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Municipality assessment of temperature-related mortality risks in Norway

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A R T I C L E I N F O

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A B S T R A C T

Background & aim: Understanding local vulnerability to heat and cold is crucial for public health planning, yet few studies have provided a nationwide analysis of temperature-related mortality across diverse communities. This study analyses the association between ambient air temperature and non-accidental mortality across mainland Norway, using a constrained hierarchical clustering algorithm to group municipalities with similar geographic, environmental, socioeconomic, and demographic patterns.

Methods: This study analysed the association between ambient air temperature and non-accidental mortality across 356 Norwegian municipalities, using daily data from 1996 to 2018. We applied a case time series design with distributed lag non-linear models. A downscaling procedure assessed the effect of 21 vulnerability factors on temperature-related mortality risks, using Principal Components Analysis to explore heterogeneity across clusters.

Findings: Cold temperatures contributed to an estimated 3879 deaths per year (95% CI 3718-4130), while heat was associated with 44 deaths annually (95%CI: 29–58). The highest heat-related mortality risk occurred in the South-East, and the highest cold-related risk in the Central-East. Greater heat-related mortality correlated with medium-to sparsely-populated areas, while higher education levels were linked to reduced vulnerability to both heat and cold.

Interpretation: By providing the first comprehensive assessment of temperature-related excess mortality and associated risk factors in Norway, our findings underscore the need for targeted, equitable health policies that integrate environmental and socioeconomic factors. These insights are essential to guide climate adaptation strategies, prioritising vulnerable rural communities and socioeconomically disadvantaged groups to mitigate future climate-related health impacts.

1. Introduction

Exposure to non-optimal temperatures has been linked to numerous negative health outcomes, and this association is widely recognised. Most studies have reported an increased risk associated with non-optimal temperatures (Gasparrini et al., 2015; Son et al., 2019; Zhao et al., 2021). Specifically, the relationship between air temperature and mortality in temperate climates exhibits an inverse J- or U-shaped curve (Scovronick et al., 2018; Tobías et al., 2021), showing a higher risk of mortality from all causes in the presence of high or low temperatures, with the minimum risk occurring at mild temperate ranges. The global mortality burden attributable to non-optimal temperatures is estimated at around 9.4% of all deaths annually, equating to 74 deaths per 100,000 people (Zhao et al., 2021). Cold temperatures account for most of this

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burden, with 8.5% of all deaths compared to 0.9% for heat. Notably, the percentage excess in global mortality increased by 4.6% (3.7%–5.3%) between 2000 and 2019, largely due to yearly temperature variability (Wu et al., 2022).

The impact of non-optimal outdoor temperatures on health outcomes is widespread, resulting in significant increases in mortality rates across different geographic regions (Son et al., 2019). This heterogeneity may likely depend on the distribution of risk drivers linked to individual and contextual characteristics, such as socioeconomic and demographic factors, as well as climatic and environmental conditions. Previous studies have predominately focused on urban locations, where exposure data is available and health outcomes provide sufficient statistical power, leaving a gap in evidence for non-urban and small-city contexts. Limited research suggests small impacts in rural areas (Odame et al., 2018; Son et al., 2019). Thus, it is crucial to investigate differences in the effects of non-optimal temperatures on mortality risk and understand the underlying mechanisms contributing to this variation, particularly between urban and rural settings. Understanding vulnerable population subgroups and potential sex-related disparities in thermoregulation is also essential.

Norway spans a variety of climatic zones, highlighting the need to understand the role of climatic variables on health outcomes. Previous studies have primarily focused on temperature impacts on mortality in Norway's capital and largest cities (Masselot et al., 2023; Nafstad et al., 2001; Vázquez Fernández et al.). Recent literature indicates that rural areas in Norway continue to bear a larger mortality burden due to lower education and greater poverty (Bremberg, 2020). Consequently, there is a pressing need to investigate how environmental and physical influences, medical care, and social factors interact in influencing mortality across urban and rural populations in Norway.

This study aims to investigate the spatial disparities in the impact of ambient air temperature on non-accidental mortality across mainland Norway and examine the effect of regional vulnerability factors. We use a state-of-the-art statistical framework (Gasparrini et al., 2022), as well as a novel, constrained hierarchical clustering algorithm to categorise municipalities into clusters based on geographic, environmental, socioeconomic, and demographic similarities (Chavent et al., 2018). This method consolidates 30 adjacent municipalities, enabling a more precise application of the case times series design. This allows for a clearer assessment of the impact of regional vulnerability factors across Norway—such as air pollution, sex, and area-based indicators including urbanisation, education, income, and proximity to hospitals—on temperature-related mortality. Understanding these dynamics is essential for implementing health equity policies in Norway that are grounded in environmental and socioeconomic factors. To the best of our knowledge, this is the first integrated study combining the impact of environment and socioeconomic variables on mortality in Norway.

2. Methods

2.1. Study setting

Norway's unique topography naturally results in a higher population concentration along the coastline and in the southern regions. This preference is influenced by a combination of climatic and environmental factors, giving Norway a distinctive tapestry of diversity. However, these distinctions are not fully represented by the eleven administrative counties established as of 2020 (Appendix, p. 15, Fig. S1), which underscores the need for a different regional clustering.

To better capture the true heterogeneity and diversity across the country, this study employs a Ward-like hierarchical clustering method (Chavent et al., 2018), combining the 356 Norwegian municipalities into 30 distinct cluster regions. This method provides a more nuanced perspective, highlighting the multifaceted characteristics of Norway beyond the county boundaries.

2.2. Definition of the 30 clusters

We established a set of 30 clusters by amalgamating the 356 municipalities utilising the previously mentioned Ward-like algorithm (Appendix, p. 16, Fig. S2), along with geographical constraints, employing municipality-level data on six vulnerability factors: temperature mean and range, ageing index, population density, social index and impervious surfaces (de Schrijver et al., 2023). This algorithm is a constrained hierarchical clustering method designed to enhance a convex combination by using two dissimilarity matrices and a blending parameter, resulting in a new higher agglomerative layer composed of municipalities that are both alike and proximate. More detailed explanations are provided in the Appendix (p. 5, Methods S1: Ward-Like Hierarchical Clustering Algorithm).

We find this custom definition of clusters more suitable for the purposes of this study in comparison to the higher-level administrative unit of counties as has been used in previous studies (Gasparrini et al., 2022). The municipalities within the aggregated clusters exhibit greater homogeneity, allowing for a more accurate characterisation of population vulnerability, which enhances our ability to detect potential variations in the vulnerability's impact, as well as increases the statistical power of the meta regression.

2.3. Temperature and mortality data

We employed a high-resolution observational dataset of average daily temperatures for Norway, available at a 1 km resolution, spanning from January 1, 1996 to December 31, 2018, to examine temperature exposures at the municipality level (Lussana et al., 2019). Municipality-specific daily temperature series were derived by computing the average of the all the grid cells within each municipality's borders. The seNorge_2018 dataset, described in detail by Lussana et al. (2019), provides daily mean temperatures based on a spatial interpolation method with mean absolute errors ranging from 0.5 to 1 C in summer to 1.0–2.0 C in winter.

The health data comprised daily counts for all non-accidental mortality in Norway (International Classification of Diseases, ICD-10: A00-R99) between January 1, 1996 and December 31, 2018, provided by the Norwegian Death Registry (Norwegian Cause of Death Resgistry), disaggregated by sex and age.

2.4. Vulnerability factors

We compiled an integrated dataset comprising measures on various characteristics potentially associated with differential vulnerability to non-optimal temperatures. The dataset encompassed 21 variables, categorised into demographic factors (proportion of population aged older than 65 years and population density), socioeconomic indicators (including measures of income, employment, and education), health-related metrics (such as life expectancy and drive time to hospital), as well as land use and topographical (degree of urbanisation, latitude, longitude, elevation, and coast distance). Additionally, the dataset featured environmental parameters, specifically annual concentrations of fine particulate matter ($PM_{2.5}$), nitrogen dioxide (NO_2), and ozone (O_3), alongside climatological attributes, notably the average annual mean and range of temperatures.

All these variables were gathered at the municipality level and then aggregated to the new higher agglomerative cluster level (defined in section 2.2). Details and data sources are provided in the Appendix (pp. 7–10, Table S1).

To enhance predictive capabilities and analyse the collective impacts of these potentially correlated attributes, we performed a principal component (PC) analysis across the 21 variables, reducing dimensionality by deriving a series of uncorrelated variables known as principal components. Selecting the initial three principal components, which encapsulated the majority of the dataset's information, we aimed to elucidate the heterogeneity between clusters. Subsequently, we incorporated these components to address cluster-specific confounding factors within each area. The selection of the number of components was informed by the total percentage of variance explained (with a cut-off established at 80%) and the Akaike Information Criterion (AIC) (see Appendix, p. 5, Methods S1: Ward-Like Hierarchical Clustering Algorithm).

2.5. Statistical analysis

We assessed the association between temperature and non-accidental mortality across municipalities using a two-stage analysis followed by a downscaling procedure (Gasparrini, 2021; Gasparrini et al., 2015). In the first stage, we conducted a case time series analysis adapted to model cluster-wide data disaggregated into municipalities (Gasparrini, 2021; Gasparrini et al., 2022), representing an extended version of the two-stage design previously utilised in multilocation time series studies (Gasparrini et al., 2015).

To model multiple municipality-specific series within each cluster, we employed a time- and municipality-stratified conditional Poisson regression that allows for overdispersion, along with distributed lag nonlinear models (DLNM) (Gasparrini et al., 2010). The first-stage models were conducted separately by sex for each of the 30 clusters. The limited counts within specific age groups rendered stratification by age unfeasible. The models included indicators of day of the week and holidays, along with flexible terms to control for long-term trends utilising a matching stratum defined by the year, month, and day of the week by municipality. We defined a quadratic B-spline with three internal knots positioned at the 10th, 75th and 90th percentiles of the cluster-specific temperature distribution. The knot positions were chosen based on the lowest mean quasi-Akaike Information Criterion (qAIC), providing a balance between model complexity and goodness of fit by adjusting for overdispersion ("Information and Likelihood Theory: A Basis for Model Selection and Inference," 2002). For details on the sensitivity analysis regarding the choice of knots, see Appendix, p. 11, Table S2. Additionally, we modelled the lag-response function using a natural spline with three internal knots, evenly distributed on the log scale and window lag of 0–21 days to account for the effects of heat and cold and to accommodate short-term harvesting, as done in previous studies (Gasparrini et al., 2015).

In the second stage, we derived the overall cumulative exposure-response associations by sex through a multivariate meta-regression model (Sera et al., 2019). The second-stage model included sex and PC indicators as meta-predictors to explain variations across clusters. We evaluated their contribution by likelihood ratio tests and assessed residual heterogeneity by the multivariate extension of the Cochran's Q test and I^2 statistic.

The downscaling of the risks at the municipality level was performed using the combination of PCs vulnerability factors defined by the respective municipality values. We then derived exposure-response functions (ERF) at the municipality level and determined the minimum mortality temperature (MMT) and MMT-related percentile (MMP) for each municipality. We refer to the MMT and MMP as the optimal temperature, representing the lowest temperature value within the range between the 1st and the 99th percentiles temperature distributions for which the temperature-mortality risk is minimum. Following this, we calculated the risk for heat and cold by determining the relative risk (RR) and the related 95% confidence interval (CI) at the 99th percentile versus the MMT and at the 1st percentile versus the MMT, respectively. We also estimated sex-specific excess mortality, both the total number of deaths and fraction of deaths, attributable to temperatures above and below the MMT, using previously described method (Gasparrini and Leone, 2014). We calculated rates of excess non-accidental mortality per 100,000 using the 2018 population from Statistics Norway (SSB) as the reference.

The exposure-response functions predicted by sex at each municipality were finally used to predict county-specific associations, taking into account the stronger dependencies across locations in each county (Gasparrini et al., 2022). The justification for also forecasting associations specific to each county lies in its utility for informing regional public health and climate policies. Our stratified approach is intended to provide tailored insights suitable for policymakers, be they local authorities or those at county or national level. The nominal level of statistical significance was established at 5%.

All statistical analyses were performed with R (version 4.1.3), using *dlnm* and *mixmeta* packages.

3. Results

Table 1 provides an overview of the descriptive statistics related to temperature and mortality data across the eleven administrative counties of mainland Norway. Geographical subdivisions based on the counties and the 30 clusters are depicted in the Appendix (pp. 15–16, Figs. S1 and S2). Mean daily temperatures in the municipalities were higher along the coastline and in the southern regions, gradually decreasing towards the interior and the northern parts of the country (Appendix, p. 17, Fig. S3). Mean daily temperature values per municipality ranged from 0.4 °C in Troms og Finnmark in the North to 6.5 °C in Rogaland in the South-West.

The geographical distribution of the first three principal components, representing the composite measure of vulnerability among the Norwegian population, is detailed and further discussed in the Appendix (p. 6, Methods S2: Principal Component Analysis; pp. 18–21, Figs. S4–S8).

Fig. 1a depicts the pooled estimates of the overall cumulative exposure-response association by sex group, predicted at the mean value of the other meta-regressors. The pooled relationships follow the classical inverse J-shape from the 3rd percentile of temperatures, reaching a quite high MMP, 94th in the male's group and 93rd in the females group. However, between the lower minimum at −22 °C until −11 °C (3rd percentile) we found an anomalous behavior in which the risk of mortality appears to increase with increasing temperatures, contrary to the inverse J-shape. Fig. 1b provides a close-up view of the temperature range (5.0–18.2°) where the overall trends for each group are not overlapping. While the females' curve exhibited a gradual increase towards colder temperatures, the males' curve displayed a more pronounced ascent. Notably, within the 6.0–14.3 °C interval, the RRs for men exceeded those for women. Likewise, in the narrow 14.7–17.0 °C range, the RRs for women surpassed those for men. Outside these temperature bands, the RRs for women remained higher than those for men. At the 1st percentile, cold-related RRs were somewhat lower in men than in women, with a RR of 1.26 (95% CI: 1.23–1.29) and 1.30 (95% CI: 1.24–1.36) respectively. Similarly, at 99th percentile, the heat-related RRs were 1.09 (95% CI: 1.06–1.12) for men and 1.11 (95% CI: 1.08–1.13) for women.

Fig. 2 presents maps illustrating downscaled, municipality-specific rates of excess mortality related to cold and heat per 100,000 person-years, categorised by sex in Norway. Both cold- and heat-related excess mortality rates show marked geographical variability, with the cold-related rates not exhibiting the same clear clustering observed as for heat-related mortality rates. Nevertheless, lower impacts are noticeable along the coastline. On average, municipalities located further inland exhibit higher rates for both heat- and cold-related excess mortality. These inland municipalities also experience the coldest and warmest temperatures. The south-eastern municipalities, particularly Agder, exhibited the most pronounced RRs for heat, while the central-eastern region, notably Innlandet, faced the most significant risks from cold. There exists a discernible spatial gradient, with the risk of heat-related impacts peaking in the south-east and diminishing towards the north, whereas the risk from cold is more acute in the central-east (see Appendix, pp. 22–23, Figs. S9 and S10). The MMTs exhibited a consistent trend across sexes. In each municipality, the MMT for men

Table 1
Descriptive statistics of municipalities by county according to definition in 2020.

County	No. municipalities	Partition in 30 clusters	Population	Average annual deaths	Mean temperature (IQR) in Celsius (°C)
Oslo	1	1	673469	4310	5.3 (−0.7–12.3)
Rogaland	23	2, 3	473526	2732	6.5 (2.1–11.6)
Møre og Romsdal	26	4, 5	264421	2133	5.0 (0.6–10.2)
Nordland	41	6, 7, 8, 9	237601	2218	3.1 (−1.7–8.9)
Viken	51	10, 11, 12	1213729	8211	4.7 (−1.1–11.7)
Innlandet	46	13, 14, 15	370994	3858	1.8 (−4.2–8.7)
Vestfold og Telemark	23	16, 17	415777	3629	4.8 (−0.8–11.4)
Agder	25	18, 19	303754	2267	5.5 (0.4–11.5)
Vestland	43	20, 21, 22	631594	4512	4.4 (−0.2–9.8)
Trøndelag	38	23, 24, 25	457891	3473	3.6 (−1.4–9.5)
Troms og Finnmark	39	26, 27, 28, 29, 30	243925	1863	0.4 (−5.5–7.2)

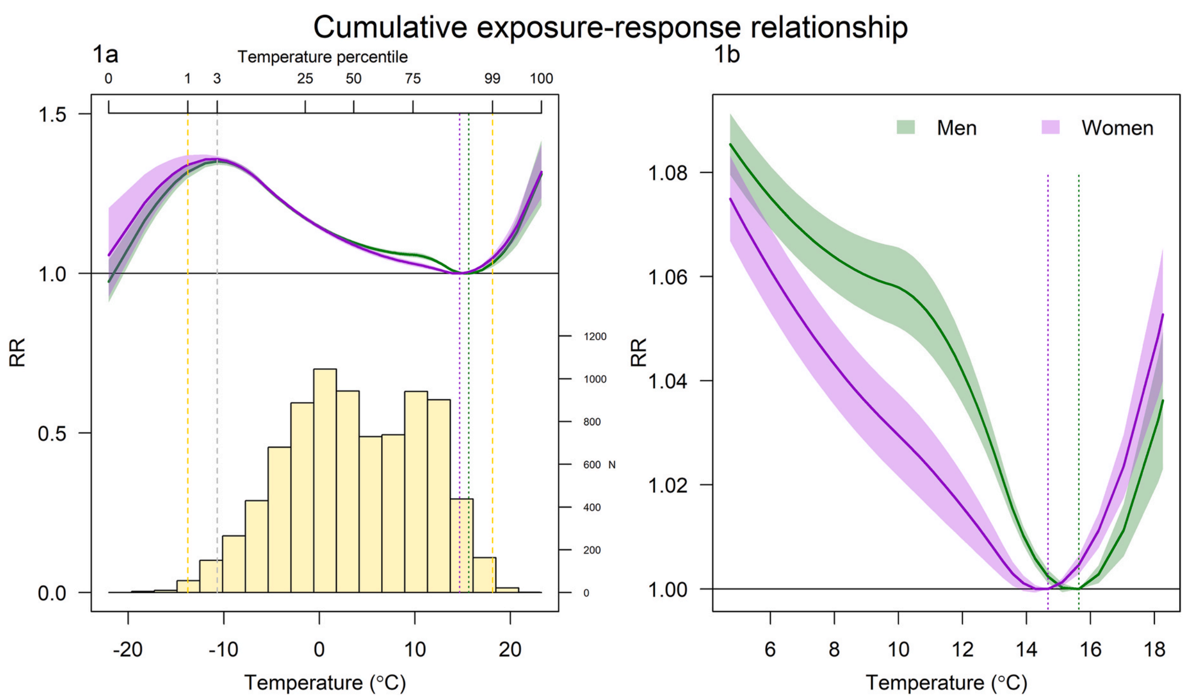

Fig. 1. Pooled estimates of the overall cumulative exposure-response functions between temperature and non-accidental mortality by sex group.
Temperature used the average temperature distribution of all municipality-specific distributions. Shaded areas on the curves are 95% CIs. RR = relative risks. Dotted lines correspond to the MMTs and the yellow dashed line depicts the 99th percentile of the temperature distribution.
The right panel shows a restricted temperature range of the pooled estimates of the overall cumulative exposure-response functions between temperature and non-accidental mortality by sex group.

consistently surpassed that of women. Additionally, a distinct pattern emerged in the MMT distribution, showing a decrease from the coastline to the interior and northern regions of the country. The overall MMT ranged from 8.6 to 18.6 °C, with the men's MMTs averaging 0.7° higher than those of women (see Appendix, p. 24, Fig. S11).

Table 2 presents the annual excess number of deaths, the mortality rates per 100,000 person-years and the attributable fractions across the eleven counties and overall. Between 1996 and 2018, non-optimal temperatures contributed to an average of 3879 (95%CI: 3683–4076) cold-related and 44 (29–58) heat-related excess deaths yearly. Notably, excess deaths were higher among women than men for both heat and cold. Specifically, women had up to 28 (95% eCI: 19–37) heat-related excess deaths annually, while men had 16 (95% eCI: 7–24) heat-related excess deaths. For cold-related excess deaths, women had up to 1960 (95% eCI: 1836–2079) while men had 1919 (95% eCI: 1807–2019) annually (see Appendix, pp. 12–13; Tables S3 and S4). Excess non-accidental mortality rates and attributable fractions, further detailed by county and sex, are outlined in the Appendix (pp. 13, 25–26; Table S4, Figs. S12 and S13).

Fig. 3 illustrates crude excess mortality rates across the eleven regions, categorised by income quartiles, degree of urbanisation, quintiles of percentage of tertiary education and driving time by road to the nearest hospital. Notably, Innlandet recorded the largest excess mortality rate at 103.50 per 100,000 person-years (empirical 95% CI: 97.59–108.89), with rates of 104.88 per 100,000 person-years (97.87–111.27) for men and 102.10 per 100,000 person-years (95.66–108.94) for women. Conversely, Oslo and Rogaland (where the main city is Stavanger) exhibited the lowest excess mortality rates due to cold, with rates of 62.49 per 100,000 person-years (51.02–74.11) and 55.60 per 100,000 person-years (52.67–58.43), respectively. In contrast, regional heat-related excess mortality rates showed less variability compared to the cold-related rates (standard deviation of 0.23 versus 11.80). Rogaland once again had the lowest excess mortality rate at 0.45 (95% eCI: 0.26–0.63), followed by Oslo at 0.56 (95% eCI: 0.19-1.32). The highest excess mortality rates due to heat by sex were found also in Innlandet, with rates of 1.08 per 100,000 person-years (95% eCI: 0.54–1.66) for men and 1.76 (95% eCI: 1.17–2.33) for women (see Appendix pp. 13 and 22; Table S4, Fig. S9). Regarding income, the lowest excess mortality rates were observed in municipalities within the highest income quartile: for cold, it was 56.32 per 100,000 person-years

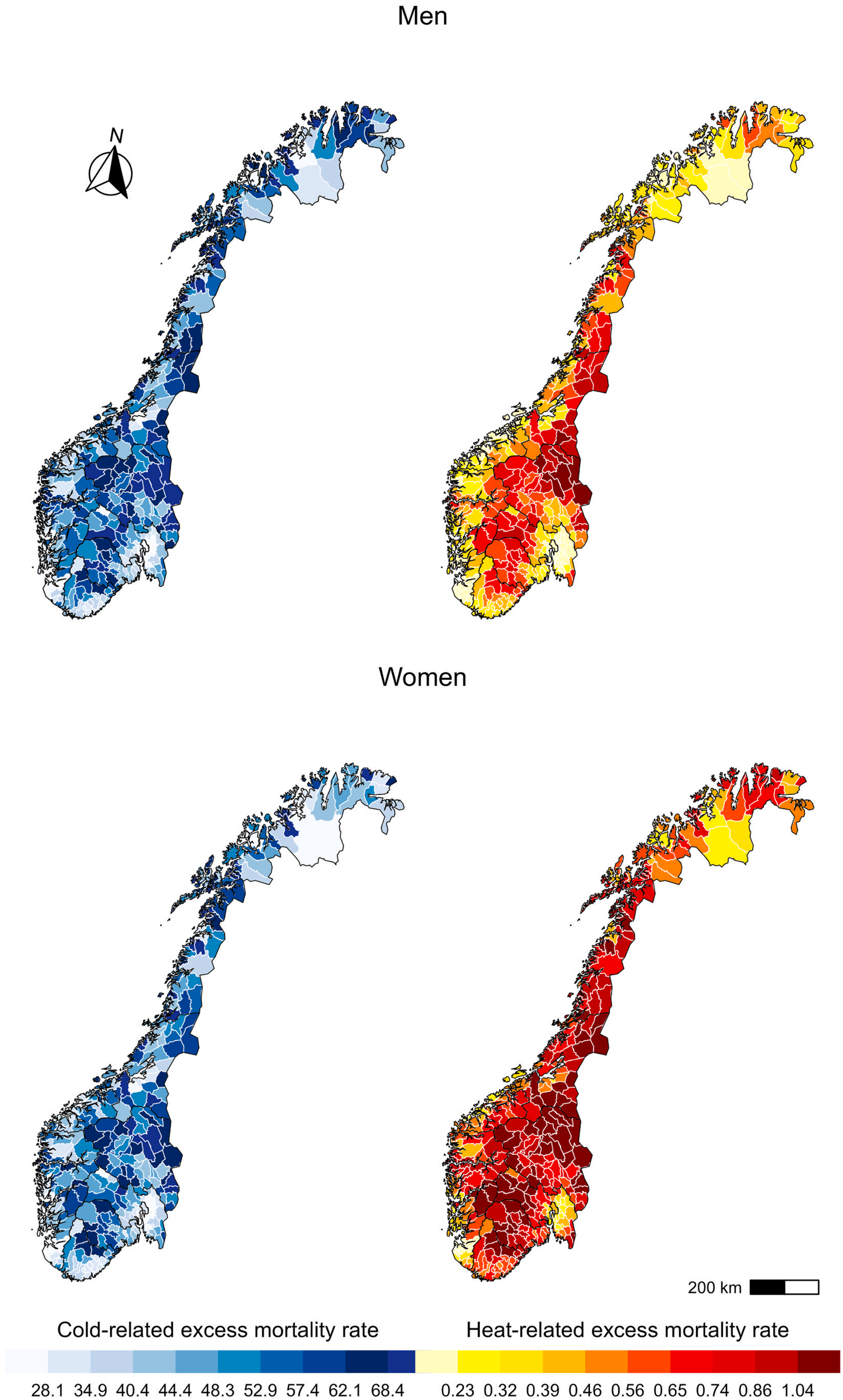

Fig. 2. Geographical distribution of cold- and heat-related excess mortality rates per 100,000 person-years across municipalities and sex group. Municipal boundaries are represented with white lines while the boundaries of the eleven administrative counties are delineated with black lines.

Table 2
Annual excess deaths, standardised excess mortality rates and fractions attributable to cold and heat by counties of Norway in the period 1996–2018.

Region	Annual excess deaths		Excess mortality rate deaths per 100,000 person-years		Attributable fractions (%)	
	Cold	Heat	Cold	Heat	Cold	Heat
Oslo	421 (344–499)	4 (-1–9)	62.5 (51.0–74.1)	0.6 (−0.2–1.3)	9.8 (8.0–11.6)	0.1 (−0.0–0.2)
Rogaland	263 (249–277)	2 (1–3)	55.6 (52.7–58.4)	0.5 (0.3–0.6)	9.6 (9.1–10.1)	0.1 (0.1–0.1)
Møre og Romsdal	205 (197–213)	2 (1–2)	77.6 (74.7–80.6)	0.6 (0.4–0.8)	9.6 (9.3–10.0)	0.1 (0.1–0.1)
Nordland	232 (223–240)	3 (2–3)	97.4 (93.8–101.0)	1.2 (0.9–1.4)	10.4 (10.1–10.8)	0.1 (0.1–0.2)
Viken	813 (771–855)	9 (5–12)	67.0 (63.5–70.4)	0.7 (0.5–1.0)	9.9 (9.4–10.4)	0.1 (0.1–0.2)
Innlandet	384 (352–404)	5 (3–7)	103.5 (97.6–108.9)	1.4 (0.9–1.9)	9.9 (9.4–10.5)	0.1 (0.1–0.2)
Vestfold og Telemark	367 (352–382)	4 (3–6)	88.3 (84.7–91.9)	1.1 (0.8–1.4)	10.1 (9.7–10.5)	0.1 (0.1–0.2)
Agder	226 (218–235)	3 (2–4)	74.5 (71.8–77.3)	1.1 (0.8–1.3)	10.0 (9.6–10.4)	0.1 (0.1–0.2)
Vestland	443 (423–462)	5 (4–7)	70.1 (67.0–73.1)	0.9 (0.6–1.1)	9.8 (9.4–10.2)	0.1 (0.1–0.2)
Trøndelag	336 (321–349)	5 (4–5)	73.3 (70.3–76.2)	1.1 (0.8–1.3)	9.7 (9.3–10.0)	0.1 (0.1–0.2)
Troms og Finnmark	189 (180–198)	2 (1–2)	77.4 (73.7–81.0)	0.7 (0.5–0.9)	10.1 (9.7–10.6)	0.1 (0.1–0.1)
Norway	3879 (3683–4076)	44 (29–58)	73.4 (69.7–77.1)	0.8 (0.6–1.1)	9.9 (9.4–10.4)	0.1 (0.1–0.2)

Data are point estimate (empirical 95% CI).

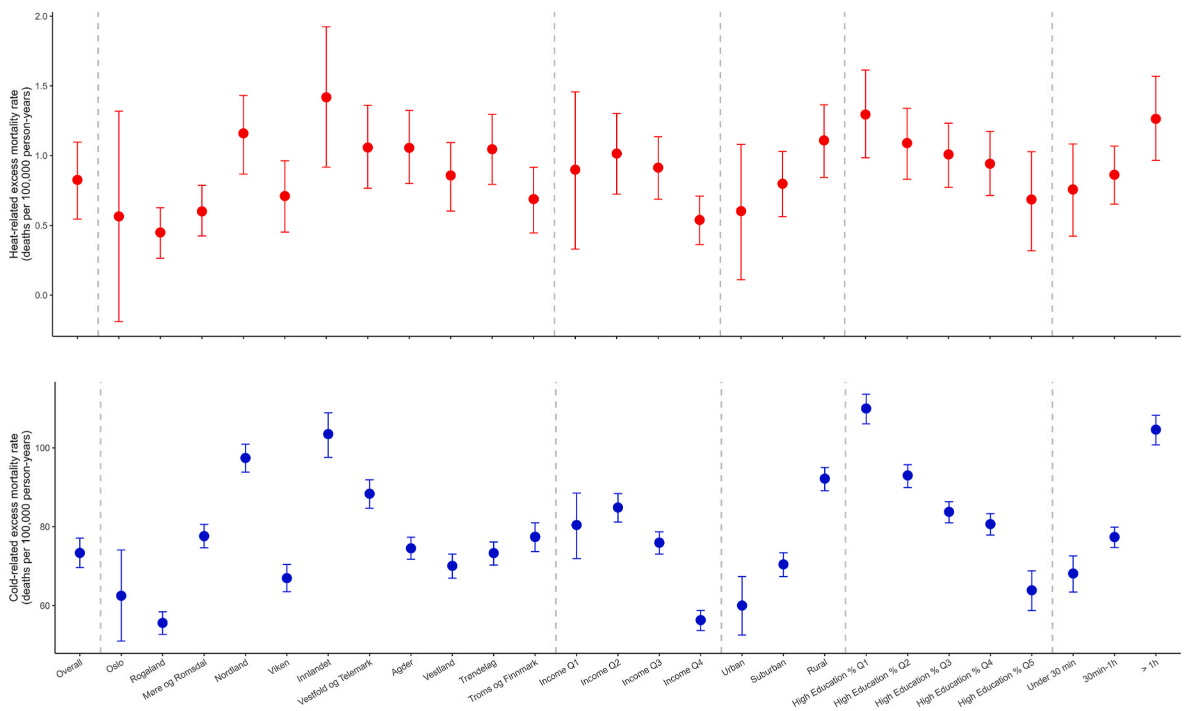

Fig. 3. Excess mortality rates attributable to heat and cold in Norway, stratified by region, quartiles of income, degree of urbanisation, quintiles of percentage of tertiary education, and driving time by road to the nearest hospital (under 30 min, 30 min to 1 h, and more than 1 h).
Error bars are empirical 95% CI.

(53.65–58.79), and for heat, it was 0.54 (95% CI: 0.36–0.71).

With respect to the degree of urbanisation, higher excess mortality rates were observed in rural areas compared to urban counterparts for both cold and heat; however, only the differences between the cold-related rates were statistically significant. A gradient in excess mortality rates became evident when municipalities were classified by urbanisation, with females generally exhibiting higher RRs than males across different levels of urbanisation, though these differences were not statistically significant (see Appendix, p. 14, Table S5). Similarly, we detected decreasing excess mortality rates with increasing quintiles of percentage of tertiary education for both cold and heat. The differences between categories were statistically significant for the cold-related excess mortality rates. Regarding driving time by road to the nearest hospital, both heat- and cold-related excess mortality rates increased with longer driving times. A detailed breakdown of the results is available in the Appendix (pp. 14, 27; Table S5, Fig. S14).

4. Discussion

This study provides the first comprehensive assessment of non-optimal temperature related mortality across the 356 municipalities of mainland Norway. It includes results by sex and investigates arrange of area level factors to further assess these results.

Our investigation reveals an annual average excess mortality of 3922 (95% eCI: 3718–4130), comprising 3879 (95% eCI: 3683–4076) deaths attributable to cold and 44 (95% eCI: 29–58) to heat. Due to the generally low temperatures typical of Norway, we expect cold conditions to markedly dominate the toll from non-optimal temperature conditions (Nafstad et al., 2001; Vázquez Fernández et al). This concurs with studies from various parts of northern Europe, including the Czech Republic (Vésier and Urban, 2023), England and Wales (Gasparrini et al., 2022), and subarctic Russian cities (Revich and Shaposhnikov, 2022). All these findings underscore the greater influence of cold in contributing to attributable mortality in Norway.

Between −22 °C and −9.7 °C, the ERFs deviate from the expected inverse J-shape, showing a decrease in mortality risk as temperatures drop. This anomaly is consistent with other results from Nordic countries (Gasparrini et al., 2015; Orru and Åström, 2017), but emphasizes the need for further investigation to comprehend potential underlying mechanisms and implications for public health interventions in cold climates. One possible explanation may lie in the disparity between the outdoor temperatures and individuals' actual exposure, as they are likely shielded from extreme cold while indoors. Building insulation standards and heating practices in Norway may account for the observed reduction in mortality risk at very low temperatures.

The estimated excess mortality equates to a rate of 73.37 deaths per 100,000 person-years attributable to cold, and 0.83 deaths per 100,000 person-years resulting from heat. The respective AFs of cold are 9.90% (9.40–10.40) and heat 0.11% (0.07–0.15). These findings are consistent with results reported from Gasparrini et al. (2022) for England and Wales, Masselot et al. (2023), which studied 854 cities across Europe, and de Schrijver et al. (2023) for Switzerland.

Our study revealed MMTs at the 93rd and 94th percentiles of the temperature distribution for the pooled results at the country level, as showed in Fig. 1. These findings align closely with those of Gasparrini et al. (2022), who reported that MMTs in England and Wales were close to the 95th percentile of the temperature distribution. In our analysis, MMTs ranged from 9.4 to 18.6 °C for males and 8.6–17.8 °C for females, averaging near the 93rd percentile of the local temperature distribution, with the most frequent daily temperature being 10.7 °C. This underscores adaptation to local climatic conditions (Yin et al., 2019). Although lower MMTs in women suggest a higher vulnerability than in men, our results did not show noticeable sex differences in mortality due to either heat or cold. This finding stands in contrast to previous studies that reported such differences; including significant sex differences in heat-related mortality identified in a global systematic review (Son et al., 2019), studies conducted in the Netherlands (Folkerts et al., 2022), the Czech Republic (Janoš et al., 2024) and Norway (Vázquez Fernández et al.). One possible explanation for the lack of sex-based differences observed in our study could be the municipality-level focus, which may mask broader demographic patterns. Additionally, in Norway, the proportion of individuals living alone varies by sex and age, with more men living alone at younger ages and more women at older ages due to women's longer life expectancy (Statistics Norway (SSB), 2018), potentially moderating sex-based vulnerability differences. Our findings also contrast with studies like that in Scotland, where women were found to be more susceptible to cold-related mortality than men (Wan et al., 2022).

Our study also found higher rates of heat-related mortality in medium- and sparsely-populated areas compared to urban areas. In rural municipalities, heat-related excess mortality rate for men was twice that of urban areas (0.83 (0.24–1.38) vs 0.38 (−0.09 – 0.83)), with a similar, though less pronounced, pattern for women (1.40 (1.02–1.76) vs 0.83 (0.24–1.38)). While some studies (Gasparrini et al., 2022; Wang et al., 2018) suggest greater susceptibility to heat-related impacts in urban areas, others report similar (Odame et al., 2018) or higher (Lee et al., 2021) vulnerability in rural settings. Regional disparities in mortality rates across Norwegian counties, particularly in areas with older populations (Statistics Norway (SSB), 2020), may help explain these findings (Clarsen et al., 2022).

In terms socioeconomic status, populations with higher levels of educational attainment were found to be less vulnerable to both heat and cold, suggesting that education contributes to overall improved living conditions, including better access to medical care and air conditioning. In rural areas, increased driving times to hospitals contribute to higher excess mortality rates, as timely access to medical care is crucial in managing heat- and cold-related health issues. This highlights the potential adverse effects of centralising hospitals, particularly for rural populations (Mungall, 2005). Ensuring more evenly distributed healthcare facilities could help mitigate these risks, and decentralising medical healthcare may be critical in reducing heat- and cold-related excess mortality rates, emphasising the need for policies that enhance access to medical care across all regions.

The municipalities in Norway mainly focus on lifestyle and healthcare related measures and there is still a lack of knowledge and coordination related to integrating the social determinants of health. The challenge of supporting an aging population to become digitally self-sufficient is also pressing. Another critical area for enhancement is reducing wait times, where implementing notification systems that encourage behavioural changes in response to weather warnings could have a substantial impact. We argue for concerted multi-level action at the municipality level and need to better understand the gap between national and municipal approaches. We suggest further research to illuminate the challenges faced at local levels. This research is essential for developing health-equitable adaptation measures in Norway.

Strengths of the present research include nationwide analysis that utilises high-resolution temperature measurements at the municipality level, thereby inhibiting reliance on regional level aggregated data, which might obscure fine-scale differences. The application of cutting-edge methodology, specifically the case time series design, facilitated the investigation of dependencies and multiple effect summaries. Geographic differences were interpreted through several local characteristics with principal components, a methodology that bypasses potential bias and limitations from separate assessment of each vulnerability factor. Additionally, the completeness of the health data sourced from the Norwegian Cause of Death Registry enhances the robustness of our findings, ensuring a comprehensive understanding of the impacts of temperature on health across different demographic groups.

Nevertheless, our study has several limitations. For instance, it assumes that the risk pattern at the cluster level accurately represents the risk within the municipalities they encompass. Although we utilised the Ward-like algorithm for clustering to ensure similarity among clusters and employed a downscaling procedure to highlight differences between municipalities, even within the same cluster. We note that the temperature data is reconstructed, which may result in the smoothing of extreme temperature values. Additionally, we conducted the analysis across the eleven (counties) regions, yielding similar results that appear reasonable. However, due to insufficient data points for meta-regression in the second stage, we opted to utilise the clusters instead. Because of the method's nature, PCA prevented the identification of independent contributions from the actual drivers of risk. The length of the study period, spanning 23 years, was comprehensive, but does not account for the variations in risks over time. We acknowledge the ambiguity in distinguishing between rural and urban classifications. We analysed records of non-accidental mortality despite the availability of cause-specific mortality (cardiovascular and respiratory) due to a small sample size, rendering insufficient statistical power. For similar reasons, we could not perform the analysis categorised by age groups. Since both cold and heat-related mortality risks are influenced by age distribution, they could not be accounted for. While we used the available vulnerability factors in our analysis, we acknowledge that other factors, such as humidity and other socioeconomic disparities (e.g. social support networks), could also influence the results. Furthermore, microclimate variations may not be fully captured when using municipality-averaged temperatures across grids cells. Future research should focus on individual-level exposure rather than area-level measurements.

5. Conclusion

This study provides a comprehensive examination of the mortality risks associated with temperature across different sex groups in Norway from 1996 to 2018. The analysis offers insights into the effects of heat and cold temperatures and identifies locally optimal temperatures. The findings, presented across various geographical stratifications—including income levels, degrees of urbanisation, tertiary education percentages, and driving distances to the nearest hospital—contribute valuable data that could inform more equitable health policies in Norway. Furthermore, the results are crucial for projecting future risks and impacts in models that simulate diverse scenarios of climate change.

CRediT authorship contribution statement

Liliana Vázquez Fernández: Writing – original draft, Visualization, Software, Methodology, Formal analysis, Data curation, Conceptualization. **Alfonso Diz-Lois Palomares:** Writing – review & editing, Validation, Software, Data curation. **Ana María Vicedo-Cabrera:** Writing – review & editing, Supervision, Methodology, Conceptualization. **Antonio Gasparrini:** Writing – review & editing, Methodology, Funding acquisition. **Birgitte Freiesleben de Blasio:** Writing – review & editing, Supervision, Methodology, Conceptualization. **Francesco Di Ruscio:** Writing – review & editing, Methodology. **Pierre Masselot:** Writing – review & editing, Methodology. **Torbjørn Wisløff:** Writing – review & editing, Methodology. **Shilpa Rao-Skirbekk:** Writing – review & editing, Supervision, Methodology, Funding acquisition, Conceptualization.

Data sharing statement

The individual mortality data used in this study were provided by the Norwegian Cause of Death Registry (Dødsårsaksregisteret, DÅR), which is managed by the Norwegian Institute of Public Health (NIPH). These data are confidential and cannot be shared by the authors. Interested researchers must request access directly from DÅR via NIPH. Daily temperature data were sourced from the seNorge_2018 dataset, and air pollution data were obtained from regional atmospheric modelling. Further details, including relevant links and dataset information on the vulnerability factors, are provided in the appendix.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.envres.2024.120614.

Data availability

A Data sharing Statement has been included in the main document

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