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Research article

TEMPERATURE-RELATED MORTALITY RISKS: EFFECTS OF DIFFERENT SOURCES OF CLIMATIC DATA IN THE RF REGIONS IN 2004–2019

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Climate change and increasing thermal stress highlights the need to investigate the temperature-mortality relationship using long-term aggregated temperature data. Globally, two primary sources of temperature data are utilized: ground-based meteorological observations and raster datasets. Ground-based observations from meteorological stations offer precise local temperature measurements but lack comprehensive spatial coverage. In contrast, raster data provide complete spatial coverage but may not accurately represent local microclimatic conditions. This study aims to compare these data sources for analyzing temperature-related mortality across regions of Russia.

To assess the exposure-response relationship, a two-stage modeling approach was applied. At the first stage, region-specific estimates were derived using a distributed lag model. At the second stage, pooled estimates were computed through random-effects meta-regression.

The temperature-mortality relationship in Russia is characterized by a typical J-shaped curve, with cold temperatures posing a higher mortality risk. Heat-related risks were generally higher when estimated using raster data compared to in-situ observations. Minimum mortality risk temperatures typically fall between 15 and 20 °C, with higher thresholds observed in warmer regions.

This study suggests general comparability of raster and point-based temperature data for mortality analysis. However, in certain regions, particularly large and sparsely populated ones, estimates diverged due to multiple factors.

Keywords: *climate change, atmosphere reanalysis, air temperature, temperature stress, raster data, ground-based meteorological observations, mortality, regions of Russia.*

Climate change leads to more frequent and more intense heat waves as well as longer periods of stably high ambient air temperatures during which mortality risks grow disproportionally faster, especially for the most susceptible population groups [1]. Some studies report that a potential decrease in cold-related deaths does not balance a steep rise in heat-related excess mortality [2]. In particular, the number of temperature-related deaths is predicted to grow practically everywhere in Europe, even taking adaptation into account [3]. In this respect, studies that focus on temperature effects on population health and mortality are becoming more and more relevant and the issue requires more detailed analysis.

The greatest attention has been paid to the relationship between mortality risks and exposure to extremely high temperatures. Since drastic rises in mortality during heat periods have always been a serious challenge for public health, they have long been examined within epidemiological studies [4]. Accumulated data give evidence of a considerable health effect produced by heat waves including a significant growth in cardiorespiratory risks [5–7]. In addition, pollutant concentrations grow in ambient air during heat waves due to wildfires, air stagnation, occurring ‘heat islands’ and other factors; this is an additional health risk factor [8, 9].

At the same time, excess mortality in cold periods has been given much less attention by researchers and available data on causal relationships and physiological pathways are provided with a limited evidence base [10].

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Nevertheless, epidemiological studies show that it is cold-related risks that make the greatest contribution to the overall temperature-related mortality [11].

An accurate estimate of a temperature stress perceived by people is the most difficult task from the meteorological point of view. This is due to the fact that temperature effects depend on several concomitant factors such as humidity, wind speed, atmospheric pressure, etc. [12]. Various biometeorological indices are used to consider these factors; they are mostly calculated relaying on a combination of these parameters with air temperatures to estimate the integral heat stress value [13–15]. Nevertheless, basic results are quite similar in most cases when mean daily temperatures are employed to predict excess mortality risks [12].

Russian experience gained in investigating temperature-related mortality is, as a rule, based on studies accomplished in various cities across Russia. The first studies focused on analyzing cold-related risks and peculiarities of people's adaptation to low temperatures[1]. However, systemic epidemiological studies were first conducted only in mid-2000ties [16–18]. They revealed a significant rise in mortality in certain groups during the heat waves in 1999 and 2001 as well as the cold wave in 2006.

In particular, excess mortality has been evidenced during heat and cold waves in the southern regions [19–21], north regions [7, 14, 22], northwestern regions [23], Siberia [24], Far East [25, 26], and Moscow [9].

The considerable part of Russian studies focuses on estimating excess mortality during heat or cold waves per age groups or causes of death; another focus is determining associations between air temperatures and mortality risks within specific cities. Various biometeorological indices as mortality predictors have been compared as well [14, 21]. Special attention has been paid to interactions between air temperatures and ambient air pollution as an additional risk factor [9]. In addition, impacts exerted on mortality rates by duration of heat or cold waves have also been given some attention [20].

Common conclusions made in these studies give evidence of excess mortality both during heat and cold waves; however, specific risk levels depend on geographical conditions, analyzed population groups, heat waves criteria, meteorological parameters, etc. For example, using Volgograd, Rostov-on-Don and Astrakhan as examples, researchers have shown that mortality risks during heat waves are higher than similar risks during cold ones [19, 20]. On the contrary, cold-related risks have turned out to be higher in Murmansk, Arkhangelsk and Magadan [7]. Studies accomplished in Khabarovsk and Krasnoyarsk have established that the population in both cities faces excess mortality both during heat and cold waves. For Khabarovsk, the highest mortality risks were established during heat waves [26], whereas for Krasnoyarsk during cold waves [24].

There are comparatively few studies with their focus on estimating temperature effects on mortality at the regional level [27–29]. In general, cold-related risks are established to be higher in them; however, the analysis gets too complicated due to too wide confidence intervals in estimates.

Approaches to data analysis in environmental epidemiology. Data on the environmental conditions (temperatures, ambient air pollution, etc.) are usually obtained by ground-based observations or are raster (gridded) datasets. Ground-based observations provide highly accurate data directly at measuring points and are often considered the 'golden standard' due to it. However, they cannot provide the complete geographical coverage. Moreover, observation stations (especially meteorological ones) are often located in atypical places such as airports or outskirts

[1] Donaldson G.C., Tchernjavskii V.E., Ermakov S.P., Bucher K., Keatinge W.R. Winter mortality and cold stress in Yekaterinburg, Russia: interview survey. *BMJ*, 1998, vol. 316, no. 7130, pp. 514–518. DOI: 10.1136/bmj.316.7130.514; Donaldson G.C., Ermakov S.P., Komarov Y.M., McDonald C.P., Keatinge W.R. Cold related mortalities and protection against cold in Yakutsk, eastern Siberia: observation and interview study. *BMJ*, 1998, vol. 317, no. 7164, pp. 978–982. DOI: 10.1136/bmj.317.7164.978

of large cities; this makes them much less eligible for assessing health risks in densely populated residential areas [30, 31].

Gridded data on temperatures are created by using remote sensing or by interpolating and using various geostatistical methods. This approach provides complete coverage of the whole analyzed area. However, errors in measurements, calculations and aggregations limit their accuracy and applicability as a source of data on the environment [32]. Global gridded products, though having comparable time-specific detailing, often have too low spatial resolution and describe actual conditions only as averaged without considering local patterns [33] and turn out to be available only with a certain lag. Gridded datasets with extremely high resolution tend to have very limited coverage; therefore, they do not allow analysis within spacious regions.

Atmospheric reanalyses are a source able to provide gridded data on temperatures used in environmental epidemiology. They are based on remote sensing data, ground-based observations and atmospheric circulation models, which allows creating continuous time series and make retrospective forecasts. However, since these are model calculations, they are often unable to represent local weather conditions [34]. Nevertheless, multiple studies describe their mutual compatibility with other data sources for mortality analysis [35, 36].

Additional complications are associated with calculating an aggregated temperature level within a specific area since the choice of a concrete calculation method can turn out to be as crucial as the choice of a this or that data source [37]. Averaging of all available values seems to be the simplest and intuitively understandable aggregation method [38]. However, such estimates often turn out to be non-representative. For example, a situation in a border area can be reflected by observations made in other regions much more accurately; given that, sometimes it is advisable to expand a selection of meteorological stations by including a buffer area. Averaging also does not make it possible to consider differences related to population distribution variability. To overcome that, a possible solution might be to consider each meteorological station with a weight, which is inversely proportional to the distance between this station and the center of the region. In this case, the population center becomes the most representative central point, which reflects peculiarities of population distribution. The population center in a region is a point with the smallest distance from it to all other points in this region considering their weights per population numbers.

A similar issue related to the necessity to consider uneven population distribution arises when gridded data are used for aggregated estimation of heat stress [39]. Gridded surfaces of population density are used additionally to resolve it. Temperature values, which are weighted per population numbers, are much more accurate as aggregated heat stress estimates.

In Russian practice, most studies with their focus on temperature-related mortality have been conducted in specific cities; therefore, ground-based observations have been usually used as temperature data [40]. As a rule, information about temperatures beyond Moscow is available only from the station network of the Federal Service for Hydrometeorology and Environmental Monitoring (Rosgidromet); these data have been used by most Russian researchers. Since their analyses have been performed within boundaries of one specific city, they have not faced the issue of data aggregating and averaging. Studies that examine changes in temperature-related mortality at the regional level are rather scarce and they also rely, as a rule, on point data obtained at ground-based stations [28, 29]. Gridded data and reanalyses data have been used to investigate mortality rather rarely so far regardless of their considerable potential for analysis due to an opportunity to ensure full coverage of an analyzed area.

This study aimed to perform regional estimates of temperature-related mortality risks calculated using two data sources, ground-based observations and gridded reanalysis data. We assumed that considerable differences would not be found between these two data sources; however, small deviations would be observed for heat-related risks.

Materials and methods. The study covered the period between 2004 and 2019, which was characterized with a stable descending trend in the national-level mortality in Russia. The analysis included 80 RF regions with continuous time series. Crimea and Sevastopol were excluded from the analysis since data for these regions are available only starting from 2015. In addition, the Khanty-Mansi Autonomous Area and Yamal-Nenets Autonomous Area were included into the Tyumen region; the Nenets Autonomous area, the Arkhangelsk region.

All data on mortality and averaged temperatures in the analyzed regions were aggregated on a weekly basis. Although daily series can reflect impacts of short-term effects more accurately, use of weekly data shows the results, which are comparable per quality and representativeness [41].

The Russian Database on Short-Term Fluctuations in Mortality (RDSTFM) was used as a major source of demographic data. It contains weekly statistical data on mortality per RF regions over 2000–2021[2]. The database uses depersonalized micro-data provided by Rosstat and aggregated per regions on the weekly basis[3]. Weekly age-standardized death rates (ASDR) were taken as a research object using the Revision of the European Standard Population 2013[4]; it helped exclude effects produced by an age-specific structure on estimates of relationships between mortality and temperatures [42]. Data taken from the Russian Database on Birthrates and Mortality were used to estimate average annual population numbers; these data are calculated based on Rosstat data and the database itself was created by the Center for Demography Studies of the Russian School of Economics[5]. Data on population numbers were taken without recalculation considering the results of the 2021 Census.

Mean air temperatures were calculated for each region to estimate risks associated with heat stress; calculations were made for each region per weekly basis using two data sources, ground-based meteorological observations and gridded data of atmospheric reanalysis.

Mean weekly air temperatures were used as point data sources; they were calculated based on data collected at ground-based meteorological stations of the Aisori-M database provided by the Russian Scientific Research Institute for Hydrometeorological Information – Global Data Center[6]. This data array includes prompt meteorological observations from 600 stations that cover the whole territory of Russia and some countries of former Soviet Union. Since continuous data series were not available for all meteorological stations and not all of them were located near the Russian border, overall, 571 stations were included in the analysis. In addition, the Aisori-M database contains a reference book with description of possible changes in the measurement methodology for each station as well as their geographical coordinates, which were employed in further calculations.

Gridded data were obtained from EAC4 (ECMWF Atmospheric Composition Reanalysis 4) conducted by the European Centre for Medium-Range Weather Forecasts (ECMWF) on the global scale [43]. EAC4 Reanalysis has spatial resolution 0.75 per 0.75 degrees and is available at the Copernicus Atmosphere Data

[2] Rossiiskaya baza dannykh kratkosrochnykh kolebanii smertnosti [The Russian Database on Short-Term Fluctuations in Mortality (RDSTFM)]. *International Laboratory for Population and Health Studies, SRI HSE*. Available at: https://demogr.hse.ru/russtmf (April 17, 2025) (in Russian).

[3] Excluding weeks 9–13 in 2012 in the Pskov region.

[4] Eurostat. Revision of the European Standard Population. Report of Eurostat's task force: 2013 edition. *Publications Office of the European Union*. DOI: 10.2785/11470

[5] Tsentr demograficheskikh issledovanii [Center for Demography Studies]. *Russian School of Economics (RSE)*. Available at: https://www.nes.ru/demogr/ (April 17, 2025) (in Russian).

[6] Aisori-M: Spetsializirovannye massivy dlya klimaticheskikh issledovanii [Aisori-M: Specialized data arrays for climatic research]. Available at: http://aisori-m.meteo.ru (April 14, 2025) (in Russian).

Store[7]. The reanalysis data have been published since 2003 and are still renewed twice a year with a several months lag. Moreover, EAC4 has data on some other meteorological parameters as well as levels of various chemicals in ambient air. Initial data time resolution is 3 hours but they were aggregated per weeks within our analysis.

To allow for uneven population distribution within the analyzed regions, gridded data were taken from the Gridded Population of the World, Version 4 (GPWv4), one of the most commonly used data source on population numbers for making regional estimates of various square indicators. This data array is provided by the NASA Socioeconomic Data and Applications Center (SEDAC)[8] and has spatial resolution 0.5 per 0.5 degrees[9]. GPWv4 is based on the official demographic statistics; in particular, the municipal level is used in the analysis for Russia. Additionally, GPWv4 allows for peculiarities of the Earth surface; due to it, population density is more consistent with actual population distribution. The GPWv4 data set for 2010 was selected as a data source as reflecting population density in the middle of the analyzed period.

Three approaches were used to estimate mean weekly temperatures aggregated per regions; two of them were based on data collected at ground-base stations. For the first method, the population center was determined in each region based on population density taken from the GPWv4. Next, weights were assigned to all meteorological stations located within a given region and within a 200-km (in accordance with [29]) buffer area around it. These weights were inversely proportionate to distances between them and the regional population center. Mean weekly temperatures were calculated as a weighted sum of temperatures per all selected meteorological stations.

In addition, mean weekly temperatures were calculated per regions using an alternative way for additional verification of the estimates. It involved estimating weekly temperatures at the municipal level. Similarly, a population center was established for each municipality, meteorological stations were selected within a relevant buffer area, and weights were assigned in conformity with the distance between them and the municipality center. After that, a mean regional temperature was calculated as a weighted mean temperature per municipalities where weights were established based on a population number in each territorial unit.

Images from the EAC4 reanalysis averaged over weeks were used to calculate mean temperatures based on gridded data. These data were reduced to the spatial resolution of the population density grid to provide mutual compatibility. Therefore, mean temperature values were calculated for each region as mean temperature values in relevant grid cells weighted per the number of people living within each cell.

To estimate the relationship between mortality risks and temperatures, the two-level model with quasi-Poisson regression was used for each region at the first level and meta-analysis of regional estimates to obtain aggregated results at the second level. In particular, at the first stage, the dose-response curve was built for each region using the Distributed Lag Model (DLM) [44] to describe influence of temperatures on mortality considering remote temperature-related effects. Next, these regional estimates were aggregated to calculate this relationship for Russia as a whole and to subsequently adjust the regional results per these figures.

In this context, the dose-response curve reflected estimates of Relative Risks (RR) of mortality for all observed temperatures. Since it has a non-linear shape, as a rule, it is given as non-parametric functions. The Minimum Mortality Temperature (MMT) was taken as

[7] Atmosphere Data Store. Available at: https://ads.atmosphere.copernicus.eu (April 14, 2025).

[8] Gridded Population of the World (GPW), v4. *Socioeconomic Data and Applications Center (SEDAC)*. Available at: https://beta.sedac.ciesin.columbia.edu/data/set/gpw-v4-population-density-rev10 (April 17, 2025).

[9] Gridded Population of the World, Version 4 (GPWv4): Population Density Adjusted to Match 2015 Revision UN WPP Country Totals, Revision 11. *Center for International Earth Science Information Network, Columbia University (CIESIN)*, 2018.

the reference level, against which all temperature-related risks were calculated. Therefore, the minimum level of relative mortality risk was equal to 1 [45]. This methodology is described in greater detail in [46]. Time series were analyzed using quasi-Poisson regression; its formula can be written as:

$$\log\left(E\left(Y_{week}\right)\right) = \\ = intercept + ns\left(week,\ df\ = 7\ per\ year\right) + \\ + cb\left(ns\left(T,\ \ knots = 3\right), lag = 0,1,2,3\right) + \\ + offset\left(\log\left(Pop\right)\right),$$

where $E\left(Y_{week}\right)$ is expected value of weekly ASDR in the region;

$intercept$ is the free equation member reflecting mean ASDR in the region;

$\mathrm{ns}\left(week,\ df\ = 7\ per\ year\right)$ is the natural cubic spline with 7 degrees of freedom for each observation year included in the analysis to allow for seasonality and long-term trends in mortality.

The model $cb(ns\left(T,\ \ knots = 3\right)$, $lag = 0,1,2,3)$ is a distributed lag model (DLM), which is used for considering influence of temperatures on mortality risks allowing for remote effects.

The dose-response curve, which reflects the association between mortality risks and temperatures, was built using the natural cubic spline with three knots located evenly at the 25^{th}, 50^{th} and 75^{th} percentiles of temperature distribution in each region. This approach makes it possible to most accurately describe non-linear relationships between temperature and mortality and is common in similar research. Categorical variables were employed to take the lag structure into account. Therefore, influence exerted by temperatures on mortality was estimated not only at the current moment but also considering their effects over three previous weeks.

The parameter $offset\left(\log\left(Pop\right)\right)$ is used in the library *glm* of the machine language R when mortality ratios are employed as a dependent variable since both Poisson and quasi-Poisson regression requires enumerable data analysis. Therefore, the logarithm of the mean population number over the respective period was introduced as an additional model parameter to make mortality estimates in different regions compatible with each other.

The most optimal spline parameters as well as length and structure of lags were based on minimization of the Akaike information criterion (AIC) within modeling the dose-response curves.

A meta-analysis was performed to investigate regional dose-response relationship with its aim to obtain aggregated assessments of temperature-related risks [47, 48]. This approach makes it possible to combine results obtained for different regions allowing for variability between them due to using a meta-regression model with random effects.

The aggregated relationship between mortality and temperatures was calculated for the whole country on the basis of regional assessments; it was then used to adjust the latter. This involves using Best Linear Unbiased Predictors (BLUP), which consist of two components. Primarily, they include parameters of dose-response curves obtained for each region at the first level of the analysis. Adjusting these assessments per their deviation from aggregated results can raise accuracy of regional indicators. This BLUP component is random effects that have already been obtained by using meta-regression [47]. Regional variations of the MMT BLUP assessments were shown to present regional differences in the relationship between mortality and temperatures; these variations were calculated based on each of three methods for temperature data aggregation.

All data were statistically analyzed in the RStudio integrated development environment. In particular, such libraries as *glm, splines, dlnm, mvmeta* and *mixmeta* were used for building aggregated dose-response curves for analysis [44].

Results and discussion. On average**,** weekly ASDRs taken over the whole analyzed period (2004–2019) turned out to be the highest in Chukotka (28.6 ‰), Tyva (26.5 ‰), the

Jewish Autonomous Area (24.6 ‰), and the Amur region (24.1 ‰). The lowest values were observed in Ingushetia (11.6 ‰), Moscow (13.4 ‰), Dagestan (14.4 ‰), and Saint Petersburg (15.7 ‰). Mortality was declining quite rapidly in Russia over the whole analyzed period; in 2005, the mean weekly ASDR equaled 25.2 ‰ per all regions but it went down to 16.2 ‰ in 2019. It is noteworthy that these assessments are based on mean weekly mortality ratios; therefore, they can be rather different from annual mortality rates reported in other sources.

Over the analyzed period, an all-time low mean weekly temperature was detected in late December 2024 in Yakutia. It was equal to -43.15 °C as recorded at ground-based observation stations, -45.01 °C when using weighted mean temperatures in municipalities, and -44.66 °C according to gridded reanalysis data. Mean weekly temperatures reached their peak in the Volgograd region during a heat wave in August 2010 when the peak mortality was detected there; they equaled 31.53 °C, 32.18 °C and 32.34 °C for the same data sources respectively. All-time temperatures were registered both for extreme heat and extreme cold in the same period regardless of which data source was used; quantitative estimates also turned out to be quite similar.

The total number of weekly observations amounted to 66,640 in all regions over 2004–2019. Mean temperature values for regions, which were obtained using different methods, showed high consistency (Table 1). The correlation coefficient between temperature time series was 0.991 when calculated using ground-based observation data. The correlation coefficient between reanalysis data and aggregated regional data was 0.969 and 0.978 between reanalysis data and weighted mean temperatures per municipalities.

At the regional level, mean weekly temperatures established by using three different methods showed not only a close linear connection with each other but also absence of any shifts associated with systemic errors in most regions (Figures 1 and 2). However, estimates for temperatures above zero in general tended to be more consistent. Still, there were some exceptions, for example, Chukotka where data from meteorological stations obtained by using different aggregation methods were not consistent. Regional and municipal population centers in Chukotka do not allow obtaining a comparable picture and due to it estimates based on using different methods are not consistent with each other. Similar, although less apparent, differences were found in some other regions with low population density and uneven population distribution, in particular, in the Tyumen region, Krasnoyarskii Krai and the Altai Republic.

Table 1

Descriptive statistics of time series of weekly data over 2004–2019 per 80 regions used at the first level of analysis for three models, each of which relies on temperatures calculated by using diriment methods

Indicator	1st quartile	Median	Mean	3rd quartile
Dependent variable:				
Weekly ASDR, per 1 thousand people	17.20	19.50	20.08	22.40
Independent variables:				
Mean weekly temperatures detected at ground-based stations per municipalities, °C	-3.509	5.600	4.728	15.067
Mean weekly temperatures detected at ground-based stations per regions, °C	-3.468	5.586	4.727	15.064
Mean weekly temperatures based on reanalysis (EAC4), °C	-3.625	5.369	4.499	14.767

Note: results of the author's calculations using RDSTFM, Aisori-M, and EAC4 data

Figure 1. The graph to show spreads of mean weekly temperature estimates over 2004–2019 obtained by aggregating point data allowing for population centers in regions and EAC4 reanalysis data weighted per population density (RF regions are given with different colors; estimates for Chukotka are red; based on the author's calculations using Aisori-M, EAC4)

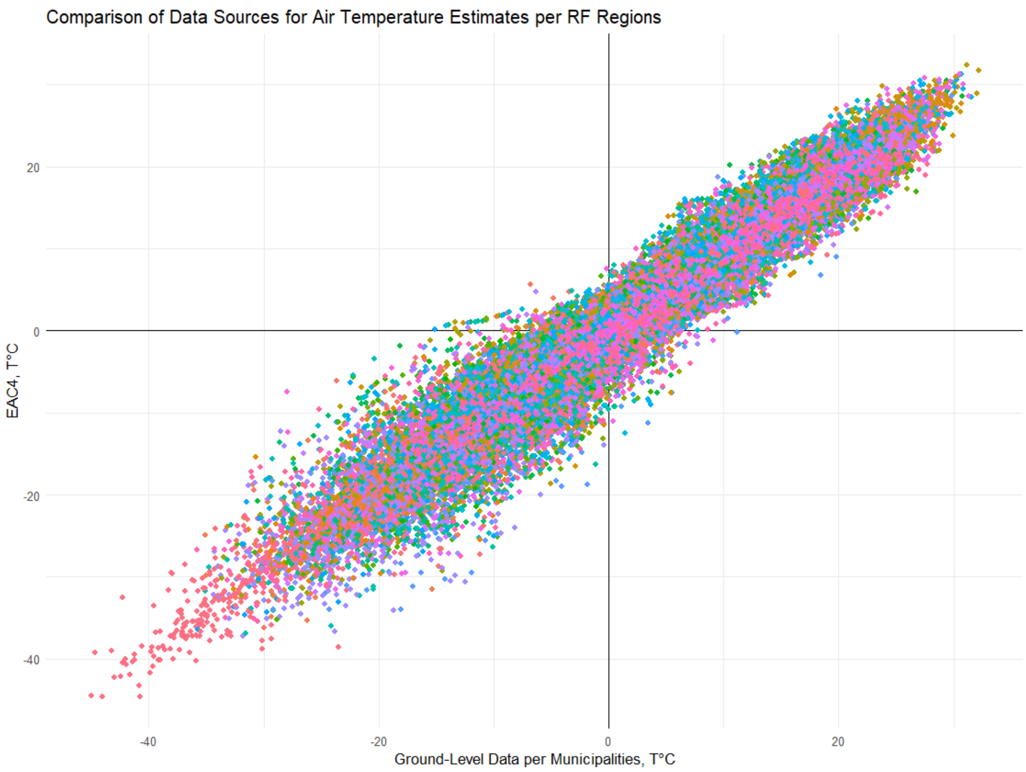

Figure 2. The graph to show spreads of mean weekly temperature estimates over 2004–2019 obtained by aggregating point data allowing for population centers in municipalities and EAC4 reanalysis data weighted per population density (RF regions are given with different colors; based on the author's calculations using Aisori-M, EAC4)

The dose-response curves that show the relationship between mortality and temperature were obtained for the whole country by using meta-regression; they have similar shape, which corresponds to the most common relationship between mortality and temperatures. Both cold and heat cause a rise in mortality risks; for most RF regions, MMT is within 15–20 °C, which is consistent with conclusions made in most other studies [3]. However, risks related to extreme cold turned out to be more statistically significant.

This is not consistent with the results reported in many studies where the highest risks are considered to be associated with heat [11] and might be due to two factors. First, a considerably long lag (3 weeks) was used in this study, which makes it possible to take remote cold-related effects into account more effectively. Heat-related risks usually turn out to be much higher when associations between temperatures and mortality are considered within a week and without allowing for lags. However, such a model based on statistical indicators tends to have weaker predictive ability. Secondly, our results are consistent with conclusions made in other Russian epidemiological studies where mortality risks are often higher during cold waves than heat ones[10] [22]. In any case, this estimate is only an averaged picture based on aggregated data from different regions with considerably different conditions.

The aggregated estimated minimum mortality temperature was found to be equal to 19.12 °C when using ground-based observation data aggregated per regions. The MMT was 19.34 °C for mean weighted temperatures per municipalities and 17.17 °C for reanalysis data. In terms of long-term temperature distribution, the MMT corresponded to the 88.4th, 88.8th and 83.0th percentile respectively. These relatively high percentile values can be explained by climatic peculiarities of Russia where winter season is very long in most regions; this is not observed in other regions where similar research has been accomplished [45, 49].

The shapes of the dose-response curves built relying on ground-based observations were very similar to each other for the whole range of the observed temperatures. Risks related to extreme temperatures turned out to be slightly higher for data based on regional estimates; the difference was insignificant though. More substantial inconsistencies were found between the results based on gridded data and aggregated ground-based observations. They were particularly substantial for extremely high temperatures (Figure 3).

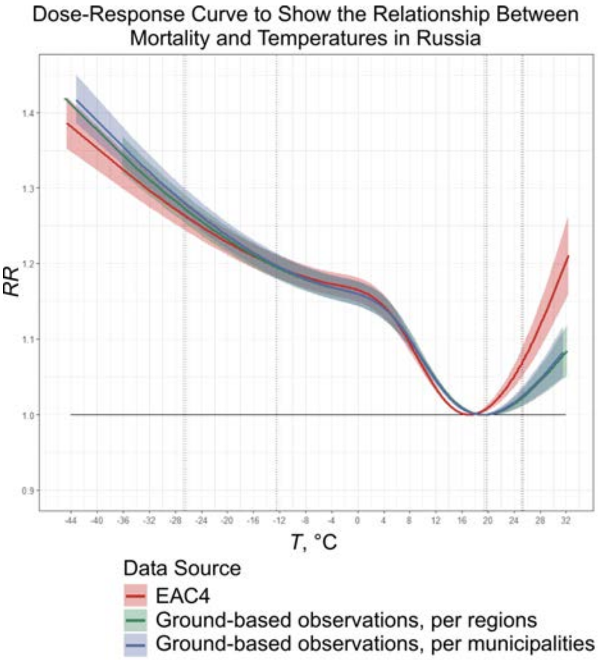

Figure 3. Assessments of temperature-related mortality risks obtained by using different methods: the dotted line show 1-th, 10-th, 90-th and 99th percentiles of temperature distribution in all Russian regions over the analyzed period (2004–2019) (based on the author's calculations using RDSTFM, Aisori-M, and EAC4)

Point estimates of relative risks at certain boundary values, for example, 95th or 99th percentiles of long-term temperature distribution for heat-related effects, can be used as indicators of mortality risks associated with extreme temperatures [50]. Thus, relative risks of deaths due to extreme cold based on temperature reanalysis data turned out to be lower than those established using ground-based observations.

[10] Donaldson G.C., Tchernjavskii V.E., Ermakov S.P., Bucher K., Keatinge W.R. Winter mortality and cold stress in Yekaterinburg, Russia: interview survey. *BMJ*, 1998, vol. 316, no. 7130, pp. 514–518. DOI: 10.1136/bmj.316.7130.514

Differences in risks for the upper percentiles of long-term mean weekly temperature distribution turned out to be much more significant. Relative mortality risks were equal to approximately 1.02 for the 99th percentile based on meteorological observations in the distributed lag model whereas they were 1.07 for gridded data and the difference turned out to be significant (Table 2). It should be noted that temperatures corresponding to these percentiles did not differ very much.

On average, BLUP values of MMT estimates per regions that were calculated using ground-based observations turned out to be 2–3 °C degrees higher than estimates based on using gridded data. In most cases, calculations based on using different methods yielded consistent results. Within federal districts, regions located further to the south with higher temperatures, as a rule, tended to have higher MMT values (the Belgorod Region in the Central Federal District, Kalmyk Republic in the Southern Federal District, the Saratov region in the Volga Federal District). However, it was not the case everywhere; for example, the Komi Republic in the North-Western Federal District was an exception.

We did not find any interrelations between ASDR and MMT levels. Although regions with higher mortality rates are, as a rule, located in colder climate, this did not have any influence on the ultimate regional differentiation. MMT corresponded to 75–85th percentiles of long-term temperature distribution in most regions when reanalysis data were used to estimate it. MMT established by using meteorological data was, as a rule, between the 80th and 90th percentiles. No values below the 70th percentile were detected whereas they were close to the 99th percentile in some regions (Kamchatka, Sakhalin, Komi, and Tyva), which is due to both cold climate and insufficient validity of BLUP estimates given small population numbers in them.

The greatest discrepancies between MMT estimates obtained by using different methods were found in some sparsely populated regions with low density of meteorological station coverage, for example, in Chukotka, where their representativeness turned out to be lower for aggregated regional temperature estimates. Meteorological networks have greater coverage in the Central, Volga and Southern Federal Districts and physical-geographic characteristics of regions in them do not differ greatly; given that, BLUP estimates of MMT turned out to be the most consistent. However, some specific regions, for example, Adygei, the Ivanovo region, the Arkhangelsk region, Primor'e, Yakutiya and Saint Petersburg showed abnormal spreads in MMT estimates between all three of them. This can be explained by data aggregation artifacts and failure to allow for local climatic peculiarities (Figure 4).

Table 1

Relative risks related to extreme temperatures, calculated using different methods for the 1st, 5th, 95th and 99th percentiles of temperature distribution in all Russian regions over the analyzed period (2004–2019)

Data aggregation method		1st percentile to MMT	5th percentile to MMT	95th percentile to MMT	99th percentile to MMT
Ground-based observations per municipalities	T, °C	-26.39	-17.65	21.8	25.43
	RR	1.272 (95 % CI: 1.253–1.291)	1.219 (95 % CI: 1.203–1.236)	1.004 (95 % CI: 1.000–1.008)	1.023 (95 % CI: 1.012–1.035)
Ground-based observations per regions	T, °C	-26.77	-17.63	21.74	25.31
	RR	1.282 (95 % CI: 1.262–1.302)	1.223 (95 % CI: 1.206–1.24)	1.005 (95 % CI: 1.001–1.009)	1.025 (95 % CI: 1.012–1.038)
Based on reanalysis (EAC4)	T, °C	-26.62	-17.89	21.41	25.05
	RR	1.264 (95 % CI: 1.245–1.283)	1.218 (95 % CI: 1.202–1.235)	1.021 (95 % CI: 1.013–1.028)	1.066 (95 % CI: 1.048–1.085)

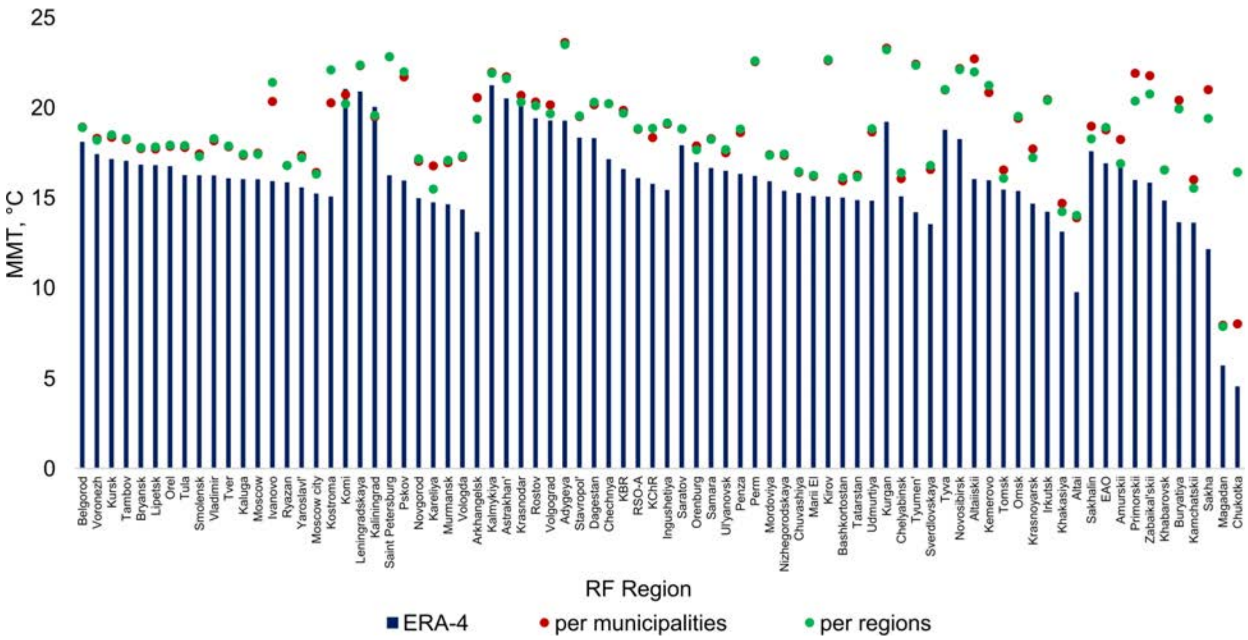

Figure 4. BLUP estimates of MMT for temperatures calculated using different methods, per RF regions over 2004–2019 (based on the author's calculations using RDSTFM, Aisori-M, and EAC4)

The resulting estimates of the relationship between mortality and temperatures have the J-like shape where cold-related risks prevail. These data allow calculating the temperature stress burden and predict population losses due to climate change as well as to develop regional measures for prevention and prophylaxis of negative outcomes caused by temperature exposures.

Experience gained by Russian researchers does not allow unambiguously identify what risks (cold- or heat-related ones) are more significant since conclusions depend on geographical coverage and a methodology [26]. Prevalence of cold-related risks in this study might be due to using a model with distributed lags, which considers temperature effects over three weeks. This method is eligible for analyzing annual dynamics but tends to underestimate mortality caused by heat waves [41]. Moreover, weekly data do not consider short-term effects produced by high temperatures, which are usually manifested several days after an exposure [44]. This might also make for underestimation of mortality related to high temperatures. It is also important to remember that all-cause mortality was analyzed in this study, including external causes that held a significant place in the beginning of the analyzed period. Clear relationships with temperatures have not been established for many external causes of death, which makes it difficult to identify them on the example of the employed data.

We did not find a significant relationship between initial ASDR values and temperature risks. A considerable proportion of deaths occur due to external causes and alcohol poisoning in regions with high mortality rates; these death causes have a very weak relationship with temperatures. Therefore, the overall mortality rate did not have any substantial influence on the relationship between temperature and mortality.

Regional differences in MMT reflect regional natural and climatic peculiarities. MMT tends to be higher in warmer regions, which is explained by people getting adapted to prevailing conditions [49]. MMT values similar to those established in most Russian regions (15–18 °C) were also observed in cities in Finland, Sweden, and Norway [45]. The best estimates are those based on reanalysis in accordance with percentiles of temperature distribution that correspond to MMT. As a rule, percentiles with minimum mortality risks are also between the 75th and 85th percentiles in similar climatic conditions [49]. A decline in

MMT at higher latitudes and lower mean annual temperatures reflects differences in adaptation potential of the Russian population.

Abnormally low MMT values were found in some regions, for example, in the Magadan region or Chukotka; this might be associated with high spreads in the data collected for these regions and low validity of the model. On the contrary, MMT turned out to be overestimated in Kamchatka, Komi, and the Zabaikal'skii Krai, where they were close to the maximum percentiles. In case when meteorological data are used, this can be related to low quality of initial data and peculiarities of BLUP-estimates.

In this study, assessments of temperature-related mortality risks obtained by various methods at the regional level turned out to be similar, which is consistent with the results reported in other studies [15, 30, 50–53]. Moreover, even a quite large aggregation level, both as regards time (per weeks) and space (per RF regions), in general, did not influence comparability of the obtained assessments.

Uneven distribution of meteorological stations was another difficulty. Most such stations were located in large settlements, which made them less representative for sparsely populated areas. The study [54] recommends considering stations located with the 50-km radius from the regional center to calculate temperatures. In [29] and in this study, a 200-km distance was used, which allowed increasing the sample size and make estimates more stable.

The dose-response curves based on various data sources were similar. However, heat-related risks turned out to be higher when reanalysis data were used. Other studies also reported the greatest discrepancies for high temperatures whereas cold-related risks remained comparable. In some studies, gridded data also overestimated heat-related risks [30], but an opposite trend was observed in some other cases [15, 52, 54].

Atmospheric reanalyses based on modeling do not always allow for local micro-geographical effects and extreme temperatures due to data averaging. However, meteorological observations are not representative either for such large areas due to uneven coverage.

The smallest discrepancies between data sources were found in regions with even population distribution and flat terrains. In other cases, certain problems occurred. The estimates were the most inconsistent in Chukotka; excessive number of meteorological stations that reflected local conditions rather poorly was used in Adygei; the reanalysis data were distorted in Saint Petersburg because the city is located so close to the sea [51].

Therefore, estimates of temperatures and related risks based on different data sources are consistent in the simplest cases only. Reanalyses are preferable in regions where a meteorological network has low density whereas meteorological data are more eligible for analysis within cities. Meteorological data are available in real time, which is very convenient for operative estimates; however, they can have some gaps or be fragmentary. Reanalysis data are more eligible for long-term series due to their wide coverage and completeness provided that reanalyses have been created following the same methodology.

When comparing approaches to aggregation of meteorological data, we found temperature estimates per municipalities to be more effective than those made per regions. The population center poorly reflects actual population density in large and sparsely populated areas thereby reducing data accuracy. Therefore, a more correct solution would be to estimate mean temperatures at a sub-regional level with subsequent aggregation of the results for a region as a whole.

Problems and limitations. In this study, temperature-related risks were estimated at the regional level in Russia and various sources of temperature data were compared as regards their eligibility. The study findings are consistent with conclusions made by other researchers, who used more detailed data and analyzed short-term fluctuations in mortality. However, several limitations should be considered since they may have influenced interpretation of the obtained results.

Firstly, despite overall stability of time series of mortality in most regions, the data were found to be highly volatile in some of them (for example, Chukotka and the Magadan region). This made it difficult to obtain authentic results, although use of meta-analysis was a partial solution to the problem. Nevertheless, we were not able to obtain adequate estimates of temperature-related mortality risks for some regions.

Secondly, specification of the dose-response function may have influenced the modeling results. Although we used the best values of information criteria in the selected model, location of spline knots and lag structure might have distorted the ultimate estimates.

Thirdly, the analysis was limited by absent data on ambient air pollution. In Russia, such data are available at the regional level only within reanalyses since the country does not have an extensive network for observation of ambient air quality with open and accessible data. Therefore, we were not able to include such data in our analysis.

Conclusions. The aim of this study was to analyze temperature-related mortality using data of atmospheric reanalysis EAC4 and meteorological observations. Regional temperatures were calculated using three different methods, which showed similar patterns of time series.

The relationship between mortality and temperatures in Russian regions had a J-like shape: risks were higher at low temperatures. Thus, relative risks reached 1.25 for the 1st percentile whereas they were 1.02 (according to meteorological data) and 1.07 (according to reanalysis) for the 99th percentile. This is due to considering lag effects on health produced by temperature exposures over several weeks, which makes it possible to allow for negative outcomes of cold exposure more effectively.

In most regions, MMT was within 15–20 °C corresponding to 75–85th percentiles of temperature distribution (per reanalysis data). Minimum mortality temperatures turned out to be several degrees higher when meteorological data were used. Optimal temperatures are often higher in warm regions and this indicates people's adaptation to prevailing conditions. Knowledge on threshold risk levels allows more effective assessment of threat for people's lives and health and helps develop relevant measures for preventing negative outcomes of temperature exposures. Such measures include systems for notifying, informing and warning people about a coming heat or cold wave.

Both data sources were found to be applicable for the task; however, meteorological data tended to become less authentic in sparsely populated regions with low density of meteorological observation networks and this influenced consistency of risk assessments. For example, the minimum mortality temperature tended to be overestimated per meteorological data relative to reanalysis data.

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