)
3. 45–64 age-old	22.92	−44.16	26.56**	68.19**
	(23.35)	(22.72)	(11.67)	(28.37)
4. > 64 age-old	49.79	−41.69	32.72*	81.93**
	(31.33)	(37.46)	(18.24)	(39.37)
5. Population weighted	22.27	−46.57	30.29***	57.21*
	(20.96)	(22.53)	(10.28)	(32.65)

Notes: This table reports estimates of $\hat{\theta}_j$ from Eq. (6) by age-group a using monthly observations between 2015 and 2019. The number of observations is $N = 1080$ (province (*departamento*) by month by year). Hospitalization and doctor visits rates are per 100,000 inhabitants. Standard errors are clustered at the province level. Specifications 1–4 also include precipitation, relative humidity and province-by-year- and month-fixed effects, while Specification 5 is the age-group population weighted average of the previous estimates. The reference (omitted) optimal temperature bin is 20–25 °C.
* Significance levels are: $p < 0.10$.
** Significance levels are: $p < 0.05$.
*** Significance levels are: $p < 0.01$.

Table 4
Impact of an extra day of non-optimal temperature by cause.

Panel A. Hospital admissions rate	< 15°	15–20°	25–30°	> 30°
1. Respiratory	0.20	−0.06	0.04	0.09
	(0.14)	(0.17)	(0.12)	(0.20)
2. Cardiovascular	0.01	0.02	−0.06	0.01
	(0.05)	(0.05)	(0.04)	(0.07)
3. Infectious	−0.62	−0.29	0.33***	0.24*
	(0.12)	(0.13)	(0.08)	(0.13)
4. Mental	−0.01	0.02	0.01	0.06
	(0.02)	(0.03)	(0.01)	(0.07)
5. Neoplasm	0.04	0.03	0.00	−0.02
	(0.03)	(0.03)	(0.02)	(0.03)
Panel B. Doctor visits rate	< 15°	15–20°	25–30°	> 30°
1. Respiratory	31.67***	−4.65	4.10	−6.87
	(6.22)	(7.08)	(6.06)	(14.94)
2. Cardiovascular	3.09**	−1.78	1.53	2.36
	(1.43)	(1.88)	(1.16)	(2.06)
3. Infectious	−8.06	−5.26	3.61**	3.14**
	(3.02)	(2.31)	(1.43)	(1.45)
4. Mental	0.20	−0.67	0.85***	0.99
	(0.42)	(0.55)	(0.30)	(1.17)
5. Neoplasm	0.27	−0.00	−0.04	0.92***
	(0.28)	(0.14)	(0.07)	(0.34)

Notes: This table reports estimates of $\hat{\theta}_j$ from Eq. (6) by cause using monthly observations between 2015 and 2019. The number of observations is $N = 1080$ (province (*departamento*) by month by year). Hospitalization and doctor visits rates are per 100,000 inhabitants. Standard errors are clustered at the province level. Specifications 1–4 also include precipitation, relative humidity and province-by-year- and month-fixed effects, while Specification 5 is the age-group population weighted average of the previous estimates. The reference (omitted) optimal temperature bin is 20–25 °C.
* Significance levels are: $p < 0.10$.
** Significance levels are: $p < 0.05$.
*** Significance levels are: $p < 0.01$.

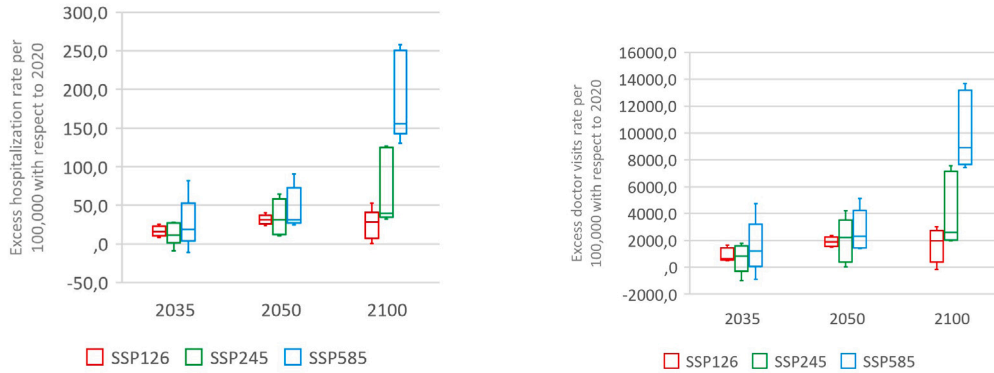
increase, there is a corresponding rise in the rates of infectious diseases compared to the optimal temperature range of 20 to 25 °C. This effect is statistically significant for both hospitalizations and doctor visits. This finding is consistent with the frequent outbreaks of vector-borne diseases such as dengue and the recent chikungunya outbreak in the country, which have notably impacted hospitalization rates.[12] On the other hand, lower temperatures are associated with an increase in respiratory and cardiovascular diseases.

When considering the combined impact of additional days with non-optimal temperatures, as well as the number of days annually that fall below or above comfortable levels (Eq. (8)), we observe changes in monthly hospitalizations and doctor visits for all age groups within the 2015–2019 period. Specifically, these changes amount to 29 additional hospitalizations and 2279 additional doctor visits per 100,000 inhabitants.

Utilizing these rates in conjunction with the population, and taking into account Eq. (9), our estimation indicates that there are 2013 additional hospitalizations and 157,300 extra doctor visits annually linked to non-optimal temperatures. In the context these figures represent 0.94% and 1.97% respectively, in relation to the average number of respective health outcomes observed during the 2015–2019 period.

Once the contemporaneous impacts of non-optimal temperatures on morbidity have been determined, we extrapolate the coefficients from Specifications 5 (Panels A and B) in Table 3 to estimate the effect of temperature changes in 2035, 2050, and 2100 on morbidity rates. Specifically, we multiply the coefficients of the $\hat{\theta}_j$ parameters in Eq. (6) by the projected changes in the number of days within each

[12] See https://www.telesurtv.net/news/paraguay-acumula-nuevos-casos-chikungunya-20230224-0029.html.



(a) Excess hospitalizations rate

(b) B. Excess doctor visits rate

Fig. 10. Excess morbidity rates attributable to temperature changes with respect to 2020.
Notes: Own elaboration based on data from the Ministry of Health. Blue bars show the annual number of hospitalization within the public health care system, while the solid orange line shows the annual number of doctor visits.

temperature interval for each scenario, model, and time period, relative to the baseline year 2020 (as per Eq. (8)).

Fig. 10 illustrates the projected impacts of temperature changes on morbidity across different time periods and climate scenarios. The box plots highlight the associated uncertainty by incorporating results from five climate models. Under the SSP126 scenario, which represents a milder projection of climate change, the excess burden on morbidity peaks around 2050 and subsequently decreases by 2100. Conversely, in the more severe SSP585 scenario, the peak in the excess burden occurs in 2100. For example, in 2050 under the SSP585 scenario, climate change is projected to result in an average of 46 additional hospitalizations per 100,000 people and 2735 extra doctor visits. This means that the number of patients admitted to the public health system due to non-optimal temperatures would double, while the number of doctor visits would triple compared to 2020 levels.

The effects of climate change on health outcomes are dynamic, shaped by shifting climate patterns and fluctuations in population size and composition. It is important to account for the age distribution of the population since specific age groups, such as the very young and the elderly, are typically more susceptible to temperature-related hazards. As the population undergoes demographic changes, marked by declining birth rates and extended life expectancy, the proportion of individuals at heightened risk rises. Consequently, it is relevant to include population dynamics in the evaluation of the health consequences of climate change. However, only few studies have fully integrated this factor into their analyses. In this regard, a literature review conducted by Cole et al. (2023) identified 131 articles that projected the heat health burden, and only 45 percent of these studies included changes in population size, while only 23 percent accounted for changes in population structure. In our study, we do consider changes in population. Hence, to distinguish the specific effects of temperature changes from those of population change, we construct a ‘‘baseline case’’ where temperature remains at the 2020 level, while only the population changes, and a ‘‘counterfactual case’’ where both temperature and population dimensions vary. By comparing these cases, we can isolate the impact of temperature changes on health outcomes.

The results for the year 2050 for this exercise are summarized in Table 5. It is noteworthy that when the impact of temperature changes is isolated, the estimated health impact decreases compared to scenarios where population dynamics are also considered. This analysis underscores the importance of accounting for both temperature changes and population dynamics when projecting the health impacts of climate change.

5. Conclusions

Climate change is expected to bring about substantial shifts in Paraguay’s temperature distribution in the years to come, with consequential implications for future human health. This paper assesses and quantify the potential consequences of these temperature changes on morbidity and mortality. We extend our analysis across distinct time horizons, considering various greenhouse gases emission scenarios and changes in the demographic structure, thus offering a comprehensive assessment of these impacts in both the medium-term and long-term future. Our primary contribution lies in estimating the impact of projected temperature variations on different health outcomes, thereby enhancing our understanding of the potential health risks associated with climate change.

According to the GBD project in 2019, non-optimal temperatures are responsible for an estimated 640 deaths annually, with 58 percent attributed to low temperatures and the remaining 42 percent caused by heat-related conditions. Our estimates for 2020 are around the same magnitude, with mean mortality estimates around 660 and 690, depending on the climate model and the emissions scenario. Additionally, within the period spanning from 2015 to 2019, we estimate that there were 2013 annual hospitalizations and 157,300 annual doctor visits within the public health system attributable to non-optimal temperatures. These health impacts represent approximately 1.6%, 0.94%, and 1.97% of annual total deaths, hospitalizations, and doctor visits, respectively, during that period.

Our analysis reveals heterogeneous impacts of present temperatures across different age-groups and genders. The elderly population appears to be more vulnerable to the effects of non-optimal temperatures. Both hospitalization and doctor visit rates exhibit an upward trend during periods of elevated temperature. Gender disparities indicate that while hospitalizations among men surge during hot weather, both men and women increase visitations under such conditions. Furthermore, the most prominent effects due to heat exposure are observed for infectious diseases, although cardiovascular diseases contribute significantly to higher mortality rates.

When comparing the impact of climate change for 2050 with respect to 2020, we find that the mortality rate attributable to non-optimal temperatures increases by an average of 21.6% under the worst climate scenario, SSP585, followed by an increase of 3.7% under SSP245 and by a 1.5% increase under SSP126. By 2100, the rise in the attributable mortality rate would reach 94.1% under SSP585, 11.9% under SSP245 and 5.3% under SSP126. Furthermore, the rate of hospitalizations due to temperatures outside comfortable ranges doubles during the 2020–2050 period under SSP585, while the rate of doctor visits triples in the same period.

Table 5
Baseline case versus counterfactual.

Year	Climate scenario	Hospitalizations		Doctor visits	
		Baseline	Counterfactual	Baseline	Counterfactual
2035	SSP26	1,071	1,376	68,955	77,897
	SSP45	926	1,225	51,798	60,931
	SSP85	1,872	2,160	117,326	129,073
2050	SSP26	1,918	2,498	157,688	175,245
	SSP45	2,321	2,878	165,743	183,563
	SSP85	3,441	3,936	230,508	252,607
2100	SSP26	1,785	2,695	141,326	174,650
	SSP45	5,475	6,299	365,351	398,621
	SSP85	22,238	22,764	938,273	974,765

Notes: Baseline represents the additional number of hospitalizations or visitations due to a change in the population and its age-structure. Counterfactual includes both changes in population and temperature. This table reports the average for all six climate models.

Our findings align with existing evidence that incremental temperature rises contribute to a greater burden of disease. We observe a noteworthy impact on morbidity among males, corroborating the conclusions drawn in the study by Gifford et al. (2019), which suggests that the incidence of heat-related illnesses is substantially higher in men than in women. This gender disparity may arise from behavioral considerations rather than physiological ones. Furthermore, our results show that advanced age groups experience a heightened prevalence of heat-related health concerns.

This analysis bears three caveats that deserve mention. Firstly, our estimates only capture a fraction of the overall impacts of non-optimal temperatures on health. The synergy between heat and air pollution, for instance, might exert more significant effects when both risk factors are considered together. However, it is important to note that comprehensive quantification of multiple risk factors is not commonly undertaken in the existing literature.[13] This limitation in the literature may, in part, be attributed to constraints in available data. Future research in Paraguay could potentially address this knowledge gap, especially when considering air pollution from wildfires. Secondly, owing to data constraints, our analysis of morbidity effects solely encompasses the health impacts on the segment of the population reliant on the public healthcare system. This limited scope disregards other dimensions of Paraguay's healthcare institutions, which may involve more substantial healthcare provisions. Thirdly, our estimates do not incorporate adaptation strategies that individuals might adopt to shield themselves from rising temperatures. Strategies like heat avoidance, as well as improved access and the enhancement of healthcare system quality, can significantly contribute to mitigating the effects of heat. In the absence of this consideration of potential adaptations, our estimates represent an upper bound of the genuine impacts of rising temperatures. Nevertheless, the absence of information on adaptation measures precludes its inclusion in our analysis.

Despite the aforementioned limitations, our findings emphasize the growing health challenges associated with non-optimal temperatures. Understanding the consequences of these conditions on health is crucial for policymakers to implement effective interventions. Likewise, it provides valuable insights for all stakeholders within the healthcare system, helping them make it more resilient. This becomes increasingly critical for Paraguay, given the projections in the IPCC AR6 (Zhongming et al., 2022), which anticipate substantial warming as climate change unfolds.

To address these findings, several policy options can be considered. Firstly, launching informational campaigns and issuing heat warnings could be a cost-effective strategy (Rabassa et al., 2021). These initiatives should emphasize the importance of adequate hydration and the avoidance of prolonged exposure to high temperatures, particularly for older individuals and those with underlying health conditions. Second, healthcare providers need to prepare for an increase in hospitalizations and doctor visits due to non-optimal temperatures. This preparation can involve creating protocols for virtual healthcare consultations, allowing elderly individuals and patients with mental health conditions to access medical advice while staying indoors and avoiding heat-related risks. Fragmentation is inherent to the Paraguayan health care system, and the country public expenditure on health accounted for 3.3 percent of GDP, which is below the average for Latin America (4 percent) and is far from the 7.7 percent of OECD countries. Moreover, part of the problem in financing the Paraguay health system is the high levels of labor informality. Third, employers should be encouraged to ensure that workplace temperatures meet established standards. Paraguay, like many other countries, has laws in place to protect workers' well-being, and it is even more crucial to follow these standards as temperatures rise.

Furthermore, it is essential to recognize that putting these policies into action will necessitate sufficient funding. Presently, a relatively small share of multilateral adaptation funding is channeled toward the healthcare system. As per Jabakhanji et al. (2022), during the period between 2018 and 2020, only 3% of such funding was allocated to the health sector, with 13.6% designated for projects indirectly influencing health. In light of our study's findings, which emphasize the societal advantages of directing adaptation resources toward health measures, it is rational to propose that a portion of these resources should be reallocated to address the health consequences of non-optimal temperatures.

CRediT authorship contribution statement

Paulina Schulz-Antipa: Conceptualization, Data curation, Formal analysis, Methodology. **Christian M. García-Witulski:** Data curation, Investigation, Methodology, Software, Writing – original draft, Writing – review & editing. **Mariana Conte Grand:** Conceptualization, Funding acquisition, Supervision, Writing – original draft, Writing – review & editing. **Mariano J. Rabassa:** Formal analysis, Investigation, Methodology, Supervision, Validation, Writing – original draft, Writing – review & editing.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Mariana Conte Grand reports financial support was provided by World Bank Group. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

[13] Anenberg et al. (2020) conducted a review of various estimates concerning the combined impact of multiple risks and found few studies, mostly conducted in urban areas of Europe, North America, and Asia, that identified synergistic effects between heat and exposure to ozone and PM2.5 A similar result is reported by other authors as Grigorieva and Lukyanets (2021), among others.

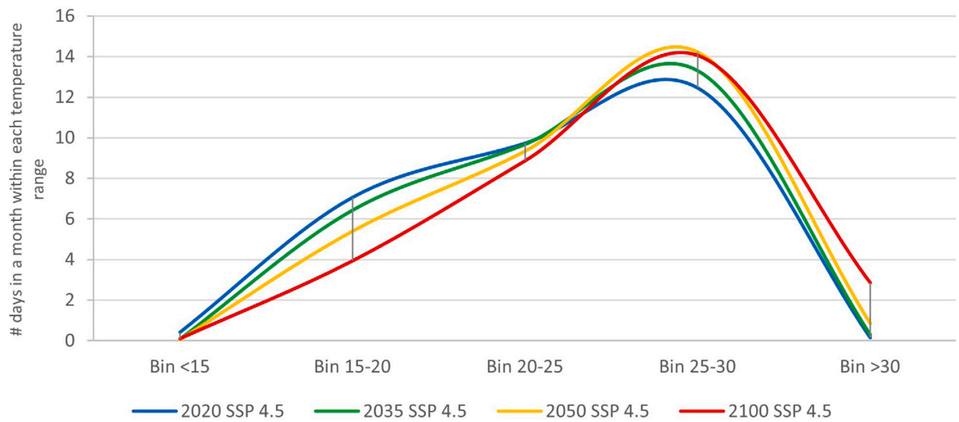


Fig. A.1. Temperature rise under the climate scenario SSP245.*Notes*: Own elaboration based on Climate Data Factory (2022).

Table B.1
Death rates in Paraguay in 2019, causes related to non-optimal temperatures.
Source: (Global Burden of Disease Collaborative Network, 2020).

Cause id	Cause name	Rate	Upper	Lower
294	all causes	493.06	616.38	391.45
322	lower respiratory infections	21.26	26.72	16.29
493	ischemic heart disease	68.58	86.45	53.85
494	stroke	48.01	62.64	36.63
498	hypertensive heart disease	12.10	15.32	8.73
499	cardiomyopathy and myocarditis	2.51	3.49	1.85
509	chronic obstructive pulmonary disease	14.05	17.95	10.79
689	road injuries	21.66	28.22	15.36
695	other transport injuries	0.51	0.69	0.35
698	drowning	2.61	3.46	1.95
587	diabetes mellitus	35.30	44.52	27.38
589	chronic kidney disease	27.17	34.57	21.12
729	exposure to forces of nature	0.25	0.27	0.22
704	exposure to mechanical forces	1.01	1.42	0.72
709	animal contact	0.23	0.33	0.07
716	other unintentional injuries	2.69	3.59	1.88
718	self-harm	6.17	8.10	4.13
724	interpersonal violence	11.88	16.11	8.57

Rate are expressed per 100,000 inhabitants.

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Annex A. Supplementary material: temperature scenarios

We utilize daily temperature data for three climate scenarios and five climate models, as described in Section 2. As anticipated, the number of hot and cold days changes over time, varying with different climate models and scenarios. For instance, under the SSP245 climate scenario, the average across climate models indicates a decrease in the frequency of cold days and an increase in hot days as time progresses. Specifically, in 2020, there are typically 7 days per month with a daily mean temperature ranging from 15 to 20 °Celsius. By 2100, this number is expected to drop to 4 days per month. Conversely, the number of days per month with a daily mean temperature exceeding 30 degrees Celsius, currently at most 1 day, is projected to rise to 3 days by 2100.

Annex B. Mortality incidence rates for temperature related mortality causes

(See Table B.1.)

Annex C. Bin distribution by climate scenario, model and time

(See Table C.1.)

Annex D. Alternative specification for morbidity estimations

(See Table D.1.)

Annex E. Population dynamics

(See Table E.1.)

Table C.1
Number of days per month within each temperature bin by climate scenario, model, and time.

Model	SSP126				SSP245				SSP585			
	2020	2035	2050	2100	2020	2035	2050	2100	2020	2035	2050	2100
Number of days per month with temperature <15 °C												
GFDL-ESM4	0.88	0.21	0.19	0.82	0.82	0.34	0.05	0.15	0.60	0.34	0.27	0.00
IPSL-CM6A-LR	0.23	0.24	0.04	0.91	0.16	0.00	0.01	0.03	0.23	0.25	0.00	0.00
MPI-ESM1-2-HR	0.21	0.07	0.01	0.15	0.12	0.05	0.04	0.24	0.17	0.00	0.07	0.00
MRI-ESM2–0	0.55	0.26	0.38	0.17	0.48	0.04	0.07	0.10	0.29	0.08	0.05	0.00
UKESM1-0-LL	0.36	0.04	0.00	0.37	0.50	0.03	0.08	0.00	0.16	0.00	0.00	0.00
Number of days per month with temperature 15–20 °C												
GFDL-ESM4	7.15	6.49	4.58	6.16	6.44	6.25	6.45	4.63	5.75	6.40	4.83	1.73
IPSL-CM6A-LR	6.69	6.61	5.33	4.72	7.35	5.59	3.80	2.14	6.33	5.48	3.66	0.68
MPI-ESM1-2-HR	7.07	6.77	5.69	7.72	8.17	7.22	6.03	5.94	7.80	5.77	5.00	2.10
MRI-ESM2–0	7.72	5.82	6.04	5.16	6.51	7.32	5.74	4.33	7.28	6.71	6.38	2.37
UKESM1-0-LL	6.67	5.19	5.17	4.72	6.87	5.82	4.93	2.63	6.59	3.37	3.49	0.32
Number of days per month with temperature 20–25 °C												
GFDL-ESM4	8.73	9.07	9.29	9.07	9.78	9.32	10.05	9.47	8.53	9.23	8.06	7.52
IPSL-CM6A-LR	10.19	9.23	8.99	9.22	10.04	9.94	8.81	7.65	10.10	9.44	9.22	5.19
MPI-ESM1-2-HR	10.97	10.03	10.62	9.84	9.79	10.04	9.46	8.94	10.14	10.92	11.32	7.82
MRI-ESM2–0	10.24	10.75	8.84	11.75	9.32	10.13	9.51	10.22	9.97	8.83	8.80	8.25
UKESM1-0-LL	9.19	9.92	8.90	8.79	9.76	9.01	8.84	8.07	10.28	9.09	8.35	4.54
Number of days per month with temperature 25–30 °C												
GFDL-ESM4	13.05	13.98	15.48	13.46	12.75	13.85	13.03	14.84	14.70	13.80	15.17	9.21
IPSL-CM6A-LR	12.65	13.53	14.92	14.10	12.25	14.03	15.97	14.56	13.15	14.15	15.54	7.22
MPI-ESM1-2-HR	11.55	12.89	13.29	12.01	11.71	12.44	14.08	14.06	11.72	13.06	13.12	11.83
MRI-ESM2–0	11.31	12.89	14.44	12.53	13.39	12.15	14.36	14.44	12.21	14.00	14.20	12.60
UKESM1-0-LL	12.83	13.69	14.67	12.07	12.23	14.09	13.65	12.43	12.59	13.35	13.28	7.70
Number of days per month with temperature >30 °C												
GFDL-ESM4	0.04	0.10	0.30	0.33	0.05	0.07	0.26	0.75	0.26	0.07	1.51	11.37
IPSL-CM6A-LR	0.07	0.24	0.55	0.88	0.04	0.27	1.25	5.44	0.02	0.51	1.42	16.75
MPI-ESM1-2-HR	0.03	0.07	0.23	0.12	0.04	0.09	0.22	0.65	0.00	0.09	0.33	8.08
MRI-ESM2–0	0.01	0.12	0.14	0.23	0.13	0.19	0.16	0.74	0.08	0.22	0.41	6.61
UKESM1-0-LL	0.78	0.99	1.10	3.89	0.47	0.89	2.34	6.70	0.21	4.03	4.72	17.27

Notes: This table shows the number of days per month that fall within specific temperature bins, categorized by climate scenario, model, and time. The temperature bins are <15 °C, 15–20 °C, 20–25 °C, 25–30 °C, and >30 °C. The scenarios are denoted as SSP126, SSP245, and SSP585, representing different Shared Socioeconomic Pathways used for climate projections. For each scenario, data is presented for the years 2020, 2035, 2050, and 2100, providing a comprehensive view of how temperature distribution is expected to change over time according to various climate models.

Table D.1
Alternative specifications of impacts of non-optimal temperature.

Panel A. Hospital admissions rate	< 15°	15–20°	25–30°	> 30°
1. Interaction with temp. and precipitation	−1.13	−0.25	0.61*	1.65*
	(0.82)	(0.45)	(0.34)	(0.91)
2. Logarithm of hospitalization rate	−0.26	−0.65	0.33	1.29
	(0.56)	(0.84)	(0.42)	(1.04)
3. Lags of temp. bins	0.06	−0.08	0.02	1.10
	(0.61)	(0.71)	(0.52)	(1.05)
4. Women	−0.63	−0.68	0.60	1.13
	(0.60)	(0.75)	(0.46)	(0.93)
5. Men	−0.55	−0.34	0.45*	1.26*
	(0.41)	(0.44)	(0.24)	(0.70)
Panel B. Doctor visits rate	< 15°	15–20°	25–30°	> 30°
1. Interaction with temp. and precipitation	−34.00	0.34	−31.58	31.30***
	(89.19)	(28.12)	(22.17)	(10.13)
2. Logarithm of hospitalization rate	−46.84	66.55	−91.53	38.08***
	(77.10)	(62.12)	(45.15)	(13.05)
3. Lags of temp. bins	167.83***	−68.06	−46.03	−38.47
	(51.82)	(19.43)	(35.07)	(20.72)
4. Women	3.96	14.83	−77.61	37.33***
	(62.52)	(37.02)	(30.52)	(12.48)
5. Men	46.72	28.06*	−15.61	23.70**
	(30.14)	(14.67)	(20.92)	(9.33)

Notes: This table reports estimates of $\hat{\theta}_j$ from Eq. (6) using monthly observations between 2015 and 2019. The number of observations is N = 1,080 (province (*departamento*) by month by year). Hospitalization and doctor visits rates are per 100,000 inhabitants. Standard errors are clustered at the province level. Specifications 1–5 include precipitation, relative humidity and province-by-year- and month-fixed effects. The reference (omitted) optimal temperature bin is 20–25 °C.

* Significance levels are: $p < 0.10$.

** Significance levels are: $p < 0.05$.

*** Significance levels are: $p < 0.01$.

Table E.1
Distribution of population by age-group.

Age-group	Year			
0–4	36,260 (10%)	34,016 (8%)	30,609 (6%)	19,120 (4%)
5–44	249,666 (68%)	269,043 (62%)	265,039 (56%)	190,084 (40%)
45–64	57,740 (16%)	87,816 (20%)	114,983 (24%)	113,942 (24%)
> 64	24,038 (7%)	40,997 (9%)	66,674 (14%)	154,910 (32%)
All (mean by department)	367,704	431,872	477,305	478,056
All (total country)	6,618,689	7,773,695	8,591,484	8,605,015

Notes: Based on UN population projections (United Nations, 2022).

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