Extended Abstract Submission: IPC 2025
Weighting Game: Comparing Different Population-Weighted Climate Exposure Methods

Introduction and Motivation

Climate change significantly influences the intensity and variability of environmental exposures (Thornton et al., 2014), with climate extremes expected to continue to occur, increasing in frequency and intensity (Fischer et al., 2021). Extreme temperatures, both hot and cold, have had a demonstrated impact on excess deaths (Alahmad et al., 2020; Clemens et al., 2021), and the study of excess deaths due to climate and other environmental factors has been gaining more attention in demography in recent years. In order to measure a particular population's exposure to extreme temperatures, fine-grained estimates from remote sensed land surface temperature are often used (Thomas et al., 2021). As the temperature estimates are often at a finer scale than available population or deaths data, the climate raster surface must be aggregated to the same spatial resolution as the demographic outcome of interest. Simply averaging raster cells within a spatial unit ignores the spatial heterogeneity of population density, and as such population weighted estimates of temperature within a spatial unit are often used (Weinberger et al., 2019).

While using population-weighted estimates is common, there has been minimal work investigating the method of how weighting should be carried out. For example, as older adults are often the most vulnerable to heat exposure, it may sense to weight based on the proportion of the population over 65, rather than purely population density. Aggregate environmental exposure estimates, such as temperature, present a unique issue because populations are not distributed uniformly across space (i.e., urban vs rural) and population level exposure estimates may not adequately capture the spatial variation that occurs within a spatial unit. While other papers have compared raster vs point and their subsequent performance as exposure estimates, there is significantly less research on extreme temperature measures, their subsequent aggregation methods, and the impact that may have on excess mortality estimates.

The aim of this project is to compare several aggregation methods of temperature measures, weighted with different population estimates. The aggregation methods will be assessed based on annual and regional patterns, and the sensitivity of excess death models to the differing temperature measures will also be assessed. Preliminary work uses France as a case study as it is topographically varied; future work will focus on simulation studies.

Data

Spatial Data

NUTS3 spatial data (shapefiles) were collected from Eurostat. NUTS3 are the smallest spatial unit of which weekly death data and census population data are available. The average land area of a NUTS3 spatial unit is 6,322 km^2 (min: 105 km^2, max: 83,751 km^2) and an average population size of 663 people (min: 76, max: 2,598) (European Commission. Statistical Office of the European Union., 2022).

Temperature

The E-OBS Daily Gridded temperature data was collected for France was collected from the Copernicus Climate Data Store (Copernicus Climate Change Service, 2020). The data was collected from the ensemble mean product type, variables mean temperature, maximum temperature, and minimum temperature were obtained at the 0.1° grid resolution. The time of the data collected was 2014-2023. The version selected was 29.0e; which was the most recent version when the final analytic set was developed, in August 2024. Temperature measures represent air temperature in degrees Celsius measured around 2 meters above the surface. (Copernicus Climate Change Service, 2020).

Population

Population data were collected in two formats, raster and census based. Census population estimates by age and NUTS3 region were collected from the demographic data on Eurostat's webpage. In addition to collection of population data for the time period of interest (Eurostat, 2024b), a standard population (2001) was collected for creating age standardized death estimates (Eurostat, 2015). Annual population raster data were collected from the WorldPop website, a site that hosts international demographic data, based at University of Southhampton. Gridded population data (100m raster format) were collected for total pop and age and sex groupings. The data were collected in the unconstrained format, meaning the estimates are derived from the top down. Assuming that infrastructure datasets are never completely accurate, the infrastructure data is used to estimate areas in which there are no inhabitants only (Reed et al., 2018). The age data were grouped into four tiles for men and four for women The gridded population data were available for the years 2014-2020 (WorldPop, 2018b, 2018a), therefore, years 21-23 are weighted using 2020 grids.

Deaths

Death count data by age and NUTS3 region were collected from Eurostat at the weekly temporal resolution (Eurostat, 2024a). The earliest death data for France is from 2014, therefore, this analysis is limited to 2014.

Methods

Temperature measurements were processed first at the daily temporal unit. NUTS3 polygon files were first reprojected into the geographic coordinate system of the temperature raster data. Each temperature (for each measure: minimum, maximum, average) raster, for each day was estimated at the NUTS3 level. We considered four different aggregation methods, described below. For weighted measurements, the population raster data were projected to the spatial reference of the temperature data. The population data were then resampled to align with the temperature grids, so that weighting could be conducted (Hijmans, 2023). All aggregations were conducted using the R Package ExactExtractr (Daniel Baston, 2019). After weighting was conducted for each day and year within the period of interest, temperature measures were averaged across week and year to align with deaths.

Simple Average

A simple average was calculated across all raster cells within a NUTS3 region were averaged, to form a temperature exposure estimate for the NUTS3 region. This simple average estimate was used without any weighting schema as a comparator.

Weighted Average

The weighted average measure was calculated by multiplying a resampled population raster for a given year and area by a temperature raster for a given day, area, and year. The weighted tiles are then divided by the sum of the population counts used for weighting rasters in each NUTS3 region. Specifically, the calculation is:

$$W_{dy,a} = \frac{\sum_{dy,a}^{n} w_{y,a} \cdot X_{dy,a}}{\sum_{y,a}^{n} w_{y,a}}$$

Where: $W_{dy,a} = the\ weighted\ average\ of\ a\ given\ area\ on\ a\ given\ day\ and\ year$

$w_{y,a} = the\ weight\ (population\ count)\ for\ a\ given\ area\ and\ a\ given\ year$

$X_{dy,a} = the\ temperature\ raster\ surface\ for\ a\ given\ area\ on\ a\ given\ day\ and\ year$

a = *area (NUTS3 Region)*

n = the number of NUTS3 regions in France for a given year

The result is a population weighted average temperature measure for one NUTS3 region on one day and one year. The process of weighted averaging for rasters is illustrated in Fig 1. This weighting process was repeated for each of the three temperature measures (minimum, maximum, average)

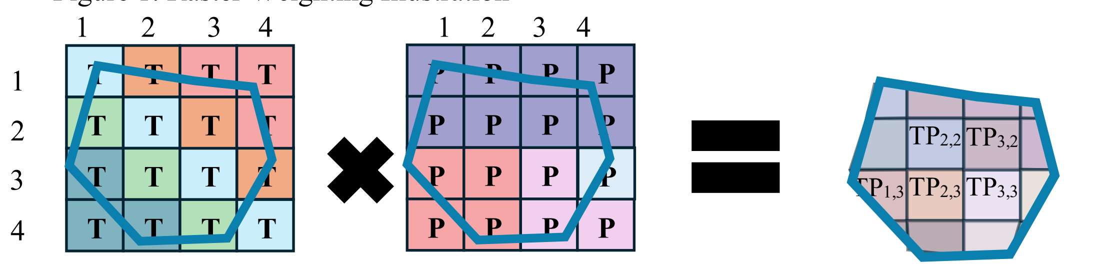
Log Weighted Average

Log weighted average was calculated similarly to weighted average, however the raster used represented the log of the population raster for each year, which was then resampled and used as the weighting raster.

65+ Weighted Average

Aged 65+ weighted average was derived by summing the population rasters over 65 for males and females (rasters 65-70, 70-75, 75-80 and 80+ for each sex) each year, providing an estimate of total population over 65 in a raster grid. The data were then resampled and used as the weighting raster.

Figure 1: Raster Weighting Illustration



Temperature Raster Population Raster Population Weighted Raster

Standardized deaths

Death data were age standardized using the corresponding year's census data and the 2001 standard population. Age standardized mortality counts were first divided by their respective census year's population and multiplied by 100,000, for a resultant crude estimate of deaths per 100,000 people. The crude rates were then multiplied by the age grouping population proportions of the standard 2001 population.

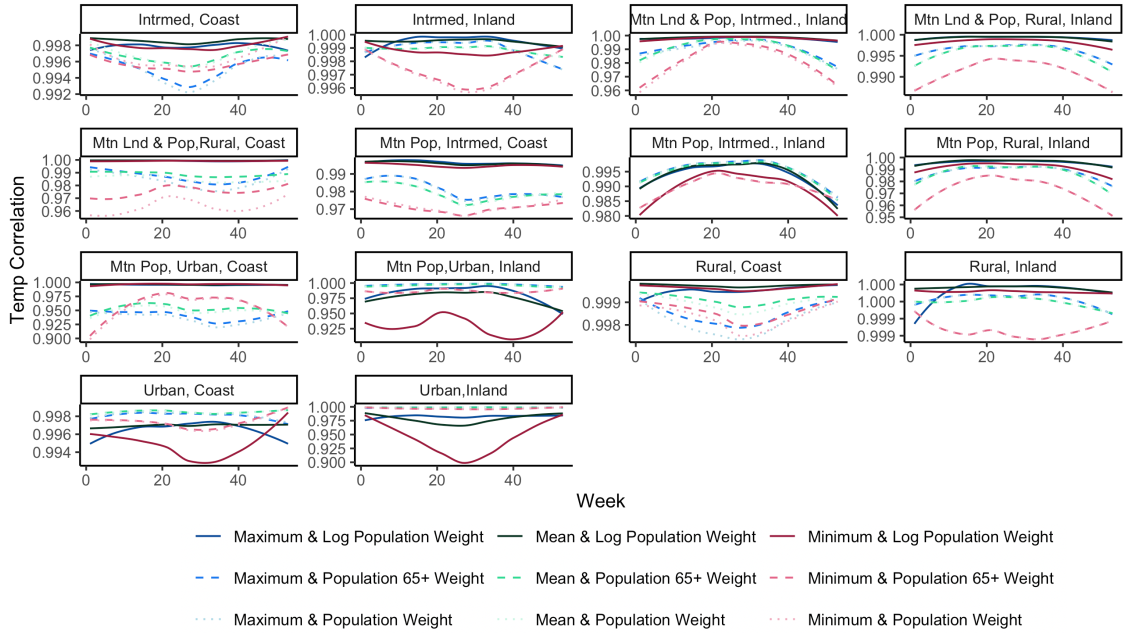
Excess deaths estimation

Linear regression models with log of standardized death and fixed time (year, week, location) effects were run. Further analysis on lag effects will be conducted in the future. Demeaned death rates were calculated by demeaning the death rates with the fixed effects models.

Preliminary Results

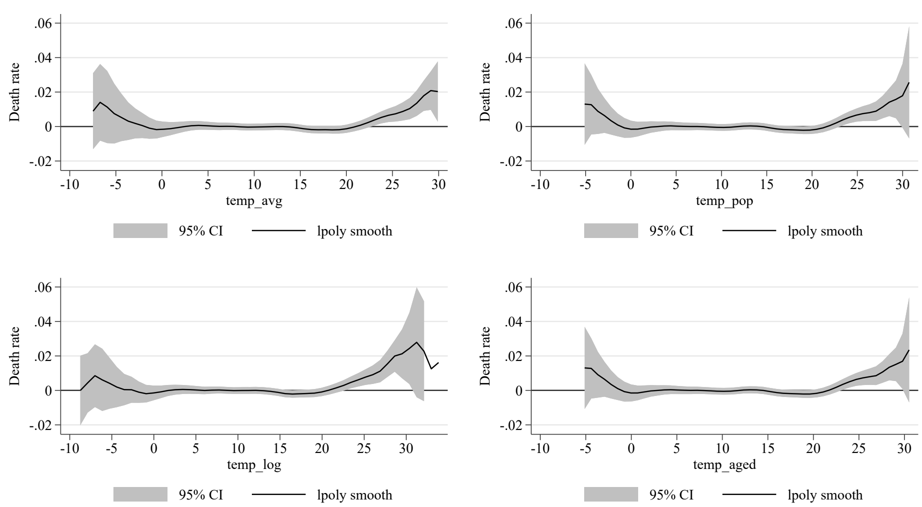
The median weekly correlation between various weighted means measure with the simple mean varies in seasons with more extreme cold temperatures, documented in Figure 3. The correlation time series in mountainous areas has an inverse 'U' shape, indicating that cold weather brings increasing variability in temperature exposure measurements. The shape becomes a 'U' for regions where with more warm temperatures (e.g., non-mountainous, intermediate) Further, variability appears to differ by types of land use, and diverse terrain (i.e. towns near mountain regions).

Figure 2: Weekly Temperature Weighting Schemes' Correlation with Simple Average for Each Measure in Each Land Type



Preliminary demeaned graphs (fig 4) indicate that in general model results do not change with population weighting methods, however, minor differences are apparent in each weighting method demeaned graph, particularly for the model using the log of the population raster for weighting schema.

Figure 4: Demeaned Model



Future Work

Future work will include simulations, as stronger models may have differing sensitivity as compared to the standard models used in this analysis. In addition, the inclusion of larger areas (e.g., North America) or countries which have proven to be especially sensitive to climate change (e.g., Australia) could impact these results. Finally, more finely spatially resolved death data may respond differently to the nuances in population weighting; this should be explored when considering the implications of population weighting.

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