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Adapting everyday activities to summer heatwaves: a multi-country analysis of mobile phone location data

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Abstract

In the 21st century, record-breaking summer heatwaves have had devastating impacts on people's health, well-being, and livelihoods. In light of this urgent threat, government institutions across the globe are developing guidelines and planned interventions to increase resilience to heatwaves. These measures require an understanding of how people adapt to extreme heat within the constraints of daily life. Existing studies have used large-scale mobility data to characterize heatwave adaptation at population levels, but skew towards cities and regions in high-income countries, have diverse methodologies that limit generalizability to other contexts, and focus on 'activity level' changes without discerning which activities are being altered. Addressing these gaps, this study combines climate reanalysis, mobile phone location, socio-demographic, and physical-geographical data across Brazil, France, India, Nigeria, Turkey, the USA, and China during 2022/2023 summer heatwaves. Google Community Mobility Reports data is used in multivariate multi-level modelling for the first six countries to examine daily activity changes during heatwaves (home, work, transit, grocery/pharmacy, retail/recreation, parks). In China, Baidu data on activity levels is analysed in a complementary multi-level model. The results show a widespread tendency to withdraw into homes but also highlight unequal substitutions of activities, and—under some circumstances—visits to potentially cooler locations away from home. This study highlights the global nature of heatwave adaptation and the value of considering adaptation within the context of people's everyday lives.

1. Introduction

Unprecedented heatwaves have become characteristic of summers worldwide, increasing in intensity, frequency, and duration due to climate change (Perkins-Kirkpatrick and Lewis 2020). Summer heatwaves, defined here as prolonged periods of extreme heat which surpass regional norms (Perkins and Alexander 2013), are a global threat to human health, well-being, and livelihoods (McGregor 2024). Across Africa, the Americas, Asia, and Europe, extreme heat is estimated to cause hundreds of thousands of excess deaths each year (Zhao *et al* 2021). These disasters represent a new reality of the 21st century as over 5 billion individuals are projected to be exposed annually in 2030–2100, even under sustainability-focused development scenarios (SSP1-2.6) (Yin *et al* 2022). Given this threat, government institutions across the globe are developing guidelines and planned interventions, known as heat action plans (HAPs), to increase the resilience of heat-vulnerable populations. Among their various guidelines, HAPs commonly recommend that people unable to cool at home visit public locations to seek refuge from extreme heat (Kotharkar and Ghosh 2022). These facilities can be 'formal' cooling centres established by governments in libraries, community centres, or other air-conditioned or shaded locations, or 'informal' cooling centres such as indoor retail and recreation facilities, parks, or swimming pools (Widernyski *et al* 2017).

Inequalities in heat exposure cut across social and material vulnerabilities, causing heatwaves to be a 'nuisance' for some but a 'catastrophe' for others (Guardaro *et al* 2022). These inequalities are reflected in people's ability to seek cooling in their everyday lives, which is conditioned by limited adaptive capacity, heat-exposing space and time constraints, or both. As an example, lower-income individuals have less air conditioning ownership—thus lacking a highly protective response—while also being more constrained to heat-exposing environments by living in hot, dense urban areas and working during the day in outdoor and/or informal sectors (Sampson *et al* 2013, Gronlund 2014, Hoffman *et al* 2020, Pavanello *et al* 2021, Laue *et al* 2022, Trahan *et al* 2023). Other examples include greater isolating behaviours among older people who lack critical networks of social support during heatwaves, while also facing greater constraints to seeking cool environments due to reduced mobility and other comorbidities (Klinenberg 2015, Diniz *et al* 2020, Arsad *et al* 2022). From a policy perspective, it is essential to understand people's everyday adaptations to better align the actions of those vulnerable to heatwaves with the adaptation projects aiming to protect them (Oppermann *et al* 2018, Castro and Sen 2022, Teebken *et al* 2023).

To characterize behavioural adaptations at a population level during heatwaves, retrospective studies using large-scale mobility data have examined various mechanisms linked to heat exposure and adaptive responses (Derakhshan *et al* 2023, Fan *et al* 2023, Ly *et al* 2023, Stechemesser and Wenz 2023, Gu *et al* 2024, Kumakura *et al* 2024, Tian *et al* 2024, Liang and Wang 2025, Yücel and Schwanen 2025). To date, this line of research has tended to face three main issues: (1) an under-representation of low-and middle-income countries (LMICs), which are facing greater increases in extreme temperatures (Herold *et al* 2017) while having reduced capacity to develop HAPs (Andrijevic *et al* 2021, Kotharkar and Ghosh 2022, Singh and Nirwan 2024); (2) a lack of generalizability and comparability of analyses due to their diverse methodologies, which include varying data sources, model types, and definitions of a 'heatwave' (Perkins and Alexander 2013); and (3) a focus on aggregate changes in 'activity levels' without considering how people alter their various everyday activities. This third issue is critical given that heatwave adaptation requires alterations of diverse daily activities—including time at home, work obligations, and indoor/outdoor leisure (Graff Zivin and Neidell 2014)—and that these adaptations vary widely across geographical contexts (Yücel and Schwanen 2025). In addition to these limitations, existing research has focused predominantly on single cities. While adaptation is a local phenomenon, heatwaves pose a global threat. The goal of this paper is thus to demonstrate the scale at which everyday adaptation occurs while accounting for national and subnational differences. The data-driven methodology of this paper begins to shed light on broad, population-level activity changes, a complement to local qualitative research which focuses on extreme heat adaptation through people's lived experiences (Tschakert *et al* 2025).

The current paper examines summer heatwave adaptation internationally, exploring how activity participation is adapted both within and across various countries. The analysis includes countries across a range of income levels and with diverse heat-preparedness and household air conditioning ownership rates. Behavioural responses to heatwaves are compared and contrasted across the summer-equivalent seasons of Brazil, France, India, Nigeria, Turkey, the USA, and China (table 1), each projected to be among the 15 most exposed populations and/or economies between 2030 and 2100 (Yin *et al* 2022). These countries are also among the most populous countries in the world, effective for highlighting the mass scale at which heatwave adaptations occur. To isolate mobility changes resulting from short term exposure to heat, this study uses a heatwave-control day matching approach, akin to an aggregated space-time-stratified case-crossover design (STSCC). For the first six countries, county-level Google Community Mobility Reports data is used in multi-level regression modelling to explore changes to various everyday activities during 2022 summer-equivalent heatwaves (home, work, transit, grocery/pharmacy, retail/recreation, parks). For China, where Google data is unavailable, Baidu mobility data is analysed in a complementary multi-level regression model which examines changes in intra-prefecture city activity levels in response to summer heatwaves in 2023. The inclusion of China—despite its separate and more aggregate mobility data—highlights the value of using comparable methods to explore international patterns of heatwave adaptation.

The heat metric in this study is the 'heat index' (HI), which incorporates both temperature and humidity to estimate a 'feels like' temperature in degrees Celsius (Anderson *et al* 2013) (referred to as HI temperature). This compound metric captures the amplifying effect of high humidity on human heat stress, which occurs through reducing the human body's capacity for evaporative cooling (Fischer and Knutti 2013, Raymond *et al* 2022). Compared to other commonly used metrics, such as a simplified wet-bulb-globe-temperature (Chen *et al* 2019), the 'heat index' is chosen for its greater interpretability and prevalence in global HAPs (Kotharkar and Ghosh 2022). At the county or local equivalent-level in

Table 1. Summary of each country's summer-equivalent period, presence of a national heat action plan (Kotharkar and Ghosh 2022), and national household air conditioning ownership rates (Andrijevic *et al* 2021).

Country	'Summer' period (m/d/y)	HAP	AC Ownership (Household %)
Brazil	11/1/2021–04/30/2022	X	8.0
France	05/01/2022–09/30/2022	✓	14.0
India	03/01/2022–08/31/2022	✓	17.9
Nigeria	11/01/2021–04/30/2022	X	2.1
Turkey	05/01/2022–09/30/2022	✓	11.7
United States	05/01/2022–09/30/2022	✓	87.8
China	05/01/2023–09/30/2023	✓	41.3

each country (second administrative regions—ADM2), heatwaves are defined as two or more days where the maximum HI temperature surpasses a relative intensity threshold (90th percentile). Subsequently, a matched pair algorithm identifies closely matched 'control' days against which heatwave days are compared, and activity differences between the two are regressed on a series of climate/weather, temporal, and contextual variables at the levels of the day, heatwave, and county or local-equivalent region.

Heatwave intensity is measured in both absolute (HI temperature) and relative terms, with the latter defined as the HI temperature *increase* between heatwave and matched control days. This relative metric accounts for the influence of short-term, relative increases in temperature on adaptive responses, found to influence health-related risks due to short periods of time to acclimatize (Van Der Linden *et al* 2019). Further, precipitation levels on the heatwave and control days are also included to capture how precipitation—which commonly accompanies humid heat (Zhang *et al* 2024)—mediates how people adapt to heatwaves. Temporal features of heatwaves follow from the expectation that differences in adaptation emerge depending on how long a heatwave lasts, how early or late a day is within a heatwave, and the flexibility of different days of the week (weekend vs weekday). Contextual variables include regional population density, socio-demographics, and physical-geographical factors. Population density is an efficient summary of a region's built environment, with higher densities being conducive to the formation of urban heat islands (Li *et al* 2020b). Socio-demographics are directly relevant to the health risks heatwaves pose, and both the share of a region's population over 60 years old and its human development index score are considered. Physical-geographical factors which influence regional climate are also included as contextual variables, such as whether a region is coastal or inland and whether it lies at a high elevation.

Where Google data is available and activity types can be discerned, this paper considers heatwave adaptation through an activity participation lens introduced in Yücel and Schwanen (2025). This framework focuses on how people systematically alter the various activities of daily life in response to heatwaves. Due to the zero-sum nature of time, adaptation to heatwaves requires trade-offs and substitutions of other daily activities which vary in flexibility. Workplace activity, for example, may not only be heat-exposing, but the necessity of work constrains people in space and time and limits their ability to adapt (Bedi *et al* 2022, Puley 2022, Trahan *et al* 2023). These interdependent activity changes are explored where possible, enabled by the multivariate multi-level model.

2. Methods

This analysis generates models for each country using county or local-equivalent region (ADM2) data on activity changes from Google or Baidu. To maximize interpretability across countries, this study harmonizes common data sets where possible, including climate/weather, mobility, socio-demographic, and physical-geographical data. Methodological decisions on heatwave definitions, operationalization of variables, and model building are shared across countries to maximize comparability while also allowing country-specific adaptive responses to be explored.

2.1. Data

Climatic data is collected from the fifth generation of atmospheric reanalysis (ERA5-Land) developed by the European Union's Earth Observation Programme (Copernicus), a state-of-the-art and widely used global data set for land-based climate analyses (Muñoz-Sabater *et al* 2021). Developed through observationally constrained modelling, the spatio-temporal continuity of these estimates offer distinct advantages for measuring human-environment exposure compared to single station-estimates, which may be spatially sparse and non-representative, particularly in LMICs or remote locations (Mistry *et al* 2022).

However, given that ERA5 uses weather stations as key inputs, these data gaps have implications for ERA5 accuracy across countries. Correlation coefficients between ground observations and ERA5 tend to be higher in higher-income areas (e.g. median of 0.95+ in the United States versus 0.85+ in Brazil) (Mistry *et al* 2022). Weather station sparseness and quality issues are particularly prevalent in Africa, which was excluded in the assessment of Mistry *et al* (2022), although recent research confirms that ERA5 offers a significant improvement over past reanalysis data sets against observations of temperature and precipitation across the continent (Gleixner *et al* 2020). Despite these variations, ERA5 was deemed generally suitable for international analyses of human heat stress (Mistry *et al* 2022) and is a commonly used source of climatic data in global analyses of extreme heat (Li *et al* 2020a, Yin *et al* 2022, Heeter *et al* 2023, Zhang *et al* 2024).

Modelled estimates of 2 m air temperature, dewpoint, and precipitation are collected at an hourly granularity at a spatial resolution of $\sim$9 km^2 across the focus countries of Brazil, France, India, Nigeria, Turkey, the USA (minus Alaska), and China (People's Republic of China, minus the Special Administrative Regions of Hong Kong and Macau and excluding Taiwan). Air temperature and dewpoint values are collected for the summer-equivalent season in each country (table 1) in addition to four summers of historical data to define relative thresholds. Precipitation data is only collected for the summer of study as a control variable. Gridded data on terrain elevation above sea level is collected at a $\sim$250 m^2 resolution from SOLARGIS, accessed through the World Bank Data Catalog (World Bank Data Catalog 2020).

The Google Community Mobility Reports data, used in Brazil, France, Nigeria, India, Turkey, and the USA, is a public data set released by Google. Compared to a pre-COVID-19 baseline (Jan–Feb 2020), the original data provides county or local-equivalent region (ADM2) daily percent changes in (1) time spent in residence, and visitation to (2) workplaces, (3) transit, (4) grocery/pharmacy, (5) retail/recreation, and (6) parks. Each subsequent daily percent change value is relative to the median activity level for that specific day of the week during the baseline period. The temporal coverage of the data is from March 2020–October 2022, although only each country's latest summer is used in this analysis due to the effects of COVID-19 on mobility. Thus, the pre-COVID-19 baseline period (Jan–Feb 2020) and any daily mobility prior to each country's summer of interest are not included in this analysis. The data is based on aggregate and anonymized data of Google Location History users, with missing data where geographic regions are smaller than 3 km^2 or sample sizes are too small ($<$100 unique users) to confidently and anonymously estimate changes (Aktay *et al* 2020). For the non-home variables, activity participation is inferred based on aggregate visitation to relevant POI types categorized by Google. This data set has been used in numerous studies of COVID-19-related mobility changes (Cot *et al* 2021, Elarde *et al* 2021, Ilin *et al* 2021, Liu *et al* 2021, Kamińska and Kazak 2024), and in studies on temperature-related changes in activities (Linsenmeier 2024, Yücel and Schwanen 2025). Benchmarking studies against census and high-volume mobility data have shown it to be effective for capturing regional changes in mobility (Finazzi 2020, Gibbs *et al* 2023, Sganzerla Martinez and Kelvin 2023).

In China (as specified above), mobility patterns are derived from Baidu data, one of the largest providers of location-based services in the country. The public data set reports the daily intensity of mobility patterns in each ADM2-region (prefecture-city level), calculated as the ratio between the number of intra-prefecture city trips and its population. This data has been used in population-level studies of mobility changes (Fang *et al* 2020, Liang and Wang 2025), including joint analyses with the Google Community Mobility Reports (Liu *et al* 2021). To maximize comparability with the countries with Google data, the data is re-standardized to the same format as the Google Community Mobility Reports data. Daily percent changes in intra-prefecture city activity are calculated relative to the same baseline period of Jan–Feb 2020. Each daily percent change value is then standardized to the median value over the baseline period for each specific day of the week, in the same fashion as the Google data.

Both mobility data sources used in this analysis have various strengths and weaknesses (table 2). The Google Community Mobility Reports data includes activity types that are based on the harmonization of rich activity and location data from Google, and covers many different countries which makes it suitable for internationally comparative analysis. Its weaknesses are its pre-aggregation to county-equivalent and day-level resolutions, precluding more refined analyses of intra-city or intra-day activity changes. It also lacks detailed information on indoor/outdoor locations, does not provide stated information on trip purposes, and has risks of sampling bias—particularly in lower income countries which have lower smartphone penetration rates (Oliver *et al* 2015). Importantly, the data captures a single summer after the COVID-19 pandemic (2022), potentially hindering the generalizability of the findings to subsequent years. The Baidu data, allowing for the China sub-analysis, has large sample sizes and wide coverage across the country. It also provides a highly interpretable metric (ratio between number of intra-city trips and its population). Compared to the Google data, it lacks activity type distinctions, and similarly

Table 2. Strengths and weaknesses of Google Community Mobility reports (amended based on adapted from Yücel and Schwanen (2025). CC BY 4.0.), and the Baidu intra-city activity data.

Strengths	Weaknesses
Google community mobility reports	
Harmonizes activity and location data Diverse range of labelled activity types Covers vast spatio-temporal range	Pre-aggregated spatio-temporal data Lacks indoor/outdoor distinction Activity inferred from location Sampling bias and digital divide Single year (2022)
Baidu	
Large sample sizes Wide coverage across China Interpretable metric (intra-city activity)	Pre-aggregated spatio-temporal data Lacks activity type distinction Sampling bias and digital divide Single year (2023)

covers only a single year after China's COVID-19 restrictions (2023), is highly pre-aggregated to daily-city levels, and its coverage is likely impacted by sampling biases and digital divides. For this analysis the data is suitable to highlight broad patterns of adaptation across a diverse range of countries—and its limitations make clear the complementary importance of further qualitative research on people's lived experiences of heat.

Due to the global nature of this study, the summer or summer-equivalent seasons vary across countries. To account for the recency of the COVID-19 pandemic, the latest possible summers were chosen in this analysis within the time-frames of the Google and Baidu data. The most recent available years in the data sets are 2022 for Google and 2023 for Baidu. In India, COVID-19 restrictions were lifted in March 2022; therefore, the summer dates in table 1 (Mar 2022–Aug 2022) are used to define heatwaves and benchmark historical temperatures, but the mobility analysis begins in April 2022. In China, COVID-19 lockdowns remained prevalent during the summer of 2022. As a result, the China analysis uses data from 2023, the most recent year in the Baidu data and the one least affected by its pandemic-related policies. Having the most representative post-COVID-19 mobility patterns was prioritized for the analysis over uniformity between the Google (2022) and Baidu (2023) data sources, which have different ranges of data availability.

Population densities and age structures are derived from WorldPop, an organization which develops peer-reviewed high-resolution geospatial datasets on population distributions for development (Tatem 2017). In their data products, official population data at the level of subnational regions are downscaled as granular gridded estimates using machine learning on satellite-derived and ancillary data (Stevens *et al* 2015). This analysis uses WorldPop's population and age distribution data sets which are intersected with the ADM2 boundaries of the mobility data—interpolation flexibility is a major advantage of the granular gridded estimates. This study predominantly uses their latest *Global2* (2015–2030) data product for the USA, France, Turkey, Nigeria, Brazil, and China, where recently available censuses or official estimates from the ADM2-level or higher are present (Bondarenko *et al* 2025). Because the *Global2* data product for India is derived from ADM1-level data (and based on 2011 census data and projections), the *Global1* (2000–2020) is used for this country. For India, the *Global1* data product also draws on the 2011 census but is disaggregated to the ADM2 level. Information on population input data for *Global1* can be found here[3] and Global2 here[4], which are then aligned with UN national-level population projections. All input data underlying the population and age estimates for each country, which are all county-equivalent (ADM2) or higher, are presented in table 3. To provide consistent estimates of material and social deprivation, this analysis uses the Global Data Lab's Subnational Human Development Index values for 2022, a peer-reviewed (Smits and Permanyer 2019) composite index which captures regional education, health, and standard of living at the state/province-level (ADM1), assigned to ADM2-regions across all included countries.

[3] https://hub.worldpop.org/geodata/listing?id=69

[4] https://data.worldpop.org/repo/prj/Global_2015_2030/R2025A/doc/Global2_Release_Statement_R2025A_v1.pdf

Table 3. Table of socio-demographic data used in the analysis, all minimum ADM2 (county-equivalent) granularity or higher, including the country, the WorldPop data product, its underlying input data, and the year of alignment with UN national population projections.

Country	WorldPop product	Input data source	Annual national projection
USA	Global2	2020 Census	2022
India	Global1	2011 Census	2020
France	Global2	2019 Partial census estim.	2022
Turkey	Global2	2022 Official estim.	2022
Nigeria	Global2	2020 Official projections	2022
Brazil	Global2	2022 Census	2022
China	Global2	2020 Census	2022

2.2. Heatwaves, control days, and activity changes

Heatwaves are identified by converting all hourly temperature and dewpoint values into 'heat index' values, which estimates the 'feels like' temperature in degrees Celsius. This metric is chosen due to its interpretability and its ability to capture the amplifying effect of heat and humidity on human heat stress (Anderson *et al* 2013, Buzan and Huber 2020). The 'heat index' is calculated using the National Weather Service's algorithm, accessed through the metPy python package (May *et al* 2022), shown to be the most robust estimate of apparent temperatures of commonly used heat index metrics (Anderson *et al* 2013). After calculating the hourly heat index in each ERA5 grid cell, the maximum daily heat index values are determined in each cell across the analysis and historical period. The ERA5 modelled estimates are complete for every hour, and thus no minimum availability requirements are needed to aggregate the heat index values. The grid cells are then intersected with every ADM2-level boundary in each country, and the average daily maximum heat index values are calculated in each ADM2 region.

In this analysis, heatwaves are defined as two or more consecutive days where daily maximum values in each ADM2 region surpass each region's 90th percentile of maximum temperatures of the entire collected period. Each heatwave threshold is therefore unique to the ADM2 region. This relative measure of severity is more suitable for capturing the health risks of heatwaves, due to the impact of regional differences in adaptive capacity on excess mortality and morbidity (Anderson *et al* 2013). In robustness checks, the results were stable when heatwaves were defined using 2 m air temperature globally, and in a sub-analysis on the USA using a simplified wet-bulb globe temperature (Chen *et al* 2019)—another commonly used metric which combines temperature and humidity, but is less common in HAPs and less interpretable in degrees Celsius, where 35 °C is the limit of human tolerance (Sherwood and Huber 2010).

To isolate the impact of heatwaves on changes to people's daily activities, this study uses a heatwave-control day matching approach, akin to an aggregated space-time-stratified case-crossover (STSCC) design. Time-stratified case-crossover designs are a widely used methodology for assessing daily environmental exposure and health outcomes. These approaches typically match individual-level cases to themselves at different times—thus accounting for time-invariant confounders—and model how exposure varies between the day the event occurred ('case') and the nearby days ('control') (Wu *et al* 2021, Hanson *et al* 2024). Control days are meant to represent counterfactual exposure experiences of the cases, with strict time criteria (i.e. day-of-week within-month and year) to minimize time-varying confounders such as seasonality. These approaches have been extended to multi-location studies for daily-aggregated health outcomes (e.g. daily death counts), where within-region outcomes are compared across case and control days (Wu *et al* 2021, Tobias *et al* 2024). These multi-location applications are known as STSCC designs.

Drawing from region-level STSCC approaches, the current study aims to capture heat-related changes in mobility by comparing ADM2 regions with themselves at closely matched control days on the same day of the week. While typical STSCC approaches use methods such as a conditional Poisson regression on count data (e.g. deaths, hospitalizations), this approach subtracts heatwave and control day outcomes (activity levels) and uses multi-level modelling to examine differences according to environmental exposure levels. In this study, a bespoke control-day matching algorithm is developed (see Supplementary Material) which searches for the nearest non-heatwave day which meets certain criteria. First, the control day must be on the same day of the week as the heatwave day. Second, the control day must neither be a heatwave day nor be on the cusp of being a heatwave day (max. 80th percentile). Third, the control day must also not be among the lowest 20th percentile of temperatures due to seasonality effects at the beginning or end of summer periods. The algorithm searches backwards, week-by-week, until a suitable control day is found, and if none is found, searches forwards.

Given the region-aggregated nature of the data, there are additional time-related risks compared to traditional case-level TSCC approaches. The underlying population may vary between the case and control day, and thus choosing control days as comparable as possible to the case day is essential. The bespoke algorithm developed for this study helps to address these biases, iterating to find the closest day across relevant time/region/heat criteria. Out of the 21 086 heatwave-control pairs across the 7 countries, the majority are 1 week apart, and 75% of pairs are 2 weeks apart or less. Standards in TSCC approaches, including region-aggregated ones, divide strata by day-of-week across the same month (by default including controls up to 3–4 weeks away) (Wu *et al* 2021). While biases from changing underlying populations remains important to note, this study has comparable proximity between heatwave and control days as typical case-control designs.

Each 'activity change' value is calculated by subtracting the ADM2 region activity levels on the heatwave day by the activity levels on the control day. For the countries where Google data is available, each of the six activity types has its own 'activity change' value, and Baidu has a single activity change representing intra-prefecture city levels. All days which fall on public holidays—or replacement days in China—are removed, as are extreme outliers which are over 4 standard deviations from each country's mean. In every country's data, the calculated value is interpreted as the percent change in mobility between heatwave and control days, standardized to the pre-COVID baseline period when the Google data was benchmarked and when the Baidu data was re-standardized for comparability.

2.3. Multi-level modelling

A multi-level model is developed for each country in the analysis. Separate models were chosen as preferable to one single model with all countries included for two reasons: (1) Heterogeneities within countries are more easily explored when each country has its own coefficients with a null-hypothesis of zero relationship, than the complexity of 12 (independent vars.) × 6 (response vars.) interaction term coefficients compared against an arbitrary reference country; (2) Different countries have different levels of missing data (e.g. park and transit activity in Nigeria), and including all countries in the same model would require using the lowest common denominator, thus excluding activity-types for countries where sufficient data exists.

The data in this analysis has a hierarchical structure, where each heatwave day is nested within a heatwave, which is nested within an ADM2 (county-equivalent) region. To account for this lack of independence among observations, the grouping levels are controlled for and the traditional ordinary least squares regression is extended to a multi-level model which provides each heatwave and ADM2 region with their own intercepts, written as:

$$Y_{ijk} = \beta_{0ijk} + \beta_1 X_{ijk} + e_{0ijk} \tag{1}$$

where Y_{ijk} represents the activity change between the heatwave and control day for day i in heatwave j in region k. These values are interpreted as a percentage difference in activity relative to the Jan–Feb 2020 reference period against which they are defined. In the case of countries with Google data, the Y_{ijk} can represent each of the six activity types, and for China, it can represent the intra-city activity change in the Baidu data. The X_{ijk} represents the vector of independent variables and β_1 represents the estimated coefficients. The error term e_{0ijk} is expected to capture the random variation around days with a mean of 0 and following a normal distribution with a variance of $\mathrm{var}\left(e_{0ijk}\right)$. The intercept term B_{0ijk} contains a fixed mean γ_0 in addition to terms u_{0jk} and v_{0k} which represent the intercepts for each j heatwave and k region, respectively. The decomposition of B_{0ijk} is as follows:

$$B_{0ijk} = \gamma_0 + u_{0jk} + v_{0k}. \tag{2}$$

In this multi-level model, each heatwave and region is given their own random variation around the fixed mean γ_0. These random effects are parameterized as part of a distribution, which allows for group-level exploration of heatwave and region-level variables in addition to day-level effects.

For Baidu data, equations [1] and [2] are sufficient, but the model is extended into a multivariate multi-level model for the countries with Google data to account for the simultaneous variation in six activity types on a given day (time spent at home, visitation to workplaces, transit, grocery/pharmacy, retail/recreation, parks). These various activity changes on a given day are interdependent, and therefore a multivariate modelling approach is implemented which controls for their interrelatedness while estimating the coefficients for independent variables. A level is added below the day in the hierarchical structure, which now represents percent changes in each of the six activity types. In this model, i represents the activity type, j the day, k the heatwave, and l the region. The abbreviated equation is given by:

$$Y_{ijkl} = \underbrace{\left(\beta_{01}Z_{1ijkl} + \ldots + B_{06}Z_{6ijkl}\right)}_{\text{Fixed and random intercepts}} \quad (3)$$

$$+ \underbrace{\left(\beta_{11}Z_{1ijkl}X_{jkl} + \ldots + B_{16}Z_{6ijkl}X_{jkl}\right)}_{\text{Estimated coefficients for } X_{jkl}} \quad (4)$$

$$+ \underbrace{\left(e_{01ijkl} + \ldots + e_{06ijkl}\right)}_{\text{Residual error terms}} \quad (5)$$

where $Z_{1\mathrm{ijkl}} = 1$ for the change in time spent at home on a given day, $Z_{2ijkl} = 1$ for the change in workplace visitation, and so on. The coefficients have the same interpretation as the univariate model, except all six activity types are modelled simultaneously while controlling for their interdependencies. All models are estimated for each country separately using the R2MLwiN software (Zhang *et al* 2016). For Nigeria, due to greater missing mobility data, models are estimated without park and transit activity as response variables, and without age and population density as independent variables. For France, where sample sizes are smaller due to low numbers of county-equivalent regions, transit is removed as a dependent variable to achieve model convergence.

A linear model is chosen as the most suitable for this analysis due to the nested structure of the data and the analysis' sole focus on extreme temperatures. To control for the group-level structure of the data (days within heatwaves within regions), relationships with day-level variables, such as temperature, are estimated by comparing heatwave days within the same heatwave in the same region. As each heatwave has an average of three observations, fitting a non-linear function poses strong risks of overfitting. Additionally, this study focuses only on each region's relatively extreme temperatures (>90th percentile), which are beyond the inflection points found in other studies which cover broad ranges of temperatures and their relationships with mobility or activity patterns (Graff Zivin and Neidell 2014, Stechemesser and Wenz 2023).

In an exploratory analysis using gradient-boosted decision trees (XGBoost) (Chen and Guestrin 2016), HI temperature relationships for the countries with Google data predominantly showed similar directionality to the linear models across the activity types. In cases of non-linear effects, their reliability is impacted by heteroskedasticity problems, as different temperature intensities are associated with different regions, a form of confounding. The multi-level model used here mitigates these problems by comparing within-region relationships, thereby more robustly estimating country-level trends. More detailed explorations of subnational variations in temperature-activity relationships remain an important avenue for future work, including in the countries presented in this analysis. Finally, interpreting the impacts of the independent variables when using gradient boosting, methods such as SHAP (Shapley Additive exPlanations) (Lundberg and Lee 2017) focus on feature importance without robust estimates of effect sizes or statistical confidence, a major limitation to their use.

2.4. Independent variables

The independent variables can be categorized as climate/weather, temporal, socio-demographic, and contextual, as introduced in section 1. The first climatic variable is the absolute heatwave intensity on the heatwave day, measured using the heat index. The second climatic variable is the heat index difference between the heatwave and closely matched control day, referred to as relative intensity. The final climatic variables are standardized levels of precipitation on the heatwave day and the control day, calculated as a percentile rank of daily total precipitation in each ADM2 region.

The first temporal variable is heatwave duration, calculated as a binary variable if a heatwave's length is greater than a country's 75th percentile of heatwave durations. This relative definition is chosen to maximize comparability across countries given their unique patterns of heatwaves and what is considered a 'prolonged' heatwave. Then, a 'stage' variable is introduced to capture within-heatwave changes, reporting how far, in percentage terms, a day is within an ADM2 region's specific heatwave. Finally, a binary variable is included which captures whether a heatwave-control day pair is on a weekend or a weekday.

As contextual factors, socio-demographic variables are population density, proportion of population over 60 years old, and HDI. Each ADM2 region's values are decile ranked within their country, thus creating standardized variables which are comparable across each country's model. The physical-geographical variables are binary variables if an ADM2-region is on a coast, or if it is high-elevation, defined as its average elevation being above or below 1500 m above sea level. A robustness check which included and excluded regions above >1500 m in India showed stable results across all other variables, justifying their inclusion to explore elevation-related effects in typically cooler regions. There were no high-elevation regions with heatwaves and mobility data in Nigeria and Brazil, hence the omission of this variable from their models. Further, all regions with an average elevation >2500 m above sea level are removed due to the extreme cold temperatures at very high altitudes. The full vector of independent variables, X_{jkl}, (X_{ijk} for China) is given as:

$$X_{jkl} = \text{HITemp}_{jkl} + \text{HITempDiff}_{jkl} + \text{Precip\_heat}_{jkl} \quad (6)$$

$$+ \text{Precip\_control}_{jkl} + \text{HeatwaveDur}_{jkl} + \text{Stage}_{jkl} \quad (7)$$

$$+ \text{Weekend}_{jkl} + \text{PopDens}_{jkl} + \text{Over60}_{jkl} \quad (8)$$

$$+ \text{HDI}_{jkl} + \text{Coast}_{jk} + \text{Elevation}_{jkl} \quad (9)$$

To assess multicollinearity, variance inflation factors (VIFs) were calculated for each independent variable in each country-specific model. All VIF scores are well below the commonly cited threshold of 10, indicating that high multicollinearity is unlikely to pose a concern (Kutner *et al* 2005, Chatterjee and Simonoff 2013, Wooldridge 2020). Maximum VIF scores are 1.8 in the USA (HITemp), 3.4 in India (HITemp), 4.2 in France (PopDens), 2.3 in Turkey (Over60), 2.7 in Nigeria (HDI), 2.3 in Brazil (HITempDiff), and 2.5 in China (HITemp). Many of the correlations occur at different levels in the multi-level model, such as daily HI temperature with a region's population density. Such relationships are controlled for in the hierarchical modelling structure, where relationships at lower levels (e.g. day-level) are nested within ADM2 regions due to an expected lack of independence between them.

3. Results

3.1. Country-level heatwave characteristics

In the final data set, there are wide variations in median heatwave intensities across countries, but generally similar heatwave lengths of around 3 days (table 4). The hottest heatwaves are in India with a median heat index of 42.3 °C, followed by Nigeria (38.9 °C), China (36.9 °C), the United States (37.6 °C), Brazil (35.8 °C) Turkey (31.1 °C), and France. (30.6 °C) (figure 1A). These varying heatwave intensities highlight the differences in what are considered 'extreme' temperatures across the countries in this analysis. All countries have a majority of heatwaves of 2–3 days, after which the length tapers off with a rightward skew (figure 1(B)).

The number of distinct heatwave events across countries range as high as 11 807 in the United States and as low as 459 in Nigeria (table 4). Heatwave events per ADM2 region also vary widely, with France having 5.3 heatwaves per ADM2 region (483/91), compared to Brazil with 2.42 (3682/1519). The varying counts of heatwave region-days are a function of the number of ADM2 regions in the country, how many heatwaves occurred in each region during the summer of interest, and whether mobility data could be linked for those heatwave and control days. In Nigeria, for example, fewer heatwaves are included in the final analysis due to sparser coverage in mobility data, leading to a greater proportion of excluded ADM2 regions. The number of heatwave region-days in each country represents the sample sizes of matched heatwave-control days as inputs to each country's multi-level model. The number of distinct heatwave events and ADM2 regions in each country is relevant to the multi-level models' abilities to estimate heatwave and ADM2-level effects.

While coastal and inland regions have comparable heatwave intensities (figure 1(C)), heatwaves in high-elevation regions (1500 m) are typically much cooler than low-lying regions, a finding consistent across all countries (figure 1(D)). Heatwave intensities in high-elevation regions of India are particularly low, containing a minimum heat index of 19 °C. A sensitivity analysis confirmed that India's non-elevation results are robust to including these regions, justifying their presence in the full model to explore elevation-related effects, which—based on their divergent temperatures—may convey a lack of acclimatization to extreme heat in high-elevation regions. Note that Brazil and Nigeria are not included in figure 1(D) because they have no high-elevation regions with mobility data in the final data set.

3.2. Withdrawal into the home during heatwaves

The most common adaptation to summer heatwaves in the considered countries is to withdraw into the home. The multi-level regression modelling indicates that these withdrawals occur as heatwaves get hotter, longer, and drag on—especially on weekdays—and in regions with older populations, away from coasts, or with high elevation. Unless otherwise specified, only statistically significant effects ($p<0.05$) are discussed in the subsequent sections. The full model coefficients and standard errors are reported in the Supplementary Material.

Table 4. Summary statistics on ADM2 regions with data in each country, the number of heatwave days and heatwaves in those regions, their median duration, and their median intensity (HI temperature, °C).

Country	ADM2 regions (included/total)	Heatwave region-days (#)	Heatwaves (#)	Duration in days (50%)	Heatwave HI (°C) (50%)
Brazil	1519/5572	11 402	3682	3	35.77
France	91/96	1794	483	3	30.61
India	609/753	5741	1574	3	42.29
Nigeria	158/774	1444	459	3	38.91
Turkey	490/973	6217	1655	3	31.10
United States	2723/3141	33 879	11 807	2	37.60
China	339/366	4558	1436	3	36.93

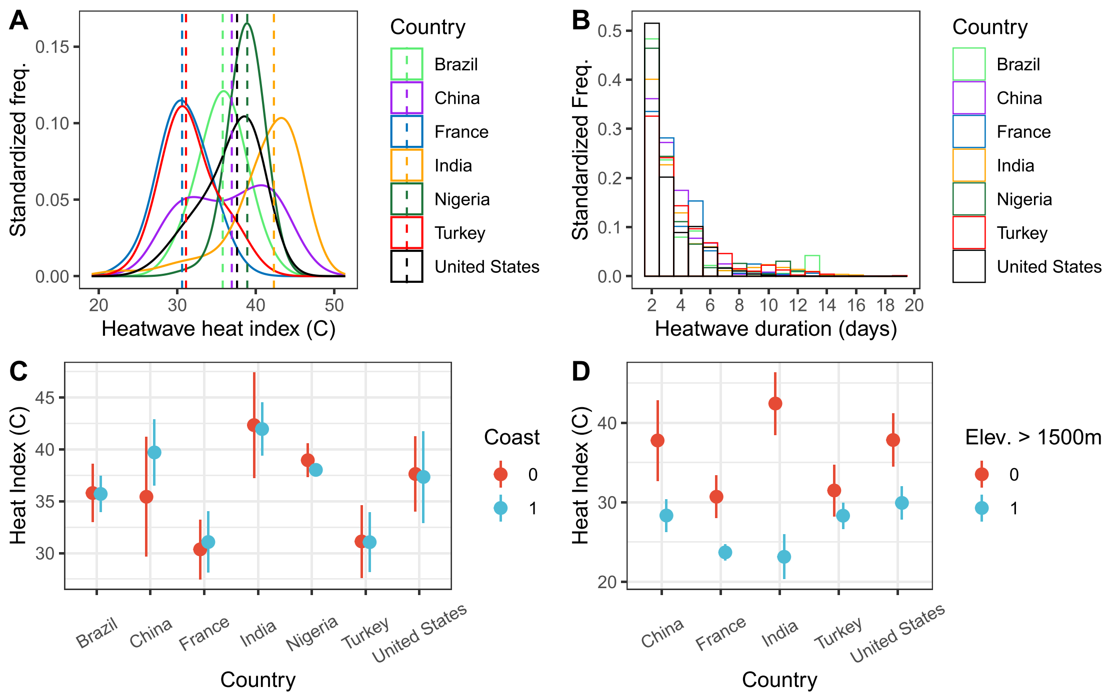

Figure 1. Top: (A) Distribution of heatwave day heat index intensities across countries (°C), and their median values (dotted line) and (B) distribution of heatwave durations across countries (in days); Bottom: Median and standard deviation of heatwave day intensities across countries, separated by (C) coastal/inland and (D) high/low elevation.

In terms of overall shifts and relationships with temperature (figure 2(A)), people spend either more time at home overall during heatwaves (Nigeria), withdraw further as heatwave intensities rise (India), or do both (France, United States). In terms of temporal relationships, broader trends of increasing time spent at home are consistent across a range of global contexts and circumstances, such as time spent at home increasing during longer heatwaves and/or as heatwaves progress from their first to final day (stage) in 4/6 countries (France, India, United States, Brazil; figures 3(A), (B), (C) and (F)).

The extent to which people increase time at home depends on whether the heatwave day falls on a weekend or weekday (figure 3). During weekend heatwaves in every country—when people's activity schedules are typically more flexible—the model coefficients indicate less withdrawal behaviour relative to weekdays (figures 3(A)–(F)). In Brazil, for example, heatwave region-days that fall on weekends are associated with less time spent at home, fewer visits to the workplace, and increases in grocery/pharmacy, retail/recreation, and park activity (figure 3(F)).

The tendency to withdraw into the home also varies according to the age of the population. It is stronger in regions with more elderly people in India, the USA, and Brazil (figures 4(B), (C) and (F)). Despite common trends, the effects of socio-demographics on heatwave adaptation can also vary across countries. This is seen in Turkey, where regions with older populations exhibit *lower changes* in time at home (figure 4(D)), and in France, where there is no statistically significant impact of age on time spent at home.

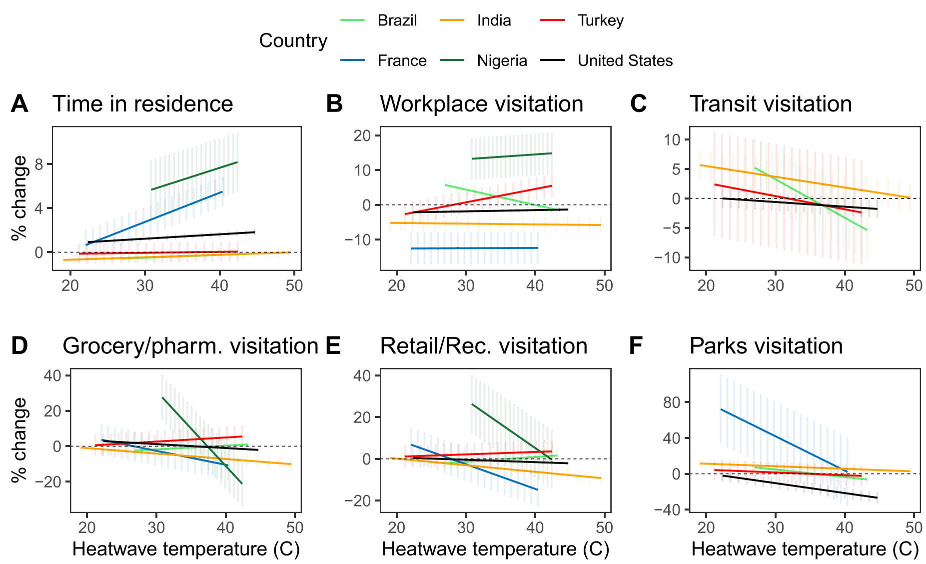

Figure 2. Marginal effects plots from the models of the 6 countries with Google Community Mobility Reports data. Depicts each country's average relationship between HI temperature and percent changes in everyday activities, across HI temperature (°C) range from each country's minimum to maximum regional heatwave (including 95% fixed intercept confidence interval). Each country's model coefficients are multiplied by the mean values of their corresponding independent variables to generate an average intercept, except for precipitation which is set to zero to eliminate precipitation-related impacts. In the text, inferences about countries' overall activity changes are made using country-level average intercept and associated confidence intervals. Note the removal of variables for Nigeria (parks, transit) and France (transit) due to sample size limitations to achieve model convergence.

Physical-geographical context, shown through coastal/inland and high/low elevation distinctions, has a strong influence on people's propensities to spend time at home during heatwaves. In coastal regions, despite having similar heatwave intensities as inland regions, people spend less time at home to visit various activity types in France, USA, and Brazil (figures 5(A), (C) and (F)). In high-elevation regions, which are typically much cooler and potentially less acclimatized to extreme heat, people adapt through greater changes in time at home in two of the four countries with high-elevation results (France, and Turkey; figures 5(A) and (D)).

While withdrawal into the home cannot be verified directly for China, the model based on Baidu data offers results that are consistent with the tendencies observed in the other countries (figure 7). Intra-prefecture city activity decreases as heatwave intensity rises (HI temp) and as heatwaves progress over time (stage). Further, weekend heatwave activity is greater than on weekdays. A main difference from the countries with Google data is that regions with older populations exhibit more intra-prefecture city activity during heatwaves. The estimated effect sizes in China are relatively low compared to the location-specific coefficients for the other countries. For instance, China exhibits a 0.4% increase in activity on weekend heatwaves compared to weekdays, whereas a 2.4% decrease in time spent at home is observed in France. These differences may result from the all-encompassing activity metric derived from the Baidu data, which potentially mask diverse changes as people spend more time in residence overall but also visit non-home facilities which offer cooling.

3.3. Not all activities are abandoned equally

While withdrawal into the home is commonly observed, differences emerge in what activities are abandoned both across and within countries. As a country-level example, people in both India and Brazil spend more time at home as heatwaves progress (stage variable); however, in India, all activities are reduced (figure 3(B)), whereas in Brazil, only workplace visits decrease (figure 3(F)). Examining within-country variation, in 4/6 countries with Google data, activity abandonment depends on a region's HDI score, with greater workplace visitation in higher-HDI regions (India, United States, Nigeria, Brazil; figures 4(B), (C), (E) and (F)). These effects may be due to the nature of work in higher-HDI regions, as more office-work and air-conditioned workspaces in higher-income regions may make *in situ* work more manageable. These findings also suggest that workplace activity in lower HDI regions may be more disrupted by summer heatwaves, potentially compounding the risks to disproportionately vulnerable populations.

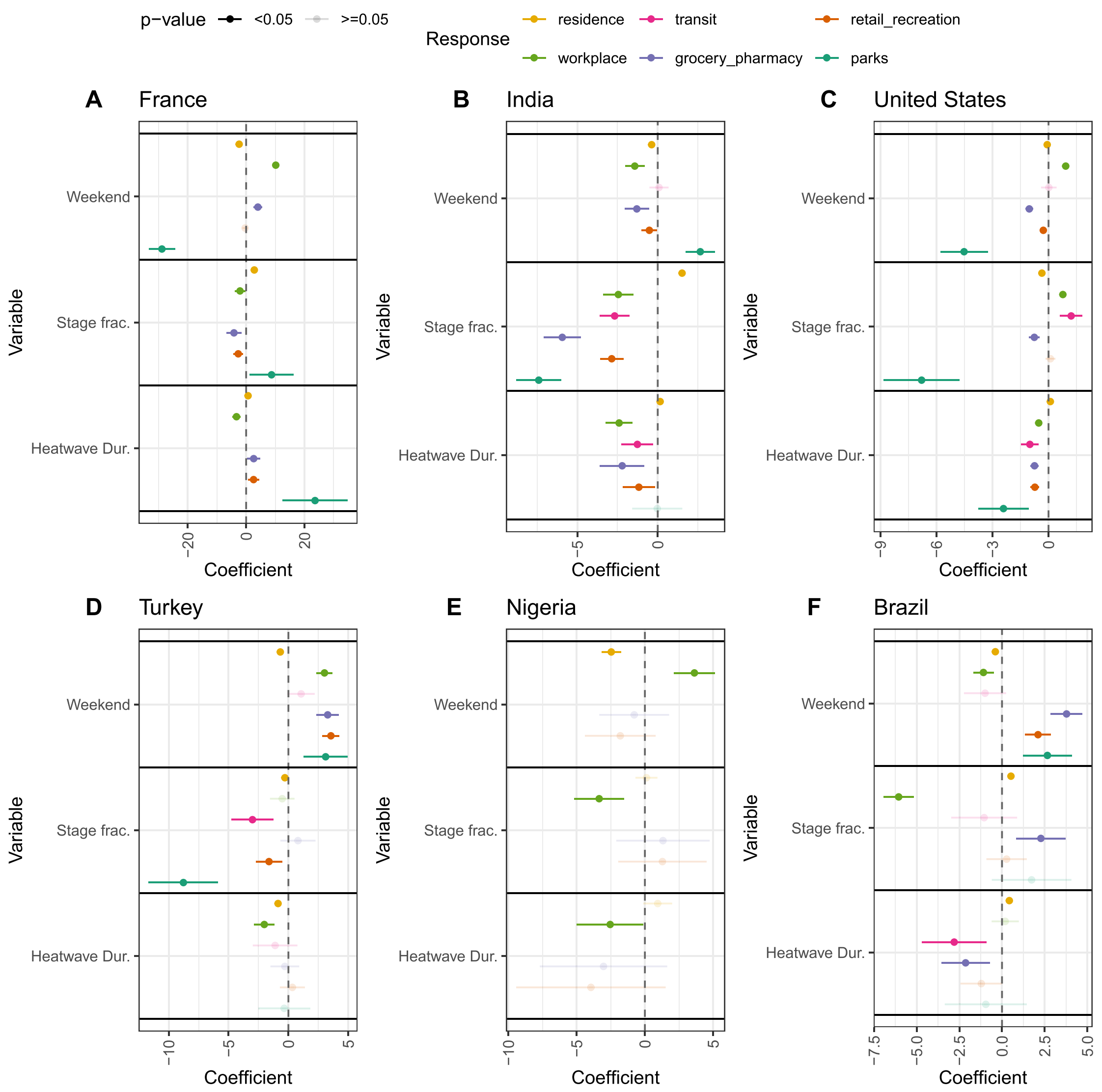

Figure 3. Temporal multivariate multi-level model coefficients, representing the heatwave activity changes for the 6 countries with Google Community Mobility Reports data. Note the removal of variables for Nigeria (parks, transit) and France (transit) due to sample size limitations to achieve model convergence.

3.4. More out-of-home activities that may offer cooling

Withdrawal into the home is the most common adaptation and variations emerge in which activities are abandoned; however, work and non-work activities outside the home are also more common depending on the country and the circumstance. These simultaneous changes in activity—both towards the home and to non-home locations—are commonplace and manifest in various ways. For instance, people in France spend more time at home during longer heatwaves by reducing visits to the workplace, but simultaneously increase visitation to grocery/pharmacy, retail/recreation, and park locations (figure 3(A)). In India, people's time spent at home rises with heatwave intensity, but overall levels of park activity are elevated during heatwaves across a range of HI temperatures (figure 2(F)). Similar mechanisms arise due to within-country variation, such as in the United States, where people in older regions tend to spend more time at home during heatwaves, while simultaneously visiting parks more (figure 4(F)).

Climatic factors also stimulate greater park activity during heatwaves, shown through the HI temperature difference and heatwave precipitation variable. With each degree of HI temperature difference between heatwave and closely matched control day, people visit parks more in France, India, and Turkey (figures 6(A), (B) and (D)). In Turkey, park visits rise by over 1% with each HI degree difference between heatwave and control days. Taken together with the findings on absolute intensity in Turkey (figure 2(F)), where no relationship with park activity is observed, these results highlight the distinct

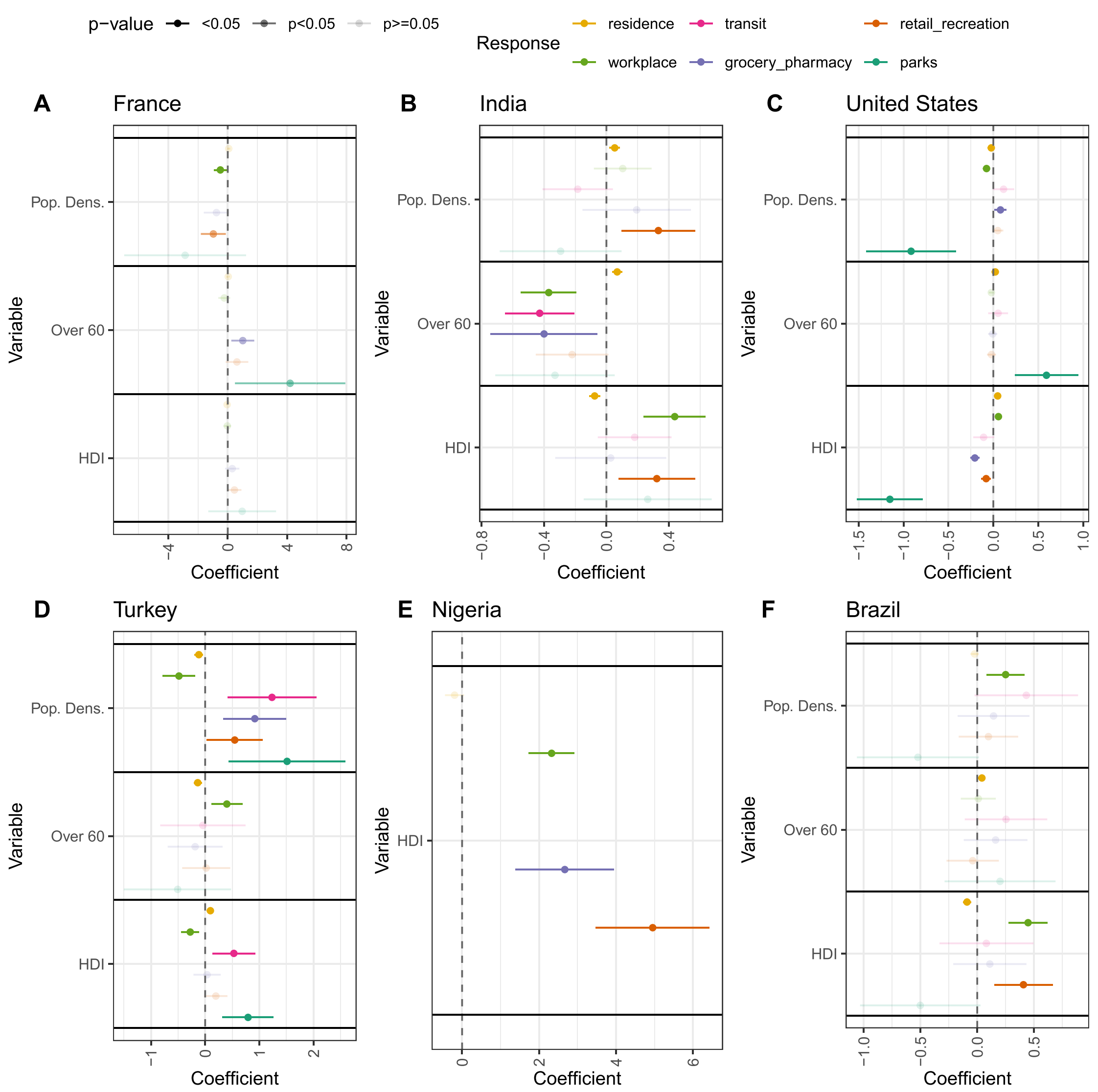

Figure 4. Socio-demographic multivariate multi-level model coefficients, representing the heatwave activity changes for the 6 countries with Google Community Mobility Reports data. Note the removal of variables for Nigeria (parks, transit) and France (transit) due to sample size limitations to achieve model convergence, in addition to population density and over 60 for Nigeria.

impacts of absolute and relative heatwave intensities on people's adaptive behaviours. Further, in every country with available data, precipitation on heatwave days is associated with less visitation to park locations (figures 2(A)–(F)). This finding is in line with prior literature on the impact of weather on everyday activities (Böcker *et al* 2013), which indicates that the deployed modelling approach is able to pick up the impacts of short-term environmental exposures. These results also highlight the mediating effect of precipitation on people's adaptive responses to heatwaves, finding that drier heatwaves are associated with greater outdoor activity. In China, where activity types cannot be discerned, there are greater activity levels as relative heatwave intensity rises and when precipitation is lower (figure 7), potentially reflecting similar mechanisms to the other countries.

Many of the effects related to population density and HDI are heterogeneous, highlighting the importance of context-specific adaptive mechanisms during heatwaves. For instance, population density in India and Turkey is associated with greater retail/recreation activity during heatwaves (figures 4(C) and (D)), among other effects, whereas the opposite is true in France (figure 4(A)). Diverse relationships are also seen with HDI for visits to parks, as greater HDI is associated with more park activity in Turkey (figure 4(D)); while the opposite is true in the United States (figure 4(C)). These examples highlight that adaptation varies in complex ways across countries and at subnational levels—including to locations away from home which may offer cooling—and emphasize that there is more to heatwave adaptation than staying home.

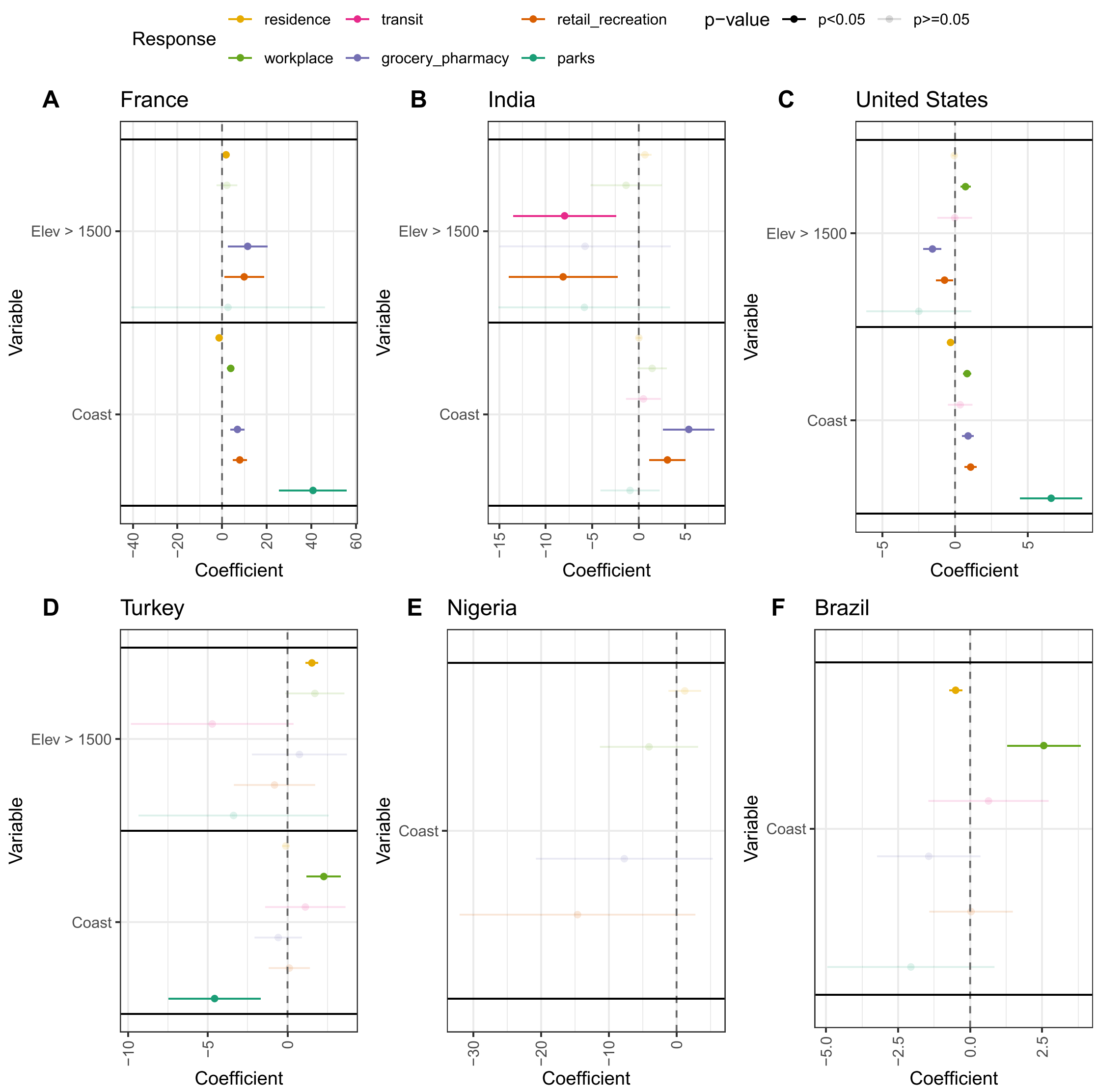

Figure 5. Physical-geographical multivariate multi-level model coefficients, representing the heatwave activity changes for the 6 countries with Google Community Mobility Reports data. Note the removal of variables for Nigeria (parks, transit) and France (transit) due to sample size limitations to achieve model convergence.

4. Discussion

The analysis reveals three main insights: (1) Withdrawal into the home is the most common behavioural adaptation strategy during summer heatwaves; (2) not all activities are abandoned equally; and (3) adaptation also involves more out-of-home activities that may offer cooling. When matched heatwave and control days at the county-equivalent level are compared across the considered countries, people spend greater amounts of time at home as heatwaves get hotter, longer, or drag on—especially on weekdays—and in regions with older populations, away from coasts, or with high elevations. These patterns align with prior research showing reduced activity levels during heatwaves, although existing research has predominantly focused on single cities in high-income countries (Derakhshan *et al* 2023, Fan *et al* 2023, Ly *et al* 2023, Stechemesser and Wenz 2023, Gu *et al* 2024, Kumakura *et al* 2024, Tian *et al* 2024). The present analysis leverages comparable data sets, heatwave definitions, and methods to highlight the international scale of such shifts, finding patterns of home-withdrawal across countries which vary widely in household air conditioning ownership rates and income levels.

Despite these common responses, there are great variations in which activities are abandoned as people withdraw into the home, and in some circumstances, people visit non-home locations which may offer cooling. These findings highlight the importance of considering heatwave adaptation through

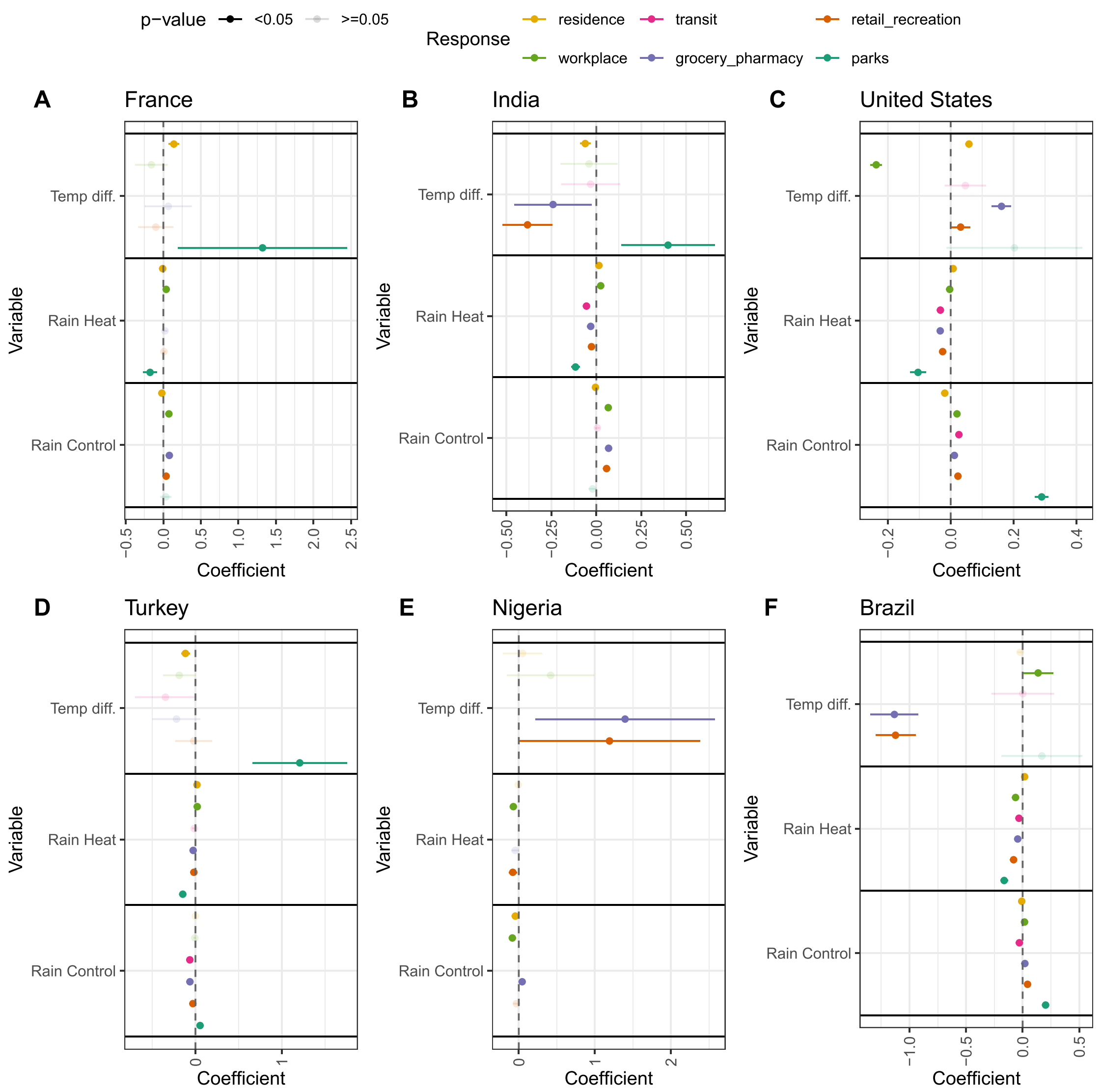

Figure 6. Climatic multivariate multi-level model coefficients, representing the heatwave activity changes for the 6 countries with Google Community Mobility Reports data. Note the removal of variables for Nigeria (parks, transit) and France (transit) due to sample size limitations to achieve model convergence.

the lens of people's daily activities and examining which activities are altered, as context-specific adaptive responses emerge across countries and at sub-national levels. The value of considering activity types is also evident from interpretations of the China sub-analysis, where similar aggregate trends emerge, although details on which specific activities are substituted or engaged in more cannot be discerned.

Residential air conditioning prevalence and cooling opportunities away from home likely influence the observed patterns of adaptation. In the United States, for example, which has the highest household air conditioning ownership rate in the world (∼88%) (Andrijevic *et al* 2021), staying home may be an effective strategy for a large proportion of the population. Similarly, the availability of non-residential cooling opportunities may influence adaptations away from home during summer heatwaves. In Turkey, for example, ∼25%–40% of existing residential buildings have air conditioning, whereas it is present in ∼70% of offices (Heperkan *et al* 2022)—potentially influencing the observed increases in visits to workplaces as heatwave temperatures rise. These mechanisms also likely impact the observed within-country variations, such as the greater workplace activity in higher HDI-regions, where air-conditioned workplaces and office work may be more common.

This analysis conveys how people adapt their daily activities during heatwaves, *not* that these adaptations effectively protect their health and well-being during heatwaves. What is considered adaptive for some may be maladaptive for others, depending largely on the context. In contrast to the USA, where air

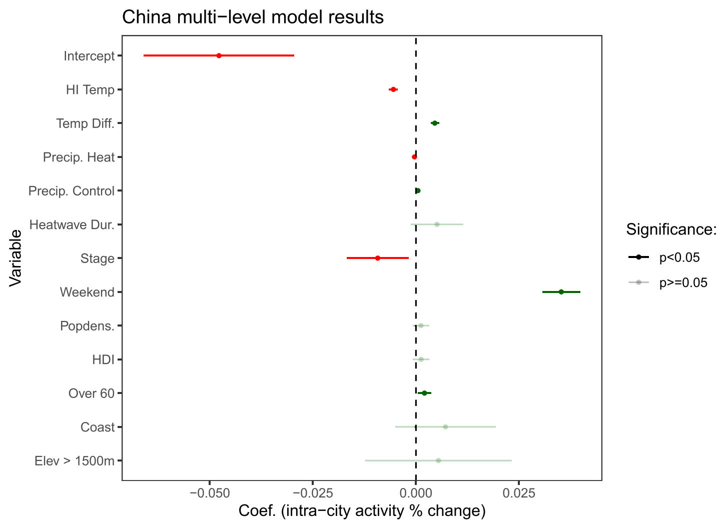

Figure 7. Coefficients and 95% confidence intervals for China's multi-level model based on Baidu data. Model estimates percentage change in intra-prefecture city activity across climatic, temporal, and contextual variables.

conditioning ownership is near-ubiquitous (∼88%), people in Brazil (∼8%), France (∼14%), and India (∼18%) (Andrijevic *et al* 2021) also adapt by withdrawing into the home according to climate/weather, prolonged exposure, or both. While these adaptive responses may be protective, they may also reflect limited cooling resources away from home, accessibility constraints, and a lack of effective HAPs to support the provision of cooling opportunities (Daramola *et al* 2018, Balogun and Daramola 2019, Bedi *et al* 2022, Puley 2022, Mazzone *et al* 2023, Trahan *et al* 2023). Similar uncertainties arise when within-country variations are considered, as greater withdrawal into the home in regions with older populations may be protective of health for those with air conditioning, but could be life-threatening for others who remain home due to mobility constraints or a lack of support networks (Sampson *et al* 2013, Klinenberg 2015, Diniz *et al* 2020, Kafeety *et al* 2020, Arsad *et al* 2022, Boni *et al* 2024). The activity changes detected in this analysis—both across and within countries—provide an important foundation for further qualitative, context-specific research on the mechanisms behind such behavioural changes.

To effectively translate knowledge of mobility-based adaptation into better heatwave policy, further research in two areas is needed. The first is to develop subnational estimates of air conditioning prevalence—especially focused on LMICs—to identify where withdrawal into the home is likely to be a protective measure versus a potentially life-threatening one. Local variations in air conditioning ownership constitute a significant data gap, as electric fans, a lower-cost alternative, have been found to be insufficient to cool core temperatures when air temperature is above 35 °C (Meade *et al* 2024). The second is to develop standardized assessments of global HAPs, including at a subnational level, to enable more in-depth examinations of how policies perform in supporting adaptation. It is evident from this analysis that people in countries with and without HAPs are adapting their daily activities to escape the threat of extreme heat; however, it remains unclear how differences in HAP implementation can successfully support people in reaching cool environments—an urgent question which can be addressed more effectively with improved and standardized metrics on HAP measures.

4.1. Limitations

Primary limitations of this study stem from the spatial and temporal characteristics of the mobile phone location data from Google Community Mobility Reports and Baidu. Activity types cannot be discerned for the Baidu data, and the Google data's broad activity categories omit details on whether workplaces are indoors or outdoors, the usage of any formal or informal cooling centres, and non-POI cooling locations such as tree shade, which is a common coping mechanism in India (Khetan *et al* 2024). The lack of workplace distinction is a key limitation, as air-conditioned or indoor workplaces may be protective while outdoor work could be detrimental to health during heatwaves—the latter occurring on greater scales in LMICs which cannot be explored in this analysis (Kjellstrom *et al* 2009). Given the ADM2 level aggregation, the analysis is also unable to discern mobilities between regions, and risks of ecological fallacy are introduced when inferences are made at the individual level based on group-level data. Concerning the temporal scale, the daily aggregation omits information on whether activities are shifted to different times of day, found to be a common response in more granular analyses of heatwave mobilities (Fan *et al* 2023, Kumakura *et al* 2024, Tian *et al* 2024).

The timescale of the mobility data is also a major limitation, as even the latest possible summer seasons are relatively soon after the COVID-19 pandemic. During this period, there may still have been behavioural adjustments related to spikes in COVID-19 cases and associated government responses, which hinder the generalizability of this study to future years. While the heatwave-control day matching aims to mitigate this influence by isolating heat-related changes in activities at a week-by-week level (not comparing across years), norms and attitudes during this period may have affected people's preferences for seeking home versus non-home locations during heatwaves. Using comparable methodologies in the Pacific Northwest of North America, Yücel and Schwanen (2025) find greater workplace activity during 2022 heatwaves compared to 2020 and 2021, highlighting changes in heatwave responses which may result from varying COVID-19 and policy landscapes. Further, due to long-term changes in travel behaviour after COVID-19 towards a 'new normal' (Van Wee and Witlox 2021), research on mobility-based heatwave adaptation in the ensuing years is an important area for future research.

Other limitations relate to sampling biases when using mobile phone location data for research purposes. The sample of users in this analysis is limited to those who use Google or Baidu features, requiring both a smartphone and subscription to mobile data, and leading to an under-representation of lower-income and elderly populations (Oliver *et al* 2015, Yabe *et al* 2022). Such data gaps are likely to be exacerbated in lower-income countries, easily observable in the fraction of ADM2 regions with missing data in table 4 in Nigeria compared to other countries. Children are another demographic group which is highly susceptible to adverse health effects of heat (Xu *et al* 2014, Brimicombe *et al* 2024, Schapiro *et al* 2024), have distinct mobility patterns compared to adults (i.e. school vs work), and yet are likely to be underrepresented in mobile phone location data sets (Kostandova *et al* 2025). While the inclusion of area-aggregated variables related to HDI, population density, and older age capture some effects of known inequalities, these biases highlight the continued need for qualitative or travel-survey-based methodologies to explore socio-demographic differences in greater depth. Additionally, mobile phones may be shared within households and usage tends to be gendered—a known disadvantage to women during heatwaves (Trahan *et al* 2023) and another source of bias in the data. A growing body of literature is examining digital gender gaps in LMICs and intersectional inequalities in heatwave adaptation (Fatehkia *et al* 2018), of great relevance to future mobile phone-based studies and climate adaptation research more broadly.

5. Conclusion

This paper conceptualizes everyday adaptation as an international phenomenon resulting from a common threat, and examines both shared and context-specific responses at a population level across various parts of the world. Focusing on seven at-risk countries with large populations of varying income levels, the analysis integrates common data sets, models, and definitions of a summer 'heatwave' to provide a comprehensive perspective on adaptive responses at multiple geographical scales. The multi-level approach allows for the inclusion of diverse climate/weather, temporal, socio-demographic, and physical-geographical factors, which are all shown to influence how people adapt their everyday lives to heatwaves. This study highlights the nature and extent of how populations are already adapting their everyday lives to escape exposure to extreme heat—adaptations which will only increase in urgency and require greater institutional support as the climate crisis worsens.

Data availability statement

The datasets and code supporting the conclusions of this article are both openly available. The code and final data sets are stored as a GitHub repository here (Python/R): https://github.com/shivyucel/global_adaptation_paper.

Supplementary Material available at https://doi.org/10.1088/2752-5295/ae4cc2/data1.

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Author contributions

Conceptualization: SGY, YL, TS; Methodology: SGY, YL, TS; Software: SGY, YL; Formal Analysis: SGY, YL; Visualization: SGY; Supervision: TS; Writing - original draft: SGY; Writing—review & editing: SGY, YL, DW, TS

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