Heliyon 10 (2024) e25222

Contents lists available at ScienceDirect

Heliyon

journal homepage: www.cell.com/heliyon

Research article

Long-term exposure to high perceived temperature and risk of mortality among patients with chronic kidney disease

Jeonghwan Lee [a,b,1], Sohee Oh [c,1], Jae-Young Byon [d], Whanhee Lee [e], Boram Weon [b], Ara Ko [f], Wencheng Jin [a], Dong Ki Kim [a,f], Sejoong Kim [a,g], Yun Kyu Oh [a,b], Yon Su Kim [a,f], Chun Soo Lim [a,b], Jung Pyo Lee [a,b,*]

[a] *Department of Internal Medicine, Seoul National University College of Medicine, Seoul, Republic of Korea*
[b] *Department of Internal Medicine, Seoul National University Boramae Medical Center, Seoul, Republic of Korea*
[c] *Medical Research Collaborating Center, Seoul National University Boramae Medical Center, Seoul, Republic of Korea*
[d] *National Meteorological Satellite Center, Korea Meteorological Administration, Jincheon, Chungcheongbuk-do, Republic of Korea*
[e] *Data Science, School of Biomedical Convergence Engineering, Pusan National University, Pusan, Republic of Korea*
[f] *Department of Internal Medicine, Seoul National University Hospital, Seoul, Republic of Korea*
[g] *Department of Internal Medicine, Seoul National University Bundang Hospital, Seoul, Republic of Korea*

ARTICLE INFO

Keywords:
Perceived temperature
Chronic kidney disease
Mortality
Kriging

ABSTRACT

Health risks due to climate change are emerging, particularly from high-temperature exposure. The perceived temperature is an equivalent temperature based on the complete heat budget model of the human body. Therefore, we aimed to analyze the effect of perceived temperature on overall mortality among patients with chronic kidney disease. In total, 32,870 patients with chronic kidney disease in Seoul participated in this retrospective study (2001–2018) at three medical centers. The perceived temperature during the summer season was calculated using meteorological factors, including the air temperature near the automated weather station, dew point temperature, wind velocity, and total cloud amount. We assessed the association between perceived temperature using Kriging spatial interpolation and mortality in patients with CKD in the time-varying Cox proportional hazards model that was adjusted for sex, age, body mass index, hypertension, diabetes mellitus, estimated glomerular filtration rate, smoking, alcohol consumption, and educational level. During the 6.14 ± 3.96 years of follow-up, 3863 deaths were recorded. In multivariable analysis, the average level of perceived temperature and maximum level of perceived temperature demonstrated an increased risk of overall mortality among patients with chronic kidney disease. The concordance index for mortality of perceived temperature was higher than temperature, discomfort index, and heat index. When stratified by age, diabetes mellitus, and estimated glomerular filtration rate, patients with chronic kidney disease with young age (age <65 years) showed higher hazard ratio for mortality (interaction $P = 0.049$). Moreover, the risk of death in the winter and spring seasons was more significant compared to that of the summer and autumn seasons. Therefore, long-term exposure to high perceived temperature during summer increases the risk of mortality among patients with chronic kidney disease.

* Corresponding author. Department of Internal Medicine, Seoul National University Boramae Medical Center and Seoul National University College of Medicine 20 Boramae-ro 5-gil, Dongjak-gu, Seoul, 07061, Republic of Korea.
E-mail address: jungpyolee@snu.ac.kr (J.P. Lee).
[1] These two authors contributed equally as co-first authors.

https://doi.org/10.1016/j.heliyon.2024.e25222
Received 6 August 2023; Received in revised form 21 January 2024; Accepted 23 January 2024
Available online 24 January 2024

1. Introduction

Chronic kidney disease (CKD) affects 8–13 % of the general population and is a global public health problem with poor patient survival and increased comorbidities and socioeconomic burden [1,2]. In patients with CKD with various comorbidities and increased systemic inflammation, the risk of mortality increases by two to ten times that of the general population owing to the increased risk of infection and cardiovascular disease [3,4]. Factors such as old age, diabetes mellitus, hypertension, decreased estimated glomerular filtration rate (GFR), and proteinuria are major contributors to the increase in mortality in patients with CKD [5]. In recent years, there has been an increasing interest in correctable risk factors that can be controlled, such as dietary and environmental factors, but were previously overlooked [6,7].

According to the World Health Organization, environmental factors account for 12.6 million deaths, accounting for approximately 23 % of all deaths worldwide [8]. In recent times, people have been exposed to a greater number of health risks than before due to recent climate change, and approximately 5,083,173 (11 %) global deaths are estimated to be associated with nonoptimal cold or hot temperatures [9]. The global average temperature is rising and was 1.11 ± 0.13 °C above pre-industrial levels (1850–1900) in 2021. Moreover, in the last 50 years, the range of temperature increase has been increasing at a rate of approximately 1.7 °C per century (https://www.ipcc.ch/sr15/chapter/chapter-1/; https://public.wmo.int/en/media/press-release/2021-one-of-seven-warmest-years-record-wmo-consolidated-data-shows). High environmental temperatures are associated with an increased risk of mortality with increased incidence of cardiovascular, respiratory, and cerebrovascular diseases. Furthermore, individuals with black ethnicity, female sex, low socioeconomic status, and old age are susceptible to increased mortality [10]. The sensory and health effects of temperature on the human body are affected by other factors such as humidity and wind. Apparent temperature, heat and discomfort indices, and other indices have been used as temperature indices to indicate effects related to high temperature. The perceived temperature, which reflects the actual effect of temperature on the human body, has recently been used by comprehensively considering dew point temperature, wind velocity, cloud amount, and humidity information. Perceived temperature is also more predictive of death than temperature alone or other temperature indicators [11].

Although several studies have reported changes in mortality risk in the general population due to hot temperatures, studies on the health effects of high-temperature exposure in CKD are lacking. Moreover, studies on long-term survival risk due to hot temperature exposure, especially from the perspective of perceived temperature, are rarely reported. Therefore, we aimed to investigate the effects of high perceived temperature, evaluated using Kriging methods, on long-term patient survival in patients with CKD and the differential effects among temperature indices, including perceived temperature, air temperature (at 2-m height), and heat and discomfort indices.

2. Materials and methods

2.1. Study population

We enrolled 32,870 patients with CKD who visited three tertiary university hospitals (Seoul National University Hospital, Seoul Metropolitan Government Seoul National University [SMG-SNU] Boramae Medical Center, and Seoul National University Bundang Hospital) between January 2001 and December 2018. Only patients residing in Seoul Metropolitan City were included in the analysis, whereas those from other areas were excluded for matching address and temperature information. Data on patients' address, demographics, laboratory data, and clinical outcomes were retrospectively collected via electronic medical record review. Estimated GFR was calculated using the four-variable modification of diet in renal disease equations [12]. The institutional review board of each center approved the study protocol and data collection (Seoul National University Hospital [J-1704-121-848], Seoul National University Bundang Hospital [B-1706/401–402], and SMG-SNU Boramae Medical Center [20170414/16-2017-65/051]).

2.2. Temperature-related parameters' interpolation according to the address

Seoul Metropolitan City consists of 25 districts, and each district has one or more automated weather stations (AWSs, with 29 AWSs in Seoul) to collect weather information. We collected the hourly weather information for the summer season (from July to September, at each year) including temperature, dew point temperature, and wind velocity from all 29 AWSs from January 2001 to December 2018. However, cloud and humidity information was not measured from all AWSs before December 2010. Therefore, cloud and humidity information were replaced by the representative AWS (AWS number 108, located in Songwol-dong). Four temperature indices, including perceived temperature, air temperature at 2 m (dry bulb air temperature measured from a 2-m height of each of the 29 AWSs), discomfort index, and heat index, were calculated from the raw data gathered from each station. Perceived temperature was calculated using the equation proposed by Staiger et al. [13]. The heat index combines air temperature and relative humidity and is calculated using the equation suggested by Anderson et al. [12]. Discomfort index combines air temperature measured with both dry and wet bulb and is calculated using the following formula: temperature $-0.55 \times (1 - 0.01 \times \text{relative humidity}[\%]) \times (\text{temperature} - 14.5)$ [14].

We calculated the daily maximum and average temperatures for the summer season (from July to September, at each year) at each of the 29 AWS from 2001 to 2018. Using the geocoded address of each patient and nearby AWS, we performed spatial interpolations using the Kriging method, which estimated the temperature and temperature indices of each patient based on the Gaussian process from the temperatures of each AWS [15,16]. Kriging interpolation estimates the optimal linear prediction at unmeasured locations with more weights in a nearby location from the measured points [17].

2.3. Statistical analyses

Categorical data are presented as frequencies and percentages, whereas continuous variables are presented as means and standard deviations. The normal distributions of the variables were represented by histograms, and Kolmogorov–Smirnov techniques were used to evaluate the normality of the distributions. A time-varying Cox proportional hazards model was employed to investigate the long-term association between CKD patient mortality and summer temperature exposure levels. Based on the daily maximum and average temperature levels from June to August of each year, we calculated the summer high-temperature exposure of the patients for each temperature index. At the time of the survey, patients were assigned summertime temperature exposure based on their geocoded domicile. To evaluate the long-term effects, we calculated the annual averages for perceived temperature, temperature (2-m height), and heat and discomfort index based on daily temperatures. To represent the time-varying properties of temperatures, annual average estimates were revised from 1 year before the cohort's enrolment date to the censoring date. In the multivariable adjustment model, we included covariates of sex, age, body mass index, hypertension, diabetes mellitus, and estimated GFR in model 1 and of covariates in model 1 and smoking, alcohol consumption, educational level, and socioeconomic status in model 2. Information on the socioeconomic status was obtained from the patients' reported survey and categorized into 3 levels. Harrell's concordance (C)-index was used to evaluate the prediction performance of temperature indices for mortality. We performed subgroup analysis stratified by age (age 65 years), diabetes mellitus, and estimated GFR (smoking and drinking status) to identify relevant confounders. Statistical analyses were performed using SPSS version 27.0 and R version 4.0.3. $P \leq 0.05$ was considered statistically significant.

3. Results

3.1. Demographics and clinical characteristics

In total, 32,870 adult patients with CKD from Seoul were enrolled in this study. The locations of the addresses of the enrolled patients are presented in Fig. 1. The participants' addresses were evenly distributed throughout Seoul. The clinical information of the enrolled patients with CKD is summarized in eTable 1. The mean age was 54.76 ± 16.95 years, and males accounted for 15,604 (47.47

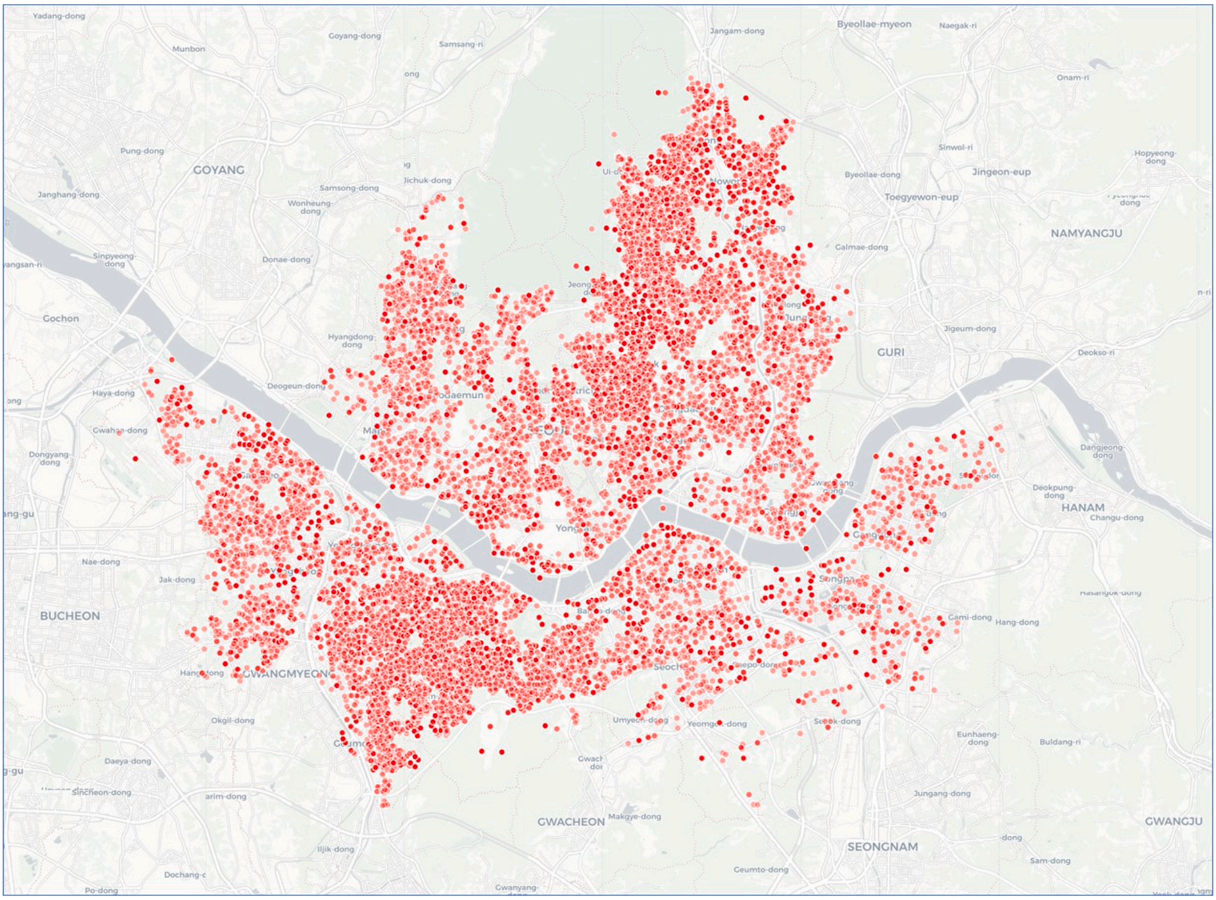

Fig. 1. Distribution map of enrolled participants' addresses.

%) of the patients. The mean serum creatinine level and estimated GFR of the patients were 1.59 ± 2.42 mg/dl and 64.33 ± 23.20 ml/min/1.73 m^2, respectively, and the incidence rates of diabetes and hypertension were 21.27 % and 32.22 %, respectively. The proportions of smokers and drinkers were 10.07 % and 14.73 %, respectively.

3.2. Temperature indices

Annual maximal, average, and minimal temperatures and temperature index longitudinal trends are illustrated in eFig. 1. Since 2010, the discomfort index and temperature have shown slightly increasing trends. The perceived temperature and heat index showed a more prominent increasing trend than the discomfort index and temperature itself. Regarding perceived temperature, the maximal, average, and minimal levels showed the most distinct differences among the four temperature indices. The correlations among the maximum, average, and minimum levels of the four temperature indicators are shown in eFig. 2. The average levels of the temperature indices showed a relatively high correlation (correlation coefficient R from 0.682 to 0.935) among the four indicators. The average perceived temperature was sequentially correlated with the average discomfort index (R = 0.935), average temperature (R = 0.933), and average heat index (R = 0.711). However, the average temperature itself showed a low correlation with the heat index (R = 0.682), and the correlation between the average heat index and the average discomfort index was also low (R = 0.719). The maximal levels of perceived temperature indices showed a correlation in the order of the maximal heat index (R = 0.821), maximal discomfort index (R = 0.774), and temperature itself (R = 0.444). The correlation between the average temperature and perceived temperature was relatively high, whereas that between the maximum level of temperature and perceived temperature was significantly lower.

3.3. Temperature indices and chronic kidney disease patient mortality

During the 6.14 ± 3.96 years of follow-up, 3863 (13 %) deaths were recorded. The mortality risk according to the four temperature indices is summarized in Table 1. An increased risk of mortality was significant in all temperature and temperature indices. In the univariable analysis of the average level of temperature indices, the C-index of hazard ratio (HR) for mortality was high in the order of perceived temperature, temperature, discomfort and heat index (C-indices, 0.583, 0.560, 0.555, and 0.547, respectively). The maximal level showed a slightly higher C-index than the average level, and the risk of maximal perceived temperature was followed by the discomfort and heat index, and temperature (C-indices, 0.591, 0.552, 0.547, and 0.527, respectively). Particularly, the maximum level of temperature had a lower C-index than the average temperature level. In multivariable analysis (model 2), the maximal or average level of perceived temperature showed an increased risk of mortality, and the C-index for mortality was followed by the discomfort and heat index, and temperature (average levels, 0.791, 0.786, 0.786, and 0.785; maximal levels, 0.790, 0.784, 0.783, and 0.782, respectively).

The risk of mortality according to the perceived temperature is shown in Fig. 2. Fig. 2(A) is unadjusted model and Fig. 2(B) is multivariable restricted cubic splines adjusted for age, sex, body mass index, hypertension, diabetes mellitus, estimated glomerular filtration rate, smoking, alcohol, education level, and socioeconomic status. Mortality risk gradually increased over the entire perceived temperature range, and a perceived temperature of 27 °C was noted as a point of steeper increased risk of mortality. Changes in the risk of death according to the increase in perceived temperature were identified by stratification according to age, sex, and estimated GFR. Table 2 shows the risk of mortality in both the young (aged ≤65 years) and old (aged >65 years) age groups. The HRs of all four temperature indices showed higher trend in the young age group than in the old age group, and interaction between age group and perceived temperature was statistically significant ($P = 0.049$). The analysis results according to the presence of diabetes mellitus and estimated GFRs are also summarized in Table 2 and eFig. 3. In the non-diabetic group, the C-index of each temperature index was higher than that in the diabetic group. Additionally, the C-index in the high estimated GFR group was higher than that in the low estimated GFR group. The C-index of perceived temperature was superior to the C-index of other temperature indices in all subgroups according to the presence of diabetes mellitus or estimated GFR. However, interaction between diabetes mellitus or estimated GFR subgroup with perceived temperature was not statistically significant ($P = 0.751$ and 0.129, respectively).

Table 1
Risk for overall mortality according to perceived temperature and other associated indices.

		Univariable model		Multivariable model 1		Multivariable model 2	
		HR (95 % CI)	C-index	HR (95 % CI)	C-index	HR (95 % CI)	C-index
Perceived temperature	Average	1.281 (1.253–1.309)	0.583	1.303 (1.268–1.339)	0.804	1.292 (1.255–1.331)	0.791
	Maximal	1.382 (1.344–1.422)	0.591	1.374 (1.329–1.421)	0.804	1.356 (1.309–1.404)	0.790
Temperature	Average	1.333 (1.279–1.388)	0.560	1.322 (1.258–1.389)	0.798	1.315 (1.246–1.388)	0.785
	Maximal	1.259 (1.220–1.299)	0.527	1.254 (1.211–1.299)	0.796	1.220 (1.175–1.265)	0.782
Heat Index	Average	1.514 (1.455–1.575)	0.547	1.480 (1.421–1.542)	0.800	1.445 (1.383–1.509)	0.786
	Maximal	1.071 (1.062–1.081)	0.547	1.092 (1.079–1.106)	0.797	1.086 (1.072–1.101)	0.783
Discomfort	Average	1.410 (1.344–1.478)	0.555	1.472 (1.387–1.562)	0.799	1.467 (1.376–1.534)	0.786
	Maximal	1.401 (1.347–1.458)	0.552	1.555 (1.474–1.640)	0.798	1.510 (1.426–1.598)	0.784

Multivariable model 1 included covariates of age, sex, body mass index, hypertension, diabetes mellitus, and estimated glomerular filtration rate. Multivariable model 2 included covariates of model 1 and smoking, alcohol, education level, and socioeconomic status.

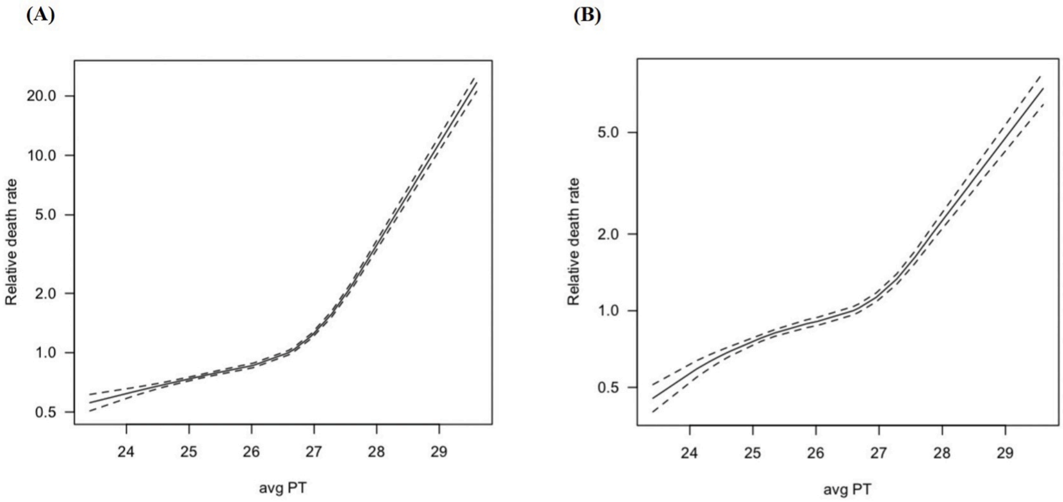

Fig. 2. Restricted cubic splines for mortality according to perceived temperature. (A) Unadjusted model. (B) Multivariable restricted cubic splines adjusted for age, sex, body mass index, hypertension, diabetes mellitus, estimated glomerular filtration rate, smoking, alcohol, education level, and socioeconomic status.

Table 2
Temperature indices and risk for all-cause mortality according to age, diabetes mellitus, and eGFR.

	Age below 65 years old (n = 22,228)		Age equal or above 65 years old (n = 10,652)		Interaction
	HR (95 % CI)	C-index	HR (95 % CI)	C-index	*P*-value
Perceived temperature	1.371 (1.302–1.443)	0.772	1.342 (1.275–1.412)	0.818	0.049
Temperature	1.417 (1.287–1.56)	0.762	1.366 (1.244–1.500)	0.812	0.170
Heat Index	1.550 (1.423–1.688)	0.764	1.540 (1.420–1.670)	0.814	0.042
Discomfort index	1.567 (1.403–1.751)	0.765	1.558 (1.398–1.736)	0.814	0.470
	Patients without diabetes mellitus (n = 25,880)		Patients with diabetes mellitus (n = 6,990)		
Perceived temperature	1.308 (1.257–1.360)	0.809	1.273 (1.217–1.332)	0.747	0.751
Temperature	1.364 (1.268–1.467)	0.804	1.253 (1.157–1.357)	0.740	0.444
Heat Index	1.486 (1.402–1.575)	0.804	1.401 (1.311–1.497)	0.741	0.590
Discomfort index	1.541 (1.417–1.677)	0.805	1.376 (1.364–1.623)	0.740	0.490
	Patients with eGFR <60 (n = 11,400)		Patients with eGFR ≥60 (n = 17,550)		
Perceived temperature	1.253 (1.208, 1.299)	0.753	1.342 (1.275–1.412)	0.818	0.129
Temperature	1.272 (1.192, 1.358)	0.748	1.366 (1.244–1.500)	0.812	0.404
Heat Index	1.380 (1.31, 1.453)	0.748	1.540 (1.420–1.670)	0.814	0.044
Discomfort index	1.396 (1.29, 1.511)	0.748	1.558 (1.398–1.736)	0.814	0.260

Temperature indices are all average level of each temperature.
Multivariable model included covariates of age, sex, body mass index, hypertension, diabetes mellitus, estimated glomerular filtration rate, smoking, alcohol, education level, and socioeconomic status.
Interaction between subgroup and temperature indices are noted.
eGFR, estimated glomerular filtration rate (ml/min/1.73 m^2).

3.4. Sensitivity analyses

We compared how the prediction of mortality changed when a heat wave watch or warning was defined based on perceived temperature, and the results are summarized in Table 3. A heat wave watch was defined as a condition in which the daily maximum temperature was 33 °C or higher, lasting for more than 2 days based on the temperature. A heat wave warning was defined as a condition in which the daily maximum perceived temperature was 35 °C or higher for 2 days or longer. A linear correlation between temperature and perceived temperature was confirmed to determine the degree of perceived temperature corresponding to temperature (eFig. 4). The perceived temperatures corresponding to the temperature standards of 33 °C and 35 °C were approximately 42 °C and 45 °C, respectively. The heat wave warning at 35 °C indicated the risk of death (HR, 1.083 [95 % confidence interval: 1.072–1.093]; C-index, 0.786), and at the corresponding perceived temperature of 45 °C, it indicated a higher risk of death (HR, 1.428 [95 % CI: 1.394–1.462]; C-index, 0.788).

To compare the persistence of the effects of high summer season temperature on mortality, the HR of perceived temperature for seasonal mortality risk was analyzed (Table 4). The HRs of the average level of perceived temperature in summer for summer and autumn season mortalities were 1.406 (95 % CI: 1.318–1.500) and 1.309 (95 % CI: 1.226–1.397), respectively. Moreover, the risk of

Table 3
Heat wave warning according to perceived temperature and impact on mortality.

	Univariable model		Multivariable model 1		Multivariable model 2	
	HR (95 % CI)	C-index	HR (95 % CI)	C-index	HR (95 % CI)	C-index
Heat wave watch by temperature – 33 °C	1.071 (1.067–1.075)	0.581	1.046 (1.041–1.050)	0.802	1.044 (1.039–1.049)	0.788
Heat wave warning by temperature – 35 °C	1.139 (1.130–1.148)	0.540	1.090 (1.080–1.099)	0.801	1.083 (1.072–1.093)	0.786
Heat wave watch by perceived temperature(a) – 38 °C	1.060 (1.057–1.063)	0.617	1.047 (1.044–1.051)	0.809	1.047 (1.044–1.051)	0.796
Heat wave warning by perceived temperature(a) – 40 °C	1.059 (1.056–1.062)	0.600	1.041 (1.038–1.044)	0.809	1.041 (1.038–1.044)	0.795
Heat wave watch by perceived temperature(b) −42 °C	1.086 (1.082–1.090)	0.591	1.059 (1.055–1.063)	0.807	1.058 (1.053–1.062)	0.792
Heat wave warning by perceived temperature(b)-45 °C	1.566 (1.530–1.603)	0.554	1.458 (1.427–1.491)	0.803	1.428 (1.394–1.463)	0.788

No spatial interpolation applied. Weather information of AWS (AWS number 108, located in Songwol-dong, that is near center in Seoul) was only applied.
Multivariable model 1 included covariates of age, sex, body mass index, hypertension, diabetes mellitus, and estimated glomerular filtration rate.
Multivariable model 2 included covariates of model 1 and smoking, alcohol, education level, and socioeconomic status.

death in winter and spring seasons was significant (HRs, 1.156 [95 % CI: 1.092–1.224] and 1.069 [95 % CI: 1.016–1.125], respectively) according to the increase in perceived temperature.

Since the patients were enrolled for a long time (18 years), the effect of temperature on mortality was separated out according to the enrollment period (before 2010 and after 2011). The HRs of maximal perceived temperature showed higher trend in the period after 2011 compared to the period of before 2010 (eTable 2). All mixamal temperature indices including perceived temperature showed significant interaction with time period. We also compared the prediction ability between the two spatial interpolation methods (Kriging and Inverse Distance Weighting methods). HRs were similar and C-indices were higher in Kriging method (eTable 3).

4. Discussion

Patients with CKD are vulnerable to environmental and medical factors [18,19]. Recently, studies on the health effects of high temperatures have been actively conducted along with the gradual increase in average temperature and heat wave frequency. However, studies on the effect of high temperature among patients with CKD are relatively scarce. Moreover, most studies have reported short-term mortality associated with high-temperature exposure. In this study, we applied the time-varying Cox analysis method to analyze the effect of exposure to high perceived temperature in summer on the long-term prognosis of patients with CKD. Our results showed that high-temperature exposure in summer had a significant effect on the long-term survival of patients with CKD and that the perceived temperature was more suitable for predicting the risk of death compared to other temperature indices. Additionally, the risk of high temperature was more prominent in patients with CKD with young age group. Moreover, the effects of high temperature on mortality lasted more than months or years in that increased mortality risk was maintained in mortality cases in autumn, winter, and spring and death cases in summer.

Various previous studies have reported on high-temperature exposure and the increase in mortality risk. Recent studies, mostly

Table 4
Effects of perceived temperature on seasonal mortality.

	Summer season mortality					
	Univariable model		Multivariable model 1		Multivariable model 2	
	HR (95 % CI)	C-index	HR (95 % CI)	C-index	HR (95 % CI)	C-index
Average	1.395 (1.329–1.464)	0.601	1.445 (1.359–1.536)	0.850	1.406 (1.318–1.500)	0.846
Maximal	1.546 (1.448–1.651)	0.608	1.491 (1.382–1.610)	0.849	1.432 (1.324–1.550)	0.845
	Autumn season mortality					
Average	1.406 (1.339–1.476)	0.602	1.338 (1.259–1.422)	0.841	1.309 (1.226–1.397)	0.830
Maximal	1.500 (1.406–1.600)	0.603	1.368 (1.271–1.473)	0.841	1.318 (1.221–1.424)	0.829
	Winter season mortality					
Average	1.219 (1.169–1.272)	0.574	1.160 (1.100–1.224)	0.839	1.156 (1.092–1.224)	0.826
Maximal	1.305 (1.236–1.377)	0.583	1.197 (1.125–1.274)	0.839	1.191 (1.114–1.273)	0.825
	Spring season mortality					
Average	1.080 (1.038–1.123)	0.535	1.038 (0.990–1.088)	0.820	1.069 (1.016–1.125)	0.813
Maximal	1.176 (1.124–1.230)	0.553	1.096 (1.041–1.154)	0.822	1.127 (1.066–1.190)	0.815

Multivariable model 1 included covariates of age, sex, body mass index, hypertension, diabetes mellitus, and estimated glomerular filtration rate.
Multivariable model 2 included covariates of model 1 and smoking, alcohol, education level, and socioeconomic status.

conducted using time-series or case-crossover designs on the association between temperature and mortality have suggested that these methods produce comparable findings [20,21]. In most cases, the scope of time-series analysis includes a sizable population spread across various regions. Death tolls or rates are matched with data on how often people are exposed to a given substance. The covariates and smoothing functions are used to account for seasonality and other confounding factors that shift over time [22]. Over the past decade, the case-crossover method has been increasingly used for analyzing the correlation between air pollution and temperature [23,24]. Each participant in a case-crossover study acts as his or her own control, making this study design similar to that of matched case-control studies. Therefore, the study design controls for biases related to observable and unobservable confounders. In survival analysis, time-varying Cox analysis considers the effects of covariates that change with time [25]. It is typically used in studies analyzing the effect of air pollution on long-term survival [26,27]. If it can be assumed that the effect of high temperature on survival occurs over a relatively wide high-temperature range and that these effects accumulate over time and affect long-term prognosis, the time-varying Cox analysis method may be suitable for this study. Through this study, it was confirmed that the risk of high temperature was significant at the maximal perceived temperature and at the average perceived temperature, and the effect of high temperature stress was also shown in the moderate temperature range.

Recently, interest in the prognosis of patients with CKD exposed to high temperatures has increased. Borg et al. used negative binomial regression models and reported that a daily temperature increase was associated with an increased incidence of kidney diseases [28]. In their study, the influence on kidney disease was significant in the order of minimum, average, and maximal daily temperatures. Furthermore, an increase in the incidence of kidney disease and kidney disease-related hospitalization due to high-temperature exposure has been proven through other follow-up and meta-analysis studies [29–31]. Recently, He et al. reported that high-temperature-related deaths have increased since 1990, and patients with CKD with male sex and old age are more vulnerable to high-temperature-related mortality [32]. Although several studies have reported an increased incidence of kidney disease morbidity due to high temperature, studies on whether the long-term survival prognosis can be affected by daily high temperature among patients with CKD are lacking. Through this study, we found that daily exposure to high perceived temperature in the summer season has a significant association with the deterioration of the long-term survival of patients. Moreover, increased kidney disease morbidity can be one cause of increased mortality due to high temperature among patients with CKD.

The strength of this study is that we analyzed long-term survival according to perceived temperature for patients with CKD living in a large metropolitan city. However, because it is limited to one city, future studies are required to determine whether similar results can be obtained in other regions. Moreover, as the participating patients with CKD were limited to the Asian population, it may be difficult to generalize the results of this study to patients of other ethnicities in other countries. A limitation of the study is that we did not correct for environmental factors significantly related to the health effects of temperature. Another limitation of this study is that although the risk of high-temperature exposure continued significantly by season by assessing the seasonal risk of death from high perceived temperature exposure in summer, a study on the mechanism of high temperature on the long-term survival of patients was not conducted. Therefore, future studies are warranted to investigate these aspects.

5. Conclusions

In conclusion, exposure to high temperature in summer significantly increases long-term mortality and results in short-term health effects. The risk of high temperature is more pronounced in the young patients group with CKD. Moreover, a heat wave warning or heat watch based on the perceived temperature rather than the temperature itself is superior in predicting mortality. High-temperature exposure can affect the long-term prognosis of patients with CKD, and preventive efforts to improve the prognosis of patients with CKD are required.

Funding

This work was supported by a public clinical research grant from the Seoul Metropolitan Government Seoul National University (SMG-SNU) Boramae Medical Center (04-2020-3).

Ethics approval and consent to participate

The need for informed consent was waived by the ethics committee of each participating hospital, because of the retrospective nature of the study. The institutional review board of each center approved the study protocol and data collection (Seoul National University Hospital [J-1704-121-848], Seoul National University Bundang Hospital [B-1706/401–402], and SMG-SNU Boramae Medical Center [20170414/16-2017-65/051]). The entire investigations were conducted in accordance with their regulations and guidelines.

Data availability statement

Dr. JP Lee had full access to all of the data in this study and took responsibility for the integrity of the data and the accuracy of the data analysis. Data except private information will be made available on request to the corresponding authors.

CRediT authorship contribution statement

Jeonghwan Lee: Writing – original draft, Software, Funding acquisition. **Sohee Oh:** Writing – review & editing, Visualization, Methodology, Formal analysis. **Jae-Young Byon:** Writing – review & editing, Software, Methodology, Conceptualization. **Whanhee Lee:** Writing – review & editing, Validation. **Boram Weon:** Investigation. **Ara Ko:** Investigation. **Wencheng Jin:** Investigation. **Dong Ki Kim:** Supervision, Investigation. **Sejoong Kim:** Supervision, Investigation. **Yun Kyu Oh:** Supervision, Investigation. **Yon Su Kim:** Supervision, Investigation. **Chun Soo Lim:** Supervision, Investigation. **Jung Pyo Lee:** Project administration, Methodology, Investigation, Conceptualization.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:Jeonghwan Lee reports financial support was provided by Seoul Metropolitan Government Seoul National University (SMG-SNU) Boramae Medical Center.

Acknowledgements

The authors thank the study participants.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.heliyon.2024.e25222.

References

[1] E.F. Carney, The impact of chronic kidney disease on global health, Nat. Rev. Nephrol. 16 (5) (2020) 251, https://doi.org/10.1038/s41581-020-0268-7.
[2] B.L. Neuen, S.J. Chadban, A.R. Demaio, D.W. Johnson, V, Perkovic Chronic kidney disease and the global NCDs agenda, BMJ Glob. Health 2 (2) (2017) e000380, https://doi.org/10.1136/bmjgh-2017-000380.
[3] J.S. Thurlow, M. Joshi, G. Yan, K.C. Norris, L.Y. Agodoa, C.M. Yuan, et al., Global epidemiology of end-stage kidney disease and disparities in kidney replacement therapy, Am. J. Nephrol. 52 (2) (2021) 98–107, https://doi.org/10.1159/000514550.
[4] Y.A. Hong, T.H. Ban, C.Y. Kang, S.D. Hwang, S.R. Choi, H. Lee, et al., Trends in epidemiologic characteristics of end-stage renal disease from 2019 Korean Renal Data System (KORDS), Kidney Res Clin Pract 40 (1) (2021) 52–61, https://doi.org/10.23876/j.krcp.20.202.
[5] J.N. An, J.K. Kim, H.S. Lee, S.G. Kim, H.J. Kim, Y.R. Song, Late stage 3 chronic kidney disease is an independent risk factor for sarcopenia, but not proteinuria, Sci. Rep. 11 (1) (2021) 18472, https://doi.org/10.1038/s41598-021-97952-7.
[6] L.Q. He, X.H. Wu, Y.Q. Huang, X.Y. Zhang, L. Shu, Dietary patterns and chronic kidney disease risk: a systematic review and updated meta-analysis of observational studies, Nutr. J. 20 (1) (2021) 4, https://doi.org/10.1186/s12937-020-00661-6.
[7] J. Lee, S. Oh, H. Kang, S. Kim, G. Lee, L. Li, et al., Environment-wide association study of CKD, Clin. J. Am. Soc. Nephrol. 15 (6) (2020) 766–775, https://doi.org/10.2215/CJN.06780619.
[8] A. Pruss-Ustun, J. Wolf, C. Corvalan, T. Neville, R. Bos, M. Neira, Diseases due to unhealthy environments: an updated estimate of the global burden of disease attributable to environmental determinants of health, J. Public Health 39 (3) (2017) 464–475, https://doi.org/10.1093/pubmed/fdw085.
[9] Q. Zhao, Y. Guo, T. Ye, A. Gasparrini, S. Tong, A. Overcenco, et al., Global, regional, and national burden of mortality associated with non-optimal ambient temperatures from 2000 to 2019: a three-stage modelling study, Lancet Planet. Health 5 (7) (2021) e415–e425, https://doi.org/10.1016/s2542-5196(21)00081-4.
[10] R. Basu, High ambient temperature and mortality: a review of epidemiologic studies from 2001 to 2008, Environ. Health 8 (2009) 40, https://doi.org/10.1186/1476-069X-8-40.
[11] Y.M. Kim, S. Kim, H.K. Cheong, E.H. Kim, Comparison of temperature indexes for the impact assessment of heat stress on heat-related mortality, Environ Health Toxicol 26 (2011) e2011009, https://doi.org/10.5620/eht.2011.26.e2011009.
[12] G.B. Anderson, M.L. Bell, R.D. Peng, Methods to calculate the heat index as an exposure metric in environmental health research, Environ. Health Perspect. 121 (10) (2013) 1111–1119, https://doi.org/10.1289/ehp.1206273.
[13] H. Staiger, G. Laschewski, A. Gratz, The perceived temperature - a versatile index for the assessment of the human thermal environment. Part A: scientific basics, Int. J. Biometeorol. 56 (1) (2012) 165–176, https://doi.org/10.1007/s00484-011-0409-6.
[14] N.R. Council, A Guide to Environmental Research on Animals, Natl. Acad. Sci., Washington, DC, 1971.
[15] V.D. Agou, A. Pavlides, T. D, Hristopulos spatial modeling of precipitation based on data-driven warping of Gaussian processes, Entropy 24 (3) (2022), https://doi.org/10.3390/e24030321 (Basel).
[16] N. Cho, E. Kim, J.-H. Lim, B. Seo, S. Kang, Developing drought stress index for monitoring Pinus densiflora diebacks in Korea, J Ecol Environ 44 (1) (2020), https://doi.org/10.1186/s41610-020-00156-9.
[17] R.P. Parman, N. Kamarudin, F.H. Ibrahim, A.A. Nuruddin, H. Omar, Z. Abdul, Wahab geostatistical analysis of mangrove ecosystem health: mapping and modelling of sampling uncertainty using kriging, Forests 13 (8) (2022), https://doi.org/10.3390/f13081185.
[18] H.J. Tsai, P.Y. Wu, J.C. Huang, S.C. Chen, Environmental pollution and chronic kidney disease, Int. J. Med. Sci. 18 (5) (2021) 1121–1129, https://doi.org/10.7150/ijms.51594.
[19] V.A. Luyckx, K.R. Tuttle, G. Garcia-Garcia, M.B. Gharbi, H.J.L. Heerspink, D.W. Johnson, et al., Reducing major risk factors for chronic kidney disease, Kidney Int. Suppl. 7 (2) (2017) 71–87, https://doi.org/10.1016/j.kisu.2017.07.003.
[20] R. Basu, W.Y. Feng, D. B, Ostro Characterizing temperature and mortality in nine California counties, Epidemiology 19 (1) (2008) 138–145, https://doi.org/10.1097/EDE.0b013e31815c1da7.
[21] A. Zanobetti, J. Schwartz, Temperature and mortality in nine US cities, Epidemiology 19 (4) (2008) 563–570, https://doi.org/10.1097/EDE.0b013e31816d652d.
[22] N. Thomas, S.T. Ebelt, A.J. Newman, N. Scovronick, R.R. D'Souza, S.E. Moss, et al., Time-series analysis of daily ambient temperature and emergency department visits in five US cities with a comparison of exposure metrics derived from 1-km meteorology products, Environ. Health 20 (1) (2021) 55, https://doi.org/10.1186/s12940-021-00735-w.

[23] S.B. Henderson, J.S. Gauld, S.A. Rauch, K.E. McLean, N. Krstic, D.M. Hondula, et al., A proposed case-control framework to probabilistically classify individual deaths as expected or excess during extreme hot weather events, Environ. Health 15 (1) (2016) 109, https://doi.org/10.1186/s12940-016-0195-z.
[24] M. Lee, L. Shi, A. Zanobetti, J.D. Schwartz, Study on the association between ambient temperature and mortality using spatially resolved exposure data, Environ. Res. 151 (2016) 610–617, https://doi.org/10.1016/j.envres.2016.08.029.
[25] Z. Zhang, J. Reinikainen, K.A. Adeleke, M.E. Pieterse, M. C G, Groothuis-Oudshoorn Time-varying covariates and coefficients in Cox regression models, Ann. Transl. Med. 6 (7) (2018) 121, https://doi.org/10.21037/atm.2018.02.12.
[26] J.D. Higbee, J.S. Lefler, R.T. Burnett, M. Ezzati, J.D. Marshall, S.Y. Kim, et al., Estimating long-term pollution exposure effects through inverse probability weighting methods with Cox proportional hazards models, Environ Epidemiol 4 (2) (2020) e085, https://doi.org/10.1097/EE9.0000000000000085.
[27] J. Jung, J.Y. Park, Y.C. Kim, H. Lee, E. Kim, Y.S. Kim, et al., Effects of air pollution on mortality of patients with chronic kidney disease: a large observational cohort study, Sci. Total Environ. 786 (2021) 147471, https://doi.org/10.1016/j.scitotenv.2021.147471.
[28] M. Borg, P. Bi, M. Nitschke, S. Williams, S. McDonald, The impact of daily temperature on renal disease incidence: an ecological study, Environ. Health 16 (1) (2017) 114, https://doi.org/10.1186/s12940-017-0331-4.
[29] W.S. Lee, W.S. Kim, Y.H. Lim, Y.C. Hong, High temperatures and kidney disease morbidity: a systematic review and meta-analysis, J Prev Med Public Health 52 (1) (2019) 1–13, https://doi.org/10.3961/jpmph.18.149.
[30] S.E. Kim, H. Lee, J. Kim, Y.K. Lee, M. Kang, Y. Hijioka, et al., Temperature as a risk factor of emergency department visits for acute kidney injury: a case-crossover study in Seoul, South Korea, Environ. Health 18 (1) (2019) 55, https://doi.org/10.1186/s12940-019-0491-5.
[31] J. Liu, B.M. Varghese, A. Hansen, M.A. Borg, Y. Zhang, T. Driscoll, et al., Hot weather as a risk factor for kidney disease outcomes: a systematic review and meta-analysis of epidemiological evidence, Sci. Total Environ. 801 (2021) 149806, https://doi.org/10.1016/j.scitotenv.2021.149806.
[32] L. He, B. Xue, B. Wang, C. Liu, D. Gimeno Ruiz de Porras, G.L. Delclos, et al., Impact of high, low, and non-optimum temperatures on chronic kidney disease in a changing climate, 1990-2019: a global analysis, Environ. Res. 212 (Pt A) (2022) 113172, https://doi.org/10.1016/j.envres.2022.113172.