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Spatiotemporal Dynamics of Heatwave Vulnerability and Maternal–Child Health Risk in Zambia

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Abstract

Evidence on spatially differentiated heatwave exposure and heat-related vulnerability in sub-Saharan Africa remains limited. This study examines the spatial-temporal patterns of daytime, night-time and compound heatwaves in Zambia and their implications for maternal and child health vulnerability. Daily maximum and minimum 2-m air temperature from ERA5-Land reanalysis (1980–2024) were used to identify heatwave events on a grid-cell basis. Heatwaves were defined as periods of at least three consecutive days exceeding the local 90th percentile threshold (1981–2010 reference period). Heatwave frequency, mean duration and mean intensity were derived and summarized across Zambia’s agro-ecological regions (AERs). These metrics were integrated with demographic, environmental and health-system indicators to construct a composite Heat Vulnerability Index. The results show spatial differentiation in heatwave exposure aligned with AERs. AER I and IIb emerged as major heatwave-exposure and heat vulnerability hotspots. The south-central part of AER IIa also showed high heat vulnerability despite having a moderate heat exposure because it coincided with a wider spatial distribution of sensitive populations and low-moderate adaptive capacity. Mean temperature was strongly correlated with heatwave frequency ($r = 0.86$, $p < 0.0001$) and duration ($r = 0.81$, $p < 0.0001$), indicating that warming is associated more with repeated and sustained heat exposure than with intensity alone. El Niño years were associated with higher night-time and compound heatwave frequency. MAM ONI provided the strongest antecedent ENSO indicator of heatwave risk. Future studies should further examine the potential for using MAM ONI and seasonal weather forecasts for strengthening heat-health early-warning systems.

Keywords: ERA5-Land reanalysis, ENSO, compound heatwaves, Heat Vulnerability Index, health risk, Demographic and Health survey, agro-ecological regions

1. Introduction

1.1 Background

With global temperature projected to increase by not less than 1.5° Celsius by 2050, the frequency, duration and intensity of heatwaves are expected to increase, reaching beyond critical tolerance thresholds and posing severe risks to human health (Barkhof et al., 2022; Campbell et al., 2018). Currently, an estimated 559 million children globally are exposed to more frequent heatwaves, a figure that is projected to rise to over two billion by 2050 (Barkhof et al., 2022). Young children under the age of five are particularly vulnerable to heat stress due to physiological factors such as a higher surface to body ratio, lower rates of sweating and acclimatization as their immune system is still developing and higher metabolism rates that cause them to heat up faster (Barkhof et al., 2022). Similarly, pregnant women are less able to thermoregulate due to physiological changes, making them more susceptible to heat stress and pregnancy-related complications, including preterm birth, low birthweight and stillbirth (Kuehn and McCormick, 2017; Abunyewah et al., 2025; Bansal et al., 2023; Bratti et al., 2021; Cil and Cameron, 2017; Barkhof et al., 2022). Furthermore, these health impacts are magnified by socio-economic vulnerabilities and limited adaptive infrastructure in sub-Saharan Africa (SSA) (Bratti et al., 2021; Barkhof et al., 2022).

Heat vulnerability research has increased substantially in recent years, particularly following the pioneering work of Reid et al. (2009) on the development of the Heat Vulnerability Index (HVI). On the other hand, the concept of thermal inequity has developed within the Vulnerability framework of the IPCC (Parry, 2007) to denote uneven distribution of heat exposure and effects among different socio-economic and demographic groups often driven by socioeconomic, demographic, and spatial disparities (Hsu et al., 2021; Li et al., 2024). However, many of the resulting analyses have not focused on specific groups such as pregnant women and children in SSA. For example, Russo et al., (2019) examined vulnerability to heatwave exposure in global cities and projected that low and middle incomes countries (LMICs) will suffer the disproportionate burden of heat risk at a rate 1.2 times higher than that of higher income countries. Additionally, much of the existing literature on heat vulnerability and thermal inequity has focused on urban areas in high-income countries, in the United States of America, Europe, Australia and China (Klingelhöfer et al., 2023) where evidence demonstrates that lower socio-economic groups

are more vulnerable to heat stress due to limited access to services and cooling systems (Chen et al., 2023; Gao et al., 2024; Zhou and Luo, 2025).

Consequently, most LMICs facing an increased heat burden are underrepresented in the current research (Campbell et al., 2018; Klingelhöfer et al., 2023). As a result, a critical knowledge gap remains regarding the spatial patterns of heatwave vulnerability among children and women of reproductive age in SSA. The region faces substantial disparities in both exposure and adaptive capacities driven by inequitable access to healthcare, essential medicines, and cooling infrastructure. Yet few studies in SSA have holistically integrated exposure, sensitivity, and adaptive capacity to map heatwave vulnerability. Such studies are needed given the region's high susceptibility to climatic extremes (Bobde et al., 2025; Campbell et al., 2018; Chambers, 2020a). Zambia exemplifies these challenges as the country continues to report poor maternal and child health indicators. While national reports acknowledge increasing heat stress, these concerns are often overshadowed by more visible climate extremes such as floods and drought. As a result, there is a lack of spatially disaggregated, data driven vulnerability indices for heat in Zambia that could guide interventions at a local scale to reduce the impacts of heat stress on maternal and child health outcomes.

This study addresses this gap by developing high-resolution heatwave metrics and a composite vulnerability index across Zambia to inform context-specific health interventions. Specifically, this study contributes to the literature by: (1) developing a heat vulnerability index (HVI) for Zambia using high resolution gridded datasets; (2), applying a thermal inequity lens to identify the spatial patterns of vulnerability among infants and women of reproductive age, an often overlooked focus in conventional climate-health research; (3) leveraging gridded climate, environmental, and socio-economic datasets to enable reproducibility, scalability, and updateability of vulnerability modeling. The study therefore presents a replicable and policy-relevant framework to guide health and climate adaptation strategies aimed at strengthening the resilience of pregnant women and children to extreme heat. The aim of this study is to quantify the spatial and temporal dynamics of heatwave exposure and vulnerability in Zambia, with a focus on maternal and child health. Specifically, the study addresses the following research questions: (1) How do heatwave characteristics (frequency, duration, and intensity) vary across space and time? (2) What is the role of compound heatwaves in shaping cumulative exposure? (3) How do

exposure, sensitivity, and adaptive capacity interact to determine vulnerability? (4) Which regions face the greatest risks for maternal and child health under increasing heat extremes?

1.2 The heat vulnerability framework

The study uses the IPCC vulnerability framework, which conceptualizes climate vulnerability as a function of Exposure, Sensitivity, and Adaptive Capacity (Parry, 2007; IPCC 2014). Exposure refers to the degree to which a population, area or system is subjected to extreme climate hazards, such as heatwaves (Li et al., 2024). Sensitivity represents the degree to which a population or system is susceptible to harm from climate hazards such as heatwaves. Adaptive capacity is the ability of systems, institutions, and individuals to adjust to potential damage, or respond to reduce the impact of the climate hazard, in this case heatwaves. The IPCC vulnerability framework is commonly applied in public health and environmental resilience studies due to its adaptable and scalable nature, making it effective even in areas with limited data like SSA. The number and type of indicators for each of the three vulnerability components (exposure, sensitivity and adaptive capacity) can vary depending on relevance, focus and data availability. For example, studies often use different indicators with a minimum of two up to a maximum of thirty indicators per component (Li et al., 2024). Additionally, the availability of global gridded datasets enables spatially explicit assessments of heat vulnerability even in areas with limited *in situ* data.

This study extends the conventional IPCC heat vulnerability framework (Parry, 2007; IPCC 2014) by incorporating the concept of thermal inequity, which captures how social, economic, and spatial disparities compound the burden of heat risk for vulnerable groups, especially women of reproductive age and infants. The integration of thermal inequity thus allows for the assessment of spatial heterogeneity in heat vulnerability by highlighting environmental disparities in exposure (topography, access to shade/green space), capturing differential sensitivity (children and women of reproductive age), and identifying limits to adaptive capacity (access to health facilities and cooling options). These dimensions are operationalized using spatial datasets on vegetation cover, population density of infants, women of reproductive age and maternal and child health indicators such as the proportion of women delivering in health facilities, literacy, ANC visits and vaccination coverage. The integration of these factors enables the development of a Heat

Vulnerability Index (HVI) that reflects not only heat hazard intensity but also underlying social and environmental inequalities that exacerbate vulnerability (Figure 1).

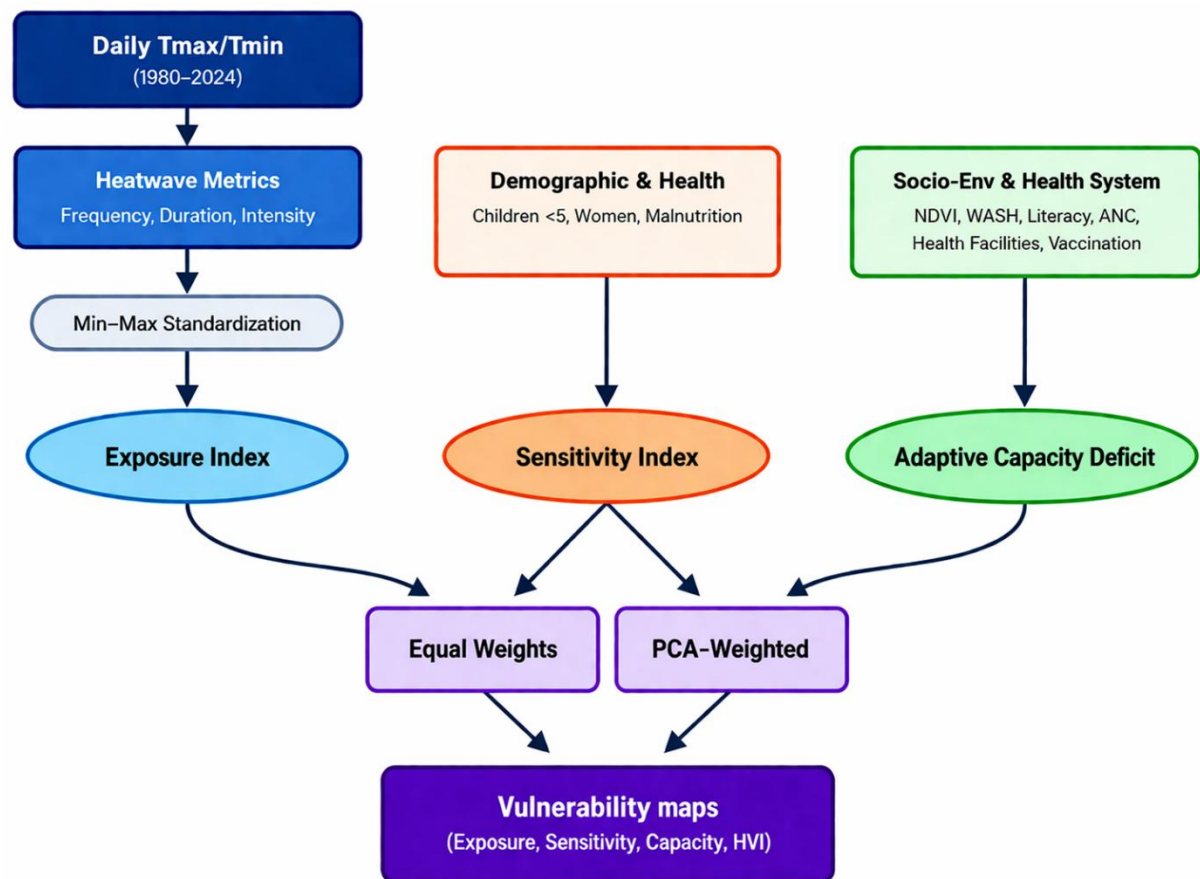


Figure 1: Heat Vulnerability Index framework. *AER* – Agro-Ecological Region, *ANC* – Antenatal Care, *HVI* – Heat Vulnerability Index, *NDVI* – Normalised Difference Vegetation Index, *PCA* – Principal Component Analysis, *WASH* – Water, Sanitation and Hygiene, *Tmax* – Maximum temperature, *Tmin* – Minimum temperature

2. Data and methods

2.1 Data sources

This study used multiple gridded datasets to characterize heatwave exposure, sensitivity, and adaptive capacity across Zambia. The primary climate variables, daily maximum (*Tmax*) and minimum temperature (*Tmin*), were obtained from the ERA5 reanalysis dataset (ERA5-Land daily aggregated statistics) at a spatial resolution of $0.1^\circ \times 0.1^\circ$ (~ 10 km) for the period 1980 to 2024.

The data were downloaded from Copernicus Climate Change Service (C3S)(2019) portal <https://cds.climate.copernicus.eu/datasets/reanalysis-era5-land?tab=download>. These data were used to determine hot days and heatwave events in terms of their intensity, frequency and duration.

To assess population exposure and sensitivity, the study utilized gridded, constrained population data (adjusted using building footprints) from WorldPop on <https://hub.worldpop.org/geodata/summary?id=50339> focusing on women of reproductive age and infants (operationalized as the sum of gridded population counts for ages 0 and 1). The study used gridded (spatially interpolated) data from the Zambia 2018 Demographic and Health Survey (DHS) <https://spatialdata.dhsprogram.com/modeled-surfaces/#survey=ZM|2018|DHS> for the other socio-economic and health indicators (Table 1) related to sensitivity and adaptive capacity for children and women of reproductive age. Other datasets used are the gridded Normalized Difference Vegetation Index (NDVI) data derived from Sentinel 2, and health facilities shapefile from the Ministry of Health in Zambia (Table 1).

Table 1. Gridded population, socio-economic and health service indicators

Variable code	Meaning of variable	Units	Indicator	Source
WSSRCEPIMP	Households using improved source of drinking water (e.g. piped water, borehole, protected well etc.)	% household	Adaptive capacity	*DHS 2018
CHVACCCDP3	Proportion/count of children receiving 3rd dose of DPT (Diphtheria–Pertussis–Tetanus) vaccine	% children	Adaptive capacity	DHS 2018
EDLITRMLIT	Adult male literacy rate	% males	Adaptive capacity	DHS 2018
EDLITRWLIT	Adult female literacy rate	% females	Adaptive capacity	DHS 2018
RHANCNWN4P	Women attending ≥ 4 antenatal care (ANC) visits	% women	Adaptive capacity	DHS 2018
RHDELPCDHF	Deliveries occurring in health facilities	% births	Adaptive capacity	DHS 2018
NDVI	Normalized Difference Vegetation Index	Unit less (-1 to 1)	Adaptive capacity	Derived from Sentinel 2
Health facilities	Facility density	Number per grid	Adaptive capacity	Ministry of Health
Age 0 and age 1	Infants	Total number per grid	Sensitivity	WorldPop 2020
zmb_f_datasets	Women of reproductive age	Total number per grid	Sensitivity	WorldPop 2020

*DHS – Demographic and Health Survey

2.2 Justification for indicator selection

The indicators used in this study were selected from existing literature on heat vulnerability (Azhar et al., 2017; Parker et al., 2025) based on their relevance to the Zambian context. Their relevance to heat vulnerability studies is further explained in the sub-sections that follow.

2.2.1 Adaptive capacity indicators

Normalized Difference Vegetation Index

The NDVI provides a good proxy for vegetative cooling. It is a common practice for people, especially in rural Zambia, to seek shade under a tree while at home or when travelling to health facilities using non-motorized transport as a way of cooling. Vegetation provides a natural micro-environment that enhances local cooling, making it one of the most frequently recommended nature-based solutions for mitigating heatwaves (Sahani et al., 2023).

Density of health facilities

The density of health facilities was selected as an indicator of medical care availability in times of heat stress, as proximity to healthcare can influence adaptive capacity. Therefore, it is an indicator of potential care delivery during heatwaves.

Households using improved source of drinking water

Improved access to water reduces the risk of dehydration, supports hygiene practices, and lowers the incidence of heat-sensitive diseases such as diarrhoeal infections, especially among infants and young children. Moreover, the World Health Organization, (2023) points out that pregnant and postpartum women are disproportionately exposed to heat-related risks due to gendered roles such as water collection and outdoor cooking. These activities increase direct exposure to extreme temperatures and associated health stressors. In addition, elevated temperatures can accelerate the proliferation of pathogens in water and food, thereby increasing the risk of diarrhoeal diseases in children (World Health Organization, 2023). In this regard, access to safe and reliable drinking water such as piped water, boreholes and protected wells is thus an important component of adaptive capacity in heat vulnerability contexts.

178 ***Proportion of children receiving third dose of DPT (Diphtheria–Pertussis–Tetanus) vaccine***

179 This indicates immunization coverage, which reflects the ability of the health system to provide
180 essential services thus increasing the resilience of communities in terms of health service coverage
181 (Ghosh and Laxminarayan, 2017). Communities with access to essential services are better able to
182 respond to heat-related illnesses, thereby improving adaptive capacity.

183 ***Adult male literacy rate***

184 Male literacy influences household decision-making, access to climate information, and ability to
185 adopt protective measures (Simpson et al., 2021).

186 ***Adult female literacy rate***

187 Women's education directly affects maternal health behaviour, infant care, and heat risk
188 mitigation. For example, Ghosh and Laxminarayan, (2017) found that women with no education
189 were 2.3 times more likely to fail to complete the childhood vaccination programme compared to
190 educated women, thereby demonstrating how education levels influence health behavior and infant
191 care. Education and awareness are key to reducing heat-related maternal health risks.

192 ***Women attending ≥ 4 antenatal care visits***

193 ANC provides opportunities for guidance on hydration, nutrition, and heat risk. Heat exposure
194 during pregnancy increases risks of complications such as hypertension and preterm birth.

195 ***Deliveries occurring in health facilities***

196 Institutional delivery reduces maternal and neonatal mortality risks, especially under heat stress
197 conditions that can complicate labor (Salam et al., 2014). Delivery at health facilities guarantees
198 the availability, quality and accessibility of health services for both women and newborn babies
199 (World Health Organization, 2023).

200

201

2.2.2 Sensitivity indicators

Population of infants (0–1 year)

Infants are among the most heat-sensitive populations due to immature thermoregulation, dependence on caregivers, and have a high risk of dehydration (Bhanbhro and Ali, 2025). The Lancet Countdown reports have been focusing on this cohort with the latest report (Lancet countdown report, 2024) indicating that in 2023, every infant experienced about 8 more heatwave days than in 1986-2005.

Population of women of reproductive age (15–49 years)

Women of reproductive age were included as a proxy for pregnant women, based on well-established evidence linking heat exposure to maternal health vulnerabilities (Bhanbhro and Ali, 2025; Lakhoo et al., 2025). Women of reproductive age, especially pregnant women, are highly vulnerable to heat, with increased risks of preterm birth, stillbirth, and maternal complications (Bhanbhro and Ali, 2025).

2.2.3 Exposure indicators

The exposure indicators were based on the fact that heatwaves manifest in three dimensions, namely, intensity, frequency and duration, and can occur during the day, night or concurrently across both day and night (Bobde et al., 2025). Populations and health systems may struggle to cope when tolerable thresholds in one or more of these dimensions are exceeded, highlighting the need for multidimensional exposure assessment. These are further discussed in section 2.3.2 and in Table 2.

2.3 Data analysis

2.3.1 Data validation

The first step in the analysis involved validating ERA5 temperature data against local weather station data. To achieve this, we obtained observed local station data from a selection of meteorological stations reflecting Zambia's Agro-Ecological Regions (AERs) to ensure spatial representativeness. Zambia is divided into four agro-ecological regions (Figure 2). Region I is in

the southern part of the country, receiving the lowest rainfall, and covering the main valley areas. Region II lies in central Zambia and receives more rainfall than Region I. It is divided into IIa and IIb due to slight differences in rainfall and soils, with region IIb dominated by the deep Kalahari sands. Region III is in the northern part of the country and is characterized by high rainfall.

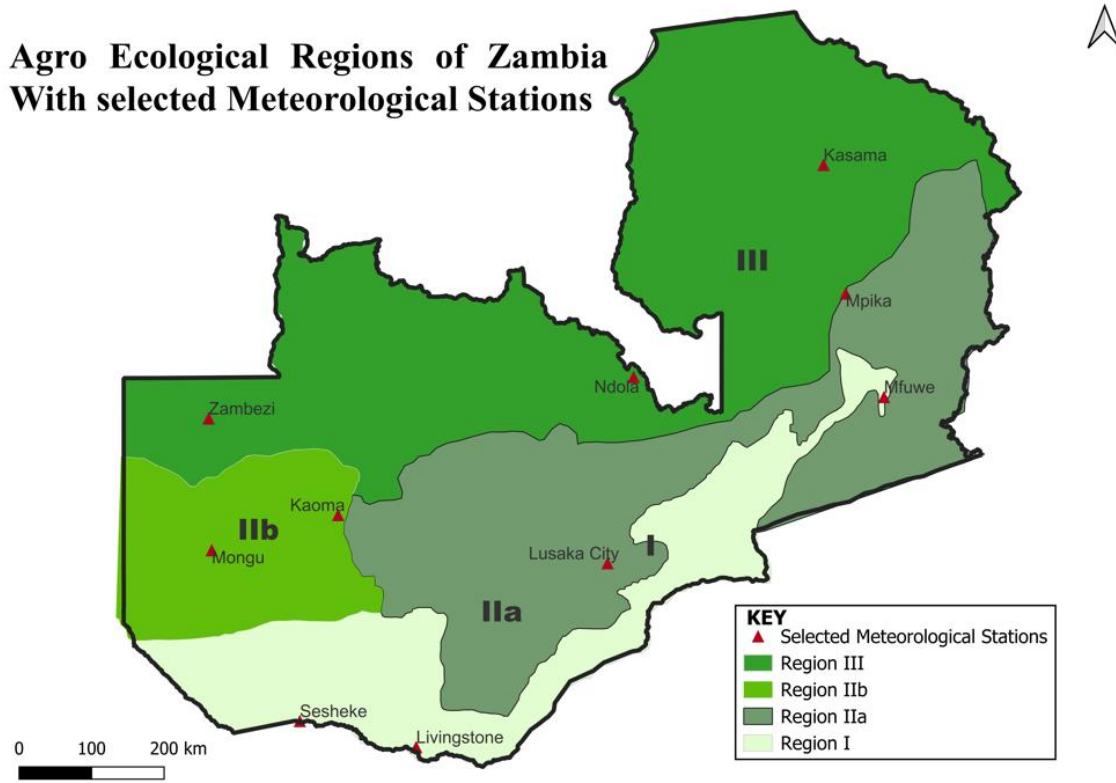


Figure 2: Agro-ecological regions in Zambia with selected meteorological stations used for validating the performance of the ERA5 dataset

The meteorological station data had substantial data gaps after 2013. Therefore, comparisons with the ERA5 data were conducted over the period 1980 to 2013. The patterns in Figure 3 show that ERA5 captures the local temporal variations in temperature across Zambia very well, with Pearson correlation values between ERA5 and observed data ranging from 0.71 to 0.84. However, ERA5 under predicts the temperature by about 2°C to 3 °C. We decided not to apply a bias correction technique in order to preserve the temporal variability and extremes in the ERA5 data. Because the same ERA5 series were used to compute the percentile thresholds for detecting hot days, any systematic bias cancels out in the computation of heatwaves.

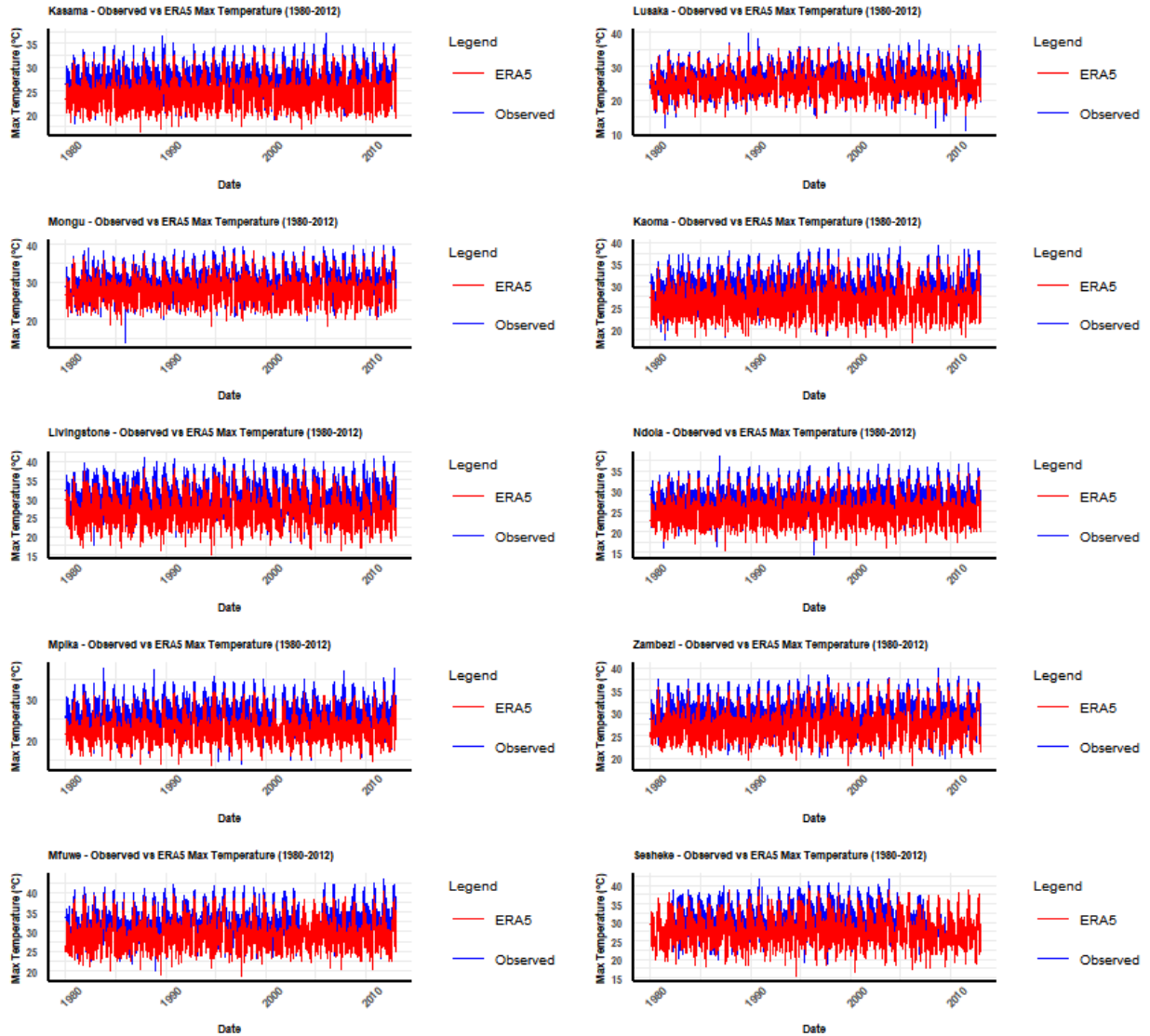


Figure 3: Observed Vs ERA5 Maximum Temperature (1980 – 2013)

2.3.2 Heatwave metrics

The threshold above which a hot day could occur was obtained by calculating the 90th percentile of daily temperature over the 1980–2010 baseline period. This threshold was applied to the gridded ERA5 daily maximum and minimum temperature data (Tmax and Tmin, respectively) to obtain local heatwave thresholds (T90) per pixel (10 x 10 km area). A heatwave event was identified when the daily temperature for that pixel exceeded T90 for three or more consecutive days, consistent with the definition of a heatwave by the Zambia Meteorological Department (ZMD).

Typically, maximum temperature (Tmax) is indicative of daytime heatwaves, while minimum temperature can be used to detect night-time heatwaves (Bhattarai et al., 2024; Bobde et al., 2025). Therefore, the Tmax data were used to derive daytime heatwaves, while the minimum temperature values were used to compute nighttime heatwaves. In addition, we considered periods when heatwaves occur concurrently during the day and the night, referred to as compound heatwaves (Bobde et al., 2025). The heatwave metrics were computed for the period 1980 to 2024. Table 2 summarizes the heatwave definitions and conditions used in this study.

Table 2: Heatwave definitions used in the study

Heatwave category	Heatwave condition	Minimum duration
Day	$T_{max} > T_{max90}$	3 consecutive days
Night	$T_{min} > T_{min90}$	3 consecutive days
Compound (day and night)	$T_{max} > T_{max90}$ and $T_{min} > T_{min90}$	3 consecutive days

For each heatwave category (Day, Night and Compound), we calculated the frequency, duration, and intensity of the heatwave events:

Frequency: *Number of heatwave events (runs ≥ 3 days).*

Mean duration: *Average number of days per heatwave event.*

Mean intensity: *Mean exceedance above the threshold (T90) during heatwave days.*

Thus, we derived nine heatwave metrics (frequency, duration and intensity) for day, night, and compound (day and night). These metrics were normalized to a scale of 0-1 individually, using the Min-Max Scaler method (Equation 1).

$$X' = \frac{X - X_{min}}{X_{max} - X_{min}} \quad \text{Equation 1}$$

where:

271 X' = is the normalized value (scaled between 0 and 1) of the heatwave metric
 272 (frequency, duration, intensity for day, night and compound heatwaves),

273 X is the raw value of the heatwave metric (frequency, duration, intensity for day, night
 274 and compound heatwaves),

275 X_{max} is the maximum value of metric across the study domain and period,

276 X_{min} is the minimum value of metric across the study domain and period.

277 ***2.3.3 Hotspot analysis***

278 Heatwave hotspots were identified using long-term averages of frequency, duration, and
 279 intensity at the grid level. Each metric was scaled between 0 and 1, and combined into a
 280 composite index representing areas where heatwaves are more frequent, longer, and more
 281 intense.

282 ***2.3.4 Seasonal heatwave climatology***

283 To understand when heatwaves occur, events were analysed on a seasonal basis using the four
 284 standard seasons of December-January-February (DJF), March-April-May (MAM), June-July-
 285 August (JJA), and September-October-November (SON). Seasonal values of frequency, total
 286 heatwave days, duration, and intensity were calculated for each Agro-Ecological Region (AER)
 287 and heatwave type. The peak heatwave season was then identified as the season with the highest
 288 long-term average for each metric over the study period. This step helped separate the timing of
 289 heatwave occurrence from the timing of ENSO influence.

290 ***2.3.5 El Niño–Southern Oscillation data and seasonal indices***

291 The El Niño–Southern Oscillation (ENSO) data were sourced from the Kaggle ENSO dataset
 292 compiled by Shabanamir (available at: <https://www.kaggle.com/datasets/shabanamir/enso-data>).
 293 This data provide standardized climate indices from 1950 to 2024 based on NOAA and related
 294 datasets. The analysis focused on the Oceanic Niño Index (ONI), using the 1980–2024 period to
 295 match the heatwave data. Seasonal ONI values were calculated for DJF, MAM, JJA, SON, and

296 OND, along with selected lagged periods. Years were classified as El Niño (ONI ≥ 0.5), La Niña
297 (ONI ≤ -0.5), or Neutral ($-0.5 < \text{ONI} < 0.5$).

298 **2.3.6 ENSO-heatwave association analysis**

299 The relationship between ENSO and heatwaves was assessed by comparing conditions during El
300 Niño years with those during non-El Niño years (combining Neutral and La Niña). For each region,
301 heatwave type, and metric, Cohen's d was used to measure the difference between the two groups.
302 Positive values indicated higher frequency, duration, or intensity during El Niño years, while
303 negative values indicated the opposite. Statistical significance was tested using Welch's two-
304 sample t -test, with the Mann–Whitney U test used as a non-parametric check. To account for
305 multiple comparisons, p -values were adjusted using a false discovery rate approach, with
306 significance evaluated at $p < 0.05$, $p < 0.01$, and $p < 0.001$. Because heatwave peaks do not always
307 coincide with the timing of ENSO signals, the results were interpreted as associations rather than
308 direct causal relationships.

309 **2.3.7 Heat Vulnerability Index**

310 The Heat Vulnerability Index (HVI) was computed using the IPCC vulnerability framework
311 where vulnerability is expressed as a function of exposure, sensitivity and adaptive capacity;

312 ***Exposure***

313 The normalized indices were arithmetically averaged to formulate a composite heat exposure index
314 (Equation 2). This unified metric consolidates the multidimensional characteristics of heatwaves,
315 specifically frequency, duration, and intensity (Perkins & Alexander, 2013) into a single indicator
316 that shows the differences in geographical exposure to heat stress.

$$317 \quad EI = \frac{1}{n} \sum_{i=1}^n M_i \quad \text{Equation 2}$$

318 Where:

319 ***EI*** is the composite exposure index.

320 M_i is the normalized value of the i -th heatwave metric.

321 n is the total number of heatwave metrics evaluated (in this study, $n = 9$ encompassing the
322 frequency, duration, and intensity for day, night, and compound heatwaves).

323 *Sensitivity*

324 Sensitivity was constructed from demographic layers representing the proportion of females of
325 reproductive age and infant populations together with stunted children, as they are the most
326 physiologically susceptible to heat stress. Each of these variables was normalized (0-1) and
327 aggregated to form the sensitivity index.

328 *Adaptive capacity*

329 All seven adaptive capacity indicators were also normalized to a 0–1 scale. Since these adaptive-
330 capacity variables are protective (they reduce vulnerability), variables were converted into deficits
331 such that higher values indicate higher vulnerability (Equation 3). The adaptive capacity maps
332 generated based on Equation 3 are shown in Online Resource 1.

$$333 \qquad \qquad \qquad \textbf{Deficit} = 1 - \textbf{Scaled protective variable} \qquad \qquad \textbf{Equation 3}$$

334

335 *Heat Vulnerability Index computation*

336 The final Heat Vulnerability Index (HVI) was computed as the mean of the three vulnerability
337 indices, in this case, exposure, sensitivity and adaptive capacity (Equation 4). Dividing by three
338 ensures that the output values (HVI) remain within a range of 0 to 1, with 1 indicating the
339 highest vulnerability.

$$340 \qquad \qquad \qquad \textbf{HVI} = \frac{\textbf{Exposure} + \textbf{Sensitivity} + \textbf{Adaptive capacity}}{3} \qquad \qquad \textbf{Equation 4}$$

341 *2.3.8 Aggregating across agro-ecological regions*

To further understand the heat burden, we examined the spatio-temporal trends in heatwaves using the composite heatwave metric because it is multidimensional (covers the frequency, intensity, and duration of heatwaves for day, night and compound (day and night)). We also overlaid the AERs to better understand the geographical patterns of heatwaves and heat vulnerability. We also used the probability density function of daytime heat to understand the region-specific disparities in exposure to heatwaves.

2.3.9 Sensitivity analysis to identify vulnerability drivers

Sensitivity analysis was conducted to evaluate the robustness of the HVI and to identify vulnerability drivers. The Leave- One- Out (LOO) approach was adopted, where one sensitivity or adaptive capacity variable was omitted sequentially. With every iteration, updated PCA weights were calculated and the HVI was computed again. To determine how much the HVI changed after removing specific variables, the difference between the original HVI and the recalculated HVI was measured.

2.4 Generative AI disclosure

In line with Springer Nature's policy on the use of generative AI in academic publishing, the authors declare that generative AI and AI-assisted tools were used in the preparation of this manuscript for language editing, formatting, editing the scripts and troubleshooting of errors in the python and r scripts. The authors further declare that all the scientific content, data analysis, interpretation, and conclusions were generated entirely by the authors. The authors therefore take full responsibility for the content of the publication.

3. Results

3.1 Spatial-temporal patterns of heatwave characteristics in Zambia

Results show distinct patterns in maximum temperatures across the AERs (Regions I, IIa, IIb, and III) of the country. The probability density functions (Figure 4) show that Region III has the coolest thermal profile, with the most frequently occurring maximum temperatures at 28°C. Moving towards the warmer spectrum, it is observed that Region IIa has an intermediate temperature distribution as its density curve is shifted to the right of Region III, with maximum temperatures

mainly being at 28.5°C. The warmest conditions are observed in Regions I and IIb. These two regions show very similar right-skewed distributions with maximum temperatures concentrated at 29.5°C. Furthermore, the extended right tails of these two regions imply that they have a high probability of experiencing maximum temperatures above 35°C. With respect to heat thresholds (90th percentiles of temperature (T90)) indicated by solid vertical lines on Figure 4, Region III has a lower threshold of 31.8°C, followed by Region IIa at 32.8°C while the heat threshold in Regions I and IIb is 34.3°C. The highest temperature record is around 41°C in both AER I and AER IIb.

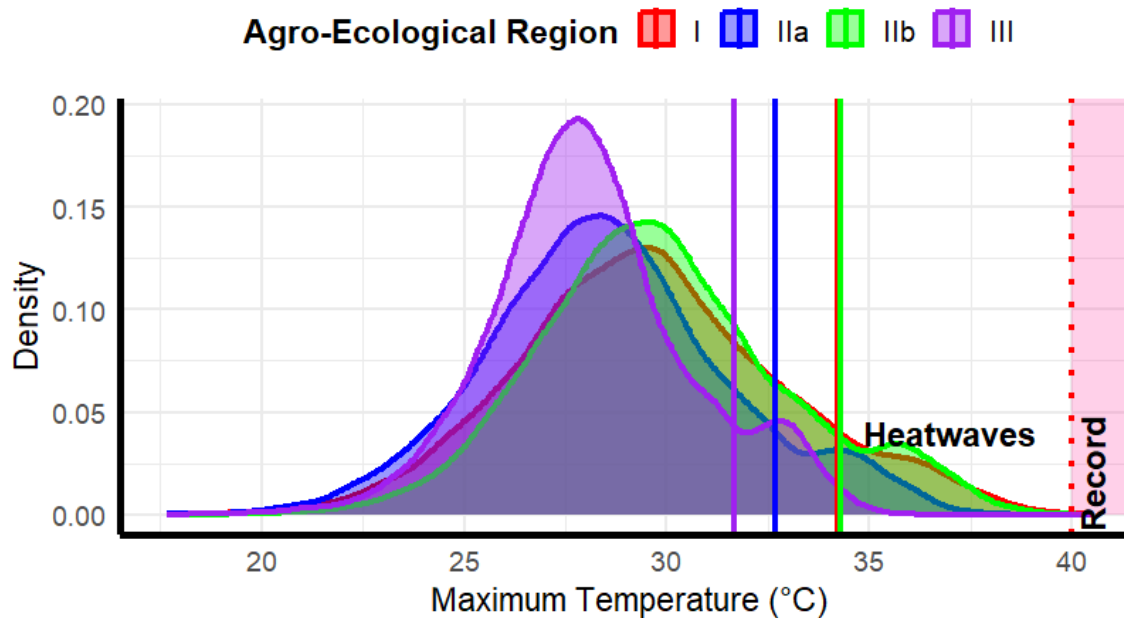


Figure 4: Probability density function of heat data by agro-ecological zone for the period 1980-2024

The hotspot analysis reveals a clear south–north gradient in heatwave severity across Zambia. Daytime, night-time and compound heatwave hotspots are consistently concentrated in the southern and south-western parts of the country, particularly within AER I and AER IIb. In contrast, AER III generally exhibits lower hotspot values, reflecting its relatively cooler and wetter climatic regime (Figure 5).

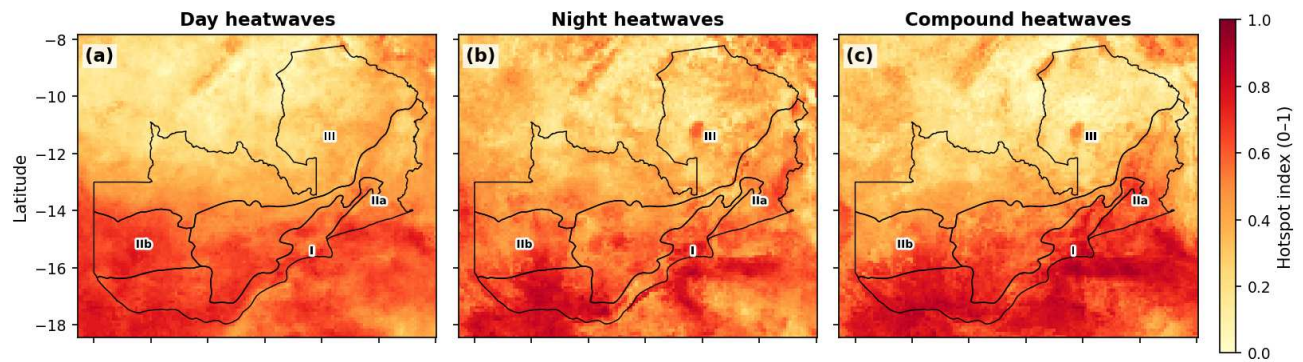


Figure 5: Heatwave hotspot patterns across agro-ecological regions in Zambia over the period 1980-2024

Daytime heatwaves occur most frequently, with mean annual frequencies ranging from 5.83 events per year in AER III to 6.27 events per year in AER IIb. Night-time heatwaves show a similarly widespread pattern, with mean frequencies varying only slightly across agro-ecological regions, from 5.39 to 5.56 events per year. By contrast, compound heatwaves are less common, occurring between 1.32 events per year in AER III and 2.29 events per year in AER I (Table 3).

Table 3: Frequency of heatwaves averaged over agro-ecological regions (1980-2024)

Heatwave type	AER	Frequency mean	Frequency max	Frequency extreme years
Day	I	6.07	15.31	1987, 1995, 2005, 2023, 2024
Day	IIa	5.91	14.34	1983, 1992, 2005, 2023, 2024
Day	IIb	6.27	16.14	1995, 2005, 2015, 2023, 2024
Day	III	5.83	12.83	1998, 2005, 2016, 2023, 2024
Night	I	5.44	15.45	1995, 2016, 2019, 2023, 2024
Night	IIa	5.39	15.03	1998, 2016, 2019, 2020, 2024
Night	IIb	5.56	16.67	1998, 2016, 2018, 2019, 2024
Night	III	5.49	13.96	1998, 2016, 2019, 2020, 2024
Compound	I	2.29	11.09	1992, 1995, 2019, 2023, 2024
Compound	IIa	1.79	9.15	1992, 2016, 2019, 2023, 2024
Compound	IIb	2.05	10.19	1995, 2016, 2019, 2023, 2024
Compound	III	1.32	4.85	2005, 2016, 2019, 2023, 2024

The findings further indicate that heatwave severity is greatest in the warmer and drier agro-ecological zones (Table 4 and Table 5). AER I consistently records the highest values for mean duration and intensity across all heatwave types. For compound heatwaves, AER I exhibits the

highest mean frequency (2.29 events per year), duration (4.23 days per event), and intensity (1.30°C above the threshold).

Table 4: Duration of heatwaves averaged over agro-ecological regions (1980-2024)

Heatwave type	AER	Mean duration (days/event)	Maximum duration (days/event)	Duration extreme years
Day	I	4.76	9.81	1992, 2019, 2021, 2023, 2024
Day	IIa	4.67	8.01	1992, 2016, 2019, 2021, 2024
Day	IIb	4.87	9.36	1983, 1994, 2016, 2019, 2024
Day	III	4.42	6.34	2001, 2002, 2018, 2021, 2024
Night	I	4.43	7.65	1992, 1994, 2019, 2023, 2024
Night	IIa	4.26	6.51	1992, 2016, 2021, 2023, 2024
Night	IIb	4.25	7.36	2006, 2016, 2021, 2023, 2024
Night	III	4.04	6.09	1998, 2016, 2021, 2023, 2024
Compound	I	4.23	7.86	1981, 1992, 2019, 2021, 2024
Compound	IIa	4	8.74	1992, 1994, 2019, 2021, 2024
Compound	IIb	3.96	6.72	1987, 1995, 2016, 2021, 2024
Compound	III	3.72	5.84	1987, 1996, 1999, 2021, 2024

In contrast, AER III generally shows the lowest values, especially for intensity, indicating comparatively milder heatwave conditions in the wetter northern parts of the country. These patterns further point to a clear agro-ecological gradient in heatwave exposure, with AER I and AER IIb emerging as the regions most at risk. AER I has a mean daytime intensity of 1.15°C above threshold, while AER III has the lowest mean intensity at 0.83°C above threshold. This suggests that although daytime heatwaves occur across Zambia, they are more thermally severe in the warmer and drier agro-ecological regions.

The results in Table 5 further show that AER I has the highest night-time heatwave intensity at 0.93°C above threshold, while AER III has the lowest at 0.65°C above threshold. The results therefore suggest that night-time heat stress is particularly relevant in AER I and AER IIb. Compound heatwave intensity is also highest in AER I, with a mean of 1.30°C above threshold, compared with 0.91°C in AER III. This confirms that AER I is the most exposed to severe combined day-night heat stress.

Table 5: Intensity of heatwaves averaged over agro-ecological regions (1980-2024)

Heatwave type	AER	Mean intensity (°C)	Maximum intensity	
			(°C)	Intensity extreme years
Day	I	1.15	2.09	1992, 1995, 2019, 2021, 2024
Day	IIa	1.03	2.19	1995, 2017, 2019, 2021, 2024
Day	IIb	1.05	1.89	1986, 1989, 2019, 2021, 2024
Day	III	0.83	1.63	1989, 1999, 2020, 2021, 2024
Night	I	0.93	1.48	1995, 2019, 2021, 2023, 2024
Night	IIa	0.8	1.22	1995, 2019, 2021, 2023, 2024
Night	IIb	0.86	1.23	1980, 1990, 2000, 2002, 2024
Night	III	0.65	0.87	1982, 2002, 2019, 2021, 2023
Compound	I	1.3	2.21	1995, 2003, 2019, 2021, 2024
Compound	IIa	1.16	2.33	1994, 2014, 2015, 2021, 2024
Compound	IIb	1.12	2.01	1986, 1987, 1996, 2021, 2024
Compound	III	0.91	1.59	1987, 1990, 1999, 2021, 2024

The results further show that years such as 2024, 2021, 2019, 2023, 2016, 1995, and 1992 repeatedly appear among the upper-decile years for frequency, duration, and intensity. Notably, 2024, which was also a year of severe drought in the region stands out across nearly all heatwave types and agro-ecological regions. The frequent appearance of recent years among these extremes suggests that severe heatwave conditions have become more prominent in recent years.

Regarding trends, there is a significant increasing trend in heat intensity in the central part of Region III and Region IIa at a rate of 0.3 °C per decade ($p < 0.05$) (Figure 6).

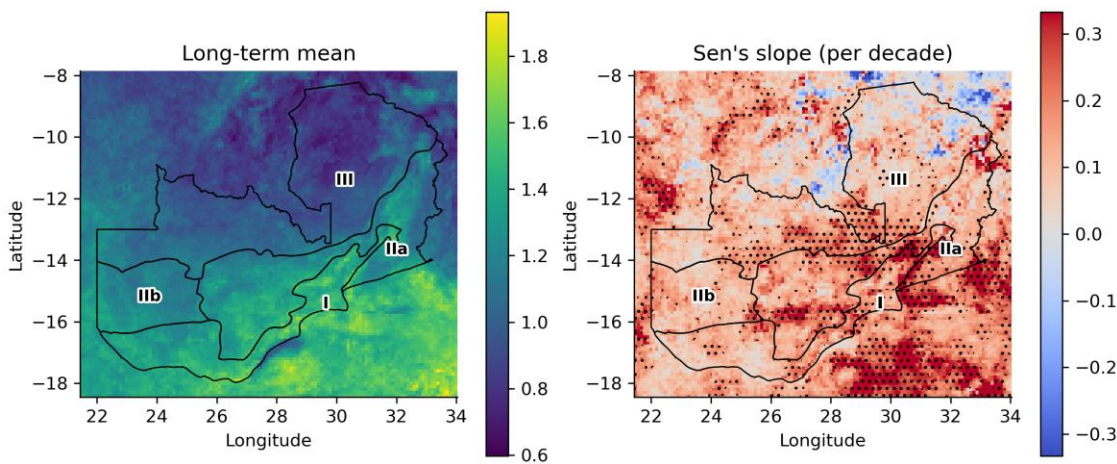


Figure 6. Average intensity (left) and trends in the intensity of the composite heatwave index (right) from 1980-2024. *Black dots show areas with statistically significant trends at $p < 0.05$.*

Heatwave durations also shows a significant increase by up to 1 day per decade ($p<0.05$), predominantly in the northern half of the country especially around AER III and AER IIb (Figure 7, right).

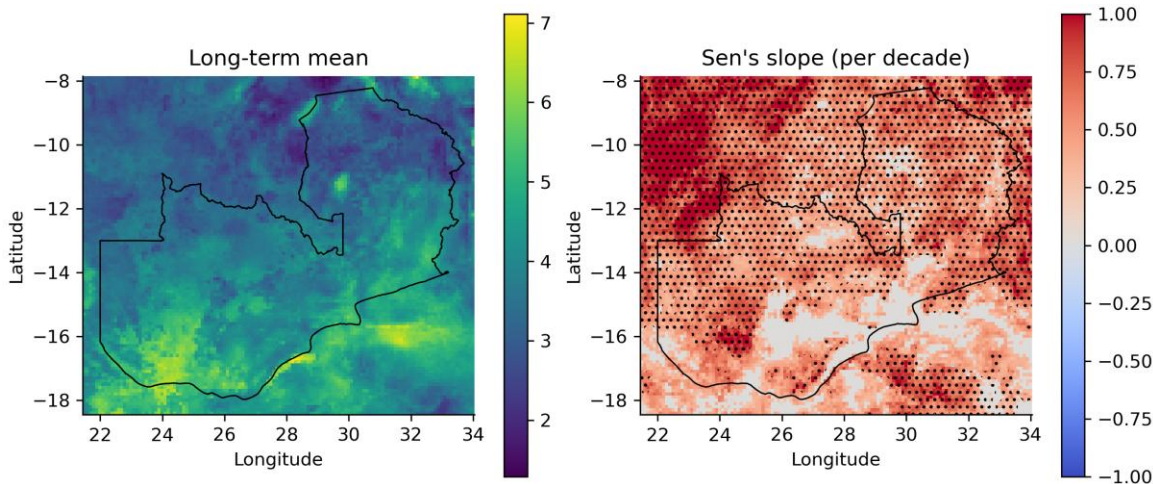


Figure 7. Average maximum duration of heatwaves in days/event (left) and trends in the duration of heatwaves (right) from 1980-2024. *Black dots show areas with statistically significant trends at $p<0.05$.*

Similarly, areas experiencing increasing trends in the frequency of heatwaves are mainly in the western and northern parts of the country, particularly in AER IIb, AER III and a portion of the western side of AER I. These areas are experiencing an increase in the frequency of heatwaves by up to 0.6 events per decade (Figure 8, right). For AER IIa, the frequency of heatwaves has not changed, except for some isolated areas in the eastern side of AER IIb where the frequency has increased significantly (Figure 8, right). Most of the significant increases ($p<0.05$) occur in the northern half of the country (AER III) and in western Zambia (AER IIb). Again, AER I and IIa where the frequency is already high, remain more stable, with the exception of a few isolated areas in the south-western part where there is a significant increase in the frequency of heatwaves.

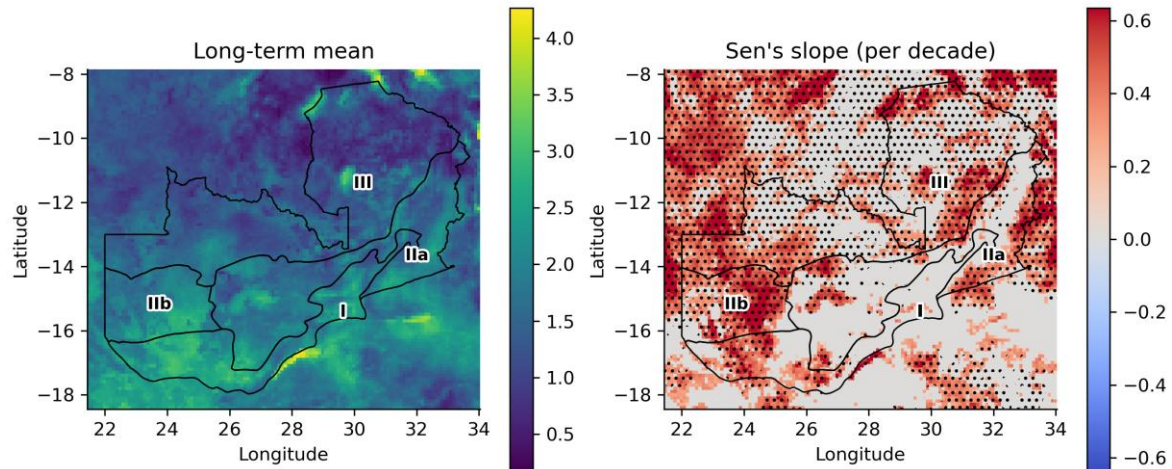


Figure 8: Average frequency (left) and trends in the frequency of heatwaves (right) from 1980-2024. Black dots show areas with statistically significant trend at $p < 0.05$.

3.2 Association between mean temperature and compound heatwave metrics

Figure 9 analyses the relationship between inter-annual changes in mean temperature and the three heatwave metrics of frequency, duration and intensity for the period 1980 - 2024. The results show that frequency and duration are the dominant heatwave response variables to warming in Zambia. For instance, there is a very strong and significant positive correlation between the change in mean temperature and the frequency of heatwaves ($r = 0.86$, $p < 0.0001$) (Figure 9). Similarly, duration of heatwave events also has a strong positive correlation with the change in mean temperature ($r = 0.81$, $p < 0.0001$). On the other hand, the intensity of heatwaves has a moderate but significant positive correlation ($r = 0.53$, $p < 0.001$) with changes in mean temperatures. These results suggest that while heatwaves are becoming more frequent and longer, their peak severity (intensity) is less tightly controlled by mean temperature alone.

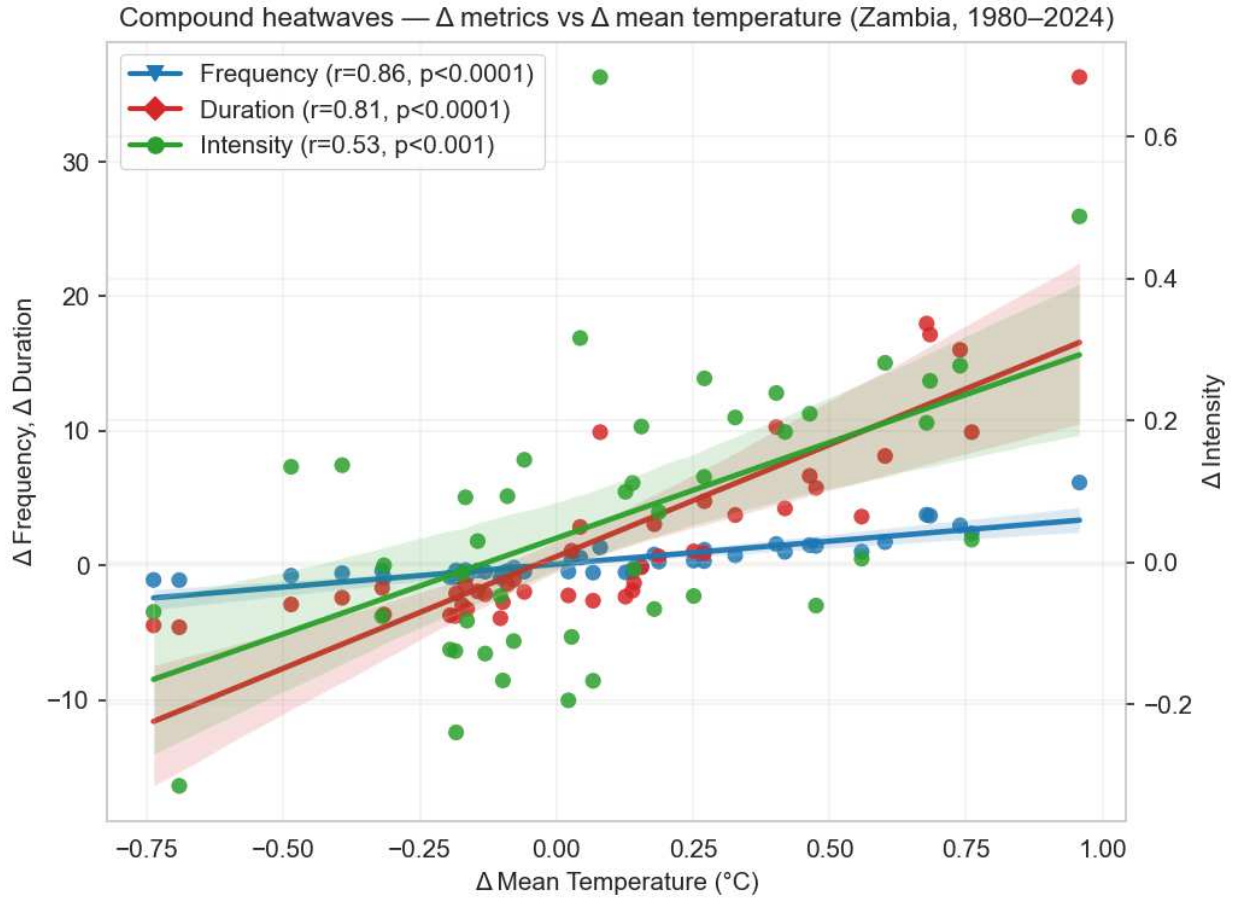


Figure 9: Association between mean temperature change and heatwave metrics

3.3 El Niño-Southern Oscillation (ENSO) related differences in heatwave characteristics

Figure 10 shows that El Niño years are mostly associated with higher heatwave metrics than non-El Niño years across Zambia's agro-ecological regions. This is reflected by predominantly positive Cohen's d values for both DJF and MAM ONI. The strength of the association varies by ENSO season, heatwave type and metric. For DJF ONI, the major signal was observed for heatwave frequency, especially night-time frequency, which showed significant positive effects across all AERs. Daytime and compound heatwave frequency also increased during El Niño years, while effects on duration and intensity were generally weaker and less consistent.

On the other hand, the MAM ONI produced even stronger and more widespread El Niño effect sizes than DJF ONI. The largest responses were again observed for heatwave frequency, especially

night-time and compound heatwave frequency. The MAM ONI also showed stronger effects on heatwave duration in most AERs, especially AER I, AER IIa and AER IIb. Intensity responses were comparatively weaker and more spatially variable, although positive effects were evident for daytime and compound intensity in AER I.

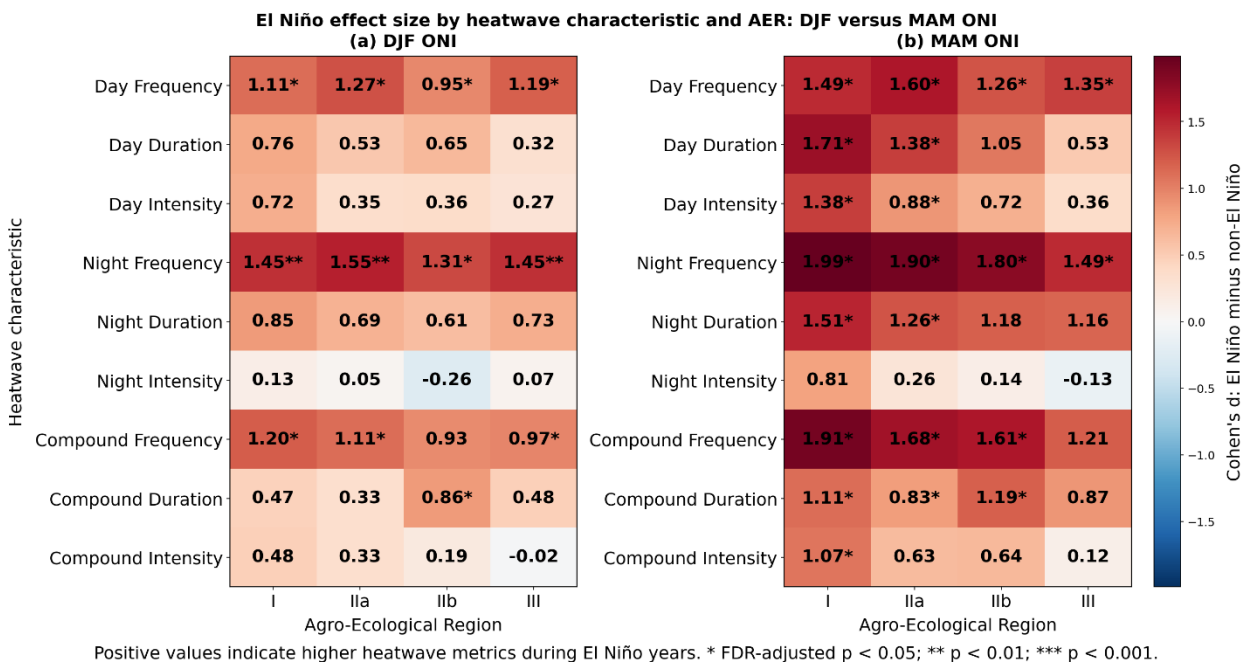


Figure 10: Comparison of El Niño effect sizes on heatwave characteristics using DJF and MAM ONI. The heatmaps show Cohen's d effect sizes comparing heatwave metrics during El Niño years with non-El Niño years using DJF ONI and MAM ONI. Positive values indicate higher heatwave frequency, duration or intensity during El Niño years, while negative values indicate lower values during El Niño years. Heatwave characteristics are shown for daytime, night-time and compound heatwaves across AER I, AER IIa, AER IIb and AER III. Statistical significance is indicated after false discovery rate correction: * $p < 0.05$, ** $p < 0.01$, and *** $p < 0.001$

The ENSO results should be interpreted together with the seasonal heatwave climatology, which showed that heatwave frequency peaks mainly in SON, while duration and heatwave-day burden are often highest in DJF (Online resource 2). Therefore, the stronger MAM ONI signal does not mean that heatwaves occur mainly in MAM. Rather, MAM ONI appears to provide a stronger antecedent ENSO indicator of annual and subsequent seasonal heatwave behaviour in Zambia.

3. 4 Heat vulnerability analysis

Figure 11d combines the exposure, sensitivity and adaptive capacity indices into a single heat vulnerability index. The results show higher Heat Vulnerability Index (HVI) of the maternal and child health proxies in AER I, and the central and south eastern portion of AER IIa, and AER IIb, consistent with the regions of higher exposure (Figure 11a), higher population distribution of infants and women of reproductive age (Figure 11b) and low-moderate adaptive capacity (Figure 11c).

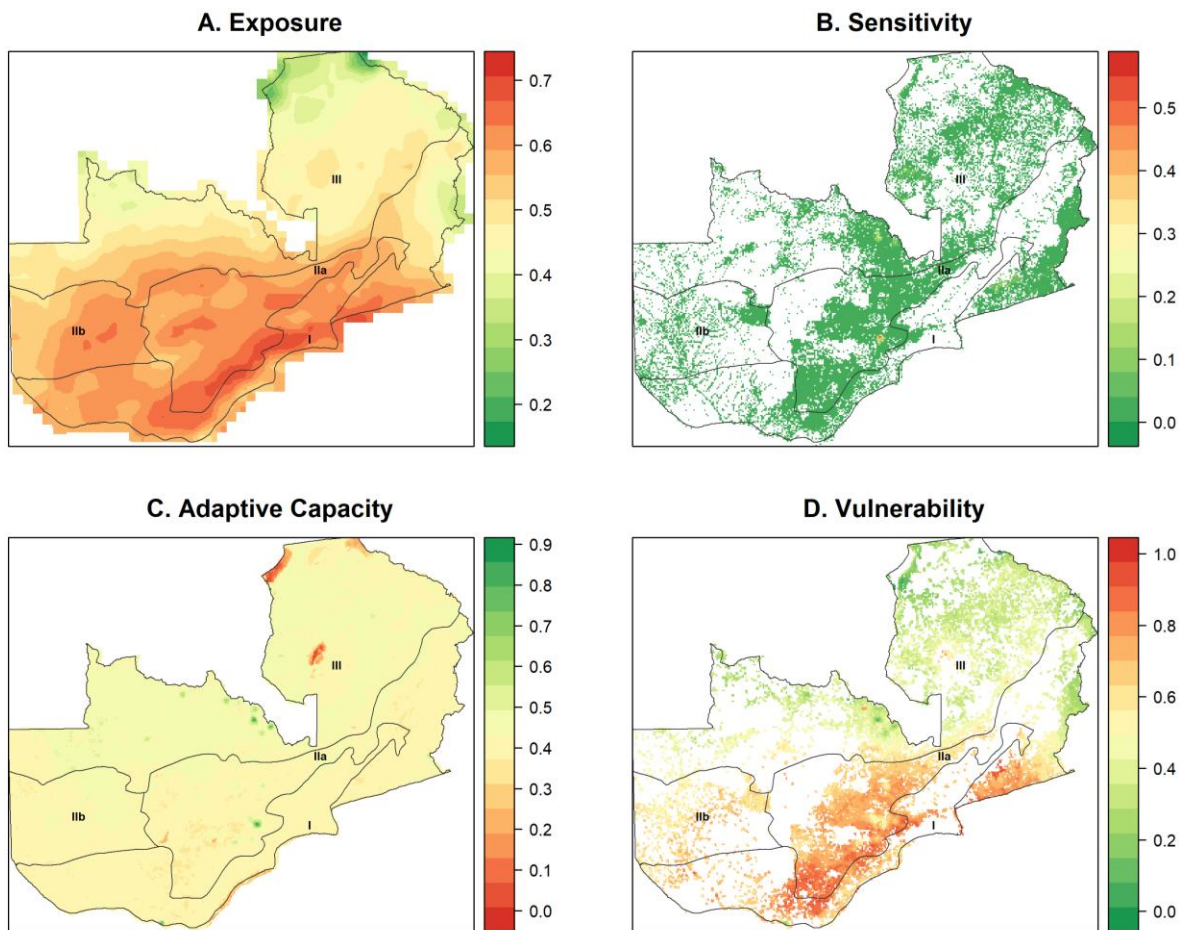


Figure 11: Heat vulnerability patterns (a) Exposure, (b) Maternal and Child-health sensitivity (c) Adaptive capacity and (d) Heat vulnerability index

The results in Figure 12 show that the national variation in the Heat Vulnerability Index (HVI) was mainly driven by adaptive capacity deficit indicators rather than demographic sensitivity

indicators. In particular, the HVI was most sensitivity to the adaptive capacity variable of three-dose vaccination deficit, as it produced the largest mean absolute change in HVI when removed from the model (Figure 12). This was followed by health facility deficit, skilled delivery deficit, WASH deficit, ANC4+ deficit, and literacy deficit. On the other hand, NDVI deficit had a comparatively smaller influence, while the demographic sensitivity indicators, namely children, women of reproductive age, and child malnutrition showed the lowest mean absolute changes in HVI.

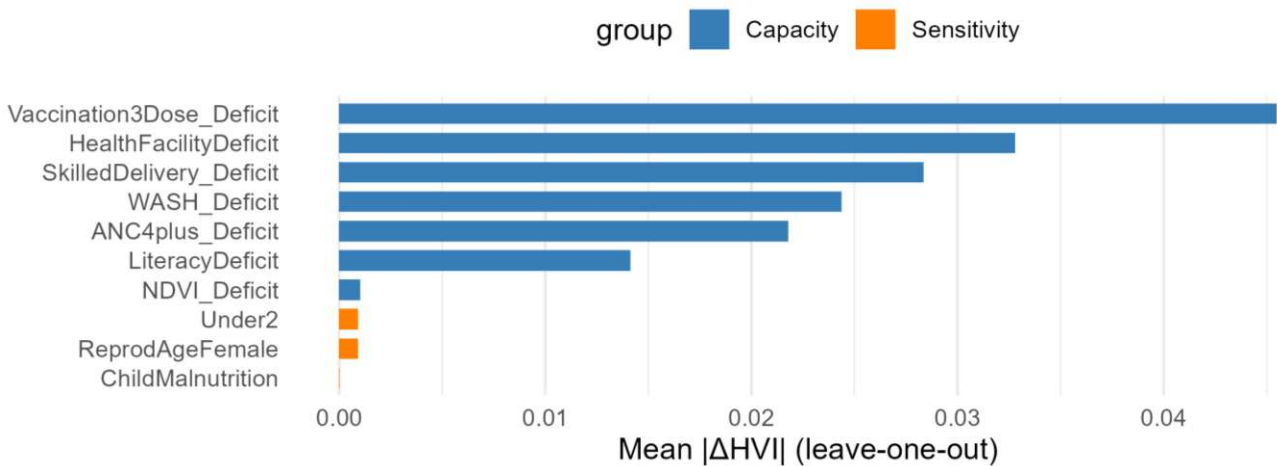


Figure 12. Drivers of vulnerability based on sensitivity analysis among health and demographic variables based on the Leave One Out sensitivity analysis

4. Discussion

The results show clear differences in heatwave exposure across Zambia's agro-ecological regions. AER I and AER IIb recorded the highest levels of exposure, reflecting their warmer baseline climates and greater likelihood of extreme temperatures. In AER I, high temperatures are partly linked to the low-lying valley areas and semi-arid conditions. In AER IIb, especially western Zambia, high exposure may be associated with drier conditions and the influence of deep Kalahari sands. For example, Clifton et al., (2016) measured surface temperatures of sand and other materials (slate, metal, cement, brick, bitumen) on hot days in Adelaide, Australia, and found that unshaded sand reached temperatures are capable of causing significant thermal injury in both clear and overcast conditions. On the other hand, AER III has a generally cooler thermal profile. However, parts of this region are now showing increases in heatwave frequency and duration. This

shows that historically cooler areas should not be ignored in heat-health planning. As warming continues, these areas may face increasing exposure to longer and more frequent heat events.

The findings on the association between heatwaves and temperature show that rising mean temperature is more strongly associated with increases in heatwave frequency and duration than with heatwave intensity. In other words, warming in Zambia appears to be producing more frequent and longer heatwave events, rather than only hotter extremes. This has important health implications in that repeated or prolonged heat exposure can reduce the time available for the body to recover, especially among infants, pregnant women and people with existing health conditions (Cheshire, 2016). In this regard, heatwave duration and frequency may be just as important as intensity when assessing potential health risks. Even in populations that have acclimatized to heat, extreme or prolonged events can increase health risks (Chambers, 2020a). Andriano (2023) shows that heat exposure during pregnancy is associated with reduced birth weight in SSA, while Lakhoo et al. (2025) report increased risks of preterm birth and neonatal complications under extreme heat.

The ENSO analysis shows that El Niño plays an important role in shaping heatwave patterns in Zambia, mainly by increasing how often events occur rather than consistently intensifying them. This aligns with Martineau et al., (2023), who found that El Niño enhances temperature variability over southern Africa, creating conditions that favour more frequent warm extremes. In this study, the effect is most evident in night-time heatwave frequency, followed by compound and daytime events. Thus El Niño years are linked to a higher occurrence of both nocturnal and combined day–night heat stress.

This pattern has important implications for public health planning, given the well-documented risks associated with elevated night-time temperatures. Consecutive hot nights reduce sleep quality, impair recovery, and increase risks of heat-related morbidity and mortality. In this regard, Chambers, (2020) notes that high minimum night-time temperatures intensify impacts by preventing physiological recovery from daytime heat stress. The high day-time (maximum) temperature on the other hand may allow for some degree of recuperation when nights are cooler (Chambers, 2020b). The results are consistent with the general trend in SSA where He et al., (2025) found that vulnerability to nighttime and compound heatwaves is increasing with significant risks for males, children under 5, and the elderly, indicating that socioeconomic resources are necessary for adaptation beyond physiological acclimatization.

The regional variation in El Niño effects also suggests that ENSO-related heatwave risk is mediated by local climatic and land-surface conditions. In this regard, AER I shows the strongest and most consistent El Niño response, affecting frequency, duration, and some intensity measures. AER IIa and IIb also show clear responses, while AER III is mainly affected through increased frequency. This shows that ENSO-related heatwave risk varies across regions, with the greatest impacts in the warmer, drier zones. El Niño appears to increase the likelihood of later heatwave activity in Zambia, particularly for night-time and compound events. These results are consistent with previously studies (Martineau et al., 2023; Mbokodo et al., 2023; Zhang et al., 2025) which also found that El Niño was linked to more frequent and often more intense heat extremes, particularly in summer.

The stronger link with MAM ONI should be interpreted with caution. While heatwave frequency tends to peak in SON and overall heatwave burden in DJF, MAM conditions are better seen as an early indicator rather than a direct driver of heatwaves. The important implication here is that the MAM ONI conditions could be used for heatwave early warning. The signal likely reflects delayed land-atmosphere processes linked to El Niño. This pattern aligns with findings from southern Africa, which show that heatwaves during ENSO-related droughts are often linked to persistent high-pressure systems in the mid-troposphere, such as the Botswana High, along with subsidence, warm air advection, and generally dry conditions (Mbokodo et al., 2023). In addition, reduced soil moisture limits evaporative cooling, allowing surface temperatures to rise more easily and increasing the likelihood of combined dry and hot conditions (Hao et al., 2020).

The inclusion of compound heatwaves strengthens the exposure assessment. Daytime heatwaves capture periods of unusually high maximum temperatures, while night-time heatwaves show when minimum temperatures remain unusually high. Compound heatwaves are particularly important because they represent periods when people are exposed to heat stress during both the day and night. This sustained exposure can limit rest, reduce sleep quality and weaken recovery from daytime heat. For infants and pregnant women, who are physiologically less able to cope with heat stress, these conditions may be especially concerning. Therefore, using daytime, night-time and compound heatwave metrics gives a more realistic picture of heat exposure than relying on a single temperature measure.

Going further, the vulnerability results show that exposure alone (to daytime, night-time and compound heat) does not fully explain the spatial pattern of heat vulnerability. Using the thermal inequity lens, the results suggest that maternal and child health heat vulnerability in Zambia is shaped by inequalities in access to healthcare, maternal and child health service coverage, household WASH conditions, and education-related adaptive capacity. Although AER I and IIb have high heat exposure, the overall heat vulnerability extends to the central region of AER IIa due to higher population exposed and the low adaptive capacity. In contrast, areas around the Copperbelt region and Lusaka, although having high population density, have lower heat vulnerability due to relatively higher adaptive capacity (mainly through higher density of health facilities and clean water availability). These results are consistent with Tran et al., (2020) who observed in Vietnam that vulnerability hotspots do not always coincide with areas of highest temperature, as some regions have developed adaptive capacity to offset exposure effects. The only exception to this is the AER III, which generally has lower vulnerability to heat due to lower heat exposure.

The spatial pattern of sensitivity also differs from the pattern of heat exposure in AER IIa where the spatial distribution of infants, and women of reproductive age contribute more strongly to potential vulnerability. This shows that some areas may not be the hottest, but may still require attention because they have larger concentrations of vulnerable groups or weaker adaptive capacity. This supports the use of a multidimensional vulnerability framework that combines hazard, population and service-access information.

The leave-one-out sensitivity analysis shows that adaptive capacity deficits are the major drivers of the national HVI. The strongest contributors were deficits in vaccination coverage, health facility access, skilled delivery, WASH, ANC4+ coverage and literacy. These indicators reflect the ability of households and health systems to prevent, manage and respond to heat-related health risks. For example, weak WASH conditions may increase the risk of dehydration and heat-related illness, while poor health facility access may delay treatment during heat stress events. Similarly, low ANC coverage, skilled delivery and vaccination coverage may indicate wider gaps in the continuity and reach of maternal and child health services.

This study contributes to heat vulnerability research by applying the HVI approach in a largely rural and data-scarce SSA context. Much of the existing heat vulnerability literature has focused

on urban areas, especially in high-income countries, where heat risk is often linked to built-up surfaces, urban heat islands and access to cooling. This study shows that, in Zambia, heat vulnerability is also shaped by rural service access, maternal and child health coverage, WASH conditions, vegetation cover and uneven health system reach. It therefore broadens the application of heat vulnerability mapping beyond urban thermal exposure and shows how publicly available gridded datasets can support climate-health planning where local health outcome data are limited.

From a policy perspective, the findings point to the need for spatially targeted heat-health adaptation. Southern, Western, Central and Eastern Zambia in AER I, IIb and IIa where high exposure overlaps with weak adaptive capacity should be prioritised for heat-health planning. At the same time, the increasing frequency and duration of heatwaves in the northern half of Zambia in AER III should also be monitored, even where current exposure remains lower than in the south half. Heat early warning systems should therefore be linked to ENSO conditions which usually inform seasonal weather forecasts in Zambia, and to vulnerability information. This would allow warnings and response actions to consider both where heatwaves are occurring and where people have fewer resources and services to cope with them.

The findings also suggest that heat-risk considerations should be integrated into maternal and child health programming. Antenatal care, immunisation, skilled delivery services, WASH outreach and community health messaging provide practical entry points for heat-health adaptation. For example, community health platforms could include messages on hydration, recognition of heat stress symptoms, infant care during hot periods and when to seek medical attention. Outreach planning could also take account of seasonal heat conditions, especially in areas where long distances, poor roads and low facility density already limit service access. In this way, heat adaptation can be built into existing health systems rather than treated as a separate climate issue.

Environmental measures also have a role as demonstrated by the WASH indicators which were among the key variables in the sensitivity analysis. Furthermore, significant negative Pearson correlations between heat and elevation ($r = -0.41$, $p < 0.05$) and also between heat and NDVI ($r = -0.61$, $p < 0.05$) suggested that increasing vegetation cover (NDVI) could reduce the heat burden. But these measures should complement rather than replace health-system interventions. Although NDVI deficit contributed less to national HVI variation than health service and WASH indicators, vegetation remains locally important for reducing heat exposure through shade and

evapotranspiration. In areas where low vegetation cover coincides with high heat exposure, restoration, shade provision and better land-cover management may help reduce local thermal stress. As Yin et al. (2023) argue, increasing surface albedo and restoring vegetative cover are not just environmental goals, but essential public health strategies to mitigate thermal disparities. However, these actions are likely to be most effective when combined with improved health service access, stronger WASH conditions and better community-level heat preparedness. Consequently, addressing heat vulnerability requires an integrated approach.

There are a few limitations in this study that should be considered. Women of reproductive age were used as a proxy for pregnant women because spatially explicit pregnancy data were not available. Health facility density was used as an indirect measure of health service accessibility, although actual access also depends on travel time, road conditions, seasonal accessibility, staffing, service readiness, affordability and the availability of maternal and child health services. Similarly, NDVI was used to represent vegetation and environmental buffering, although it does not fully capture shade or local heat-modifying processes. Some maternal and child health indicators, including ANC coverage, vaccination and literacy, were based on 2018 DHS-derived gridded surfaces because updated 2024 gridded products were not yet available at the time of analysis. The findings should therefore be interpreted as a spatial screening of relative vulnerability, rather than as a direct measure of individual-level heat-health outcomes. Also, the ENSO results should be interpreted as evidence of association rather than direct causation. Further work should test the robustness of these relationships using detrended correlations, lagged ENSO indices, and multivariate models that control for background warming and other regional climate drivers. There is also a need to further explore the idea of heatwave early warning based on ENSO conditions.

Despite these limitations, the study provides a useful framework for identifying areas where maternal and child heat vulnerability may be concentrated. Future research should strengthen this approach by incorporating direct health outcome data, pregnancy-specific population estimates, travel-time-based health accessibility measures, service readiness indicators and updated DHS-derived surfaces when available. Further work should also examine how heatwaves affect health service delivery, health worker productivity, pregnancy outcomes, child morbidity and household coping strategies. Heatwaves significantly compromise the functionality of healthcare delivery systems, particularly in resource-constrained countries (Sapari et al., 2023). It is here recognized

that extreme weather events do not just create health hazards but can actively interrupt routine services, including maternal and reproductive care (Codjoe et al., 2020; Curtis et al., 2017). This would help move heat vulnerability mapping from a screening tool towards a more operational decision-support system for heat-health adaptation in Zambia and similar data-scarce settings.

5. Conclusion and recommendations

This study assessed how heatwave exposure and heat-related vulnerability vary across Zambia, with particular attention to maternal and child health. It combined long-term daily temperature data with gridded population, health, environmental and health service-access indicators to develop a Heat Vulnerability Index. The analysis considered daytime, night-time and compound heatwaves, as well as differences in exposure, sensitivity and adaptive capacity across the country's agro-ecological regions. The findings show where heat hazards overlap with vulnerable population groups and weaker health-related adaptive capacity. The study draws four main conclusions. First, heatwave exposure is not evenly distributed across Zambia. Agro-Ecological Regions I and IIb experience the highest overall exposure, while Region III is relatively cooler but shows increasing heatwave frequency and duration. Second, rising temperatures are linked more strongly to longer and more frequent heatwaves than to intensity alone, suggesting that repeated and sustained heat exposure is an important emerging risk. Third, the findings point to a dual control on heatwave risk in Zambia associated with a spatial agro-ecological control, reflected in stronger hotspot in warmer and drier regions, and an interannual climate-variability control, reflected in the increased frequency of heatwaves during El Niño years. The dominant ENSO response is increased heatwave frequency, particularly night-time and compound heatwave frequency, while duration and intensity responses are more regionally specific and strongest in AER I. The MAM ONI provides the strongest ENSO indicator of Zambian heatwave variability, indicating that El Niño acts more as an antecedent signal of later heatwave risk than as a simultaneous heatwave-season driver. Fourth, the highest heat vulnerability occurs where high exposure coincides with weak adaptive capacity and a wider spatial distribution of sensitive populations, particularly in Southern, Western, Central and South Eastern Zambia. The sensitivity analysis further shows that vaccination coverage, health facility access, skilled delivery, WASH, ANC4+ coverage and literacy are key drivers of the mapped national vulnerability pattern. In conclusion, the findings show that heat vulnerability is not determined by temperature alone, but

699 by how heat exposure intersects with population sensitivity and unequal access to protective
700 services.

701 Based on these findings, there is need to integrate heatwave monitoring with seasonal climate
702 outlooks. In addition, maternal and child health programmes should integrate heat-risk
703 considerations into routine services, particularly immunization, antenatal care, skilled delivery,
704 WASH outreach and community health messaging.

705 **Compliance with ethical standards**

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709 **Competing Interests**

710 The authors have no relevant financial or non-financial interests to disclose.

711 **Data Availability**

712 The ERA5 land data and the DHIS datasets used in this study are freely available online. This data
713 along with the python and r scripts used in this study will be made available on GitHub.

714 **Author Contributions**

715 MNC: Conceptualisation, Methodology, Formal analysis, Data curation, writing the original
716 draft, writing the review and editing, visualisation. CMCC and JB: Supervision, review and
717 editing. MC Data curation. S.E.D, BB, CM, RB, SS,MDC, DS and CP: Review and editing. All
718 authors have read and agreed to the submitted version of the manuscript.

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