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RESEARCH ARTICLE
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Key Points:

- Heat-related mortality peaks can be successfully predicted up to 2 weeks ahead by subseasonal forecasts
- Multi-week periods of heat-related mortality can be anticipated 3–4 weeks ahead

Supporting Information:

Supporting Information may be found in the online version of this article.

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Subseasonal Prediction of Heat-Related Mortality in Switzerland

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Abstract Heatwaves pose a range of severe impacts on human health, including an increase in premature mortality. The summers of 2018 and 2022 are two examples with record-breaking temperatures leading to thousands of heat-related excess deaths in Europe. Some of the extreme temperatures experienced during these summers were predictable several weeks in advance by subseasonal forecasts. Subseasonal forecasts provide weather predictions from 2 weeks to 2 months ahead, offering advance planning capabilities. Nevertheless, there is only limited assessment of the potential for heat-health warning systems at a regional level on subseasonal timescales. Here we combine methods of climate epidemiology and subseasonal forecasts to retrospectively predict the 2018 and 2022 heat-related mortality for the cantons of Zurich and Geneva in Switzerland. The temperature-mortality association for these cantons is estimated using observed daily temperature and mortality during summers between 1990 and 2017. The temperature-mortality association is subsequently combined with bias-corrected subseasonal forecasts at a spatial resolution of 2-km to predict the daily heat-related mortality counts of 2018 and 2022. The mortality predictions are compared against the daily heat-related mortality estimated based on observed temperature during these two summers. Heat-related mortality peaks occurring for a few days can be accurately predicted up to 2 weeks ahead, while longer periods of heat-related mortality lasting a few weeks can be anticipated 3 to even 4 weeks ahead. Our findings demonstrate that subseasonal forecasts are a valuable—but yet untapped—tool for potentially issuing warnings for the excess health burden observed during central European summers.

Plain Language Summary Heatwaves can have serious impacts on human health, often leading to a rise in premature deaths. The summers of 2018 and 2022 in Europe were particularly extreme, with record-high temperatures causing thousands of heat-related deaths. Some of these extreme heat events were predictable weeks in advance by subseasonal forecasts, which provide weather predictions from 2 weeks to 2 months ahead. However, there has been limited research on how these forecasts could be used to create early warning systems for heat-related health risks at a regional level. We explore whether subseasonal forecasts could be used to predict heat-related deaths in two regions of Switzerland. First, we establish the relationship between daily temperatures and deaths in these regions during the summers from 1990 to 2017. We use this information to predict heat-related deaths during the summers of 2018 and 2022, based on subseasonal forecasts. We find that it is possible to predict spikes of a few days in heat-related deaths up to 2 weeks ahead, and longer periods of a few weeks of high heat-related deaths up to 3 or even 4 weeks ahead. Our results show that subseasonal forecasts could be a valuable tool for issuing warnings and reducing the health impacts of future heatwaves in Europe.

1. Introduction

Heat is an established health risk factor, increasing the mortality of human populations around the world (Robine et al., 2008; Zhao et al., 2021). In 2015, heat was responsible for 4 of the 10 deadliest natural disasters worldwide (Guha-Sapir et al., 2017; United Nations Office for Disaster Risk Reduction, 2016). Europe emerges after Asia as the continent with the second highest annual excess mortality due to heat in the period 2000–2019 (Zhao et al., 2021). As an especially responsive area to temperature rise under climate change (Ballester et al., 2023; Giorgi, 2006), Europe's heat-related mortality is projected to increase in the coming decades (Lüthi et al., 2023). Several European countries have adopted measures and protocols to mitigate heatwave impacts (Casanueva

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et al., 2019a). France implemented a national heatwave plan and achieved a 70% reduction in mortality rates during the 2006 heatwave episode compared to expected levels (Fouillet et al., 2008). Despite the measures implemented by some European countries, the summer of 2022, the hottest season on record in Europe to date (Copernicus Climate Change Service, 2023), caused over 60,000 excess deaths (Ballester et al., 2023). Under climate change, such summers will become average instead of extreme in the coming decades (Arias et al., 2021).

Without effective adaptation strategies and the increasing age of the population, health impacts will likely be exacerbated beyond current levels (Vicedo-Cabrera et al., 2023). Health impacts can be mitigated with proactive decision-making before heatwaves, such as safeguarding susceptible groups like children and the elderly, and guaranteeing access to preventive measures well ahead of time (Åström et al., 2012; Butler, 2016). The effectiveness of heat-health action plans relies on the implementation of a timely alert system, the preparedness of the health care system, and long-term urban planning (Lowe et al., 2016). While long-term urban planning has to be implemented on timescales of a few years to decades, the health system preparedness and alert systems would benefit from early warning systems aimed at timescales covering a few days to several weeks.

Indeed, the forecasts of subseasonal weather prediction systems can provide critical information for public health management and planning for weather-related exposure, including temperature, precipitation, and wind extremes (Anderson et al., 2019; Mariotti et al., 2018; White et al., 2022). However, only a limited number of countries have developed heat-health action plans that incorporate subseasonal forecasts (Bittner et al., 2014; Smith et al., 2014), and a global system is entirely lacking (Brimicombe et al., 2024). One explanation for the limited integration of such forecasts could be the insufficient evaluation of their predictive capabilities when coupled with exposure risk models. Despite this limitation, there is reported potential for subseasonal predictions of heat-related mortality at a national level 1 week ahead, including real-time applications, even when the risk models are coupled to the unprocessed output of forecasts (Lowe et al., 2016; Mistry & Gasparrini, 2024). The potential for subseasonal predictions of heat-related mortality might be even higher if risk models are coupled to subseasonal forecasts that are previously corrected for systematic biases.

To the best of our knowledge, no studies have combined bias-corrected subseasonal forecasts with temperature-mortality risk functions to deliver multi-weekly predictions of heat-related mortality. Showing time series of such predictions offers policymakers and health authorities critical insights into the potential impact of prolonged heat events and provides a first assessment of the accuracy of subseasonal heat-health warning systems. Europe's diverse landscape and population distribution underscore the importance to incorporate subseasonal forecasts with a high spatial resolution and after being corrected for known systematic errors (Jung, 2005; Magnusson & Källén, 2013). The positive effect of forecast bias correction and downscaling (Monhart et al., 2018), the continuous improvement of subseasonal forecast skill (Vitart, 2014), and the new methods developed toward a further increase of subseasonal prediction skill (Baker et al., 2023), including machine learning - based models (Weirich-Benet et al., 2023), are anticipated to result in enhanced potential for subseasonal forecasting of heat-related risks.

To provide quantitative evidence on the capacity of existing subseasonal forecasting systems to predict operationally the occurrence of mortality due to heat, we analyze the subseasonal prediction of heat-related mortality in two Swiss cantons using the output of bias corrected subseasonal weather forecasts downscaled to a spatial resolution of 2-km. The bias corrected subseasonal forecasts are used operationally by MeteoSwiss, Switzerland's national weather service, and are based on the extended range forecasts from the European Center for Medium Range Weather Forecasts (ECMWF). The downscaled forecasts provided by MeteoSwiss can successfully detect heat stress conditions up to 3 weeks in advance and show a similar temperature prediction skill over the different regions of Switzerland (Technical Report MeteoSwiss No. 281, 2022).

Switzerland experiences the highest annual fraction of deaths attributable to heat compared to other western European countries (Masselot et al., 2023; Ragettli et al., 2017). Among all summers between 1864 and 2022, 2018 and 2022 ranked as the hottest and third hottest summers in Swiss cities, respectively (Domeisen et al., 2023). Focusing solely on the summer seasons of the past decade, 2018 and 2022 stand out as the top two hottest years in Swiss cities. The high temperatures during these summers had significant impacts on mortality rates: In 2018, there was a 1.2% increase in mortality due to the heat (Bundesamt für Umwelt BAFU et al., 2019), while in 2022, heat-related deaths accounted for 3.5% of all-cause deaths (Vicedo-Cabrera et al., 2023). We use the summers of 2018 and 2022 as case studies to demonstrate the potential of subseasonal forecasting systems to anticipate increases in mortality caused by heat. Specifically, our analysis compares estimates of heat-related

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deaths using forecasts of temperature in two representative Swiss cantons of the Swiss Central Plateau with estimates based on observed temperatures. The Swiss cantons selected for this study are the cantons of Zurich and Geneva, located in the northern and western parts of the Swiss Central Plateau, the most densely populated part of Switzerland.

2. Data and Methods

We use daily observational temperature data, observed all-cause mortality data, and subseasonal forecast data. In a first step, we estimate the statistical heat-mortality relationship based on daily observed temperature and all-cause mortality with the help of advanced time-series regression modeling techniques of environmental epidemiology. In a second step, we combine this heat-mortality relationship with subseasonal temperature forecast data to predict heat-related mortality. A detailed description of these steps follows below.

2.1. Observed and Forecast Data

2.1.1. Observed Temperature and Mortality

Daily observed data of all-cause mortality counts are obtained for each municipality in Switzerland between 1990 and 2017, and for each canton between 2018 and 2022 from the Federal Statistical Office (BFS), as nowadays there is no municipality mortality data after 2019. For the same study period we acquire observed daily mean temperature data on a regular 2-km grid from MeteoSwiss (TabsD data set; MeteoSwiss, 2021) incorporating approximately 90 homogeneous long-term station series. The TabsD observed daily mean temperature data of 2018 and 2022 constitute the observed temperatures of the summers investigated, while the TabsD data of 1990–2017 are used for the derivation of the daily climatological temperature distribution. Prior to using the TabsD data set along with modeling techniques of environmental epidemiology we apply population-weighting on the daily mean temperature time series covering 1990–2017, using the population data of 2010 from EOSDIS gridded population, validated and used in previous studies (de Schrijver et al., 2021, 2022). The population weighted temperature data provides a closer approximation for the mean temperature that the underlying population was exposed to in reality, as opposed to the mean temperature over the whole grid (Gasparrini et al., 2015; de Schrijver et al., 2021). This is especially relevant for Switzerland as the temperatures over populated areas and non-populated areas can vary substantially even within small areas, owing to the geographical features (de Schrijver et al., 2022).

2.1.2. Subseasonal Forecast Temperature

The operational subseasonal ensemble forecast data of daily mean temperatures of 2018 and 2022 were produced by the European Center for Medium-Range Weather Forecasts (ECMWF) on a 36-km horizontal grid. The forecasting system of 2018 was using the IFS Cycle 45r1, which since then was updated four times until the IFS Cycle 47r3 that was used to produce the 2022 forecasts (Haiden et al., 2018, 2021). ECMWF's 2018 and 2022 daily mean temperature forecasts were downscaled by MeteoSwiss to a 2-km grid using the quantile mapping method and the aforementioned TabsD data set (Monhart et al., 2018), and are here used as our forecasted temperatures for the investigated summers. The 2018 and 2022 forecasts are initialized (i.e., started with the best observational estimates) twice per week (on Monday and on Thursday) and comprise ensembles (i.e., groups) of individual forecasts up to 46 days (50 ensemble members and 1 control run). Due to the initialization only twice a week, there is the opportunity to sample the forecasted temperature for each calendar date from the model forecast that was initialized in the first half or in the second half of each lead week. A lead week or forecast week corresponds to the time that a forecast is issued. For example, forecasts issued 1 week ahead correspond to forecasts of lead week 1. For each day of the two investigated summers, we select the corresponding forecast that starts approximately 1 week before (referred to as "lead week 1 forecast"), 2 weeks before ("lead week 2 forecast"), and up to 6 weeks before ("lead week 6 forecast"). Since in the prediction system used here there are always two forecasts started each week, namely on Mondays and Thursdays, we always select the forecasts initialized on Thursdays, which is why the lead week is only approximate (Figure S5 in Supporting Information S1 for schematic illustration). Selecting the earlier of the two, however, has shown to not influence any of the key results of this study.

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2.2. Ensemble Forecasts and Estimation of Forecast Uncertainty

2.2.1. Ensemble Forecasts

An ensemble or group of weather forecasts, with each ensemble member initialized from slightly different initial conditions (or forecast initializations) and encompassing model uncertainties (Buizza et al., 2005), is a set of forecasts that presents the range of future weather possibilities. Case-to-case variations in the behavior of the ensemble members (e.g., the spread among the ensemble members) provide an indication of variations in forecast uncertainty (e.g., expected forecast error), with small spread indicating low forecast uncertainty and thus high probability for low forecast error (Toth et al., 2007). Ensemble forecasts exhibit greater skill at forecasting meteorological phenomena than deterministic forecasting models (Buizza et al., 1999; Lalaurette et al., 2003) and are valuable for optimizing the prediction of impact related risks (Altalo & Smith, 2004; Taylor & Buizza, 2003).

The reliability of ensemble forecasts is commonly quantitatively assessed by looking at diagnostics that relate the ensemble spread to the ensemble mean error, using a reference ground truth for the estimation of error, for example, past observations (Christensen et al., 2015; Leutbecher & Palmer, 2008). ECMWF is routinely verifying the so called *spread reliability*, which measures the ability of the ensemble forecasts to predict the error of the ensemble mean (https://charts.ecmwf.int/products/plwww_3m_ens_tigge_spreldiag?area=Northern%20Extra-tropics). In other words, one can use the spread of the forecast to predict how likely is that the forecast will be accurate, which is one of the main points of having ensemble forecast systems. Otherwise, forecast centers would rely on the climatological spread for each location and calendar day, which represents the uncertainty derived from the climatological distribution based on historical observations, typically spanning at least 20 years. In fact, the climatological spread is used by ECMWF as benchmark to assess the added value of the ensemble forecast system (see Figure 15 in (Haiden et al., 2023)).

2.2.2. Forecast-To-Climatological Spread Ratio (FCSR)

We here use a similar concept and define the forecast-to-climatological spread ratio (FCSR) of the subseasonal temperature forecasts to identify how certain the forecasts are compared to the benchmark of climatology. The FCSR puts the uncertainty of the ensemble temperature forecast at each forecast time (e.g., uncertainty of forecast for 21-June-2018) in context to the usually expected temperature uncertainty (climatological uncertainty) at the given location and day of the year (e.g., uncertainty expected for the 21-June by the climatological temperature distribution). The FSCR can be calculated in an operational setting, being defined as the division of the forecast spread by the climatological spread for each calendar date and lead time. The forecast spread is estimated for each lead time and calendar date by computing the standard deviation of the forecast's ensemble members relative to the forecast's ensemble mean. The climatological spread is estimated by computing the standard deviation for each calendar date considering the years of the climatological distribution (1990–2017). The lower the FCSR is, the more likely is the forecast to be accurate. As explained above, the FCSR method is not intended to evaluate forecast skill, but to predict the likelihood of the prediction to have high or low skill.

Our study focuses on coupling subseasonal ensemble forecasts to heat-health impact models in an operational setting, aiming for mortality forecasts to be used in real time for the reduction of heat-health related impacts. As explained bellow in Section 2.3, the mortality predictions based on temperature ensemble forecasts incorporate both the uncertainty of the weather forecasts as well as the uncertainty of the estimated heat-mortality relationship. However, due to reasons discussed later in the result section, there are unrealistically good estimates of the accumulated mortality predictions over the course of a full season at long forecast times (i.e., forecasts longer than a week). Therefore, we show how indices such as the FCSR, that incorporate the uncertainty information of weather ensemble forecasts and the uncertainty information of our recent past climate, can be used in order to provide more realistic accumulated mortality predictions at long forecast times. This does not mean that using the FCSR the provided mortality estimates have lower errors compared to the ground truth, but that the FCSR can help to implement more realistic estimates of subseasonally accumulated impact forecasts. To assess the sensitivity of the accumulated mortality predictions, we are using FCSR values lower than 0.5, 0.8, and 1. The thresholds are chosen to range from a forecast spread lower than half of the spread indicated by climatology to a forecast spread almost equal, but still lower, than the climatological one.

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2.3. Quantification of Heat-Related Mortality in 2018 and 2022 Summers

2.3.1. Estimation of Heat-Mortality Relationships

The epidemiological analysis to assess the relationship between heat and mortality in each canton is based on a two-stage time-series regression analysis which is commonly used in multi-location time-series studies (de Schrijver et al., 2022; Vicedo-Cabrera et al., 2021). First, we perform a small-area study with separate case-time series analysis for each of the 26 Swiss cantons applying a conditional quasi-Poisson regression (Gasparrini, 2022). This analysis combines the population-weighted daily mean temperature time series and the observed daily counts of all-cause mortality data by municipality in Switzerland between 1990 and 2017 (de Schrijver et al., 2022). We model the temperature-mortality relationship for each canton using distributed-lag non-linear models to account for both delayed and non-linear dependencies, typically found in temperature-mortality assessments (Gasparrini, 2014). Since we are interested in heat only, we restrict the analysis to the summer months (June–August). We model the mortality-temperature association with a natural spline and knots in the 50th and 90th percentile of the location-specific summer temperature distribution, and 10 days of lag with a natural spline and two internal knots equally spaced in the log scale, as done in previous research (Vicedo-Cabrera et al., 2021).

In a second stage, we derive for each canton the improved predictions of the exposure-response association (i.e., Best Linear Unbiased Predictions, BLUPs) from a meta-analytical model using the information from all the temperature-mortality curves from the 26 Swiss cantons (Sera et al., 2019). BLUPs borrow information across units within the same hierarchical level and can offer more accurate estimates, especially in locations with small daily mortality counts or short series. Thus, we leverage the information from the other cantons to produce more accurate and stable exposure-response curves for the two cantons of interest (De Schrijver et al., 2023; Vicedo-Cabrera et al., 2021). The meta-analytical model uses a multivariate random effect meta-regression with average and range temperature by canton as fixed effects and a region indicator as random effects. The BLUPs represent the cumulative relative risk of death due to temperature over a 10-day lag period for each temperature value in the observed range, as prior research has demonstrated that heat risks tend to occur quickly after exposure and then disappear within 10 days (Gasparrini et al., 2016). The BLUPs are expressed as the relative risk at a given temperature, using as reference the temperature with minimum mortality risk between the 25th and 90th percentile of the exposure-response association (i.e., so-called minimum mortality temperature, MMT).

2.3.2. Heat-Related Mortality of the 2018 and 2022 Summers

To quantify the heat-related mortality for the summers of 2018 and 2022, the epidemiological analysis needs to be combined with the temperature data of these two summers. For each canton (Zurich or Geneva) we use the canton specific relative risk (RR) function defined by the BLUPs and couple it with the daily summer specific temperature following (Gasparrini & Leone, 2014). The observed heat-related mortality (ground truth) is estimated by coupling the canton specific RR to the observed summer specific temperature (TabsD data for 2018 or 2022). The climatological mortality, that is the mortality expected for that day based on the climatological daily temperature, is derived by coupling the RR to the climatological daily temperature (TabsD data daily mean for 1990–2017). The predicted mortality is derived by coupling the RR to the forecast temperature of the investigated summer (i.e., the downscaled subseasonal forecasts for 2018 or 2022).

Thus, in each day between June and August 2018 and 2022, we calculate the temperature-related mortality fraction and number using the mortality risk on that day given either the observed, climatological, or forecasted temperature, and the moving average of the observed mortality across 10 days of lag to account for the delayed effect (i.e., assuming the forward perspective (Gasparrini, 2014)). We assume that deaths due to heat were those temperature-related deaths during days with mean temperature (observed, climatological, or forecasted) above the MMT. The calculations of the attributable fraction (AF) and attributable number (AN) of deaths for the exposure x in a given day t (i.e., hot temperatures) follow Equations 1a and 1b, respectively:

$$AF_{x,t} = 1 - \exp(-\beta x_t), \tag{1a}$$

$$AN_{x,t} = n_t \cdot AF_{x,t}, \tag{1b}$$

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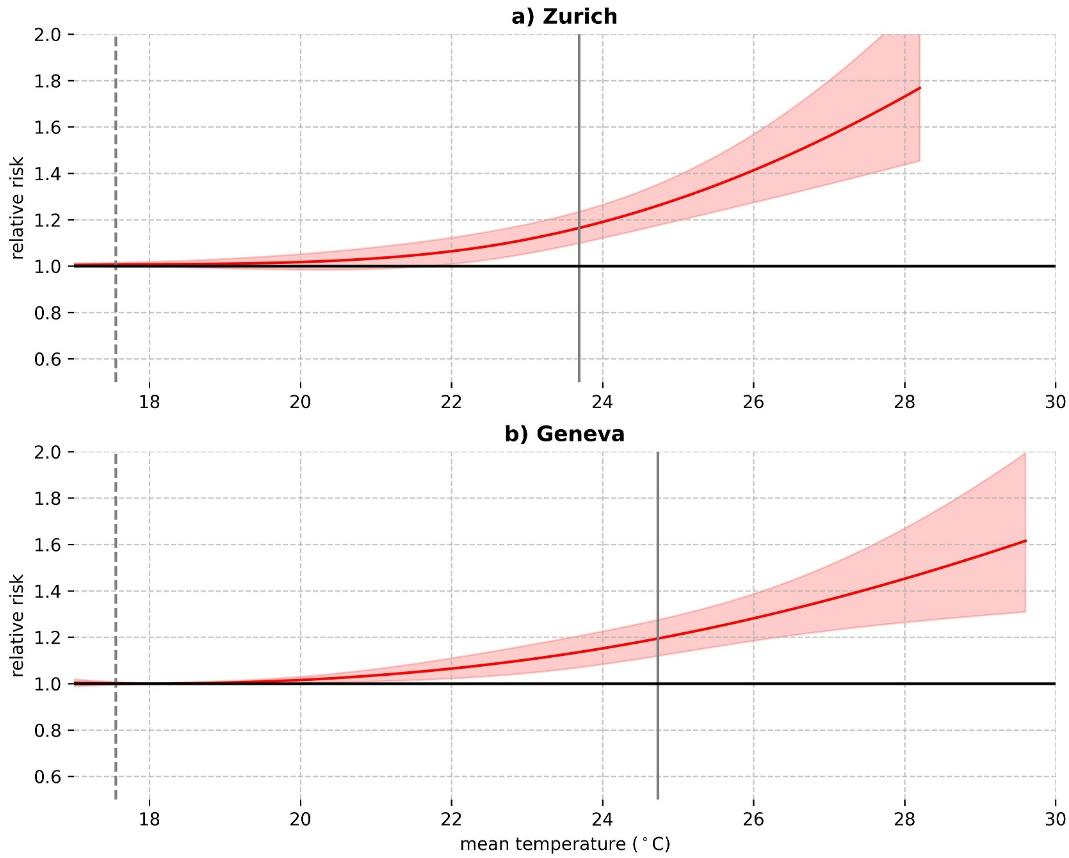

Figure 1. Heat-mortality relationship estimated as best linear unbiased predictions (BLUPs; Methods) and reported as relative risk (with 95% confidence interval, shaded red) for a cumulative 10-day lag of summer temperature versus the optimum temperature MMT (temperature of minimum mortality). The results are plotted along the observed temperature range above MMT. The vertical gray dashed and solid lines indicate the MMT and 95th percentile of location-specific summer temperature, respectively.

with n_t as the total number of cases represented as the moving average of the total number of deaths in that day t and the following 10 days. The parameter βx used in Equation 1a represents the risk associated with the exposure, and it corresponds to the logarithm of the relative risk (see for example Figure 1). The heat-related mortality fraction over the summer was computed as the sum across all daily AN (i.e., number of heat-related deaths) divided by total mortality (n_t) for that summer.

The deaths reported in mortality registries as "heat-related deaths" are a clear underestimation of the impacts, because (a) doctors tend to register deaths (by assigning a code—ICD10 code) based on the diagnosis (e.g., myocardial infarction) and not the cause (e.g., heat), and (b) reported heat-stroke deaths are usually found in populations without co-morbidities (i.e., healthy people), mainly of working age. These are the reasons why heat-related deaths must be estimated from statistical models.

Finally, we derive the 95% empirical confidence intervals (95% eCI) using Monte Carlo simulations of the coefficients defining the cumulative exposure-response function assuming a multivariate normal distribution. For the forecasted series, we derived the ensemble mean number of heat-related deaths by day and the 95% eCI using the overall empirical distribution across all model ensemble members – thus accounting for both the uncertainty of the exposure-response curve and the uncertainty of the meteorological forecast.

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3. Results and Discussion

3.1. Heat and Mortality Relationship

The heat-mortality relationship between temperature and mortality for Zurich and Geneva is expressed as relative risk and can be interpreted as the change in mortality risk at a specific temperature against an optimum temperature, the so-called *temperature of minimum mortality (MMT)* (Gasparrini et al., 2015; Vicedo-Cabrera et al., 2021). The heat-mortality relationship is presented in Figure 1 for the cantons of Zurich and Geneva between the summers of 1990 and 2017 for temperature values above the MMT (17.6°C). The mortality risk quickly increases to more than 10% (relative risk = 1.1) in both cantons for temperatures lower than the 95th percentile (gray solid vertical line in Figure 1), which is a commonly used percentile to define heatwaves (Fischer & Schär, 2010; Hoy et al., 2017). For temperatures above the 95th percentile the uncertainty in the mortality risk almost doubles due to the small sample size of these extreme temperature values. The heat-mortality relationship is expected to vary among the different cantons due to the different population characteristics (e.g., socio-economic and demographic characteristics) (Gasparrini et al., 2015; de Schrijver et al., 2021, 2022). Other possible explanations for heterogeneity in vulnerability between regions include differences in greenness, level of urbanization, and adaptation owing to climatological and topographical differences (Chen et al., 2016; Gasparrini et al., 2022; Murage et al., 2020; Pascal et al., 2021).

3.2. Subseasonal Prediction of Temperature

In the summers of 2018 and 2022, Zurich (Figure 2) and Geneva (Figure 3) experienced prolonged periods of daily mean temperature (solid black curves) higher than the 1990–2017 climatologically expected mean values (dashed black curves). In particular, 77% of the days during the 2018 summer exceeded the climatological 50th percentile, being hotter than average, in both cantons. In 2022 hotter than average days amounted to 82% in the canton of Zurich and 90% in the canton of Geneva. Among the hotter than average days, 15% and 16% correspond to observed temperatures higher than the 95th percentile during the summers of 2018 and 2022, respectively, in Zurich (dotted black curves). In Geneva, the respective percentages correspond to 10% in 2018 and 25% in 2022.

The subseasonal forecasts (colored curves and shading) capture most of the individual peaks of daily mean temperature variability in Zurich and Geneva 1–2 weeks ahead for both summers. Some individual temperature peaks are even predicted 3 weeks in advance in both cantons, although with large forecast uncertainty (shaded areas Figures 2 and 3). For example, in Zurich, the lead week 3 temperature prediction reaches the observed extremes in the middle of July in both the 2018 and 2022 forecasts. However, the ensemble mean prediction tends to underestimate observed temperatures with values higher than the 95th percentile at this forecast lead time. As here we use forecasts for only 2 summers, we cannot perform a statistically robust evaluation of the forecast performance, which, however, has been done in other studies: For instance, it has been shown that the ECMWF subseasonal forecasts underestimate daily maximum temperature over continental Europe (Dutra et al., 2021). However, compared to other heatwave characteristics such as onset and duration, heatwave intensity is the most predictable characteristic of European heatwaves (Pyrina & Domeisen, 2023). Over Central Europe, heatwave intensity is predictable by the model ensemble mean up to forecast lead times of 3 weeks (Pyrina & Domeisen, 2023; Lavaysse et al., 2019; Technical Report MeteoSwiss No. 281, 2022), which for case studies is similar to other extratropical regions (Domeisen et al., 2022).

Although the ensemble mean forecast for lead weeks 4–6 captures the tendency for extended warmer and cooler periods, the forecast overall exhibits large uncertainty and its ensemble mean tends to converge toward climatology. The increase in forecast uncertainty and the ensemble mean's convergence toward climatology is an inherent characteristic of subseasonal weather forecasts, reflecting the intrinsic predictability limit for deterministic weather forecasts of about 2–3 weeks (Domeisen et al., 2018; Lorenz, 1963; Zhang et al., 2019). Predictability on longer timescales is not expected for specific temperature peaks, but subseasonal forecasts can capture tendencies for extended periods of warm or cool temperature anomalies (Vitart et al., 2019; Vitart & Robertson, 2018).

Periods exhibiting forecast uncertainty lower than expected climatologically indicate that the forecast is more certain than on average, even though, in reality, there can be errors when retrospectively compared to observations. For example, the 2018 ensemble forecast for lead week 6 in Zurich (Figure 2) is relatively certain in the middle of July, but exhibits a large error compared to the observations. The forecast uncertainty (spread) cannot

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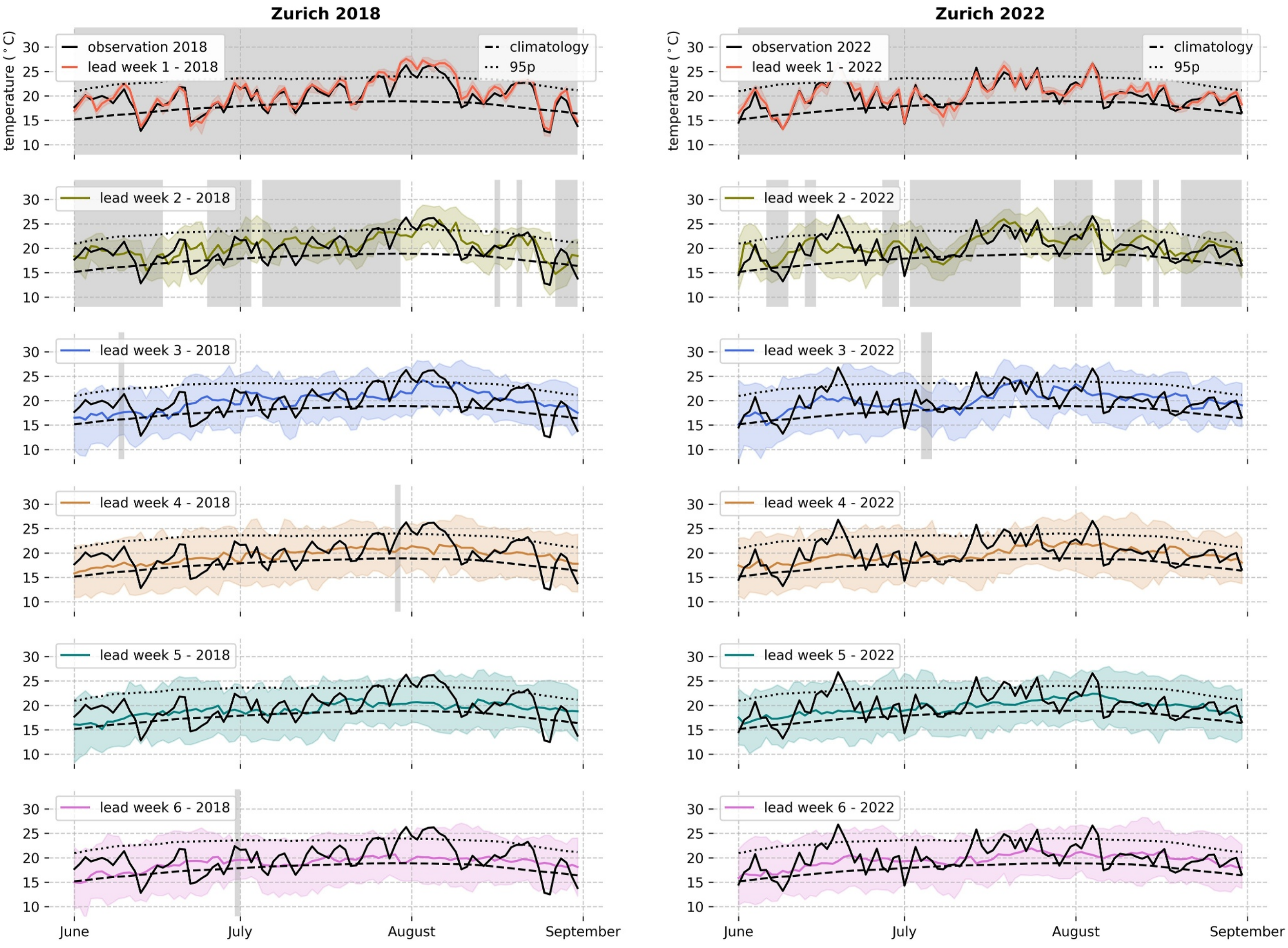

Figure 2. Observed daily mean temperature (black solid curve) and daily mean temperature forecasts for the summers of 2018 (left column) and 2022 (right column). The climatological mean and 95th percentile (1990–2017) are given by the black dashed and dotted curves, respectively. The results are shown for forecast initializations during lead week 1 (red), lead week 2 (light green), lead week 3 (blue), lead week 4 (orange), lead week 5 (dark green), and lead week 6 (purple) for the canton of Zurich. The shaded area around the solid line denoting the forecast ensemble mean for a specific lead week indicates the 5th to 95th percentile of the ensemble forecast. The gray vertical shading indicates periods where the forecast-to-climatological spread ratio (FCSR) is lower than 0.8, indicating a low intrinsic forecast uncertainty.

be used to strictly evaluate forecast skill in advance, but to indicate periods of ensemble forecast agreement, and estimate the likelihood of the forecast to have high or low skill. Indices implementing information of the forecast spread can then be used to constrain the predictions of heat-related mortality. To identify for each forecast lead week the periods with forecast uncertainty lower than expected climatologically, we use the forecast-to-climatological spread ratio (FCSR). Values of FCSR equal to 1 correspond to forecast spread equal to climatology. The lower the FCSR, the more certain the forecast is. We have calculated the FCSR for a range of values that vary from a forecast spread lower that half of the spread indicated by climatology, to a forecast spread almost equal, but still bellow, the climatological one. Here we show the results for the middle of this FCSR range being FCSR < 0.8 indicated in Figures 2 and 3 by the gray shaded areas. As expected, such high certainty periods are identified mostly during the first 2 weeks after forecast initialization.

3.3. Subseasonal Prediction of Heat-Related Mortality

To obtain a probabilistic prediction of the heat-related mortality fraction, or attributable fraction of mortality for Zurich (Figure 4) and Geneva (Figure 5), we couple the heat-mortality relationship with the ensemble temperature forecasts separately for each canton, each lead week, and each summer. The uncertainty in the mortality risk is taken into account when coupling the heat-mortality relationship to observed and predicted daily temperatures.

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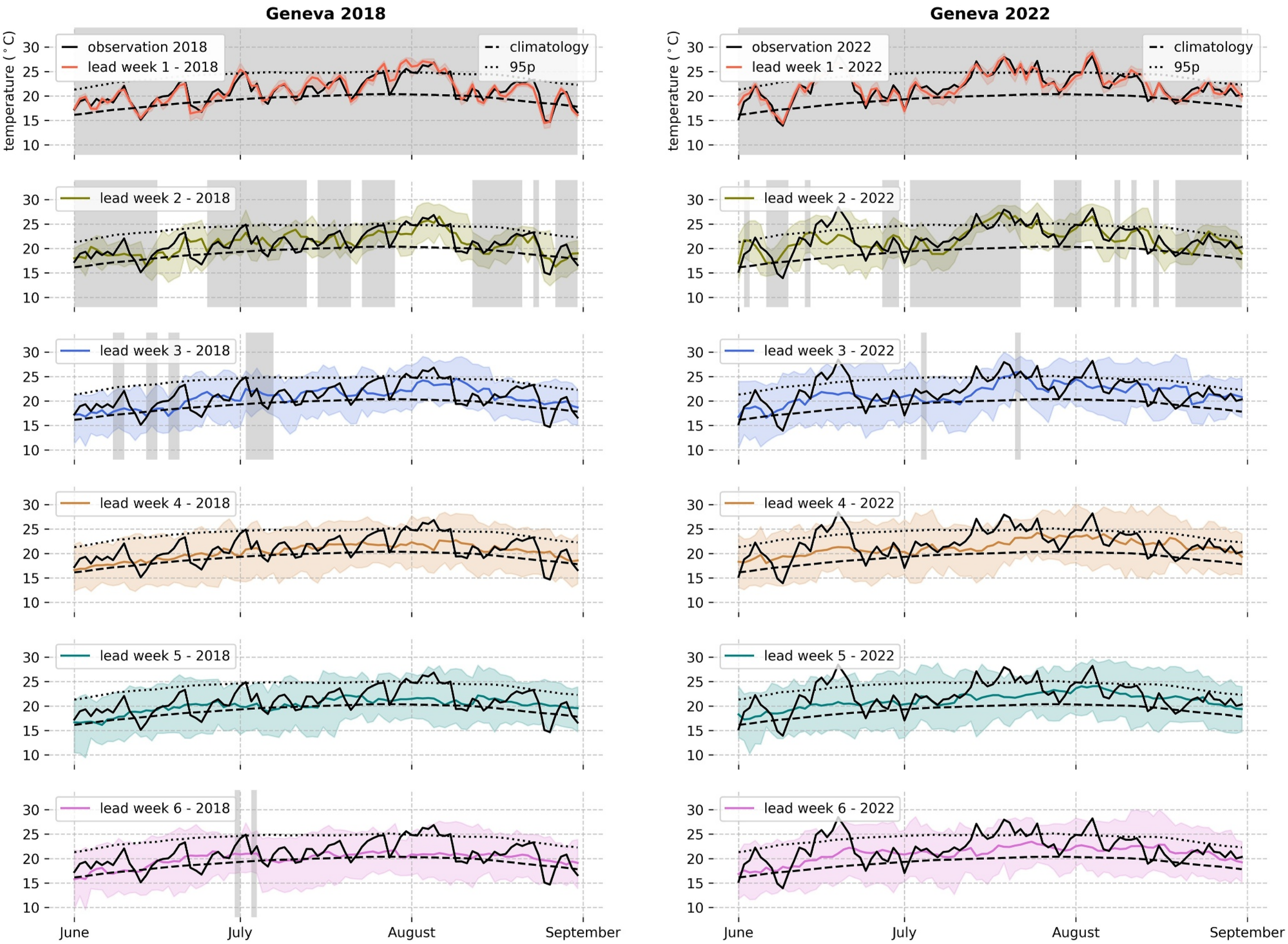

Figure 3. Same as Figure 2, but for the canton of Geneva.

Therefore, the attributable impacts account for both the uncertainty of the heat-mortality relationship, as well as the variability across the ensemble forecasts. Our attributable heat-related mortality estimates, do not account for possible uncertainties stemming from the estimation of the MMT (Tobías et al., 2017).

The probabilistic prediction of the heat-related mortality fraction is compared against the observed heat-related mortality fraction (black solid line, Figures 4 and 5), which is estimated using observed temperature and is considered the ground truth. Note that the probabilistic prediction of heat-related mortality is independent of the observed heat-related mortality estimation, as the temperature forecasts are initialized from different temperature data than those used to estimate the observed heat-related mortality here. The daily heat-related mortality fraction estimated based on climatological temperature is shown by the dashed black line.

The observed heat-related mortality peaks can be successfully predicted over the course of the 2018 and 2022 summers in Zurich (Figure 4) and Geneva (Figure 5) for lead week 1, both in terms of timing and mortality estimate number. In lead week 2, there are some successful predictions of heat-related mortality peaks as well, especially for the summer of 2022. For example, the heat-related mortality is well captured in Zurich in the middle of July and beginning of August 2022 (Figure 4). However, the heat-related mortality in mid-June 2022 in Zurich was not captured due to the model error in temperature prediction. This issue is also reflected by the large FCSR, indicated in Figure 2 by the absence of gray shading during that period. In Geneva, the lead week 2 heat-related mortality predictions of 2022 capture well the mortality peaks from almost the beginning of July until the end of August (Figure 5).

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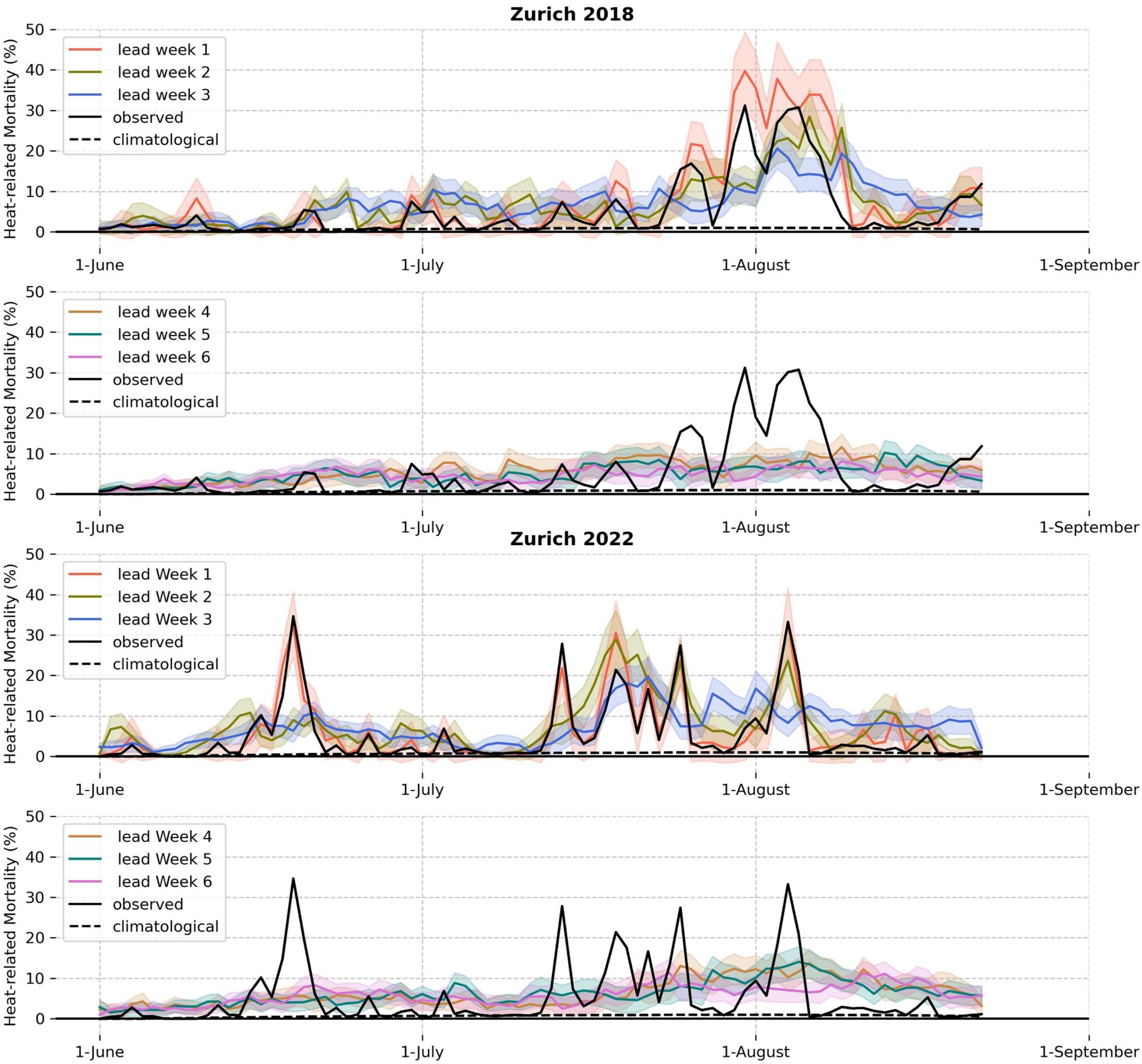

Figure 4. Observed (solid black line), climatological (dashed black line), and predicted (solid colored lines) heat-related mortality fraction in the summer of 2018 (two upper panels) and in the summer of 2022 (two lower panels) for the canton of Zurich. The results are shown for the forecast initializations as described in Figure 2. The shaded area around each lead week's mortality forecast corresponds to the 95% confidence interval.

To assess how accurately the heat-related mortality peaks are predicted across the different forecast lead times, we calculate the Mean Error (ME) between the predicted and observed heat-related mortality fractions on days when the observed temperature exceeds the 95th percentile (Figure 6). The 95th percentile is chosen to evaluate the prediction of mortality peaks, as this is also the percentile value frequently used to identify heatwave days (Fischer & Schär, 2010; Hoy et al., 2017), and the uncertainty in the associated mortality risk is much lower compared to higher percentiles (Figure 1). For both cantons and summers examined, the error in predicting heat-related mortality peaks remains below 10% for forecasts up to 2 weeks in advance, but doubles for longer lead times. Moreover, the error increases and becomes more negative for forecast times longer than a week, as the heat-related mortality peaks are mostly underestimated for these forecast times.

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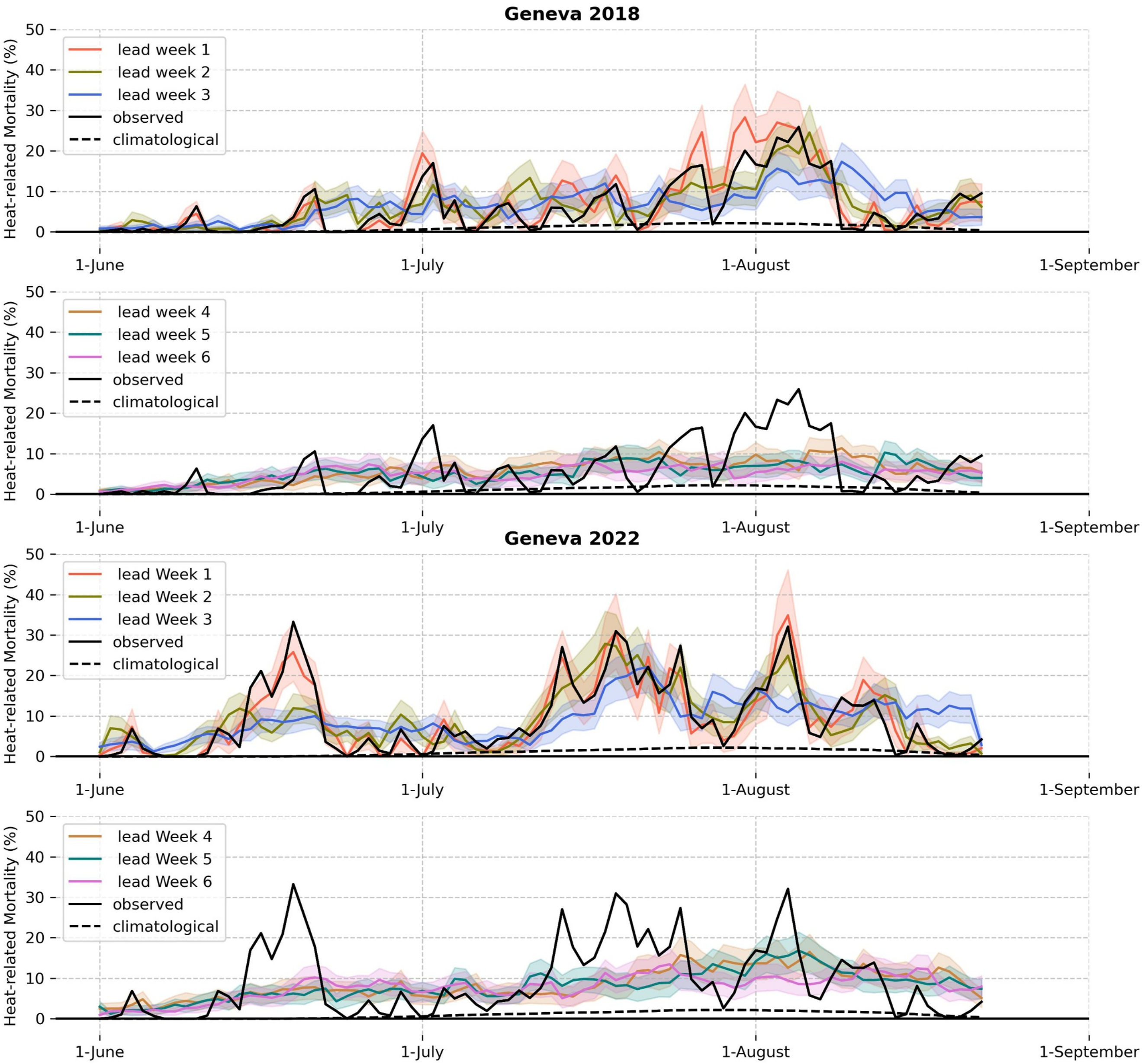

Figure 5. Same as Figure 4, but for the canton of Geneva.

Even though heat-related mortality peaks cannot be well predicted further than 2 weeks ahead, in some cases, multi-week periods of enhanced heat-related mortality can be anticipated by lead week 3. The correct tendency of the mortality predictions for such lead times is also confirmed by the correlation coefficient values being above 0.5 between predicted and observed heat-related mortality (see Tables S1 and S2 in Supporting Information S1). Examples of such periods include the beginning of August 2018 and the middle of July 2022 in Zurich and in Geneva. Moreover, in both cantons during summer 2022, there is an indication of an excess mortality period in the beginning of August as far out as lead week 5. Subseasonal forecast systems are usually not able to correctly predict daily values at these long lead times. The ensemble forecast in this particular case correctly predicts the tendency for the higher than usual temperatures, and thus heat-related mortality, over several days around the beginning of August 2022 (Figure 3). These partly successfully subseasonal temperature forecasts were possibly related to so-called *windows of opportunity*, periods typically associated with the skillful prediction of relevant precursors (Mariotti et al., 2020; Robertson et al., 2020; Yang et al., 2023). The conclusions drawn for the cantons of Zurich and Geneva regarding the successful prediction of heat-related mortality peaks 1–2 weeks in advance, as

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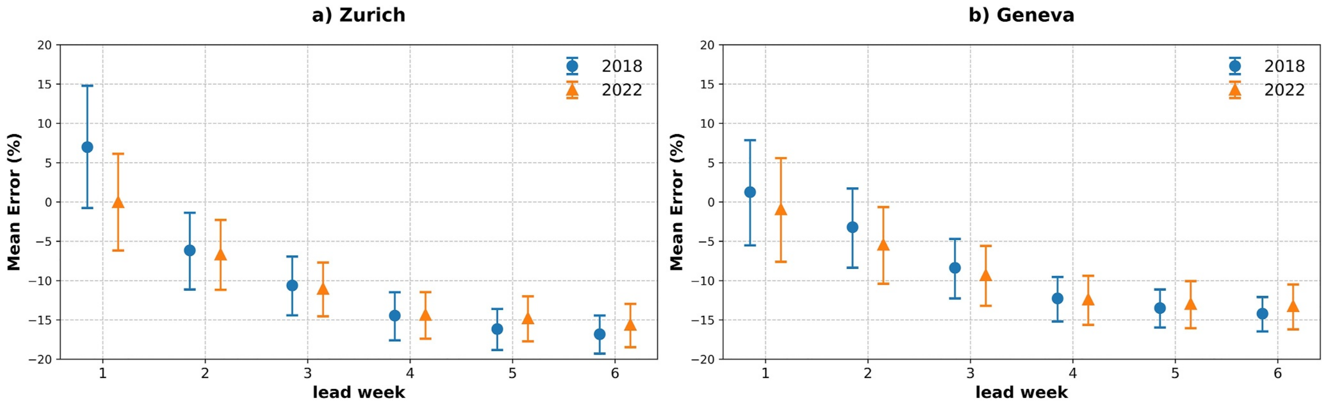

Figure 6. Mean error (ME) of predicted heat-related mortality fraction (i.e., predicted heat-related mortality fraction minus observed heat-related mortality fraction) during days with observed temperature above the 95th percentile. The results are given for the cantons of (a) Zurich, and (b) Geneva. The error bars correspond to the 95% confidence interval.

well as the ability to predict extended periods of heat-related mortality up to 3 or 4 weeks ahead, also apply to other Swiss cantons (see Supporting Information S1).

The prediction of the heat-related mortality fraction is in many cases overestimated (Figures 4 and 5). This overestimation exists during mortality peaks in lead weeks 1–2 and in lead weeks 3–6 during multi-week periods where heat-related mortality should be equal to zero, as mean temperature is below the MMT. The non-linear relationship of temperature and mortality and the increased uncertainty at the tail of the temperature distribution (Figure 1) lead to large mortality prediction uncertainty for even relatively low discrepancies between forecasted and observed temperature maxima. For example, in the summer of 2022 the mortality peak predicted in Zurich and Geneva in the beginning of August in lead week 1 differs from the observed estimation by 10% ± 10%, for a temperature absolute error of approximately 0.03°C ± 0.33°C and 0.63°C ± 0.45°C for Zurich and Geneva, respectively. The overestimation of maximum temperature can eventually lead to the overestimation of the total predicted mortality during the whole summer.

The heat-related mortality predictions summed over the course of the summer for different lead times can showcase the model's predictive capabilities for the entire summer seasons of 2018 and 2022. However, aside from lead week 1, the other lead weeks show a consistent prediction of heat-related mortality throughout the summer, which leads to unrealistically good estimates of heat-related mortality at forecast lead times further than 2 weeks. As seen in the upper panel of Figure 5 for the middle of August 2018, the predicted heat-related mortality at, that is, lead week 3, can be highly overestimated due to the prediction of heat-related mortality during periods where it should have been equal to zero (as mean temperature is below the MMT). To provide an alternative estimate of heat-related mortality for forecast lead times longer than 1 week, we explore the differences in predicted heat-related mortality summed for the entire summer and conditioned on different FCSRs.

The predicted heat-related mortality number, or attributable mortality number, summed over the course of the summer is calculated over all days (black bar), over the days that exhibit FCSR lower than 1 (moderate certainty; brown bar), lower than 0.8 (high certainty; orange bar), and lower than 0.5 (very high certainty; blue bar). The results are then given as a fraction by dividing with the total observed all-cause mortality over the summer (Figure 7). Conditioning on the FCSR does not affect the total summer heat-related mortality estimate during lead week 1, as for this forecast time the forecast uncertainty is low (e.g., Figure 2). The forecast spread increases for lead week 2 forecasts, causing the heat-mortality predictions to vary according to the FCSR. For lead weeks 3–6, only the non-conditioned mortality sum provides an estimate close to observations. However, as mentioned above and shown in Figures 4 and 5, this estimate is unrealistically good and results from the constant estimation of heat-related mortality for these lead weeks. Therefore, for the forecast weeks 3–6 a heat-related mortality estimate could be given only for the general tendency of these forecast weeks and by looking at FCSRs being lower than 1. The case of using no restriction to constrain the heat-related mortality predictions would lead to unrealistically good estimates of the total predicted mortality at lead times longer than 2 weeks.

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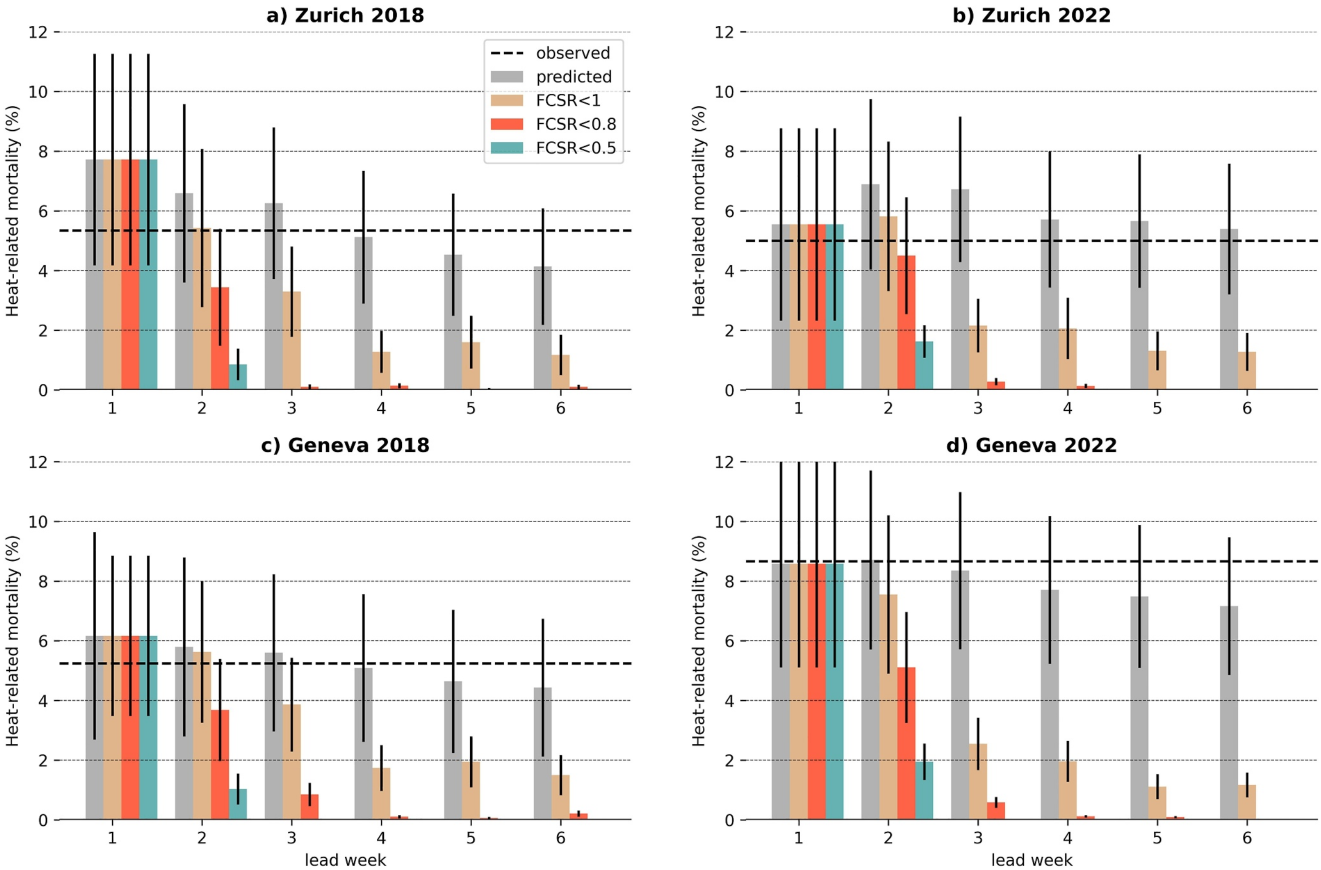

Figure 7. Heat-related mortality fraction in the cantons of Zurich (top row) and Geneva (bottom row) for the summers of 2018 (left column) and 2022 (right column). The results are given without conditioning on the FCSR (gray bar) and during days with FCSR lower than 1 (brown bar), lower than 0.8 (orange bar), and lower than 0.5 (blue bar). The error bars at each lead week's mortality forecast correspond to the 95% confidence interval.

The heat-related mortality estimated for the summer season based on observed temperature and observed-daily mortality is approximately equal to 5.5% in both cantons during the summer of 2018, as well as in Zurich in 2022 (black dashed line Figures 6a–6c respectively), but it is considerably higher in Geneva in 2022 reaching values of around 9% (Figure 6d). During both summers, the predicted heat-related mortality for the season in lead week 1 is overestimated compared to the estimation based on observed temperature and exhibits large uncertainty (vertical black lines). The maximum difference between predicted and observed mortality values is found for both cantons in the summer of 2018, and is equal to 2.4% in 2018 and 0.6% in 2022 for Zurich and 0.9% in 2018 and 0.1% in 2022 for Geneva. The strong overestimation of heat-related mortality during the summer of 2018 at lead week 1 is mainly driven by the overestimation on maximum temperatures by the forecast model during the end of August and beginning of September. This overestimation of temperature could have occurred by chance in this particular period, but it can also be related to systematic biases stemming from the forecast model version of 2018, shown to exhibit higher summer temperature biases compared to its most recent version (Haiden et al., 2021).

Currently, most European heat-health warning systems focus on issuing warnings to relevant authorities and vulnerable people some days before the onset of a heatwave (Casanueva et al., 2019b), as predicting the onset of a heatwave beyond 1 week in advance presents significant challenges (Pyrina & Domeisen, 2023). Nonetheless, the risk of cumulative mortality becomes substantial even for temperature values considerably lower than conventional heatwave thresholds. Our findings indicate that health authorities may be able to start taking action based on heat-health action plans up to 3 weeks prior to the expected onset of a hot period. While our study focuses on regions within Switzerland, similar predictive capabilities can be expected for other European regions, provided mortality models are integrated with high-resolution and bias-corrected subseasonal forecast data.

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3.4. Limitations

We acknowledge some limitations of this study. The effects of humidity in the association of heat-related mortality are not considered, as recent investigations suggest that its role and the way it is modeled in climate epidemiology remain unclear (Lo et al., 2023; Sivaraj et al., 2024). We assume, thus, that temperature alone will be a good enough proxy of the effect of heat on mortality, as done in previous work (Gasparrini et al., 2015). Moreover, we have not considered adaptation to heat stress in our assessment, in terms of changes in the association between heat and mortality between the two considered years and within each summer season. However, given the short time period considered, we believe that by accounting for adaptation, the conclusions would have not changed.

Despite having access to what is, to our knowledge, the most comprehensive data sets for climate epidemiology and subseasonal forecasts, our geographical scope is limited to central-western Europe. Hence it will have to be explored to what extent these results can be extrapolated to a larger region, or let alone the globe. At the same time, heat-related mortality is analyzed for the Swiss cantons as a whole, which leaves out details on the heat-related mortality prediction differences that can arise from intra-community differences in vulnerability due to the regional distribution of the population with regards to for example, age and gender (Ballester et al., 2023; Benmarhnia et al., 2015; de Schrijver et al., 2022). Also, important small-scale climatic differences, such as urban heat island effects, are not resolved and can overlap with vulnerable communities (Oke, 1982). We here refrain from further sub-dividing an already small sample into these characteristics, but it is clear that such information at a large-scale can further benefit early warning systems. Furthermore, as this research is based on case studies, we cannot verify the percentage of accurate mortality predictions versus false alarms. False alarms would refer to predictions of heat-related mortality exceeding a selected threshold, but do not correspond to the ground truth. It is crucial to evaluate false alarms before implementing actual warnings to ensure the effectiveness and reliability of the warning system. This evaluation will help in understanding the potential consequences of the prediction.

Coupling risk models to subseasonal forecasts is associated with two challenges: 1. Risk models require data with spatial resolutions of a few kilometers, a level of detail currently lacking in subseasonal forecasts, and 2. Dynamical weather prediction models are known to suffer from systematic errors (Jung, 2005; Magnusson & Källén, 2013), rendering their output unsuitable for direct use by risk models without prior correction by domain experts. In this study we relied on subseasonal forecasts from a state-of-the-art prediction system (Vitart & Robertson, 2018), but prior to our analysis the forecasts were downscaled and bias corrected by MeteoSwiss. This task required the expertise of domain specialists, as well as time and storage resources. Downscaled and bias-corrected operational forecasts are typically archived for only a few years by Switzerland's public services, a constraint that may also apply in other countries. Nevertheless, our examination of two case studies corresponding to two of Switzerland's hottest years highlights the potential of using such forecasts for mortality predictions.

4. Conclusions

We combine state-of-the-art techniques from climate epidemiology and subseasonal forecasting to determine the potential to predict heat-related mortality on subseasonal timescales in Switzerland at 2-km spatial resolution. This is achieved by comparing estimates of heat-related mortality based on predicted versus observed temperatures over lead times of 1–6 weeks. The analysis is conducted for the hot summers of 2018 and 2022 and the results are provided for two regions representative of the Swiss Plateau, the cantons of Zurich and Geneva. Depending on the year and canton, the heat-related mortality for these hot summers accounts for a range from 5% to 9% of all-cause mortality, with the highest percentage (9%) found for the canton of Geneva in 2022. This percentage is notably high, especially compared to the heat-related mortality of 3.5% of all-cause mortality estimated from observed temperatures across the entire country in 2022 (Vicedo-Cabrera et al., 2023).

The forecast model demonstrates a high capability to predict both the total heat-related mortality and short-term peaks lasting a few days during the summers of 2018 and 2022, with lead times of 1–2 weeks. Although the forecast model cannot accurately predict short-term mortality peaks more than 3 weeks in advance, which is not expected given the chaotic nature of weather prediction, the model can provide information about longer up-coming hot periods when excess heat-related mortality can be expected. We have shown for the first time that coupling heat-mortality models with bias-corrected subseasonal forecasts leads to robust estimates of subseasonal predictions of heat-related mortality for forecast times longer than a week. Although further studies along the

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process chain will be needed for working toward implementation in an early warning system, this result highlights the value of subseasonal forecasts for public health management and preparation for heat-related risks.

In Europe, temperatures are increasing at a pace surpassing the global average (Simmons, 2022), and in particular extreme heat events are strongly increasing in frequency (Russo & Domeisen, 2023). Hence, predicting warmer than normal days and periods as early as possible and acting upon their anticipated impacts is a crucial part of adapting to climate change. Our findings underscore the potential of employing subseasonal forecasts to anticipate hot periods and peaks in mortality well in advance, and call for heat-health platforms to initiate preventive measures for subseasonal forecast lead times. The elevated levels of heat-related mortality witnessed in Europe during recent summers alongside the capacity for timely prediction necessitate that national governments and agencies within Europe should enhance the ambition and efficacy of their heat prevention and adaptation strategies.

Conflict of Interest

The authors declare no conflicts of interest relevant to this study.

Data Availability Statement

The ECMWF subseasonal forecast are available for download at: https://apps.ecmwf.int/datasets/data/s2s/levtype=sfc/type=cf/. The quantile mapping method used to downscale the ECMWF forecasts is described in Monhart et al. (2018): https://doi.org/10.1029/2017JD027923. The observational TabsD data set can be requested at: https://hyd.ifu.ethz.ch/research-data-models/meteoswiss.html. The mortality data, relative risk curves, and R code used to generate the Figures and calculate the attributable number and attributable fraction of mortality have been archived on Zenodo: Pyrina (2024).

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References

Altalo, M. G., & Smith, L. A. (2004). Using ensemble weather forecasts to manage utilities risk. *Environmental Finance*, *20*(October), 8–9.

Anderson, G. B., Barnes, E. A., Bell, M. L., & Dominici, F. (2019). The future of climate epidemiology: Opportunities for advancing health research in the context of climate change. *American Journal of Epidemiology*, *188*(5), 866–872. https://doi.org/10.1093/aje/kwz034

Arias, P., Bellouin, N., Coppola, E., Jones, R., Krinner, G., Marotzke, J., et al. (2021). *Climate change 2021: The physical science basis. Contribution of working group I to the sixth assessment report of the intergovernmental panel on climate change; technical summary*. Cambridge University Press.

Åström, C., Orru, H., Rocklöv, J., Strandberg, G., Ebi, K. L., & Forsberg, B. (2012). Heat related respiratory hospital admissions in Europe in a changing climate: A health impact assessment. *BMJ Open*, *3*(1), e001842. https://doi.org/10.1136/bmjopen-2012-001842

Baker, L., Charlton-Perez, A., & Mattu, K. L. (2023). Skilful sub-seasonal forecasts of aggregated temperature over Europe. *Meteorological Applications*, *30*(6), e2169. https://doi.org/10.1002/met.2169

Ballester, J., Quijal-Zamorano, M., Méndez Turrubiates, R. F., Pegenaute, F., Herrmann, F. R., Robine, J. M., et al. (2023). Heat-related mortality in Europe during the summer of 2022. *Nature Medicine*, *29*(7), 1857–1866. https://doi.org/10.1038/s41591-023-02419-z

Benmarhnia, T., Deguen, S., Kaufman, J. S., & Smargiassi, A. (2015). Vulnerability to heat-related mortality. *Epidemiology*, *26*(6), 781–793. https://doi.org/10.1097/ede.0000000000000375

Bittner, M.-I., Matthies, E. F., Dalbokova, D., & Menne, B. (2014). Are European countries prepared for the next big heat-wave? *The European Journal of Public Health*, *24*(4), 615–619. https://doi.org/10.1093/eurpub/ckt121

Brimicombe, C., Runkle, J. D., Tuholske, C., Domeisen, D. I. V., Gao, C., Toftum, J., & Otto, I. M. (2024). Preventing heat-related deaths: The urgent need for a global early warning system for heat. *PLOS Climate*, *3*(7), e0000437. https://doi.org/10.1371/journal.pclm.0000437

Buizza, R., Hollingsworth, A., Lalaurette, F., & Ghelli, A. (1999). Probabilistic predictions of precipitation using the ECMWF ensemble prediction system. *Weather and Forecasting*, *14*(2), 168–189. https://doi.org/10.1175/1520-0434(1999)014<0168:ppoput>2.0.co;2

Buizza, R., Houtekamer, P., Pellerin, G., Toth, Z., Zhu, Y., & Wei, M. (2005). A comparison of the ECMWF, MSC, and NCEP global ensemble prediction systems. *Monthly Weather Review*, *133*(5), 1076–1097. https://doi.org/10.1175/mwr2905.1

Bundesamt für Umwelt (Hrsg.), Bundesamt für Meteorologie und Klimatologie (MeteoSchweiz), Bundesamt für Gesundheit, Bundesamt für Bevölkerungsschutz, Bundesamt für Landwirtschaft, Bundesamt für Energie, et al. (2019). Hitze und Trockenheit im Sommer 2018. In *Auswirkungen auf Mensch und Umwelt*. Bundesamt für Umwelt. Umwelt-Zustand Nr. 1909: 91 S. Retrieved from https://www.bafu.admin.ch/bafu/de/home/themen/klima/publikationen-studien/publikationen/hitze-und-trockenheit.html

Butler, C. (2016). *Climate change and global health*. CABI.

Casanueva, A., Burgstall, A., Kotlarski, S., Messeri, A., Morabito, M., Flouris, A. D., et al. (2019a). Overview of existing heat-health warning systems in Europe. *International Journal of Environmental Research and Public Health*, *16*(15), 2657. https://doi.org/10.3390/ijerph16152657

Casanueva, A., Burgstall, A., Kotlarski, S., Messeri, A., Morabito, M., Flouris, A. D., et al. (2019b). Overview of existing heat-health warning systems in Europe. *International Journal of Environmental Research and Public Health*, *16*(15), 2657. https://doi.org/10.3390/ijerph16152657

Chen, K., Zhou, L., Chen, X., Ma, Z., Liu, Y., Huang, L., et al. (2016). Urbanization level and vulnerability to heat-related mortality in Jiangsu province, China. *Environmental Health Perspectives*, *124*(12), 1863–1869. https://doi.org/10.1289/ehp204

Christensen, H., Moroz, I., & Palmer, T. (2015). Evaluation of ensemble forecast uncertainty using a new proper score: Application to medium-range and seasonal forecasts. *Quarterly Journal of the Royal Meteorological Society*, *141*(687), 538–549. https://doi.org/10.1002/qj.2375

Copernicus Climate Change Service. (2023). European Summer 2023: A season of contrasting extremes. Retrieved from https://climate.copernicus.eu/european-summer-2023-season-contrasting-extremes

24711403, 2025, 1, Downloaded from https://agupubs.onlinelibrary.wiley.com/doi/10.1029/2024GH001199 by Readcube (Labtiva Inc.), Wiley Online Library on [28/04/2025]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

de Schrijver, E., Bundo, M., Ragettli, M. S., Sera, F., Gasparrini, A., Franco, O. H., & Vicedo-Cabrera, A. M. (2022). Nationwide analysis of the heat-and cold-related mortality trends in Switzerland between 1969 and 2017: The role of population aging. *Environmental Health Perspectives*, *130*(3), 037001. https://doi.org/10.1289/ehp9835

de Schrijver, E., Folly, C. L., Schneider, R., Royé, D., Franco, O. H., Gasparrini, A., & Vicedo-Cabrera, A. M. (2021). A comparative analysis of the temperature-mortality risks using different weather datasets across heterogeneous regions. *GeoHealth*, *5*(5), e2020GH000363. https://doi.org/10.1029/2020gh000363

De Schrijver, E., Sivaraj, S., Raible, C. C., Franco, O. H., Chen, K., & Vicedo-Cabrera, A. M. (2023). Nationwide projections of heat-and cold-related mortality impacts under various climate change and population development scenarios in Switzerland. *Environmental Research Letters*, *18*(9), 094010. https://doi.org/10.1088/1748-9326/ace7e1

Domeisen, D. I. V., Badin, G., & Koszalka, I. M. (2018). How predictable are the Arctic and north Atlantic oscillations? Exploring the variability and predictability of the northern hemisphere. *Journal of Climate*, *31*(3), 997–1014. https://doi.org/10.1175/jcli-d-17-0226.1

Domeisen, D. I. V., Eltahir, E. A., Fischer, E. M., Knutti, R., Perkins-Kirkpatrick, S. E., Schär, C., et al. (2023). Prediction and projection of heatwaves. *Nature Reviews Earth & Environment*, *4*(1), 36–50. https://doi.org/10.1038/s43017-022-00371-z

Domeisen, D. I. V., White, C. J., Afargan-Gerstman, H., Muñoz, Á. G., Janiga, M. A., Vitart, F., et al. (2022). Advances in the subseasonal prediction of extreme events: Relevant case studies across the globe. *Bulletin of the American Meteorological Society*, *103*(6), E1473–E1501. https://doi.org/10.1175/bams-d-20-0221.1

Dutra, E., Johannsen, F., & Magnusson, L. (2021). Late spring and summer subseasonal forecasts in the Northern Hemisphere midlatitudes: Biases and skill in the ECMWF model. *Monthly Weather Review*, *149*(8), 2659–2671. https://doi.org/10.1175/mwr-d-20-0342.1

Fischer, E. M., & Schär, C. (2010). Consistent geographical patterns of changes in high-impact European heatwaves. *Nature Geoscience*, *3*(6), 398–403. https://doi.org/10.1038/ngeo866

Fouillet, A., Rey, G., Wagner, V., Laaidi, K., Empereur-Bissonnet, P., Le Tertre, A., et al. (2008). Has the impact of heat waves on mortality changed in France since the European heat wave of summer 2003? A study of the 2006 heat wave. *International Journal of Epidemiology*, *37*(2), 309–317. https://doi.org/10.1093/ije/dym253

Gasparrini, A. (2014). Modeling exposure–lag–response associations with distributed lag non-linear models. *Statistics in Medicine*, *33*(5), 881–899. https://doi.org/10.1002/sim.5963

Gasparrini, A. (2022). A tutorial on the case time series design for small-area analysis. *BMC Medical Research Methodology*, *22*(1), 1–8. https://doi.org/10.1186/s12874-022-01612-x

Gasparrini, A., Guo, Y., Hashizume, M., Lavigne, E., Tobias, A., Zanobetti, A., et al. (2016). Changes in susceptibility to heat during the summer: A multicountry analysis. *American Journal of Epidemiology*, *183*(11), 1027–1036. https://doi.org/10.1093/aje/kwv260

Gasparrini, A., Guo, Y., Hashizume, M., Lavigne, E., Zanobetti, A., Schwartz, J., et al. (2015). Mortality risk attributable to high and low ambient temperature: A multicountry observational study. *The Lancet*, *386*(9991), 369–375. https://doi.org/10.1016/s0140-6736(14)62114-0

Gasparrini, A., & Leone, M. (2014). Attributable risk from distributed lag models. *BMC Medical Research Methodology*, *14*(1), 1–8. https://doi.org/10.1186/1471-2288-14-55

Gasparrini, A., Masselot, P., Scortichini, M., Schneider, R., Mistry, M. N., Sera, F., et al. (2022). Small-area assessment of temperature-related mortality risks in England and wales: A case time series analysis. *The Lancet Planetary Health*, *6*(7), e557–e564. https://doi.org/10.1016/s2542-5196(22)00138-3

Giorgi, F. (2006). Climate change hot-spots. *Geophysical Research Letters*, *33*(8). https://doi.org/10.1029/2006gl025734

Guha-Sapir, D., Hoyois, P., Wallemacq, P., & Below, R. (2017). Annual disaster statistical review 2016. The numbers and trends, 1–91.

Haiden, T., Janousek, M., Vitart, F., & Ben-Bouallegue, Z. (2023). Evaluation of ECMWF forecasts, including the 2023 upgrade (No. 911). *ECMWF*. Retrieved from https://www.ecmwf.int/sites/default/files/elibrary/092023/81389-evaluation-of-ecmwf-forecasts-including-the-2023-upgrade.pdf

Haiden, T., Janousek, M., Vitart, F., Ben-Bouallegue, Z., Ferranti, L., & Prates, F. (2021). Evaluation of ECMWF forecasts, including the 2021 upgrade (No. 884). *ECMWF*. https://doi.org/10.21957/90pgicjk4

Haiden, T., Janousek, M., Vitart, F., Bouallègue, Z. B., Ferranti, L., Prates, F., & Richardson, D. (2018). *Evaluation of ECMWF forecasts, including the 2018 upgrade*. European Centre for Medium Range Weather Forecasts. https://doi.org/10.21957/ldw15ckqi

Hoy, A., Haensel, S., Skalak, P., Ustrnul, Z., & Bochníček, O. (2017). The extreme European summer of 2015 in a long-term perspective. *International Journal of Climatology*, *37*(2), 943–962. https://doi.org/10.1002/joc.4751

Jung, T. (2005). Systematic errors of the atmospheric circulation in the ECMWF forecasting system. *Quarterly Journal of the Royal Meteorological Society*, *131*(607), 1045–1073. https://doi.org/10.1256/qj.04.93

Lalaurette, F., Ferranti, L., Ghelli, A., & Van Der Grijn, G. (2003). *Verification statistics and evaluations of ECMWF forecasts in 2002–2003* (Tech. Rep.). ECMWF Technical Memoranda. https://www.ecmwf.int/sites/default/files/elibrary/2003/10635-verification-statistics-and-evaluations-ecmwf-forecasts-2002-2003.pdf

Lavaysse, C., Naumann, G., Alfieri, L., Salamon, P., & Vogt, J. (2019). Predictability of the European heat and cold waves. *Climate Dynamics*, *52*(3–4), 2481–2495. https://doi.org/10.1007/s00382-018-4273-5

Leutbecher, M., & Palmer, T. N. (2008). Ensemble forecasting. *Journal of Computational Physics*, *227*(7), 3515–3539. https://doi.org/10.1016/j.jcp.2007.02.014

Lo, Y. E., Mitchell, D. M., Buzan, J. R., Zscheischler, J., Schneider, R., Mistry, M. N., et al. (2023). Optimal heat stress metric for modelling heat-related mortality varies from country to country. *International Journal of Climatology*, *43*(12), 5553–5568. https://doi.org/10.1002/joc.8160

Lorenz, E. N. (1963). Deterministic nonperiodic flow. *Journal of the Atmospheric Sciences*, *20*(2), 130–141. https://doi.org/10.1175/1520-0469(1963)020<0130:dnf>2.0.co;2

Lowe, R., García-Díez, M., Ballester, J., Creswick, J., Robine, J.-M., Herrmann, F. R., & Rodó, X. (2016). Evaluation of an early-warning system for heat wave-related mortality in Europe: Implications for sub-seasonal to seasonal forecasting and climate services. *International Journal of Environmental Research and Public Health*, *13*(2), 206. https://doi.org/10.3390/ijerph13020206

Lüthi, S., Fairless, C., Fischer, E. M., Scovronick, N., Armstrong, B., Coelho, M. D. S. Z. S., et al. (2023). Rapid increase in the risk of heat-related mortality. *Nature Communications*, *14*(1), 4894. https://doi.org/10.1038/s41467-023-40599-x

Magnusson, L., & Källén, E. (2013). Factors influencing skill improvements in the ECMWF forecasting system. *Monthly Weather Review*, *141*(9), 3142–3153. https://doi.org/10.1175/mwr-d-12-00318.1

Mariotti, A., Baggett, C., Barnes, E. A., Becker, E., Butler, A., Collins, D. C., et al. (2020). Windows of opportunity for skillful forecasts subseasonal to seasonal and beyond. *Bulletin of the American Meteorological Society*, *101*(5), E608–E625. https://doi.org/10.1175/bams-d-18-0326.1

Mariotti, A., Ruti, P. M., & Rixen, M. (2018). Progress in subseasonal to seasonal prediction through a joint weather and climate community effort. *Npj Climate and Atmospheric Science*, *1*(1), 4. https://doi.org/10.1038/s41612-018-0014-z

Masselot, P., Mistry, M., Vanoli, J., Schneider, R., Iungman, T., Garcia-Leon, D., et al. (2023). Excess mortality attributed to heat and cold: A health impact assessment study in 854 cities in Europe. *The Lancet Planetary Health*, *7*(4), e271–e281. https://doi.org/10.1016/s2542-5196(23)00023-2

MeteoSwiss. (2021). Meteoswiss spatial climate analyses: Documentation of datasets for users. Retrieved from https://www.meteoswiss.admin.ch/climate/the-climate-of-switzerland/spatial-climate-analyses.html

Mistry, M. N., & Gasparrini, A. (2024). Real-time forecast of temperature-related excess mortality at small-area level: Towards an operational framework. *Environmental Research: Health*, *2*(3), 035011. https://doi.org/10.1088/2752-5309/ad5f51

Monhart, S., Spirig, C., Bhend, J., Bogner, K., Schär, C., & Liniger, M. A. (2018). Skill of subseasonal forecasts in Europe: Effect of bias correction and downscaling using surface observations. *Journal of Geophysical Research: Atmospheres*, *123*(15), 7999–8016. [Method]. https://doi.org/10.1029/2017JD027923

Murage, P., Kovats, S., Sarran, C., Taylor, J., McInnes, R., & Hajat, S. (2020). What individual and neighbourhood-level factors increase the risk of heat-related mortality? A case-crossover study of over 185,000 deaths in London using high-resolution climate datasets. *Environment International*, *134*, 105292. https://doi.org/10.1016/j.envint.2019.105292

Oke, T. R. (1982). The energetic basis of the urban heat island. *The Quarterly Journal of the Royal Meteorological Society*, *108*(455), 1–24. https://doi.org/10.1002/qj.49710845502

Pascal, M., Goria, S., Wagner, V., Sabastia, M., Guillet, A., Cordeau, E., et al. (2021). Greening is a promising but likely insufficient adaptation strategy to limit the health impacts of extreme heat. *Environment International*, *151*, 106441. https://doi.org/10.1016/j.envint.2021.106441

Pyrina, M. (2024). marpyr/AGU2024_subseasonalprediction_heatmortality_CH: Version 1.0.0 - Heat_mortality_Switzerland (v1.0.0) [Software]. *Zenodo*. https://doi.org/10.5281/zenodo.13948386

Pyrina, M., & Domeisen, D. I. V. (2023). Subseasonal predictability of onset, duration, and intensity of European heat extremes. *Quarterly Journal of the Royal Meteorological Society*, *149*(750), 84–101. https://doi.org/10.1002/qj.4394

Ragettli, M. S., Vicedo-Cabrera, A. M., Schindler, C., & Röösli, M. (2017). Exploring the association between heat and mortality in Switzerland between 1995 and 2013. *Environmental Research*, *158*, 703–709. https://doi.org/10.1016/j.envres.2017.07.021

Robertson, A. W., Vigaud, N., Yuan, J., & Tippett, M. K. (2020). Toward identifying subseasonal forecasts of opportunity using North American weather regimes. *Monthly Weather Review*, *148*(5), 1861–1875. https://doi.org/10.1175/mwr-d-19-0285.1

Robine, J.-M., Cheung, S. L. K., Le Roy, S., Van Oyen, H., Griffiths, C., Michel, J.-P., & Herrmann, F. R. (2008). Death toll exceeded 70,000 in Europe during the summer of 2003. Comptes Rendus. *Biologies*, *331*(2), 171–178. https://doi.org/10.1016/j.crvi.2007.12.001

Russo, E., & Domeisen, D. I. V. (2023). Increasing intensity of extreme heatwaves: The crucial role of metrics. *Geophysical Research Letters*, *50*(14), e2023GL103540. https://doi.org/10.1029/2023gl103540

Sera, F., Armstrong, B., Blangiardo, M., & Gasparrini, A. (2019). An extended mixed-effects framework for meta-analysis. *Statistics in Medicine*, *38*(29), 5429–5444. https://doi.org/10.1002/sim.8362

Simmons, A. J. (2022). Trends in the tropospheric general circulation from 1979 to 2022. *Weather and Climate Dynamics*, *3*(3), 777–809. https://doi.org/10.5194/wcd-3-777-2022

Sivaraj, S., Zscheischler, J., Buzan, J. R., Martius, O., Brönnimann, S., & Vicedo-Cabrera, A. M. (2024). Heat, humidity and health impacts: How causal diagrams can help tell the complex story. *Environmental Research Letters: ERL [Web site]*, *19*(7), 074069. https://doi.org/10.1088/1748-9326/ad5a25

Smith, K., Woodward, A., Campbell-Lendrum, D., Chadee, D., Honda, Y., Liu, Q., et al. (2014). Human health: Impacts, adaptation, and co-benefits climate change 2014: Impacts, adaptation, and vulnerability. Part a: Global and sectoral aspects. Contribution of working group ii to the fifth assessment report of the intergovernmental panel on climate change. Contribution of Working Group II to the fifth assessment report of the Intergovernmental Panel on Climate Change, 709–754.

Taylor, J. W., & Buizza, R. (2003). Using weather ensemble predictions in electricity demand forecasting. *International Journal of Forecasting*, *19*(1), 57–70. https://doi.org/10.1016/s0169-2070(01)00123-6

Technical Report MeteoSwiss No. 281. (2022). Operational setup and skill analysis of a sub-seasonal forecasting system for detecting heat stress. Retrieved from https://www.meteoswiss.admin.ch/services-and-publications/publications/scientific-publications/2022/operational-setup-and-skill-analysis-of-a-sub-seasonal-forecasting-system-for-detecting-heat-stress.html

Tobías, A., Armstrong, B., & Gasparrini, A. (2017). Brief report: Investigating uncertainty in the minimum mortality temperature: Methods and application to 52 Spanish cities. *Epidemiology*, *28*(1), 72–76. https://doi.org/10.1097/ede.0000000000000567

Toth, Z., Schultz, P., Mullen, S., Demargne, J., & Zhu, Y. (2007). Completing the forecast: Assessing and communicating forecast uncertainty. In *Ecmwf workshop on ensemble prediction* (pp. 7–9). Retrieved from https://www.ecmwf.int/sites/default/files/elibrary/2007/12792-completing-forecast-assessing-and-communicating-forecast-uncertainty.pdf

United Nations Office for Disaster Risk Reduction. (2016). 2015 disasters in numbers. Retrieved from https://www.unisdr.org/files/47804_2015disastertrendsinfographic.pdf

Vicedo-Cabrera, A. M., de Schrijver, E., Schumacher, D. L., Ragettli, M. S., Fischer, E. M., & Seneviratne, S. I. (2023). The footprint of human-induced climate change on heat-related deaths in the summer of 2022 in Switzerland. *Environmental Research Letters*, *18*(7), 074037. https://doi.org/10.1088/1748-9326/ace0d0

Vicedo-Cabrera, A. M., Scovronick, N., Sera, F., Royé, D., Schneider, R., Tobias, A., et al. (2021). The burden of heat-related mortality attributable to recent human-induced climate change. *Nature Climate Change*, *11*(6), 492–500. https://doi.org/10.1038/s41558-021-01058-x

Vitart, F. (2014). Evolution of ECMWF sub-seasonal forecast skill scores. *Quarterly Journal of the Royal Meteorological Society*, *140*(683), 1889–1899. https://doi.org/10.1002/qj.2256

Vitart, F., Cunningham, C., DeFlorio, M., Dutra, E., Ferranti, L., Golding, B., et al. (2019). Sub-seasonal to seasonal prediction of weather extremes. In *Sub-seasonal to seasonal prediction* (pp. 365–386). Elsevier.

Vitart, F., & Robertson, A. W. (2018). The sub-seasonal to seasonal prediction project (S2S) and the prediction of extreme events. *npj Climate and Atmospheric Science*, *1*(1), 3. https://doi.org/10.1038/s41612-018-0013-0

Weirich-Benet, E., Pyrina, M., Jiménez-Esteve, B., Fraenkel, E., Cohen, J., & Domeisen, D. I. V. (2023). Subseasonal prediction of central European summer heatwaves with linear and random forest machine learning models. *Artificial Intelligence for the Earth Systems*, *2*(2), e220038. https://doi.org/10.1175/aies-d-22-0038.1

White, C. J., Domeisen, D. I. V., Acharya, N., Adefisan, E. A., Anderson, M. L., Aura, S., et al. (2022). Advances in the application and utility of subseasonal-to-seasonal predictions. *Bulletin of the American Meteorological Society*, *103*(6), E1448–E1472. https://doi.org/10.1175/bams-d-20-0224.1

Yang, J., Zhu, T., & Vitart, F. (2023). An extratropical window of opportunity for subseasonal prediction of East Asian summer surface air temperature. *npj Climate and Atmospheric Science*, *6*(1), 46. https://doi.org/10.1038/s41612-023-00384-5

24711403, 2025, 1, Downloaded from https://agupubs.onlinelibrary.wiley.com/doi/10.1029/2024GH001199 by Readcube (Labtiva Inc.), Wiley Online Library on [28/04/2025]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

10.1029/2024GH001199

Zhang, F., Sun, Y. Q., Magnusson, L., Buizza, R., Lin, S.-J., Chen, J.-H., & Emanuel, K. (2019). What is the predictability limit of midlatitude weather? *Journal of the Atmospheric Sciences*, *76*(4), 1077–1091. https://doi.org/10.1175/jas-d-18-0269.1

Zhao, Q., Guo, Y., Ye, T., Gasparrini, A., Tong, S., Overcenco, A., et al. (2021). Global, regional, and national burden of mortality associated with non-optimal ambient temperatures from 2000 to 2019: A three-stage modelling study. *The Lancet Planetary Health*, *5*(7), e415–e425. https://doi.org/10.1016/s2542-5196(21)00081-4

24711403, 2025, 1, Downloaded from https://agupubs.onlinelibrary.wiley.com/doi/10.1029/2024GH001199 by Readcube (Labtiva Inc.), Wiley Online Library on [28/04/2025]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License