Socioeconomic inequalities in excess mortality attributable to extreme heat during the summer of 2022 in Catalonia, Spain. A Bayesian spatio-temporal model.

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Background and Objectives

During 2022, there was excess mortality worldwide, in many cases only surpassed by the excess in 2020, because of the COVID-19 pandemic. According to data from the daily mortality monitoring system (MoMo) of the Carlos III Health Institute[1], in 2022 excess mortality in Spain was the third highest since the MoMo began to be elaborated. This excess mortality has been attributed not only to the effects of the COVID-19 pandemic but also to those of extreme heat episodes, which are exceptional in the summer of 2022. However, only 22.92% in Spain and 16.22% in Catalonia have been directly attributed to extreme heat. The problem with the estimates of excesses and their attributions to extreme heat is that they are based on models that could present biases and limitations.

We first intended to estimate the excess mortality attributed to extreme temperatures in Catalonia in the summer of 2022, using much smaller units of analysis and temperature predictions obtained from a spatio-temporal Bayesian model. Second, we assessed the risk of dying from these extreme temperatures and their interactions with socioeconomic inequalities.

Methods

We used a longitudinal ecological design, from 2015 to 2022 with information on daily mortality and temperature (maximum and mininimun) and relative humidity, as well as information on the average net income per person, all at the level of 288 health areas (ABS) managed by the public health service, distributed throughout the 4 provinces of Catalonia, Spain. We used a sample that covers 6.3 million people, 81.6% of the population of Catalonia and 77% of the ABS into which Catalonia is divided.

Extreme of maximum temperature: Indicator that the maximum temperature exceeds the trigger temperature on a given day.
Heat wave: Indicator that maximum temperature extremes occur 3 or more days in a row at least 10% of the weather stations.

Objective 1

MoMo model

$$\log(\theta_{it}) = \beta_0 + \beta_{1i}\, ATO_i + spline(trend_i, 1) + spline(cyclic_i, 6) + offset(\log(Population_i))$$

Our model

$$\log(\theta_{it}) = \beta_0 + \sum_{k=1}^{7} \beta_{1i,k}\, ATO_{i,t-k} + \eta_i + S(ABS_i) + \tau_t + \tau s_t + offset(\log(Population_i))$$

Characteristics (MoMo model)	*Limitations*	*Characteristics* (Our model)	*Solutions*
Unit of analysis: Province	The between-area variability of the temperature is considerably lower than the within-area variability, which would lead to an underestimation of its effects, if it had been measured with error[2,3].	Unit of analysis: ABS	We have minimized the within-area exposure variability and maximized between-area exposure variability. The effect of measurement error, if any, may be negligible
The temperature to which each subject is exposed is the average of the observed temperatures in the province	Measurement error – Spatial misalignment When there is spatial variation in the study region, the use of the average can lead to bias and the underestimation of the health effect of interest[4].	We use a hierarchical Bayesian spatiotemporal model to make spatial predictions of the temperature values in each of the ABS[5].	Unbiased estimators with correct variances.
Does not control for individual heterogeneity	This omission leads to biased estimators and wrong variances.	We controlled for individual heterogeneity using an unstructured random effect (independent and identically distributed).	
Does not control spatial dependence	This omission leads to biased estimators and wrong variances.	We controlled for spatial dependence using a structured random effect S (normally distributed with zero mean and a Matérn covariance function).	
The coefficients associated with each lag of the ATO are equal to 0.8^{k-1}, where k denotes lag, and to be specific for each of the province.	The effects of the lags do not necessarily have to be equal	We allowed the coefficients associated with each lag of the ATO to be different and to be specific for each of the ABS.	
Trend and annual seasonality are modelled as a rigid and cyclic cubic spline of orders 1 and 6, respectively, both by province.		We control for annual trend and seasonality using random effects, τ_t and τs_t, structured according to a random walk of order 1 and a cyclical random walk of order 2, respectively (equivalent to smoothers).	
Uses a Poisson link	Heteroscedasticity is not controlled. In non-linear models this leads to biased estimators and wrong variances.	We used a zero inflated Poisson, since some days some ABS did not present any deaths.	Unbiased estimators with correct variances.

$$ATO_t = \sqrt{ATO_{t-1} + ATO_{t-2} * 0.8 + ATO_{t-3} * 0.8^2 + ATO_{t-4} * 0.8^3 + ATO_{t-5} * 0.8^4 + ATO_{t-6} * 0.8^5 + ATO_{t-7} * 0.8^6}$$

ATO (accumulated thermal overcharge) excess temperature above the trigger temperature

Objective 2

We estimated the following generalized linear mixed model (GLMM):

$$\log(\theta'_{it}) = \gamma_0 + \gamma_{1i} Extreme\ heat_{i,t-k} + \sum_{k=2}^{4} \gamma_{2k}\, QIncome_{k,i} + \sum_{k=1}^{5} \gamma_{3i,k}\, maximum\ temperature_{k,i} + \eta_i + S(ABS_i) + \tau_t + \tau_{ts} + offset(\log(Population_i))$$

Where θ'_{it} was the conditional risk of a death (all ages and 65 years and older) in the ABS i on day t, during the months June to September; Extreme heat denoted an indicator of maximum temperature extreme (with lag k=7) or heat wave (with lag k=3); *QIncome* was an indicator of the quartile of average net income per person in which the ABS i was located; maximum temperature was considered in ABS i on day t (up to 5 lags); η_i was an unstructured random effect; τ_t and τ_{ts} structured random effects capturing trend and annual seasonality; S() structured random effects controlling spatial dependence; and Population denoted the population of the ABS i.

We allowed interactions between extreme heat and: i) extremes of minimum temperature; ii) high relative humidity (fourth quartile); and iii) income quartiles. Also, the interactions between extreme heat, extremes of minimum temperature/high relative humidity and income quartiles.

Inferences were made following a Bayesian perspective, using the INLA approach[6,7]. We used priors that penalize complexity (called PC priors). These priors are robust in the sense that they do not have an impact on the results, and, in addition, they have an epidemiological interpretation[8].

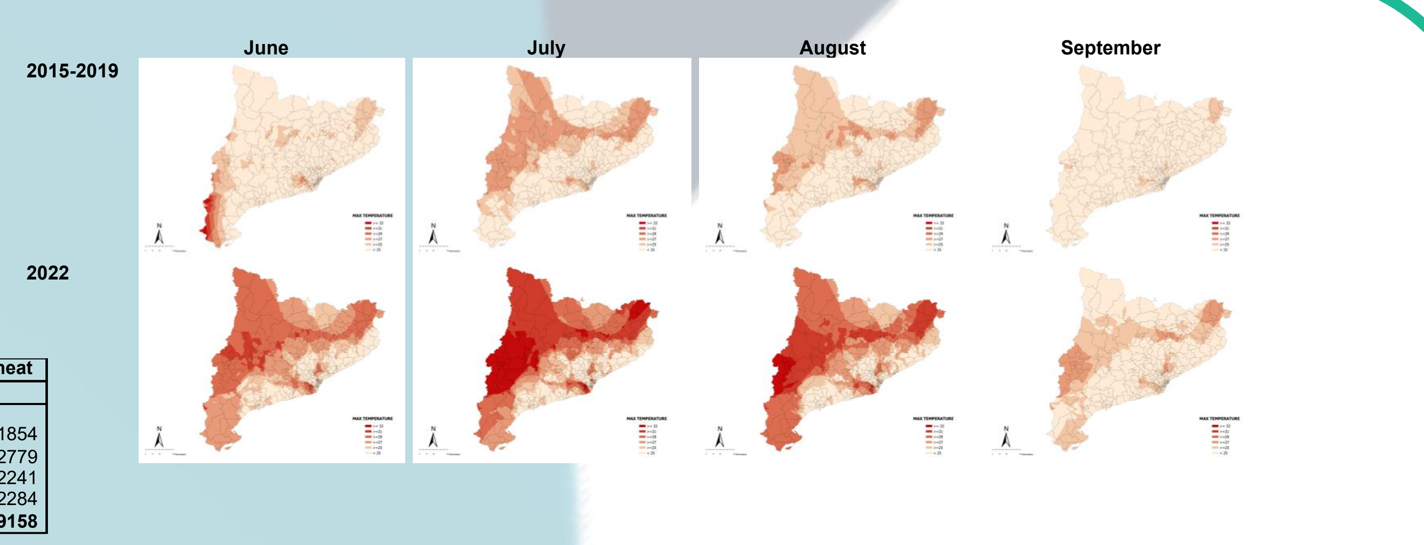
Results

Coefficient of variation of maximum temperature

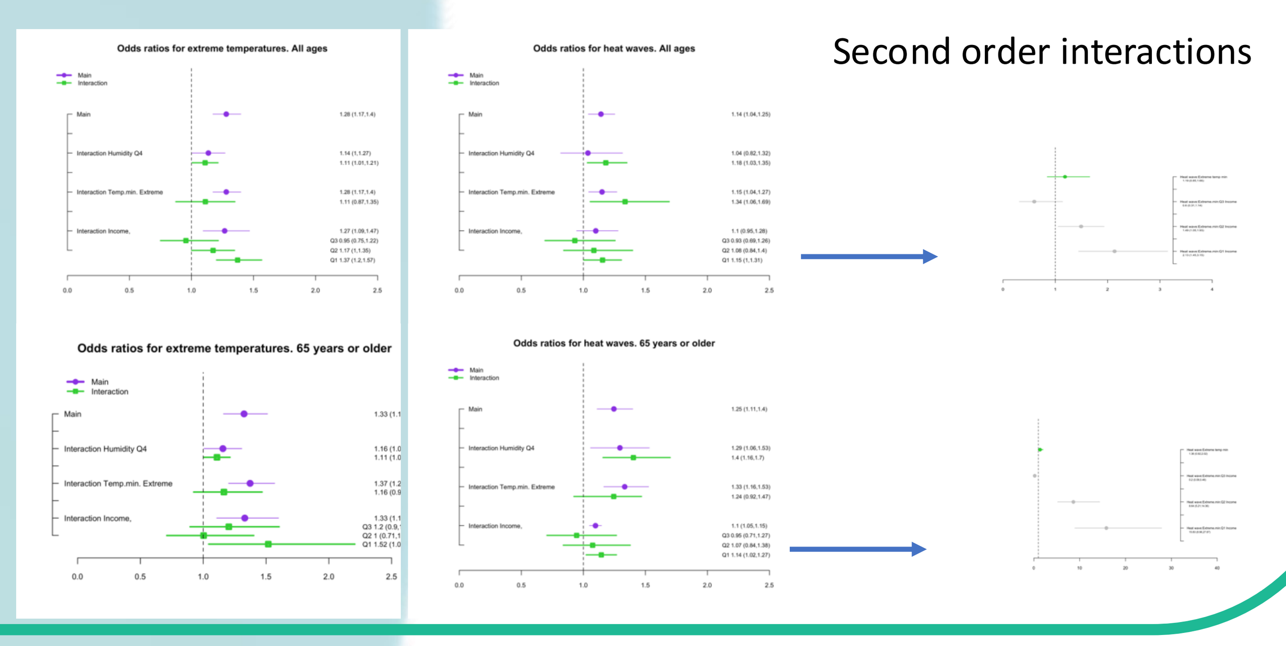
June-September 2015-2022	Between-area	Within-area
Provinces	0.1086	0.1238
ABS	0.3856	0.1836

	June 2015-2021	June 2022	July 2015-2021	July 2022	August 2015-2021	August 2022	September 2015-2021	September 2022
Maximum Temperature	25.700 (6.370) 27.000 [23.300,29.841]	30.392 (4.128) 30.300 [28.300,32.784]	28.197 (7.044) 30.150 [26.903,32.551]	32.566 (3.640) 32.800 [30.800,34.800]	27.622 (6.890) 29.500 [26.100,31.909]	31.578 (3.786) 31.830 [30.022,33.794]	24.853 (5.704) 26.111 [23.000,28.554]	26.440 (4.035) 26.600 [24.300,29.226]
Extreme	35.552 (2.212) 36.470 [35.312,38.093]	36.940 (1.855) 36.753 [35.500,38.050]	36.697 (1.475) 37.327 [36.384,38.312]	37.406 (1.961) 37.400 [36.445,38.323]	37.676 (1.368) 37.593 [36.792,38.506]	37.873 (1.406) 37.650 [37.000,38.700]	33.914 (1.592) 33.724 [32.902,34.792]	34.252 (1.590) 34.055 [33.182,35.200]
Heat wave	37.462 (2.332) 36.950 [35.725,39.000]	37.129 (1.866) 37.067 [35.721,38.377]	37.896 (1.568) 35.190 [32.200,37.285]	37.521 (1.328) 37.900 [36.800,38.886]	38.056 (1.483) 37.912 [37.010,39.900]	38.217 (1.450) 38.032 [37.247,39.084]	34.300 (1.741) 34.200 [33.200,35.306]	34.671 (1.662) 34.559 [33.511,35.723]
Minimum Temperature	15.160 (3.383) 15.282 [12.853,17.553]	17.016 (3.050) 17.200 [15.107,19.153]	17.664 (3.074) 17.900 [15.728,19.807]	19.034 (2.910) 19.300 [17.221,21.013]	17.554 (3.205) 17.784 [15.461,19.852]	18.386 (3.212) 18.618 [16.801,20.625]	14.675 (3.582) 14.900 [12.200,17.300]	14.972 (4.037) 15.100 [12.100,18.004]
Extreme	18.012 (2.809) 18.000 [16.114,19.843]	18.288 (2.518) 18.400 [16.747,19.940]	19.005 (2.316) 18.988 [17.419,20.500]	19.309 (2.334) 19.356 [17.651,20.855]	20.095 (2.238) 20.167 [18.379,21.700]	20.208 (2.419) 20.257 [18.644,21.787]	17.635 (2.666) 17.812 [15.913,19.400]	19.025 (2.159) 19.000 [17.758,20.440]
Heat wave	18.221 (2.739) 18.192 [16.364,20.005]	18.551 (2.382) 18.673 [17.066, 20.123]	19.021 (2.257) 18.981 [17.350,20.552]	19.248 (2.386) 19.300 [17.548,20.800]	20.102 (2.244) 20.291 [18.317,21.794]	20.739 (2.231) 20.735 [19.300,22.199]	18.135 (2.333) 18.133 [16.680,19.800]	19.148 (2.132) 19.352 [17.839,20.568]
Mean Temperature	20.834 (3.921) 21.265 [18.757,23.520]	23.042 (3.445) 23.472 [21.490,25.133]	23.533 (3.426) 24.185 [22.110, 25.727]	25.047 (3.204) 25.612 [23.941,27.073]	23.040 (3.586) 23.646 [21.359,25.331]	24.055 (3.499) 24.742 [22.677,26.321]	19.624 (3.705) 20.127 [17.479,22.290]	20.054 (3.862) 20.128 [17.735,22.940]
Extreme	26.493 (3.818) 26.963 [25.543,28.542]	26.489 (2.584) 26.836 [25.312,28.166]	27.368 (2.011) 27.606 [26.602,28.477]	27.382 (2.307) 27.817 [26.611,28.749]	27.312 (2.550) 27.725 [26.384,28.696]	27.538 (3.206) 28.160 [26.771,29.219]	24.497 (2.931) 25.004 [23.651,26.077]	24.895 (2.501) 25.316 [24.332,26.016]
Heat wave	27.485 (2.215) 27.441 [26.180,28.860]	27.709 (2.199) 27.668 [26.334,29.242]	27.649 (1.977) 28.016 [26.845,28.932]	28.047 (1.385) 28.068 [27.240,28.975]	28.202 (2.305) 28.446 [27.417,29.424]	28.594 (2.062) 28.756 [27.765,29.827]	25.055 (2.145) 25.342 [24.159,26.367]	25.589 (1.870) 25.736 [24.748,26.764]
Relative humidity, mean	69.449 (14.194) 67.860 [58.137,81.757]	70.491 (15.576) 69.913 [57.726,87.065]	68.235 (13.794) 65.798 [57.691,78.732]	70.244 (16.390) 68.328 [55.917,87.065]	70.318 (13.235) 68.951 [59.686,80.866]	74.549 (13.540) 74.352 [63.653,87.065]	73.795 (11.970) 74.272 [65.054,82.639]	76.324 (11.839) 77.825 [67.702,87.065]
Extreme	56.339 (15.582) 51.748 [45.083,59.681]	59.180 (18.368) 50.839 [44.728,80.830]	59.154 (15.891) 54.169 [47.865,63.201]	60.109 (16.973) 54.156 [47.380,72.537]	60.893 (16.101) 54.900 [49.548,68.117]	65.960 (16.796) 59.257 [52.635,85.283]	66.436 (13.970) 62.919 [55.218,75.987]	74.384 (10.636) 72.602 [66.570,80.830]
Heat wave	51.036 (11.292) 48.353 [43.814,54.285]	56.538 (17.498) 49.083 [43.940,63.288]	53.715 (13.064) 50.536 [45.178,56.557]	57.041 (15.988) 51.473 [45.716,60.084]	55.690 (13.866) 51.716 [47.454,57.353]	62.042 (15.864) 56.251 [50.983,69.350]	61.329 (13.329) 57.381 [52.573,64.684]	73.110 (9.182) 71.531 [66.504,80.259]

	June	July	August	September
Maximum trigger temperature	34.742 (1.168) 34.754 [34.183,35.500]	36.012 (1.199) 36.067 [35.428,36.686]	36.591 (1.099) 36.605 [36.029,37.299]	32.646 (1.002) 32.698 [32.193,33.202]



	Observed		Excess deaths attributed to extreme heat	
Number of deaths	**No COVID**	**COVID-19**	**MoMo model**	**Our model**
2022				
June	4366	358	688	1854
July	5190	873	708	2779
August	4532	230	813	2241
September	4447	96	641	2284
Jun-Sep	**18535**	**1557**	**2850**	**9158**
Medians				
2015-2019				
June	3235		334	577
July	3214		359	652
August	3375		263	651
September	3417		298	681
Jun-Sep	**13241**		**1254**	**2561**
2020-2021				
June	3615	144	28	181
July	3841	224	43	274
August	4389	657	43	302
September	4004	309	17	303
Jun-Sep	**16248**	**267**	**131**	**1060**



Conclusions

- We estimate that, during the summer months of 2022, the excess mortality attributed to extreme heat was 49.41% (15.37% in MoMo). This excess was 4 times greater than that attributed to extreme heat in the summers from 2015 to 2019.

- Not only heat waves but also temperature extremes increased the risk of dying (in both cases risk around 14%).
- The effect of the heat wave on mortality occurred earlier (3 days) than at the temperature extreme (7 days).
- The risk of dying in subjects aged 65 years or older was almost double that of other subjects.
- The risk of dying on a day with extreme maximum temperature or a heat wave practically doubled:
  - If it was a day with high relative humidity.
  - If the minimum temperature was also extreme (heat wave only)
  - In those ABS located in the second income quartile.
- The risk of dying on a day with extreme maximum temperature or a heat wave tripled in those ABS located in the first quartile

References

1.- MoMo, ISCIII. MoMo. Monitorización de la mortalidad diaria por todas las causas y atribuible a temperatura. Situación a 30 de agosto de 2022 [in Spanish] [Available at: https://www.isciii.es/QueHacemos/Servicios/VigilanciaSaludPublicaRENAVE/EnfermedadesTransmisibles/MoMo/Documents/InformesMoMo2022/MoMo_Situación%20a%2030%20de%20agosto%20de%202022_CNE.pdf, last accessed on June 27, 2024].
2.- Greene WH. *Econometric Analysis, 8th Edition*. Boston, London: Pearson, 2018, Chapter 5.
3.- Elliott P, Savitz DA. Design issues in small-area studies of environment and health. *Environ Health Perspect* 2008; 116(8):1098-1104. doi: 10.1289/ehp.10817.
4.- Wannemuehler K, Lyles R, Waller L, Hoekstra R, Klein M, Tolbert P. A conditional expectation approach for associating ambient air pollutant exposures with health outcomes. *Environmetrics* 2009; 20(7),877–894.
5.- Saez M, Barceló MA. Spatial prediction of air pollution levels using a hierarchical Bayesian spatiotemporal model in Catalonia, Spain. *Environmental Modelling & Software 2022;* 151:105369. doi: 10.1016/j.envsoft.2022.105369.
6.- Rue H, Martino S, Chopin N. Approximate Bayesian inference for latent Gaussian models using integrated nested Laplace approximations (with discussion). *J R Stat Soc Series B Stat Methodol*. 2009; 71:319-392. doi:j.1467-9868.2008.00700.x.
7.- Rue H, Riebler A, Sørbye H, Illian JB, Simpson DP, Lindgren FK. 2017. Bayesian computing with INLA: A review. *Annual Reviews of Statistics and its Applications*, 4(March), 395-421. doi: annurev-statistics-060116-054045.
8.- Simpson DP, Rue H, Martins TG, Riebler A, Sørbye SH. Penalising model component complexity: A principled, practical approach to constructing priors (with discussion). *Statistical Science* 2017; 32(1):1-46. doi: 10.1214/16-STS576.