Urban Climate 15 (2016) 16–24

Contents lists available at ScienceDirect

Urban Climate

journal homepage: www.elsevier.com/locate/uclim

Toward meta-analysis of impacts of heat and cold waves on mortality in Russian North

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ARTICLE INFO

Article history:
Received 12 May 2013
Revised 7 July 2015
Accepted 21 November 2015

Keywords:
Extreme temperatures
Circumpolar regions
Elderly
Cardiovascular mortality
Traumatic deaths
Homogeneity

ABSTRACT

Russian North experiences greater warming trends than other regions of the country. Absence of large cities in this region makes direct epidemiological studies difficult, and new methods are being developed. This study proposes a framework for a meta-analysis of health impacts of heat waves and cold spells, using four selected cities with populations between 100,000 and 350,000 as project sites. Heat waves and cold spells were identified during 1999–2007. Statistical analysis of mortality from all non-traumatic, cardiovascular, respiratory and all external causes among age groups 30–64 and $\geqslant$65 allowed to obtain site-specific and then pooled estimates of relative increases in mortality separately for heat and cold waves. The evidence of impacts of cold on mortality was more robust than the same for heat. Greater increases in mortality were observed during long cold waves than during short ones; however, the opposite was true for heat waves. Age group $\geqslant$65 was more vulnerable to cold than age group 30–64. Nearly all increase in non-traumatic mortality during cold waves was attributed to cardiovascular causes. External causes also showed significant increase during heat. The proposed methodology gives statistically significant results in cities with populations greater than approximately 100,000.

1. Introduction

Recent studies of potential health effects of climate change renewed interest in assessment of health effects of extreme temperature events all over the world, because it is very likely that global climate change will generate more heat waves (Peng et al., 2011; Shaposhnikov et al., 2011). The importance of circumpolar areas in such studies has been emphasized because these areas are experiencing more pronounced changes of near-surface temperatures than the average changes in the North Hemisphere. For example, annual average temperatures in Central Siberia increased by 1–3 °C over the last 50 years (Federal Service for Hydrometeorology and Environmental Monitoring, 2008), while the average global surface temperature increased by 0.65 °C during the same period (Solomon et al., 2007). Climate simulations performed in Russian Main Geophysical Observatory confirmed that climate change would lead to longer heat waves and shorter cold waves (Shaposhnikov et al., 2011).

Abbreviations: IHD, ischemic heart disease; CVD, cerebrovascular diseases; RD, respiratory diseases; RR, relative risk; H_0, null hypothesis; df, degrees of freedom.

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http://dx.doi.org/10.1016/j.uclim.2015.11.007
2212-0955/

The observed increases in total mortality during heat waves may reach 60–85% (McGeehin and Mirabelli, 2001; Johnson et al., 2005; Poumadère et al., 2003). However, catastrophic heat waves happen rarely, and average heat wave effects are much smaller. For example, an average increase in total mortality on heat wave days compared to non-heat wave days for all waves with duration $\geqslant$2 days ranged from 1.8% in US South to 6.8% in US Northeast (Anderson and Bell, 2011). The documented impacts of cold spells on non-accidental mortality are generally 10–15% (Huynen et al., 2001; Revich and Shaposhnikov, 2008).

While health impacts of extreme temperature events, including relative increases in mortality, have been well documented for major cities, usually with population over one million, studies of small populations present considerable statistical difficulties, because daily number of health outcomes are too small. The relationship between population size and the significance of the heat effect estimate can the illustrated by the following example: an Italian study (Conti et al., 2003) attempted to detect the differences in mortality rates in age group $\geqslant$75 between the summers of 2002 and 2003 (the latter was unusually hot in Europe) in all 21 regional capitals with populations ranging from 40,000 to 2,547,000. Only 10 out of 21 tests showed significant increases in mortality rates; these 10 were the largest cities. The smallest city where the test was significant was Bari (317,000 people); and the largest city where the test was not significant was Florence (356,000 people). For a US nationwide study of heat waves, the authors selected only communities with $\geqslant$200,000 inhabitants (Hajat et al., 2006). The same minimum population threshold was used in a Chinese study of cold spells "in order to ensure enough death counts" (Zhou et al., 2014). Given that sensitivity of statistical criteria used for hypothesis testing crucially depends upon the average number of daily outcomes, direct statistical evidence of health risks posed by temperature waves in small towns with <200,000 inhabitants is generally scarce.

Russian labor legislation established the list of "Far Northern" regions, defined on the basis of harsh climatic conditions. Total population of these regions is 10.6 million (Federal Statistical Service, 2011), of which 2.5 million live in the Arctic Circle (Ministry of Regional Development of the Russian Federation, 2010), where the largest city (Murmansk) has the population of 350,000. Although the exposed population is large, the absence of big cities in Russian North poses specific challenges for assessments of health impacts of temperature waves (Shaposhnikov et al., 2011; Revich and Shaposhnikov, 2010). In this study, we attempted to gain more information about the potential health effects pooling together site-specific estimates of mortality risks obtained at four different locations near the Arctic Circle, in circumpolar regions, as defined in Arbour et al. (2010). In particular, the following questions were addressed: Are heat waves more hazardous than cold spells, if symmetrical definitions are applied to both types of these weather events? Are long temperature waves more devastating than short waves? (The distinction between short and long temperature waves might be particularly important in future studies of climate and health projections.) Which causes of death mainly explain increases in total mortality during such events? What are the inputs of accidental and non-accidental causes? Are there any significant age-specific differences? And, finally, what is the minimum size of population which can be studied with the methods developed in this paper?

2. Methods

2.1. Study locations and data

This study consisted of two successive steps: first, site-specific estimates of relative increases of mortality during temperature waves were obtained at the four selected cities of Russian North. Then, the pooled risk estimates were calculated and several hypotheses were tested using these estimates. Table 1 lists the project sites sorted by population size. During the selection of project sites, the authors took in account the size of urban populations, their ethnic composition and massive migrations. Some cities were excluded at this step, e.g., Norilsk, because of dramatic changes in the population size during the study period (1999–2007). Some of selected cities also showed considerable declines in their populations between the beginning and the end of study period: e.g., −14% in Murmansk and −22% in Magadan, which were taken in account during statistical analysis. Although only one of the four cities (Murmansk) is situated above the Northern Polar Circle, the climate there is actually milder than in the other cities included in the study.

A database of daily death counts was obtained from Russian State Statistical Service; each death record contained cause of death coded in ICD-10 format and age at death. This database was used to construct daily time series for ten indicators of

Table 1
Geographic location, climate and population of four cities included in the study.

City	Geographic coordinates	Mean temperature (°C)		Temperature thresholds[a] (°C)		Population, thousand	
		January	July	Cold	Heat	Beginning of study period	End of study period
Archangelsk	65°N; 40°E	−13	+15	−23.8	+21.0	369	355
Murmansk	69°N; 33°E	−11	+13	−18.4	+17.3	364	318
Yakutsk	62°N; 130°E	−40	+19	−43.0	+22.8	204	246
Magadan	60°N; 151°E	−26	+13	−22.4	+13.9	122	100

[a] Cold and heat thresholds were set at the 3rd and 97th percentiles of distribution of daily mean temperatures during the study period.

mortality, stratified by two age groups and five groups of causes. The two selected age groups represented able-bodied population (30–64 years of age) and senior people ($\geqslant$65 years of age). The number of deaths in age group below 30 years was too small to analyze. The selected groups of causes of death were: all external causes and all non-accidental (non-traumatic) deaths; within the latter we specifically studied ischemic or coronary heart disease (IHD); brain strokes and other cerebrovascular diseases (CVD); respiratory diseases (RD). Calculation of mortality risks for these ten indicators substantially increased the level of detail and utility of the results for the decision makers.

2.2. Definition of temperature waves

We required that during all days of a cold spell the daily mean temperatures should be below the cold threshold, and during a heat wave daily mean temperatures should exceed heat threshold, which were location-based and set at the 3rd and 97th centiles of the site-specific distributions of daily mean temperatures during the study period. This definition, based on probability of observation of extreme temperatures, agrees with other definitions used in international studies. For example, Anderson and Bell in a US study (Anderson and Bell, 2011) defined heat wave days as those with temperatures $\geqslant$95th percentile for the community for 1 May through 30 September. Likewise, Zhou et al. in a multi-center Chinese study (Zhou et al., 2014) defined cold spell days as those with temperatures $\leqslant$5th percentile for the community for 1 December through 30 March.

These temperatures at each location were reported by Federal Service for Hydrometeorology and Environmental Monitoring (Roshydromet). To address the issue of wave duration, we defined short waves as lasting between 5 and 7 days, and long waves as lasting for 8 days or more. The waves shorter than 5 days were not considered because the applied criterion for hypothesis testing was not sensitive enough to reject the ‘no health impact’ hypothesis due to large relative standard error of daily deaths.

2.3. Calculation of site-specific mortality risks during temperature waves

A straightforward approach to analyzing impacts of a discrete weather event on mortality involves calculation of excess risk of death estimated against the background value, expected in the absence of such event (e.g., a temperature wave). In the approach, the null hypothesis (no health impact) is usually formulated and tested for an individual heat wave, like the Chicago heat in July 1995 (Kaiser et al., 2007) or an August 2003 heat in Europe (le Tertre et al., 2006). For small populations, however, this approach will most likely fail unless a heat (or cold) wave is truly exceptional. Preliminary trials in our study showed that non-parametric χ^2 test failed to reject the null hypothesis for most temperature waves. This is why we formulated null hypotheses about the *ensembles* of temperature waves, without distinguishing between the effects of individual events, following (Anderson and Bell, 2009; Arends, 2006). At each location, null hypotheses were tested for three ensembles of heat waves: short, long and a pooled sample of all heat waves with duration $\geqslant$5 days; and three ensembles of cold spells, defined in the same manner.

Most researchers have applied time series analyses or case-crossover study design to distinguish between heat wave and non-heat wave days in similar studies. We developed an alternative method, which involved normalization of the originally strongly skewed Poisson distributions of daily deaths so that a parametric Student *t*-test could be applied. After normalization procedure, it was possible to directly calculate sensitivity of the applied criterion, using the properties of underlying Poisson distribution (Eq. (3) in Discussion). This is an advantage of the alternative method, which consisted of two steps:

First, daily death count was decomposed into the sum of slow component Y_t and fast component F_t, as described in Revich and Shaposhnikov (2010). The slow component accounted for secular and seasonal trends, whereas the fast component represented all other sources of variability in daily deaths, possibly including the influence of day-to-day temperature variations. As long as $|F_t| \gg |Y_t|$, the distribution of the fast component remains almost Poisson.

The second step involved normalization of F_t distribution. Suppose an ensemble of n waves with the length of N days. As the wavelength increases, the ‘parent’ distribution of moving window averages

$$S_t = \frac{1}{N}\sum_{i=t}^{t+N} F_i \tag{1}$$

approaches a normal distribution, even if average daily death rates are small. Since most waves were observed on different years, their health effects were assumed independent from each other. Then, dispersion analysis can be applied to an independent sample of n S_t values, taken on the first day of each wave. The assumption about lagged effects can be easily incorporated. The sample mean represents average daily mortality for the ensemble. An advantage of this approach is that the dispersion of the ‘parent’ distribution can be easily calculated. In reality, however, temperature waves in the ensemble have different lengths, and we used average wave lengths N_{short}, N_{long} and N_{all} in Eq. (1) for the ensembles of short, long and all waves, instead of actual lengths of individual temperature waves. This assumption introduced additional uncertainty in the resultant risk estimates, as discussed in Shaposhnikov et al. (2011) and Revich and Shaposhnikov (2010).

2.4. Central estimates

The obtained relative risks were first transformed to the log scale. In this study, we are dealing with four site-specific estimates $\hat{\vartheta}_i = \log RR_i$ of (unknown) mean values ϑ_i and the respective standard errors s_i of these estimates. It is assumed that the estimate is normally distributed around the mean:

$$\hat{\vartheta}_i \sim N(\vartheta_i, s_i^2)$$

so that the combined likelihood function P is given by the product of Gaussian distribution functions:

$$P \sim \prod_{i=1}^{4} \exp\left(-\frac{(\vartheta_i - \hat{\vartheta}_i)^2}{2s_i^2}\right)$$

Under 'homogeneity' assumption, the mean value ϑ_i is assumed to be exactly the same in all locations. Maximization of the log likelihood function results in the following estimator of the common effect (Arends, 2006):

$$\hat{\vartheta}_{\text{hom}} = \frac{\sum_i \frac{\hat{\vartheta}_i}{s_i^2}}{\sum_i \frac{1}{s_i^2}}; \quad \text{var}(\hat{\vartheta}_{\text{hom}}) = \frac{1}{\sum_i \frac{1}{s_i^2}} \tag{2}$$

Thus, the site-specific estimates with smaller standard errors have greater relative weights in the central estimate. In this paper, the terms "common effect", "central estimate" and "pooled risk" mean the same thing. Although we did not perform a test for heterogeneity, analysis of literature suggested that the assumption of homogeneity usually holds true for small meta-analyses (Greenland, 1987).

Calculation of relative risks generated a lot of results, which could be analyzed both quantitatively and qualitatively. Quantitative comparisons were used only for statistically significant estimates. Qualitative analysis involved frequency tables which contained binary variables related to statistical significance of obtained risk estimates. To meet the usual requirements of independent Bernoulli trials, we used either χ^2 test for frequency tables based on city-specific *RR* estimates or Fisher's exact test for the pooled *RR* estimates, because the latter were derived from city-specific estimates and were not statistically independent from them.

3. Results

3.1. Overview of site-specific and common effect estimates

A total of thirty cold waves and twenty-nine heat waves were identified in the four cities during the study period. Table 2 reports all obtained site-specific risk estimates together with respective *t*-values. From these, standard errors were derived and common effect estimates were calculated using Eq. (2). Table 2 shows that most site-specific estimates were non-significant at 0.05 level. The ensembles of all waves are characterized by the greatest numbers of statistically-significant risk estimates. This is explained by greater statistical power of the samples of all waves. For example, the number of statistically significant risks for the ensembles of all cold waves were seven (out of 10 analyzed indicators of mortality) in Archangelsk, one in Murmansk, five in Yakutsk and two in Magadan. The number of significant risks depends upon the population size as well as other factors. For example, Archangelsk and Murmansk have comparable populations, but the numbers of significant effects of cold differ greatly. One possible explanation is the difference in climates (temperate continental in Archangelsk vs maritime in Murmansk).

Fig. 1 shows common effect estimates for the six ensembles of temperature waves (long, short, all cold waves; long, short, all heat waves). Each of the five Fig. 1a–e corresponds to a particular cause of death. These figures help to compare the results in several different ways as described below.

3.2. Comparing effects of cold and heat waves on mortality

Symmetrical definitions of heat and cold waves, based on equal probability of observations of extreme temperatures, ensured that the numbers of analyzed cold spells and heat waves were approximately equal. In other words, the power of statistical tests should be comparable for cold and heat. Yet, the numbers of statistically significant health effects differ greatly.

Let us consider the ensembles of all cold waves and all heat waves. One may see from Table 2 that 15 out of 40 cold-related risks and only 8 out of 40 heat-related risks are statistically significant. The null hypothesis postulates that the numbers of significant effects of cold and heat are expected to be equal. Entering these numbers in 2×2 frequency tables, we estimated Pearson $\chi^2 = 2.99$, so that H_0 could not be rejected at 95% level, but it could be rejected at 90% level. Let us also consider pooled risk estimates for the ensembles of all cold spells and all heat waves. Fig. 1a–e shows that seven out of ten cold-related risks and only two out of ten heat-related risks are significant. Fisher's exact test was used to test the H_0 for

Table 2
Statistical results for four case study cities. Relative mortality risks and two sided Student *t*-test, by cause and age of death.

	Cold						Heat					
	Long waves		Short waves		All waves		Long waves		Short waves		All waves	
	RR	*t*	*RR*	*t*	*RR*	*t*	*RR*	*t*	*RR*	*t*	*RR*	*t*
Archangelsk												
IHD[a], 30–64	1.44*	3.60	0.93	−0.65	1.18*	2.10	1.03	0.23	0.85	−1.00	0.94	−0.57
IHD, ⩾65	1.32*	2.96	1.06	0.55	1.22*	2.96	1.02	0.16	0.85	−1.17	0.93	−0.80
CVD[b], 30–64	1.29	1.47	0.94	−0.33	1.13	1.00	1.01	0.04	0.99	−0.04	1.01	0.08
CVD, ⩾65	1.37*	3.47	0.99	−0.10	1.19*	2.66	1.22*	1.96	1.36*	3.05	1.3*	3.80
RD[c], 30–64	1.41	1.90	1.09	0.43	1.31*	2.17	0.73	−1.10	1.03	0.11	0.91	−0.49
RD, ⩾65	1.32	1.02	0.99	−0.03	1.21	0.99	0.89	−0.29	1.21	0.50	1.09	0.30
NA[d], 30–64	1.26*	3.38	0.98	−0.33	1.12*	2.44	1.04	0.48	0.99	−0.13	1.02	0.27
NA, ⩾65	1.35*	4.85	1.01	0.12	1.18*	3.63	1.14	1.68	1.11	1.45	1.13*	2.39
Ext[e], 30–64	1.47*	3.90	1.10	0.79	1.29*	3.47	0.99	−0.11	1.21	1.57	1.16	1.64
Ext, ⩾65	0.99	−0.06	1.15	0.70	1.20	1.38	1.38	1.34	1.04	0.14	1.20	0.97
Murmansk												
IHD, 30–64	1.26	1.75	1.13	1.48	1.18*	2.25	1.08	0.53	0.96	−0.22	1.03	0.26
IHD, ⩾65	1.13	0.87	1.05	0.61	1.09	1.13	0.82	−1.16	0.69	−1.76	0.76	−2.10
CVD, 30–64	0.60	−1.93	1.07	0.55	1.07	0.68	0.64	−1.62	1.07	0.26	0.88	−0.71
CVD, ⩾65	1.53*	3.45	1.00	−0.04	1.14	1.63	1.08	0.52	1.24	1.52	1.25*	2.13
RD, 30–64	1.30	0.99	0.91	−0.47	1.03	0.18	1.11	0.34	1.87*	2.24	1.55*	2.20
RD, ⩾65	0.00	−1.47	0.84	−0.38	0.82	−0.48	1.13	0.17	1.61	0.66	1.42	0.72
NA, 30–64	0.92	−0.88	1.05	0.84	1.06	1.19	0.97	−0.33	1.12	1.05	1.05	0.75
NA, ⩾65	1.29*	3.04	1.03	0.58	1.09	1.81	0.93	−0.79	0.94	−0.52	0.94	−0.84
Ext, 30–64	0.81	−1.08	0.93	−0.68	0.97	−0.31	1.5*	2.83	1.34	1.83	1.43*	3.48
Ext, ⩾65	1.26	0.59	0.58	−1.76	0.71	−1.28	0.88	−0.24	1.36	0.76	1.21	0.64
Yakutsk												
IHD, 30–64	1.5*	2.22	1.17	0.58	1.38*	2.15	1.08	0.32	1.23	0.73	1.15	0.80
IHD, ⩾65	1.39*	2.07	1.37	1.46	1.41*	2.75	1.04	0.17	0.79	−0.74	0.90	−0.62
CVD, 30–64	0.60	−1.43	0.97	−0.07	0.80	−0.90	0.89	−0.33	0.97	−0.08	0.91	−0.34
CVD, ⩾65	1.44	1.69	1.85*	2.49	1.69*	3.24	1.38	1.37	1.75	1.74	1.61*	2.47
RD, 30–64	0.69	−0.90	1.05	0.12	0.89	−0.39	0.30	−1.83	0.00	−1.94	0.14	−2.89
RD, ⩾65	0.96	−0.08	2.84*	3.38	1.97*	2.87	1.80	1.58	1.21	0.30	1.47	1.19
NA, 30–64	1.01	0.08	1.06	0.45	1.04	0.54	0.95	−0.47	0.89	−0.74	0.92	−0.97
NA, ⩾65	1.15	1.44	1.32*	2.25	1.24*	2.93	1.04	0.37	0.98	−0.11	1.01	0.06
Ext, 30–64	0.80	−1.18	1.43	1.92	1.10	0.76	1.36*	2.00	1.83*	3.51	1.59*	4.20
Ext, ⩾65	1.27	0.60	1.37	0.60	1.37	1.01	0.59	−0.75	2.03	1.35	1.31	0.72
Magadan												
IHD, 30–64	0.80	−0.82	1.01	0.05	1.01	0.05	1.14	0.35	1.75	1.62	1.44	1.39
IHD, ⩾65	1.75*	2.94	1.11	0.52	1.39*	2.38	1.77	1.90	0.78	−0.46	1.23	0.70
CVD, 30–64	1.39	1.30	1.24	0.97	1.37	1.92	1.13	0.26	1.54	1.15	1.57	1.46
CVD, ⩾65	1.28	1.03	1.68*	3.19	1.66*	3.89	1.06	0.14	1.42	0.82	1.23	0.67
RD, 30–64	1.13	0.35	1.48	1.56	1.34	1.52	1.26	0.40	1.00	0.01	1.10	0.21
RD, ⩾65	1.10	0.21	0.84	−0.44	0.88	−0.44	1.86	1.11	1.75	1.03	1.78	1.42
NA, 30–64	1.01	0.10	1.00	−0.02	1.03	0.45	1.24	1.27	1.38*	2.09	1.32*	2.42
NA, ⩾65	1.19	1.64	1.03	0.30	1.13	1.57	1.28	1.36	1.00	−0.02	1.12	0.73
Ext, 30–64	0.93	−0.27	0.96	−0.19	1.02	0.10	1.20	0.55	1.16	0.38	1.17	0.58
Ext, ⩾65	1.11	0.17	0.85	−0.27	0.90	−0.25	0.44	−0.51	1.94	0.74	1.39	0.51

[*] Significant at 95% level.
[a] Ischemic heart disease.
[b] Cardiovascular diseases.
[c] Respiratory diseases.
[d] All non-accidental causes.
[e] All external causes.

pooled risk estimates, and H_0 was rejected with $p = .035$ (one-sided). Therefore, we concluded that the effects of cold waves on mortality were more pronounced than the effects of heat waves in our study setting.

This finding has been recently confirmed by the results of an international study headed by Gasparrini et al. (2015) who claimed that cold waves were more lethal than heat waves, the relative fraction of deaths caused by extreme cold was 0.63% while the same fraction for extreme heat was 0.23% (average figures for 13 countries included in the study). Why are cold waves more dangerous than heat waves? One reason is that physiological responses for cold seem to last longer than those attributed to heat (Deschênes and Moretti, 2009; Keatinge et al., 1984).

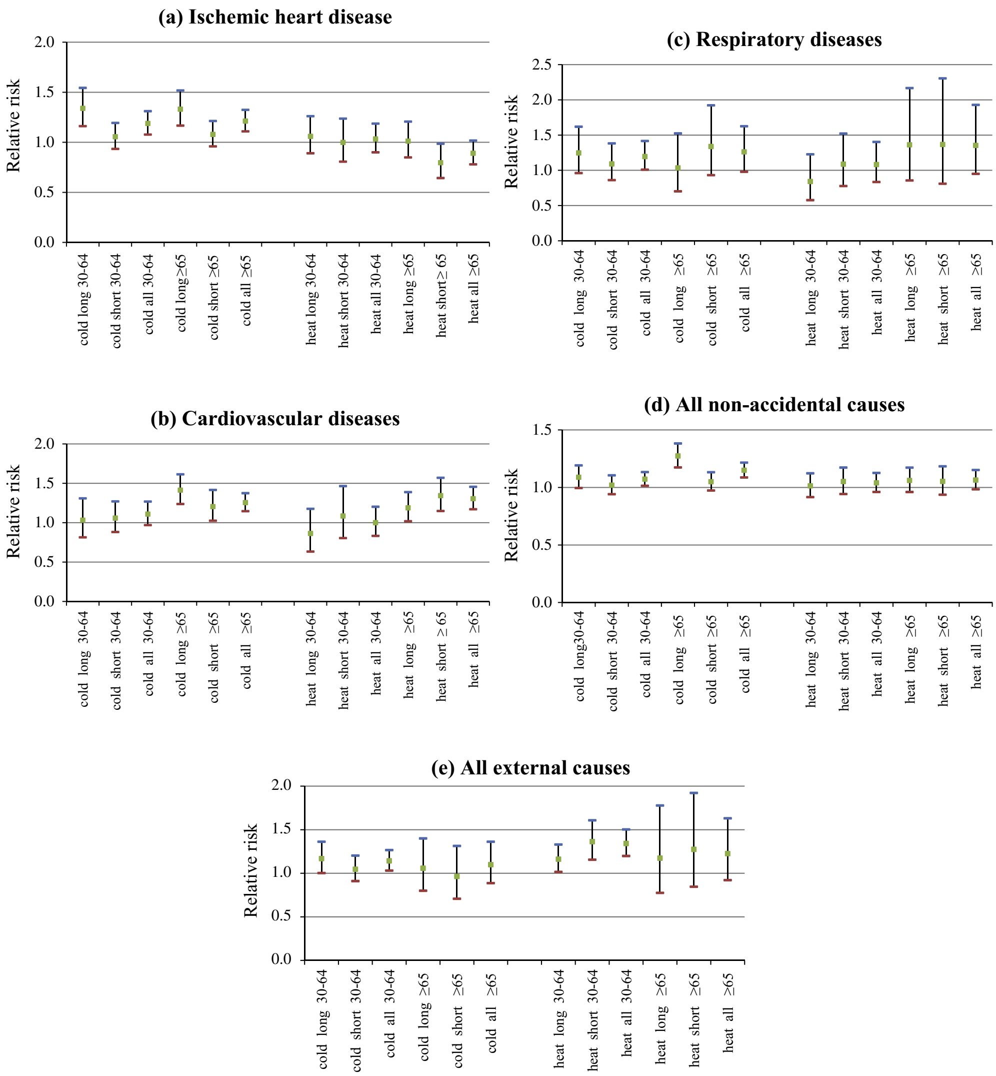

Fig. 1. Relative risks of cause- and age-specific mortality during cold and heat waves, pooled four-city estimates. Horizontal axis of each diagram marks six encembles of waves and two age groups as follows: "Cold" = cold waves; "Heat" = heat waves; "Long" = waves of 8 days and longer; "Short" = waves lasting between 5 and 7 days; "All" = all waves lasting 5 days or more; "30–64" = age group between 30 and 64 years; "⩾65" = age group of 65 years and older.

3.3. Analyzing differences in impacts of long and short temperature waves

Let us consider cold waves. H_0 in this test postulated that the numbers of statistically significant risks of long and short cold waves are equal. Table 2 lists 11 out of 40 significant risks of long cold waves, and only 4 out of 40 significant risks of short cold waves. Using these numbers, we calculated Pearson $\chi^2 = 4.02$ and rejected H_0 at 95% level. Similarly, Fisher's exact test was used to test the H_0 for pooled risk estimates, and H_0 was rejected with $p = .043$. We concluded that long cold waves tended to be more hazardous than short cold waves.

Quantitative comparisons also supported this conclusion, because the relative risks during long cold waves were greater than those during all cold waves for those indicators of mortality where both estimates of common effect were statistically significant (Fig. 1).

The opposite relationship was observed with respect to heat: long heat waves presented smaller risks than short heat waves. This is confirmed by the following comparisons of statistically significant pooled risk estimates (Fig. 1):

$RR_{long} = 1.19 \pm .08$ vs. $RR_{short} = 1.34 \pm .09$ for CVD deaths in age group $\geqslant 65$;
$RR_{long} = 1.21 \pm .09$ vs. $RR_{short} = 1.35 \pm .10$ for deaths from all external causes in age group 30–64.

Our results regarding differences in responses to long and short waves of heat and cold can be supported by the US-based study of Deschênes and Moretti (2009) who emphasized this "remarkable difference": nearly all excess mortality during heat waves is explained by short-term displacement, while cold spells have long-lasting effect on mortality.

3.4. Analyzing age-specific differences

Again, let us consider cold waves. H_0 in this test postulated no difference in the numbers of significant effects between the two age groups. In this test, we summed up the numbers of significant city-specific risks of short cold waves and long cold waves (these risks were statistically independent from each other). Table 2 lists only 4 out of 40 significant cold-related risks for age 30–64 and 11 out of 40 significant estimates for age $\geqslant$65. Calculation of Pearson $\chi^2 = 4.02$ led to rejection of H_0 at 95% level, meaning that aged people were more susceptible to cold. Quantitative comparisons also confirmed this conclusion for those two causes of mortality where both estimates of common effect were statistically significant (Fig. 1):

$RR_{30\text{–}64} = 1.18 \pm .05$ vs. $RR_{\geqslant 65} = 1.21 \pm .05$ for IHD deaths;
$RR_{30\text{–}64} = 1.07 \pm .03$ vs. $RR_{\geqslant 65} = 1.15 \pm .03$ for all non-accidental deaths.

For the latter category, the difference between $RR_{30\text{–}64}$ and $RR_{\geqslant 65}$ was statistically significant. Similar analysis of the effects of heat waves did not show any age-specific differences, presumably because of insufficient number of statistically significant results.

3.5. Which causes of death contributed to an increase in total mortality?

Firstly, we showed that almost all increase in non-accidental mortality was due to circulatory diseases. This analysis could be carried out only for impacts of cold in age group $\geqslant$65, where all three pooled risk estimates (for IHD, CVD, all non-accidental deaths) were statistically significant. The relative inputs of deaths from IHD and CVD in non-accidental mortality, summed across all four cities and averaged over the study period, were 30% and 31%, respectively. If *all* increase in non-accidental deaths were due to these two causes, then it would be equal to: $RR = 1 + .30 * (RR_{IHD} - 1) + .31 * (RR_{CVD} - 1) = 1.23$ during long cold waves, and similarly $RR = 1.14$ during all cold waves. The estimated increases in non-accidental deaths were $RR = 1.26$ during long cold waves and $RR = 1.15$ during all cold waves, which is a very close match. This finding confirmed that nearly all increase in non-accidental deaths (most likely 97%) was caused by deaths from circulatory diseases. This conclusion agrees with similar finding of a very extensive US-based study which estimated the input of cardiorespiratory causes to cold-related excess mortality as 83% for females and 94% for males (Deschênes and Moretti, 2009).

Secondly, let us consider external causes of mortality. For this group of causes, the pooled risk estimates in age group 30–64 were statistically significant both during cold waves ($RR = 1.13 \pm .05$) and during heat waves, where the greatest increase was observed during short waves ($RR = 1.35 \pm .10$). This is an important finding, especially since external causes have been grossly neglected in health impact studies. Given an estimated input of external causes in total mortality (24%), the relative risk of total mortality among middle-aged people during heat waves *due to external causes only* should be about $RR = 1.08$. We concluded that the accidens, as a contributing factor, are probably as important as non-accidental deaths.

4. Discussion

Small populations present considerable difficulties for application of standard statistical tests to access statistical significance of observed health effects. The sensitivity of applied criterion, or its ability to detect differences between the test and control samples, depends upon the sample size. Our samples consist of daily mortality counts which are proportional to the size of urban populations. The role of population size is illustrated by an Italian study (Conti et al., 2003), where Wilcoxon matched pairs test was consistently applied to detect the differences in mortality rates in age group $\geqslant$75 between the summers of 2002 and 2003 (the latter was unusually hot in Europe) in all 21 regional capitals with populations ranging from 40,000 to 2,547,000. Only 10 out of 21 tests showed significant at 95% level increases in mortality rates ($p < .05$). Of course, these 10 were mostly the largest cities. The smallest city where the test was significant was Bari (317,000 people); and the largest city where the test was not significant was Florence (356,000 people). Population data are taken from 2001 census (Instituto Nazionale di Statistica Italia, 2001). This example shows that even the most dramatic increase in mortality could not be considered statistically significant in a medium-sized city with population under 300,000.

This study in the Russian North assessed significance of the effects of ensembles of temperature waves rather than individual waves. Working with small populations, we developed an innovative method to calculate city-specific risks. The advantages of our method and its limitations can be illustrated by counting the numbers of statistically significant effects of cold waves in different cities. Six out of ten indicators of mortality showed significant increases in Archangesk (population 355,000); two in Murmansk (318,000), two in Yakutsk (246,000) and one in Magadan (100,000). Therefore, the site-specific 'detection limit' of our statistical test, in terms of population size, was close to 100,000 people. In other words, no health effects of ensembles of temperature waves could be found statistically significant in smaller populations.

The sensitivity of applied statistical criterion is based on variance of control sample. Indeed, the minimum value of RR which can be statistically significant under the developed normalization method is given by Eq. (3), where n denotes the number of waves in the ensemble, N is average wavelength (in days), t_c is the critical value of t-test:

$$RR_c = 1 + t_c/\sqrt{\lambda n(N-1)} \tag{3}$$

because the mean of Poisson distribution of daily deaths λ is equal to its variance. This equation shows that the probability of detection of health effects increases with population size: $P \sim \sqrt{size}$. Table 3 illustrates gains in sensitivity arising from working with a larger population, by comparing critical values RR_c in the largest and the smallest of the four cities (Archangelsk and Magadan). Critical values RR_c were calculated using locally established λ, n and N values for the ensembles of long cold waves and $t_c = 1.96$ for double-sided Student t-test with $p = .05$ and $df = \infty$. All RR_c values in Archangelsk are considerably lower than in Magadan, which means that sensitivity of applied statistical criterion is much higher in Archangelsk. This table also shows that all statistically significant RR values, marked with (*), were greater than the respective RR_c. Another way to increase sensitivity of the applied criterion is to use longer study periods, which is equivalent to an increase in the number of waves n. To some extent, an increase in observation period may compensate for lack of statistical power in small populations.

As follows from the above equation for RR_c, the probability of detection of health effects also increases with the average length of waves in the ensemble, as we observed with respect to cold. Then why short heat waves in our study (those lasting between 5 and 7 days) were associated with greater mortality risks than long heat waves? Harvesting effect could be the reason for this. As was noted in many studies, the health effect of heat is immediate, unlike the effect of cold. Most people die in the beginning of a heat wave, and short-term forward displacement of deaths could be quite significant, reducing additional mortality by the end of a long wave. This conjecture is supported by the result recently obtained by Gasparini and Armstrong (2011), who estimated the "heat-wave" effect on mortality as a flexible function of the number of days of sustained heat. They showed that long heat waves can hardly be more devastating than short waves: the "heat-wave" effect reached maximum on day seven and then rapidly declined reaching zero by day ten.

5. Conclusions

Our study confirmed that cold waves could be relatively more hazardous than heat waves. Given this finding, we recommend to shift the focus of studies of the effects of extreme weather events more toward cold weather.

Long cold waves tended to be more hazardous than short cold waves. For heat waves, opposite relationship was observed – short waves were associated with greater risks than long waves.

Nearly all increase in non-accidental deaths during cold waves was caused by deaths from circulatory diseases. External causes of death could be an important contributing factor to the rise of total mortality during heat waves (they were responsible for about 8% of an increase in total mortality), while they are less important during cold waves (they provided about 3% of an increase).

Cold waves were particularly lethal to older people.

Regarding minimal population size, needed to obtain significant risk estimates, several issues have to be considered, including the length of the study period and the number of mortality indicators, reasonably stratified by cause and age of death. Given the total population of four cities included in this study (close to 1 million people), we obtained fairly robust results for cold-related risks, while the results for heat-related risks were less conclusive.

Table 3
Comparison of actually established (RR) and critical values (RR_c) of relative mortality risks during long cold waves in Archangelsk and Magadan.

Cause and age of death	Archangelsk		Magadan	
	RR	RR_c	RR	RR_c
IHD[a] 30–64	1.44*	1.28	0.80	1.62
IHD, ⩾65	1.32*	1.23	1.75*	1.62
CVD[b], 30–64	1.29	1.42	1.39	1.79
CVD, ⩾65	1.37*	1.21	1.28	1.69
RD[c], 30–64	1.41	1.52	1.13	2.00
RD, ⩾65	1.32	1.73	1.10	2.31
NA[d], 30–64	1.26*	1.15	1.01	1.30
NA, ⩾ 65	1.35*	1.12	1.19	1.33
Ext[e], 30–64	1.47*	1.25	0.93	1.52
Ext, ⩾65	0.99	1.60	1.11	2.55

* Significant at 95% level.
[a] Ischemic heart disease.
[b] Cardiovascular diseases.
[c] Respiratory diseases.
[d] All non-accidental causes.
[e] All external causes.

Funding

This study was carried out within the research project “Regional Problems of Climate Change and Public Health” sponsored by the Grant program of Presidium of Russian Academy of Sciences “Fundamental Sciences for Medicine” (2011).

Acknowledgements

The authors wish to highlight the contributions of Constantine Rubinstein and Roman Ignatov of Federal Hydrometeorology Service; Tatiana Khorkova and Ekaterina Kvasha of Institute of Demography of Higher School of Economics, who supplied data for this research.

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